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Assessing performance evaluation and credit risk of energy companies with Multicriteria decision models

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List of publications

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Conferences

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Introduction

Performance evaluation is a structured process that allows to assess the management efficiency of investment projects, workforce or business progress. Organizations that focus on managerial evaluation are more competitive and sustainable than those who do not, thereby creating greatest opportunities for growth and development (Cheymetova and Scherbakov, 2017).

Performance evaluation, however, is not an easy task to perform. Firstly, because it involves several parties (the appraisal, the organization to be evaluated, and a third party in the case in which the company is engaged in commitments to be fulfilled within a certain time frame, APEC Energy Working Group, 2013). Secondly, because it implies a continuous monitoring process for providing transparent feedback in an ever-changing environment. Thirdly, because it requires to identify the most relevant indicators and to manage them simultaneously.

The need to have relevant performance measures, which reflect the whole organization value, along with reliable methods able to make, as much as possible, a proper performance evaluation, is even more important for those companies operating in the key economic sectors.

In this regard, the energy industry is one of the leading sectors of the modern society that enhances the social and economic development of a country. As stated by the document of the European bank for reconstruction and development (EBRD, 2013): “Economies run on energy; it fuels all commercial and public life”.

During the last decades, the energy sector has gone through several deregulation phases, allowing for the new entrance of competitors to buy and sell electricity. This renewed competitive structure has led different categories of stakeholders (utilities, governments, investors) to face with unprecedented complex problems, such as more alternatives to evaluate (energy companies), multiple and conflictual criteria to manage (technical, environmental, socio-economic) and a higher level of uncertainty to deal with (Diakoulaki et al., 2005), that were no longer solvable with traditional models.

Multi criteria decision aid (MCDA) models, thanks to their multi-dimensional nature, easiness of application and ability to include different Decision Maker’s preferences, appear as the most suitable models to help multiple decision makers in solving two of the most crucial issues of the energy sector: the performance evaluation and the credit risk assessment of energy companies.

The first problem arises from the more extensive role of investment plans in stimulating energy companies’ business growth, through innovations of services, delivery manner and used technologies. Thus, a closer inspection of the firm’s state of health is required in decision-making process to optimize capital allocation and therefore to identify the best alternative within the multidimensional context of the energy system performance.

The second one derives from the fact that serious episodes of energy companies' failures have occurred after liberalization policies, leading countries where they took place, to considerable economic losses. In order to prevent these potential financial crashes, it is needed the use of proper risk assessment models, which are able to predict failures with a high accuracy rate.
Despite the great relevance of the energy sector in the modern economy, the existing MCDA literature on firms' performance evaluation and credit risk assessment is not so wide and limited to the analysis of financial dimension.
In order to deal with the aforementioned issues and to fill the present research gap, this thesis is organized as follows.
Chapter 1 provides a general overview of the energy sector, in view of the recent energy transition policies towards renewable power sources. The focus is on the relationship between energy consumption and economic growth of past few years (Section 1.1) and the structure of the Electric Power System with regard to the role of government in avoiding energy companies' failures (Section 1.2). Moreover, we highlight the role of multi-criteria methods in the performance evaluation and credit risk assessment (Section 1.3) and the key notions on which the MCDA models applied in this study are based, i.e. HSMAA, M.H.DIS and PROMETHEE (Section 1.4).
Chapter 2 analyses the development of a performance assessment model, the Hierarchy Stochastic Multi-Attribute Analysis (HSMAA), for the most important listed companies operating in the energy sector, using a dataset obtained merging different sources. HSMAA is employed to handle with a hierarchical criteria structure and imprecision on criteria weights, enabling to evaluate the performances of companies under different uncertainty scenarios.
Chapter 3 presents the implementation of a non-parametric multiple criteria decision aiding (MCDA) model, the Multi-group Hierarchy Discrimination (M.H.DIS) model, with the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), to evaluate the average accuracy rate in correctly predicting the failure risk of a dataset of European unlisted companies operating in the energy sector.
Finally, Chapter 4 contains some concluding remarks and future developments.

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Chapter 1

The energy sector and the role of MCDA models

Energy is the lifeblood of the worldwide economy that provide input for all good and services of the modern society. Since early 1900s, in particular electrical energy, has improved life-standards of population and driven the social and economic growth of a country by providing the key sources for most of economic activities. Its support to the country's economic growth is twofold: firstly, it directly contributes to the creation of new job positions and to generating value through the mining, generation, transformation and distribution activities; secondly it sustains significantly the rest of the economy by providing essential Stern products and facilities to all sectors.
In this regard, the ecological economist David Stern, in his paper entitled "The role of Energy in Economic Growth", emphasized the relevance of energy sector in enhancing the economic progress of a society due to its special features of non-substitutability and storability for a long time (Stern, 2010).
In order to recognize the value of energy sector in the modern economy and therefore to understand the motivations that led us to consider multicriteria models for this study, this Chapter outlines first the link between energy consumption and economic growth up until now and for next years, in the light of the recent renewable energy sources programmes. Then the structure of the Electric Power System is presented along with the key liberalization directives, to comprehend the reasons behind the transition from the monopoly regime to the competition and the effects of energy market deregulation on energy companies. After that, the role of multicriteria methods in the performance and creditworthiness assessment of energy companies is discussed, by introducing the basic notions of multi-criteria models, the most common elements of their main applications in the energy sector and the literature review of the most employed MCDA methods in firms' performance evaluation and credit risk assessment. Finally, the key concepts of the three MCDA models employed respectively in Chapter 2 and Chapter 3 are described.

1.1 The impact of energy sector on global economy

In the wake of the energy crises in 1970's, where high-level of energy prices reduced dramatically the economic development of countries, a large number of studies have been conducted to examine the relationship between energy consumption and economic growth. Most of them argue that the increase of energy for transport, residential and industrial uses, directly causes Gross Domestic Product (GDP) to rise; some others provide empirical evidences of the high and positive correlation between energy consumptions and economic growth in different countries (see for a literature review on this topic: Ozturk, 2010; Payne, 2010; Tiba and Omri, 2017 and Waheed et al., 2019). Although the direction of causality is still debated, usually the impact of energy consumption on economic growth has been widely

measured with different macroeconomic indicators such as the gross domestic product (GDP), employment and welfare (Liko, 2019).
In order to highlight how energy consumption affects the economic development of a country, we focus on these variables to detect their worth in the current economy.
GDP is the most used indicator for income and growth that reflects the value of total output produced by an economy during a year and adjusted for inflation.
Figure 1.1 below shows the pattern of energy consumption and GDP from data provided by the World Bank between the 1990 and 2015 (Jakeman, 2019).

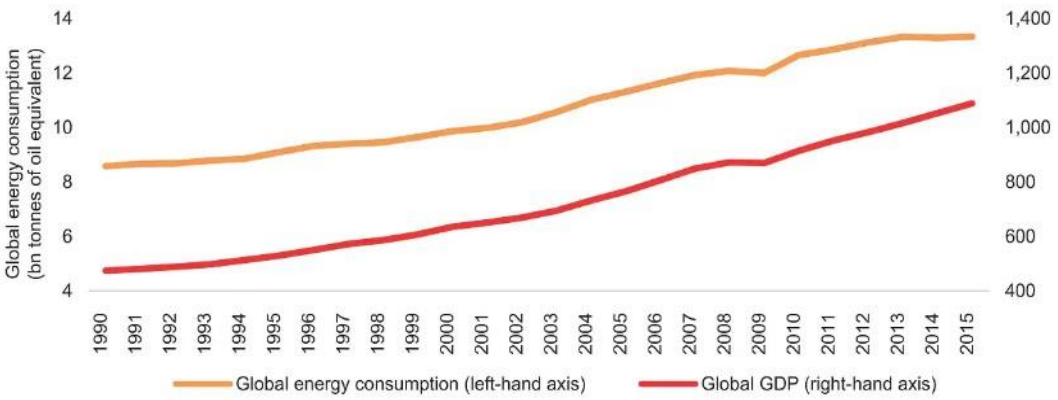


Figure 1.1 Global GDP growth and global energy consumption. Source: World Bank

As observed from this graph, energy consumption and gross domestic product have increased with a similar trend during years, highlighting a very high positive correlation. Energy consumption is required for many aspects of GDP growth such as electricity, transportation, heating and cooling and this chart is perfectly in line with what we would expect: the wider the energy use, the higher the GDP growth. Moreover, over the past 15 years, the global economic growth has increased faster (+2.8%) than the global energy consumption (1.6%) as result of energy efficiency improvement.
However, energy consumption and economic growth does not provide only benefits. For instance, the environmental effects generated by energy consumption, like the air and water pollutant emissions and the land issues related to coal mining and other power production, have to be considered for a deeper analysis. Debates about how to reduce these negative externalities are faced by current policies that promote the use of non-polluting energy sources to enhance the economic well-being of population and environment. Thus, the expansion of renewable energies and the improvement in energy efficiency will be the Action Priorities of leaders in coming years, as better explained in Section 1.1.1 (World Energy Issues Monitor, 2020).
The report issued by the International Renewable Energy Agency (IRENA) offers a good example of these new environemntal concerns, by providing a comparison between the

Planned[1] and the Transforming energy scenario[2] in terms of GDP growth, employment and welfare (IRENA, 2018). Figure 1.2 shows the positive effects of the IRENA's Renewable Energy Roadmaps (Remap) towards the global GDP of 2018-2050 in both scenarios.

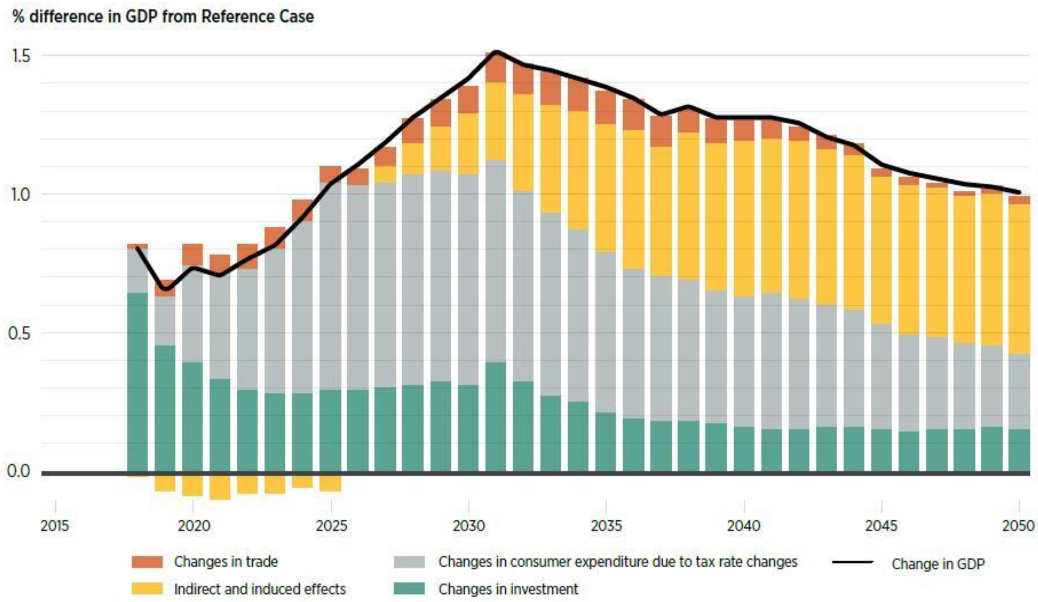


Figure 1.2 The energy transition results in GDP growth higher than the planned scenario between 2018-2050. Source: IRENA

The GDP growth under the Transforming scenario has a consistent positive effects compared to the Planned one. However, the highest value of GDP growth (1.5%) is expected to be reached in 2031 and decrease slowly in 2050 (1%) for both scenarios. Moreover, the GDP growth is driven by the change in four major elements: investments, trade, tax and other inderect and induced effects. Among these, investments in renewables, energy efficiency, infrastructures and technologies' flexibility (indicated in green), play a key role in stimulating GDP growth, especially in the first half of the energy transition, followed by changes in consumer expenditures due to tax rate changes (in grey). After the 2027, IRENA expects that the indirect and induced effects (in yellow) caused by the changes in consumer spending, contributes more to GDP growth than the change in energy and non-energy trade (in red) such as import or export.
With respect to the second economic growth indicator, the employment indicator, often considered for its ability to enhance the economic productivity, the individual benefits and the social stability, Figure 1.3 shows the estimates of jobs within the energy sector by 2030 and 2050 under the aforementioned scenarios (IRENA, 2020).

[1] Planned Energy Scenario (PES): is a projection of the energy system developments based on governments' current energy plans and other planned targets as of 2019.

[2] Transforming Energy Scenario (TES): is the most recent scenario planned to keep the rise of temperature below 2 degree Celsius (°C) through a renewables and energy efficiency based transformation.

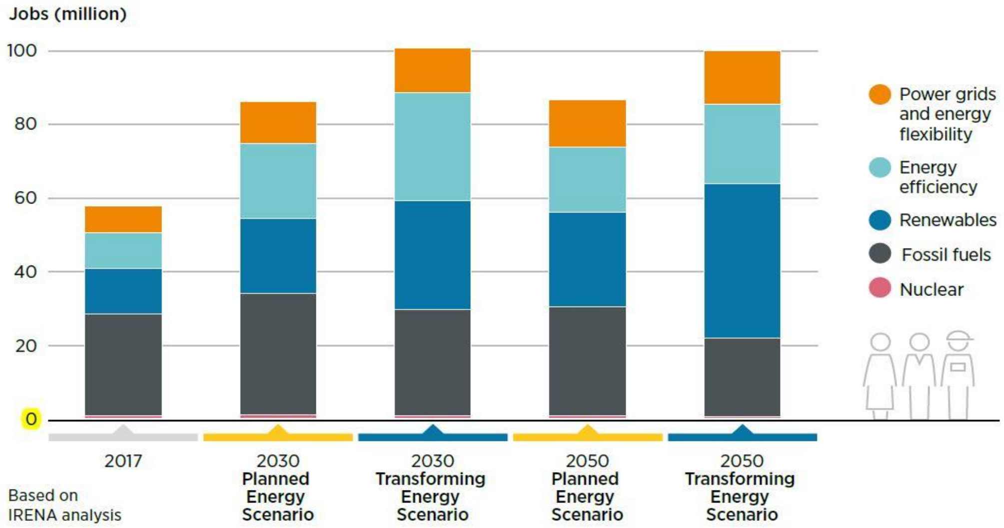


Figure 1.3 The energy sector jobs growth under the planned and transforming energy scenarios in 2017-2030-2050. Source: IRENA

In both 2030 and 2050, the transforming energy scenario is expected to be higher than the planned (+15%) and the current one (+72%). The job composition of next years is expected to be different from that of 2017, due to a wider deployment of renewable energy technologies, the transition progress towards energy efficiency and the system flexibility.
Jobs and GDP growth capture only the socio-economic condition of a country, without reflecting about the quality of life improvement arising from the energy transition. Thus, a composite indicator has been built by IRENA, to assess the multifaceted nature of welfare developments. It consists of three dimensions, economic, social and environmental, each one derived by two sub-indicators as shown in Figure 1.4. Again, the welfare is higher under the transforming energy scenario than the planned one where the environmental and social dimension prevail by limiting the pollutants.

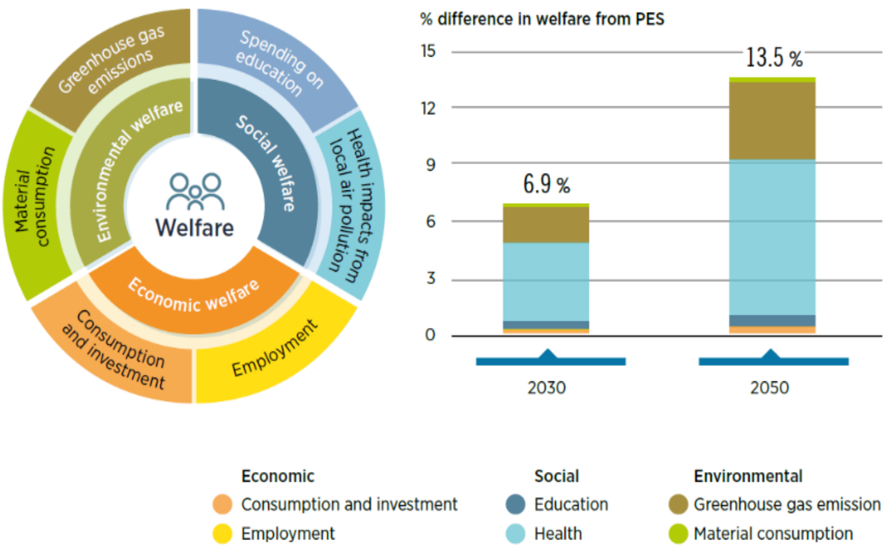


Figure 1.4 Global welfare indicator under the Transforming Energy Scenario in 2030-2050. Source: IRENA

1.1.1 The renewable energy and the sustainable development

In recent years, the global energy system has faced a dual challenge: on the one hand, the need for more energy; on the other hand the less carbon emissions. Renewables, being clean and non-exhaustible energy sources, represent an interesting alternative to deal with these issues.

Renewable energy is defined as the energy produced by non-fossil sources like hydropower, wind, solar photovoltaic, solar thermal, geothermal, tide, renewable municipal waste, solid and liquid biofuels and biogases (Union, 2018).

Their importance is growing over the years, due to the heightened attention of European policies thereafter the Kyoto Protocol of December 1997 for lowering the greenhouse gas emissions (GHGs) and increasing the energy supply security.

The original renewable energy directive in Europe is dated to 2009 (2009/28/EC) and marked the start of a policy centred on the production and promotion from renewable energy sources (Union, 2009). This directive was revised to Renewable Energy Directive (2018/2001/EU) that aim to achieve two goals: to make Europe the global leader of renewables and to lower its pollutant emissions. In order to achieve these aims, the Directive fosters to cut GHGs of at least 40% compared to 1990, boosts countries to use at least 32% of RES in total final energy consumption and encourages to improve at least 32.5% in energy efficiency (Union, 2018).

Recently, new measures have been proposed by the European Community to achieve important targets by 2030. For instance, the 2030 Agenda for sustainable development includes the goal "to ensure access to affordable, reliable, sustainable and modern energy for all", enhancing the international cooperation and expanding infrastructures to simplify access to clean energy and sustainable energy supply services (Desa, 2016).

Despite the great efforts implemented by latest political strategies, the recent Tracking SDG7: Energy Progress Report of 2020, highlights that the world is far to meet targets by 2030 under the current policies (IEA et al., 2020). Indeed, in 2018 almost 790 millions of people around the world had no access to electricity, especially in Sub-Saharan Africa. However, the number is falling compared to 1.2 billion in 2010 and data on renewable electricity consumptions reveal that mainly the developed countries are moving towards the right direction, showing an increasing of almost 6% in 2017.

Moreover, Figure 1.5 and Figure 1.6 show respectively the Global renewable electricity consumption by technology from 1990 to 2017 and the share of renewable in electricity consumption by region. Figure 1.5 displays that the share of renewables in global electricity consumption has reached the 24.7% in the last year and the hydropower generation remains the largest source of renewable electricity although it has declined in favour of wind (+35%), modern bioenergy and solar PV energy (+18%). Figure 1.6 highlights that Latin America and The Caribbean present the highest share of renewables in electricity consumptions for hydropower and bioenergy resources; while in Europe, Northern America and Oceania, hydropower remains the largest sources of renewable generation, followed by wind and solar PV.

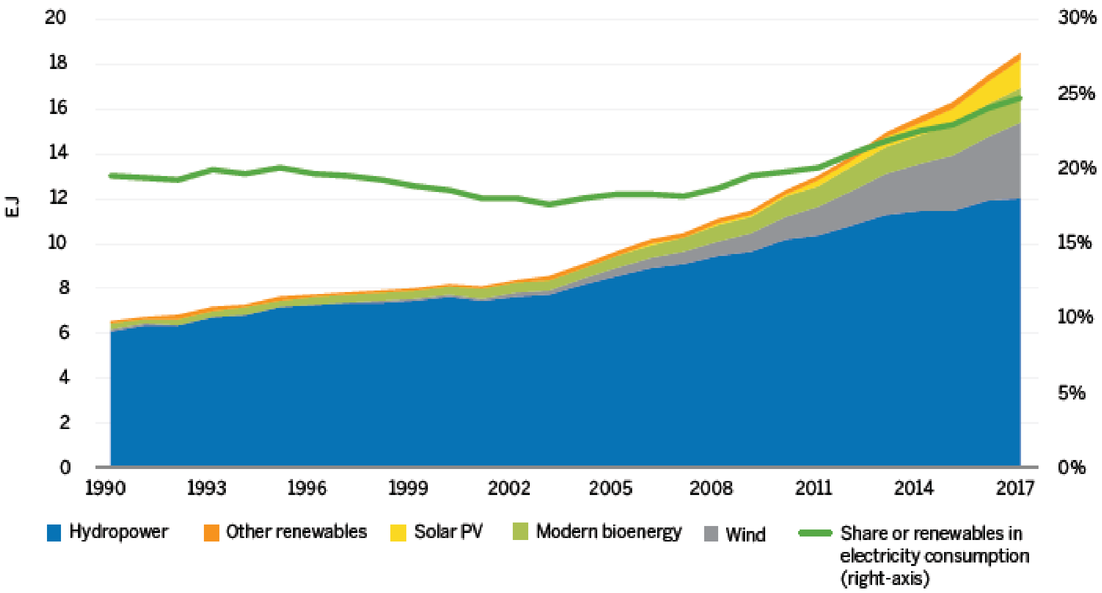


Figure 1.5 Global renewable electricity consumption by technology, 1990-2017. Source: EIA and UNS

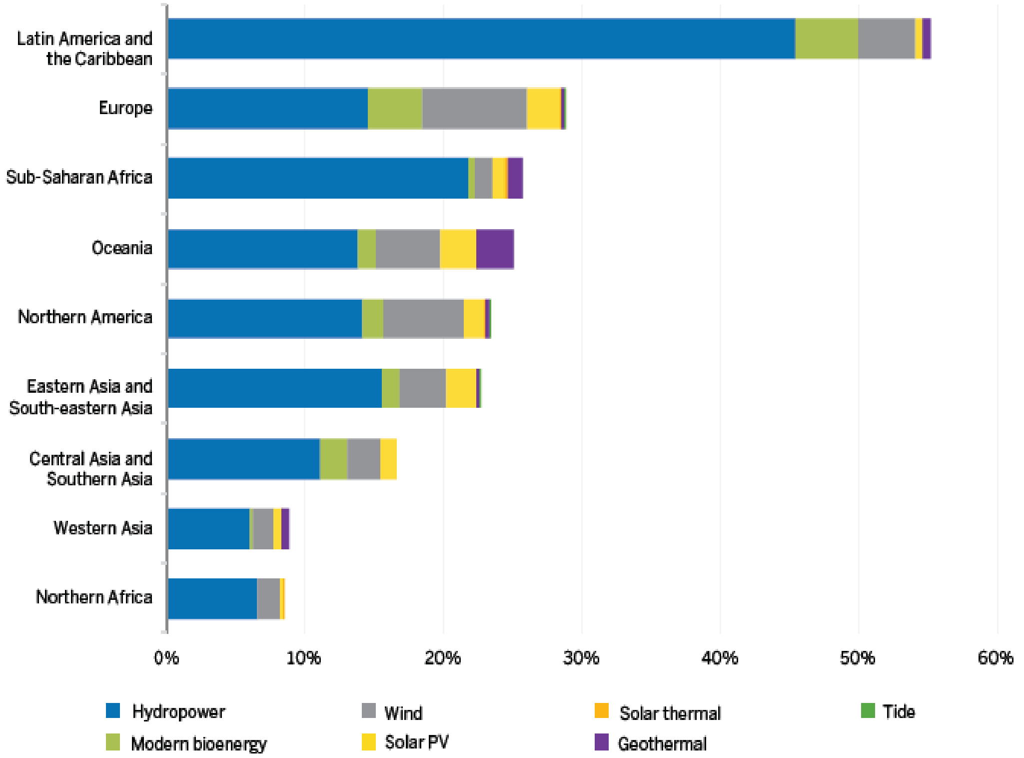


Figure 1.6 Share of renewables in electricity consumption by region, 2017. Source: EIA and UNSD.

Thus, as the share of RES deployed in energy mix production and global consumptions increases, the policies that drive organisations evolve by generating benefits in terms of new jobs and economic well-being. The relationship between energy and economic development, previously identified, is therefore realised.

1.2 The structure of the Electric Power System and the role of government.

Since the Second World War, the electricity supply model was based on a fully integrated statutory monopoly. European countries nationalized energy industry for several reasons: to reorganize production facilities eliminating territorial inequalities, to expand companies' size and their marketplace competitiveness with public funds, to provide a greater coordination between power production and transmission system and to protect particular categories of end-users.
To pursue these aims, since 1996, the most effective government tool was the introduction of competition in those electric power segments where the natural monopoly was not necessary. In order to understand deeply this aspect, we provide a brief description of the electric power system structure.
The *Electric power system* is identified with the physical structure that makes electric service available to consumers. Because of non-storability of electricity, the network system is highly complex and energy companies have to be able to respond to an ever floating demand for tackling any peaks on it. The over-production capacity is therefore the only way to ensure the continuity of the service, even in front of structural inefficiencies.
Figure 1.7 represents the structure of the Electric Power System in four different segments: the power generation, the transmission, the distribution and the selling system (US-Canada Power System Outage Task Force, 2004).

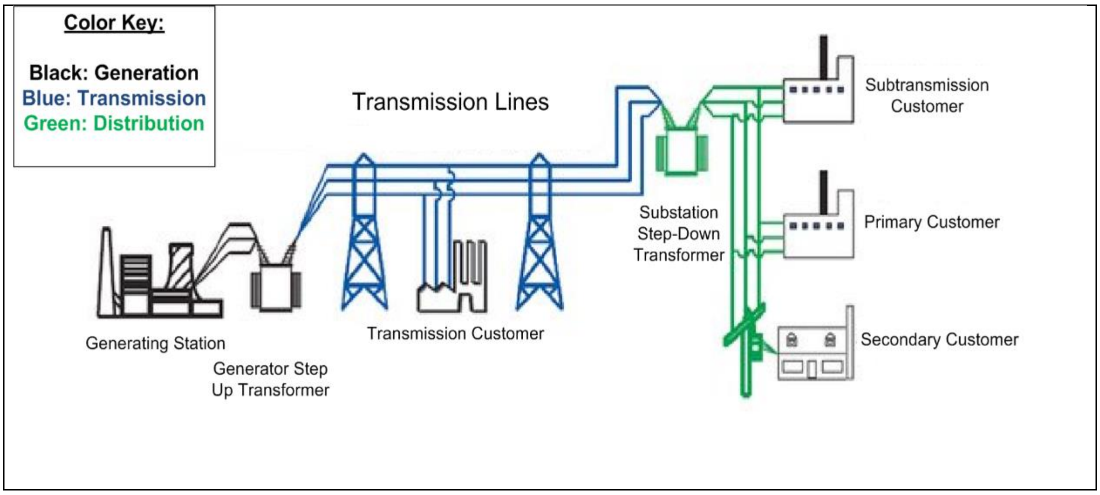


Figure 1.7 Simplified picture of a typical electric power system. Source: US-Canada Power System Outage Task Force (2004)

- Power generation: consists in the production of electrical energy through the direct or indirect primary energy sources transformation. In addition, according to whether a power plant uses renewable (like solar, wind, water, hydro, geothermal and biomass) or not-renewable energy sources (like coal, oil, nuclear, diesel and natural gas), it is distinguished in traditional (thermoelectric, hydroelectric, geothermal, nuclear) or innovative power plant (cogeneration, combined cycle, exploiting renewable energy sources);

- Transmission system: is responsible for delivering generated electricity over long distances, usually from a generating site located outside of densely populated areas to the distribution grid situated closer to the population. The main characteristic of this system is the transmission of electrical energy with *overhead lines* at very high voltage (100kV-800kV), covering long distance with minimum power losses (Stenhouse et al., 2020a);
- Distribution system: it distributes power from high-voltage transmission system to end-use consumers through lower voltages lines (26kV-69kV) like *Underground* and *Sub transmission lines* (Stenhouse et al, 2020b);
- Selling system: it consists in providing the electrical service to end-users. It involves therefore the definition of a different tariff option for type of customers, the seller's liability for the electrical power availability of end-users within the timeframe and under the conditions laid down in the agreement, the parameters measurement, the billing and the related commercial activities.

In the electric power system, energy producers (i.e. power generation) compose the supply, individual and industrial consumers constitute the demand and the transmission and distribution system, with their unique and not replicable structure, create the link between the demand and the supply. Thus, two questions arise: *what is the best organizational regime for the electric supply chain in view of this specific structure? What is the role of the government in this sector*?

In the energy industry, since the main aim is to minimize the cost of production and to increase the efficiency of companies without generating their power market abuse, the ideal solution is introducing competition and/or natural monopoly in those segments where it is necessary. Thus, power generation and selling segment are suitable to be organized competitively because of their economies of scales linked respectively to power plant production and wholesale market price variability; whereas, transmission and distribution division represent a natural monopoly system because they need fixed lines and high upfront building costs.

In view of this organization, in the early nineties, the electricity supply model was converted from a fully integrated statutory monopoly to a more competitive system. This has been made possible through the liberalization policies.

1.2.1 The Liberalization of electricity supply in Europe

The recent European Energy Directives were aimed to achieve the following two headlines targets by considering the peculiarities of this sector: the creation of a single internal energy market and the development, as far as possible, of a more competitive environment. These two targets were considered the basics for carrying out other central goals, such as the greater production efficiency, the general reduction of prices and the increasing security of supply.

However, to reach these aims, governments had to tackle with several difficulties due to the specificity of the electricity sector and its political, technical and economic setting. Firstly, electricity, being a commodity involved into the technological progress of a country, is an

essential and special good compared to the others. Secondly, from the political point of view, national monopolies, often owned by government, managed different segments of the electricity supply chain due to the vertical integration of the electricity system. Thirdly, taking into account the technical aspect, the electricity system is a tricky process to be introduced in a unique European market, because of its non-storability and the compliance to specific physical law. Compared to any other technological commodities, it takes part of a larger system where different phases are coordinated each other and if one of them delays or advances at one stage, the whole system will be affected. Fourthly, from the economic perspective, two conditions occur from the sudden market opening: consumers begin to pay less and producers start to enter in new markets and to deal with new competitors (Léautier and Crampes, 2016).
In such articulated system, it is fundamental to introduce common European policies supporting stakeholders who are in trouble.

1.2.1.1 The key European directives: the directive 96/92/EC and the more recent ones.

The *Directives 90/377/EEC and 90/547 EEC* issued in 1990, introduced the first common elements in the European energy sector. These directives were aimed to communicate all relevant information to industrial end-users and consumers in terms of prices and sale conditions, and to create an alignment of different national regimes by regulating the conditions of network access to cross-border exchanges. However, these generic rules gave national legislatures sufficient latitude based on subsidiarity.
The first significant Community Directive for the electricity market was the *Directive 96/92/EC*, undersigned by the European Parliament on 19 December 1996, which covered common electricity market principles and where all segments of the electricity industry chain were regularised properly. For instance, in the *Power generation* was allowed the construction of new power plants through authorisations or tendering procedures that brought down entry barriers and laid the foundation of a regulated competitive regime. In the *Transmission system*, each Member State designated the management (but not the ownership) of the national transmission network to only one subject responsible of dispatching and independent from other activities unrelated to the transmission system. In the *Distribution system*, the European legislator adopted a partition of national territories in local monopolies by providing a regulated charging system for customers served by distributors. Finally, in the *Selling system*, consumers were free to choose their provider according to their annual power consumption and therefore market was opened progressively to all consumers groups.
More recently, the *Directives 2003/54/EC* and *2009/72/EC* have introduced few changes in comparison to the previous ones such as, the independence and the market power of transmission and distribution providers, the consumers' protection and the greater opening up of the market, the stronger connection among national markets, the security of supply and the facilitation of competition.

1.2.1.2 Consequences of deregulation in the energy market

The aim to create a unique European market with lower wholesale electricity prices and a broader competition between producers and providers has been reached with liberalisation (Kočenda and Čábelka, 1998; Meyer, 2003). It was a great success for Europe, since any consumer could buy from any producer within the continent and any producers could have a direct access to a global market composed by millions of customers.
However, different examples offer arguments against liberalisation and in favour of a market redesign. Among the most significant:

- the financial difficulties faced by electricity suppliers;
- the government intervention for ensuring security of supply and energy transition.

With regard to electricity suppliers, some energy companies faced significant financial distress after deregulation processes, which had threatened their very survival. The specific situations depended on the companies' characteristics but the reasons of problems were analogous: the management structure of the electricity incumbents was not aligned to the creation of a unique and more competitive electricity market. Incumbents had undervalued the increasing impact of renewable energy sources (RES) in the power production, for the future development of electricity market. To strengthen their market share, they believed more on the economic and technological upgrading than the power of renewable energy and failed to grasp the police maker's desire to fund such renewal production with limited emphasis to the economic efficiency. Moreover, with the recent opening of the market, electricity suppliers could not charge customers for their mistakes, as companies also had before the reform by making prices transferrable to the end-users through the electric surplus obtained by the overcapacity of power generation with respect to the demand (Léautier and Crampes, 2016).
The only entities able to solve the financial difficulties of energy companies could be national governments. In most of cases, their attitude was positive. Indeed, governments, being shareholders of national energy suppliers, felt responsible for the financial distress of energy companies and worried about the potential impact of this crisis on the job losses and therefore on economic growth.
Thus, leaders preferred to monitor the energy industry for guaranteeing security of supply and energy transition at global level. The security of supply was ensured by maintaining the capacity adequacy with a power production able to cover the peak demand and satisfying the exceptional events. Moreover, the government intervention was justified for pursuing a global transition toward a cleaner energy with specific actions. The most important were: the reduction of negative externalities like the greenhouse gas emissions, the introduction of subsidies like the green and white certificates, the creation of new renewable technologies and the centralized planning where the production mix was decided preventively.

1.2.1.3 Examples of energy companies' failures

In the last twenty years, the electricity sector has tackled serious cases of failures as consequence of deregulation processes. In this section, we provide a brief description of the most noteworthy examples of energy crisis occurred all over the world to highlight the economic effects of such events.

One of the best-known case is the California energy crisis, which involved the distribution companies from 2000 to 2001. California was the first state to launch the competition in the energy sector (1998) and it was considered, by other American countries, as the prototype of liberalization. This energy market was one of the biggest in the United States accounting for 246 billion kWh of annual electricity consumption and the largest power grid in the world (Taylor and Van Doren, 2001; Stuebi, 2001). However, it encountered a regulatory crisis in May 2000 (Safai, 2011). According to the book of McNamara (2002), the following eight factors contributed to the energy crisis: the failure of the wholesale electricity market, the asynchrony between power supply and demand, the reduction of cross-border power imports, the unhelpful in-state generation, the rapid increase of the wholesale electricity prices, the obstacles in the transmission grid, the weather conditions and the accusation of system deceptions. Among these, the sudden rise of the wholesale prices (+ 800%) while keeping the retail prices low, was the main cause to financial indebtedness of Californian distribution companies (Razeghi et al., 2017). In this situation, the state was determinant to avoid their complete financial crash by purchasing power and issuing bonds. However, the prices of electricity rose again and some distribution companies such as Pacific Gas and Electric Co. went to bankruptcy (Ardiyok, 2008).

In 2001, the Brazilian energy system suffered the same fate as California. Here the main causes were the delay in investments and the climate conditions. Indeed, with liberalization processes, the Brazilian government did not invest in power generation and transmission systems because of the high expectations of private intervention and the fulfillment to a policy of economic stabilization. These events failed to be realized and led the risk of power outage to increase between 1998 and 2001 (Jardini et al., 2002).

In UK, the financial collapse of British Energy plc is dated 2000, when the fall in the wholesale electricity prices generated significant effects over other US electricity companies such as Edison International and AES and TXU Europe. The British Energy, being a nuclear company, had to bear large fixed costs related to fluctuations in energy prices, which compromised its operating and financial leverage and made it riskier than any other fossil fuels companies (Taylor, 2010).

A more recent example concerns the distress of Electricaribe in the north of Colombia during the period from 2015 to 2016. It faced a severe crisis due to the non-payment of electricity by a consistent share of private and public customers (over 25%) (Osorio et al., 2017). In the same years, the incident of El Nino, led the electricity price to rise considerably, creating liquidity problems for the company. Thus, the company became unable to get the credit it needed and to deliver the energy to its end-users. As consequence, electricity shortages become frequent and the state was forced to absorb the company to guarantee energy supply. Furthermore, the study of Larsen et al. (2018), suggests that other energy companies such as the Dong, EDF, Vattenfall, E.ON Endesa, Enel, Centrica, SSE, faced similar crisis like the ones just described.

As observed by these examples, in electricity sector critical companies are not allowed to go bankrupt since these failures have the potential to generate serious effects on the economy of a country such as, large expenses, power cut and reduced available sources for industrial production, that governments have to prevent. In order to properly give an idea of the impact that the energetic failures can have in terms of costs, we mention the study of Walker et al., (2014) that has estimated the cost of electricity crisis in California during the 2000-2001 to be almost $40 billion, corresponding to a GDP loss ranging from 0.7 to 1.5%.
In order to prevent domino effects on the economy, it is fundamental a constant monitoring of energy companies' financial performances. Therefore, it would likely to be expected that in the next years stakeholders such as employees, providers and owners (for small companies) or shareholders (for large companies) as well as policy makers should focus on this topic with proper methods.
In next Section, we highlight how multicriteria models are the most suitable tools to deal with the multi-dimensional issues of the energy sector.

1.3 The role of MCDA methods in the performance evaluation and credit risk assessment of energy companies

1.3.1 Basic notions of MCDA models

Multiple Criteria Decision Making and Multiple Criteria Decision Analysis are two terms that become popular respectively with the acronyms of MCDM and MCDA due to the paper of Ziont (1979). MCDA is a discipline that falls within the broader framework of Operations Research (OR) dealing with the applications of innovative mathematical methods to help a Decision Maker (DM) in making better decisions. More specifically MCDA is a collection of formal approaches to support Decision Makers (DMs), in structuring and solving complex decisions that involve a set of conflictual and multiple criteria (for some survey on MCDA see Roy, 1990; Belton and Stewart, 2002; Figueira et al., 2005). Because of the multi-dimensional nature of decision-making problems, a unique best solution does not exist and analysts need to incorporate subjective information, better known as decision maker's preferences, to solve the problem. In this regard, the statement of Belton and Stewart (2002) encloses in few lines the main objective of MCDA:

"the aim of good MCDA is to facilitate decision makers' learning about the many facets of an issue in order to assist them in identifying a preferred way forward".

In MCDA framework, some key concepts need to be defined (Belton and Stewart, 2002; Greco et al., 2016):

- *Alternatives*: constitute the options, the solutions or the actions of a decision-making problem. Usually they are denoted with the finite set $A = \{a_1, \cdots, a_j, \cdots, a_m\}$ where

m represents the total number of alternatives involved in the decision process;

- *Criteria*: are the attributes or the point of views under which alternatives are evaluated and compared each other. A coherent[3] family of criteria is represented as $G = \{g_1, \cdots, g_i, \cdots, g_n\}$ with n denoting the number of total criteria considered in the analysis (Bouyssou, 1990). Generally, the criterion is a real valued function on the set of alternatives A, i.e. $g_i : A \longrightarrow \mathbb{R}$ that allows to evaluate an alternative $a_j \in \mathrm{A}$ on a criterion $g_i \in \mathrm{G}$ with a partial score $g_i(a_j)$. According to whether the preference value is expressed in a linguistic or quantitative extent, criteria can assume an ordinal or a quantitative scale.
  Moreover, each criterion can have an increasing, decreasing or non-monotonic preference direction. If the preference direction is increasing, then the higher the evaluation of an alternative a_j with respect to g_i, the more preferred is the alternative a_j with respect to g_i. If the preference direction is decreasing, then the higher the evaluation of an alternative a_j with respect to g_i, the less preferred is the alternative a_j with respect to g_i. If the preference direction is non-monotonic, it is neither increasing nor decreasing.
- *Weights*: represent the individual formulation of trade-off existing among the different evaluations of criteria and they are usually denoted with $W = \{w_1, w_2, \cdots, w_n\}$. Through them, DM can express the relative importance of one criterion with respect to another according to its own preferences. The definition of weight differs according to what MCDA model is being applied. For instance, in value function based model the proper meaning of weight is close to that of trade-off; whereas in outranking techniques, the correct interpretation is of “voting power” allocated to each criterion (see Section 1.3.1.1 for a more detailed description on MCDA models and aggregation functions).

With these few elements, it is possible to build the *performance matrix* that summarizes in a unique table the key features of the problem and represents the starting point to develop the decision process. The following performance matrix M is formed for A x G, where $g_i(a_j) = a_{ji}$ is the evaluation in row j and column i:

[3] According to Roy (1996), a family of criteria is coherent if it is based on three notions: exhaustiveness (all the relevant attributes of a decision problem have to be considered), cohesiveness (if two alternatives a_1 and a_2 have the same evaluation of the whole set of criteria except one, and a_1 has a better evaluation on the remaining criterion than a_2, then a_1 is at least as good as a_2), non-redundancy (the withdrawal of one attribute would create a family of criteria not satisfying the former conditions).

$$M = \left[\begin{array}{c|cccccc} & g_1 & g_2 & \cdots & g_i & \cdots & g_n \\ \hline a_1 & a_{11} & a_{12} & \cdots & a_{1i} & \cdots & a_{1n} \\ a_2 & a_{21} & a_{22} & \cdots & a_{2i} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_j & a_{j1} & a_{j2} & \cdots & a_{ji} & \cdots & a_{jn} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_m & a_{m1} & a_{m2} & \cdots & a_{mi} & \cdots & a_{mn} \end{array}\right]$$

Furthermore:

- *Decision maker (DM)*: is the individual or the group of people that would like to solve a decision problem. Generally, three types of problems are identified:
  - *Choice problem* consists of the selection of a subset of alternatives from a given initial set of options;
  - *Ranking problem* requires to rank alternatives in a partial or total order;
  - *Sorting problems* assign each alternative to one or more contiguous preferentially ordered classes;
- *Analyst:* is the expert that thanks to its mathematical expertise guides DMs in all stages of the decision making process (Figure 1.8) for solving the problem;
- *Uncertainty:* in order to solve a decision problem, some elements of uncertainty involving the measurement or the quantification of criteria, the trade-off or the preferences, could arise. Often occurs for instance that criteria are evaluated on a qualitative scale or DM is unable to quantify its preferences on a criterion. However, the analyst needs to incorporate these elements into the model and in order to overcome with the uncertainty issue, different methods have been proposed, such as the interaction between aggregation and disaggregation approach (Jacquet-Lagreze and Siskos, 2001).

Figure 1.8 below shows the decision aid activity organized in three main stages. It combines objectives measurements and the subjectivity of DMs (see Belton and Stewart, 2002 and Cinelli et al., 2020 for a comprehensive taxonomy of the MCDA process characteristics):

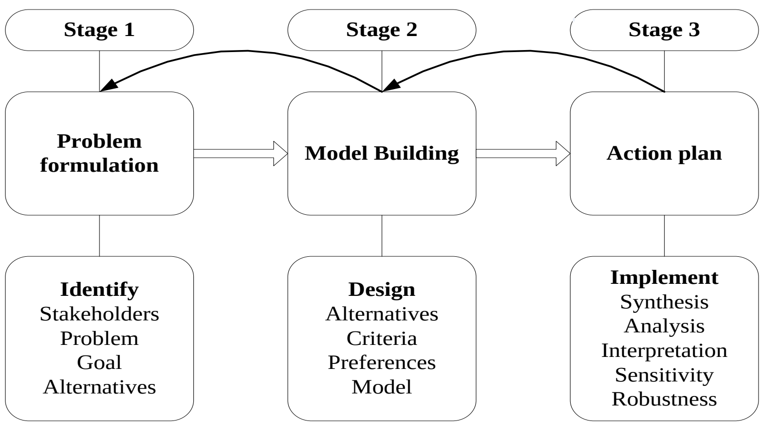


Figure 1.8 Main stages of Decision aid activity. Source: Belton and Stewart (2002)

In stage 1 DMs are advised by the analyst to provide essential information for the decision model development. In this phase, stakeholders have to discuss with analyst about the problem to solve and the goals to achieve. Thus, the identification of a potential set of alternatives, jointly to constraints and values are the key elements in order to apply any multicriteria model.
Stage 2 consists of the development of a preference model. Although it does not exist a specific classification for MCDA methods (Sen and Yang, 2012), three types of models can be identified with different aggregation procedures: value measurement, goal programming or reference level and outranking methods (Section 1.3.1.1). Despite the choice of analyst to use one model rather than another one, in this phase it is fundamental to specify alternatives, to define criteria and to elicit values. Among these, the selection, the organization and the development of appropriate criteria is crucial, and varies according to the problem under investigation. It faces with the issues of data quality, preferential dependency, imprecision and uncertainty determination. Since MCDA models manage with several criteria simultaneously, aggregation procedures have to be provided to the analyst in order to build a model able to support DMs in taking the final decision. To deal with this aim, analyst asks DMs to estimate the model parameters such as criteria weights, indifference thresholds, trade-off and so forth. Moreover, since the direct estimation of parameters is a very complex task for DMs, it can cause the interruption of the whole process. Thus, Stage 2 is crucial for the entire development of a MCDA model.
Once the MCDA model has been applied to the problem under investigation, Stage 3 consists of action plan, i.e. to interpret outcomes, synthetize information and provide a final recommendation to DMs. Since it may happen that the MCDA solution is unexpected and has to be interpreted in relation to the context of the problem, it is required therefore that the results of MCDA model have to be examined and tested for their validity and implications. Thus, this stage implies further analysis of sensitivity and robustness.

1.3.1.1 Main categories of MCDA models and aggregation functions

The following subsection presents the basic notions on the most important MCDA models classified according to Belton and Stewart (2002) in three main categories: value measurement, goal programming or reference level and outranking methods.
However, before providing a thorough description of the most traditional models, it is useful to introduce the mathematical notation employed for comparing alternatives to each other according to the evaluation criterion chosen.
More specifically, for alternatives $a_1, a_2 \in A$ it is assumed that:

- $a_1 P a_2 \Leftrightarrow g_i(a_1) > g_i(a_2)$ and
- $a_1 I a_2 \Leftrightarrow g_i(a_1) = g_i(a_2)$

where P and I indicate the binary relations between the two alternatives, respectively with the meaning of “a_1 is strictly preferred to a_2” ($a_1 P a_2$) and “a_1 is indifferent to a_2” ($a_1 I a_2$) with regard to the criterion g_i.

In some models, any kind of difference between the two evaluations, even if minimal, indicates a strict preference of one alternative over the other; in other models, it is more reasonable to assume that small differences $g_i(a_1) - g_i(a_2)$ among alternative evaluations are consistent with an indifference condition, leading to another model of comparison (Bouyssou, 1990):

- $a_1Pa_2 \Leftrightarrow g_i(a_1) - g_i(a_2) > \mathrm{q}$ and
- $a_1Ia_2 \Leftrightarrow |g_i(a_1) - g_i(a_2)| \leq \mathrm{q}$

where q is the indifference threshold. Thus, a difference $g_i(a_1) - g_i(a_2)$ wider than q gives a strict preference of an alternative over the other, also if the difference is close to q; otherwise it leads to an indifference condition. Moreover, because of the sudden variation from a strict preference to an indifferent condition, it may be useful to introduce a "baffer zone" where the hesitation between the two aforementioned conditions is introduced. This hesitation is called weak preference and it is denoted with the binary relation S, where p and q indicate respectively the preference and the indifference threshold:

- $a_1Pa_2 \Leftrightarrow g_i(a_1) - g_i(a_2) > \mathrm{q}$
- $a_1Sa_2 \Leftrightarrow q < g_i(a_1) - g_i(a_2) \leq p$
- $a_1Ia_2 \Leftrightarrow |g_i(a_1) - g_i(a_2)| \leq \mathrm{q}$

In what follows, the basic concepts of the main categories of MCDA models:

- *Value measurement methods*: have been introduced by Keeney and Raiffa (1976) with the aim to assign a score or a value (V) for each option. Initially the model evaluates a partial score for each criterion that is then aggregated into a global score by considering the whole set of criteria and their associated weights. Through the global score it is possible to delineate a preference order of alternatives such that a_1 is preferred to a_2 if and only if the value of a_1 is greater than the value of a_2 on the whole set of criteria G (i.e. $a_1Pa_2 \Leftrightarrow V(a_1) > V(a_2)$). Thus, preferences are characterized by two main properties: completeness and transitivity. Preferences are complete when, given two alternatives, one is necessarily more or equally preferred to the other; while they are transitive when, given three options $a_1, a_2, a_3 \in A$ such that a_1 is preferred to a_2 and the latter is preferred to a_3, then a_1 is preferred to a_3 (i.e. if $a_1Pa_2 \wedge a_2Pa_3 \Rightarrow a_1Pa_3$). Moreover, to take into account the importance of criteria, a partial value function $v_i(a_j)$ is created for each $g_i \epsilon G$.
  The simplest additive model is the weighted sum that expresses the value function in an additive form. More specifically the global value of an alternative $V(a_j)$ is obtained through the product between the partial value function $v_i(a_j)$ on the criterion g_i and the weight value w_i assigned by the DM to that criterion, as in the following equation:

$$V(a_j) = \sum_{i=1}^{n} w_i v_i(a_j)$$

- *Goal programming or Reference level models*: are based on reference levels of achievements for each criterion, considered as goals. The main aim of these models is to discover those alternatives that are closest to the reference levels. The model is articulated in different stages. At the beginning, DM has to prioritize criteria according to an order; the most important one is assessed on the set of alternatives until a desirable level of performance is achieved and alternatives with the less performances on the reference level are eliminated. Similarly, DM evaluates the performances on the second best criterion and alternatives with the less reference level are removed. The process continues until the worst criterion of the whole set is considered.
- *Outranking methods:* have been introduced by Roy (1996) and are based on an binary relation on the set of alternatives. Initially options are pairwise compared by considering one criterion at a time in order to detect the preference degree of one alternative over the other. Then the model is extended to the entire set of criterion by providing strong enough evidence to affirm that "a_1 is at least as good as a_2" ($a_1 S a_2$). To use this model it is required that criteria are based on the dominance notion and satisfy the preferential independence property. Dominance implies that, given two alternatives a_1 and a_2 and their corresponding preference functions $V(a_1)$ and $V(a_2)$, if $V(a_1) > V(a_2)$ then a_1 is preferred to a_2 ($a_1 P a_2$); whereas the preferential independence property entails that the set of criteria must not show any degree of interaction. However, if any alternative outranks another one, it does not imply that they present the same preference value or they are indifferent (Belton and Stewart, 2002).

1.3.2 Multi-criteria Decision Analysis in the energy sector

Multi-criteria decision analysis and its wide range of methodologies have been applied to many domains. In this study, we focus on MCDA models employed in energy decision making in view of the significance that this sector plays in the economic, political and environmental context, as stressed before.

MCDA methods, thanks to their capability to handle simultaneously with multiple and conflictual criteria, different categories of stakeholders and several uncertainty conditions, are well suitable instruments to implement in the energy industry and achieve integrated results (Mateo, 2012).

In what follows, an extensive literature review on the main applications of MCDA models in the energy sector, emphasizes the importance of these mathematical tools to solve decision-making issues related to this area and proves the recent growing attention of researchers for this field. For instance, the studies of Abu-Taha (2011) and Mardani et al. (2015) provide a review of MCDM techniques in the main areas of sustainable and renewable energy for type of multi-criteria model employed, authors' origin, kind of journal, year of publication and criteria considered. They underline the role of MCDA methods in supporting DMs for disclosing the uncertainties of environment decision-making and solving the different stages of energy system. Similarly, the paper of Wang et al. (2009)

reviewed the main MCDA models employed in each stage of sustainable energy decision-making such as criteria identification, weighting, evaluation and aggregation. Pohekar and Ramachandran (2004) offer a wide survey of 90 published papers dealing with the application of MCDA methods in the comprehensive area of sustainable energy planning that consists of seven categories: renewable energy planning, energy resource allocation, transportation and building energy management, energy projects and electric utility planning and other various areas. Instead, more oriented to energy investments question is the recent literature review of Strantzali and Aravossis (2016) that allow understanding the dynamics of evaluation in renewable energy sources investments. The authors, through the classification of energy planning papers in year of publication, method employed, energy source, area of application, criteria and geographical distribution of case studies, highlight the widespread use of MCDA methods to solve energy planning problems.
In analyzing these comprehensive studies, it is possible to bring out some common elements:

- The problems to solve
- The criteria employed
- The methods applied
- The uncertainty of data

The problems to solve: typically, the decision problems related to the energy sector applying MCDA techniques concern the following subjects:

- The choice of the power plants location involving the strategic selection of the most efficient site to locate thermal, solar or wind power plants in terms of economic and sustainable development of a country (Choudhary and Shankar, 2012; Barda et al., 1990; Ren, 2010; Wu et al., 2014; Yunna and Geng, 2014);
- The evaluation of the power generation projects consisting of the assessment of renewable energy investments for power generation (Chen et al., 2010; Atmaca and Basar, 2012; Liu et al., 2010; Mavrotas et al., 2003);
- The comparison among power generation and supply technologies concerning the sustainability assessment of power production and supply from renewable and not renewable energy sources or from traditional and renewable energy technologies (Barros et al., 2015; Maxim, 2014; Stein, 2013; Troldborg et al., 2014; Doukas et al., 2007; Hirschberg et al. 2004);
- The designing of energy plans and policies involving the strategic decision among different energy scenarios faced by energy planners or political stakeholders to comply with more sustainable energy strategies (Angilella et al., 2016; Kablan, 2004; Greening and Bernow, 2004; Diakoulaki et al., 1999);
- The system of energy transportation entailing the choice of the most environmentally sustainable transport system to mitigate the environmental risks related to pollutant emissions (Yedla and Shrestha, 2003; Awasthi and Chauhan, 2011; Sayers et al., 2003);
- The building of sustainable energy indices consisting of the development of

aggregated indicators for monitoring the energy performance at national or regional level (Song et al., 2017; Ding et al., 2018; Zhou et al., 2007; Hatefi and Torabi, 2010; Peng et al., 2017).

The criteria employed: in the framework of energy system, the most used attributes for evaluating or comparing alternatives to each other are usually grouped into four main categories: technical, economic, environmental and social criteria (Wang et al., 2009). Table 1.1 summarizes the most commonly used sub-criteria for each category. They have been derived from the main literature reviews in energy planning studies (Wang et al., 2009; Antunes and Martins, 2014; Ibáñez-Forés et al., 2014; Luthra et al., 2015; Strantzali and Aravossis, 2016). Moreover, a detailed description for each of them is provided below:

Table 1.1 Most used criteria and sub-criteria in energy planning studies employing multi-criteria methods (Wang et al., 2009; Antunes and Martins, 2014; Ibáñez-Forés et al., 2014; Luthra et al., 2015; Strantzali and Aravossis, 2016)

Technical criteria	**Economic criteria**	**Environmental criteria**	**Social criteria**
Efficiency	Fuel costs	Pollutants emissions (CO_2, NO_x, SO_2)	Risk of premature mortality
Safety	Investment costs	Particles emissions	Morbidity
Reliability	Operation and Maintenance costs	Wastewater discharge	Accidents
Maturity	Production costs	Waste and sludge generation	Social acceptability
Capacity	Levelized electricity cost	Land use	Job creation
Peak load response	Avoided costs	Noise pollution	Social benefit
Primary energy ratio	Economic impacts	Visual impact	Social equity
Fuel availability	Economic profitability (Payback	Climate change	Cultural heritage protection
Risk	Period, service life, equivalent Annual costs, net present value)		
Adaptability	Market maturity	Acidification	
Diversity	Financial capacity	Greenhouse effect	
Lifetime			
Equipment design			
Waste utilization			

- Technical criteria: usually refer to the production features of each technology. They include *efficiency* (the percentage of useful energy, namely electricity or heat, obtained from energy sources), *safety* (the security of workforces in the place of energy activity or the reduction of energy dependence), *reliability* (the capability for the power technology to perform, in a certain time span, as planned, ensuring a continuous energy service without failures or blackout), *maturity* (the technology's maturity degree with respect to other international technologies, viewed as a sort of technical advantage), *capacity* (the firm's ability to get the maximum energy production by using its installations), *peak load response* (the capability of a device or a system to respond immediately to large demand fluctuations), *primary energy ratio* (the ratio between the primary energy consumption and the user's energy demand), *fuel availability* (computes the availability of a specific kind of fuel during years over its actual consumption), *risk* (the exposition to certain dangers due to new policies or control properties), *adaptability* (the technology's ability to conform the energy production to the current situations), *diversity* (refers to the energy production mix, technology or supply sources), *lifetime* (the number of years the power plant can work before its replacement), *equipment design* (design complexity of the plant equipment in terms of involved operating stages and equipment required), *waste utilization* (volume of waste produced that can be recycled);

- Economic criteria pertain to economic costs and economic performance criteria. Economic costs refer to the whole set of expenditures faced by companies which are part of the electricity supply chain. They have been identified with: *fuel costs* (the amount of financial resources spent to provide the raw materials required to initiate the power production process according to the specific technology employed, i.e. natural gas or coal for thermal power plant; they include also any charges resulting from the extraction, transportation or processing activities), *investment costs* (comprise all those costs related to the acquisition of mechanical systems and installations, road and networks building to the national grid and other construction costs, except the labor costs associated to the equipment maintenance), *operation costs* (refer to labor costs like the wages paid to employees, the costs for energy, goods and facilities); *maintenance costs* (total funds spent to extend the energy system lifespan in order to avoid as much as possible system outages); *production costs* (allow to compare a certain power production technology over the others in terms of their market competition); *levelized electricity costs* (measures the production cost per KWh of the electricity produced by the power plant expressed as Euro cents); *avoided costs* (amount of costs saved for less primary energy consumed). While economic performance criteria refer to the efficiency attributes under the economic point of view that include: *economic impacts* (the ability of a certain energy plan or policy to stimulate the economic development of a country); *economic profitability* (consists of assessing long-term energy projects through different indicators such as net present value, payback period, service life, equivalent annual cost, in order to appraise its economic feasibility by stakeholders), *market maturity* (refers to the availability in the market and the status of penetration of a given technology for less and more than 10 years), *financial capacity* (the capability of a company to finance the amount of materials required for technology operation);

- Environmental criteria: refer to negative externalities generated by power plants during the fossil fuels burning process on the surrounding and global environment. Local externalities relate to the release of *pollutants* and *particles emissions* to the atmosphere like the nitrogen oxides (NO_x), carbon monoxide (CO), carbon dioxide (CO_2), sulphur dioxide (SO_2), methane (CH_4) and non-methane volatile organic compounds ($NMVOC_s$) that contribute to produce local air pollution and toxic products for the health of the surrounding community. Moreover they include *land use* (the landscape occupied by energy systems), *noise pollution* (the distracting noise generated by the equipment functioning that can cause permanent physiological damage to hearing), *wastewater discharge* (the amount of wastewater discharged in the surrounding environment by power plant), *waste and sludge generation* (the quantity of waste and sludge generated by power plant production) and *visual impact* (the visual alteration of nearby landscape caused by the implementation of an energy project). Similarly, global externalities are generated from the release of pollutants to the air, but relate to the overall environmental impact across the world through *climate change*, *acidification* and *greenhouse effect*, that have been recently focused by governments and industry experts to monitor the global development of energy systems;

- Social criteria: include two notions. From one side they refer to negative externalities generated by energy systems to human health, natural ecosystem and other non-environmental externalities. Literature defines these externalities as human health costs, burden by entities not directly involved with electricity generation unit such as the *risk of premature mortality* (that is the life expectancy reduction), *morbidity* (breathing or cardiovascular problems caused by a long or short greenhouse gases expositions), and *accidents* (like fatal accidents or injuries during the normal plant operations). From the other side, social criteria include the people's approval towards new energy projects and the social development of the surrounding population. In order to evaluate these aspects, the most used criteria are: *social acceptability* (the local community sentiment about the creation of new energy projects; if the population is against, it may create the slowdown in works), *job creation* (the introduction of new job vacancies in the energy system that help locale people to improve their living standards); *social benefits* (the social improvement of the surrounding population in terms of living conditions, earned income and collective well-being due to the development in energy programmes), *social equity* (a measure to assess reliable supply to the whole population); *cultural heritage protection* (refers to the impact of a new project towards surrounding heritage buildings or ancient cultural sites).

The *methods applied*: several multi-criteria methods have been implemented to solve different decision-making problems in the energy sector. The majority of literature review studies related to energy industry, agree that AHP model is the most used multi-criteria method for supporting sustainable energy planning and policy issues, thanks to its hierarchical structure and the possibility to handle with results until the consistency is obtained (Abu-Taha, 2011). Moreover, ELECTRE, PROMETHEE, MAUT, and TOPSIS models are the other multi-criteria methods widely employed within the same field (Doukas, 2013; Pohekar and Ramachandran, 2004; Mardani et al., 2015).
Following the paper of Belton and Stewart (2002) which classifies MCDA models in three main categories (value measurement, reference level and outranking methods), we provide an overview of the major multi-criteria models applied in the energy sector according to this classification:

- *Value measurement methods*: include Simple Additive Weighting (SAW), Ordered Weighted Average (OWA), Multi-Attribute Utility Theory (MAUT), Analytical Hierarchy Process (AHP), and Measuring Attractiveness by a Categorical Base

Evaluation Technique (MACBETH) models;
- *Reference level methods*: are Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIKOR and Goal Programming (GP) models;
- *Outranking methods*: refer to Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) and Elimination et choice translating reality (ELECTRE) models.

However, other multi-criteria techniques, such as Novel approach to Imprecise Assessment and Decision Environment (NAIADE) and Preference Assessment by Imprecise Ratio Statements (PAIRS) not included in the previous list, have been implemented in the energy sector and denoted here as *other approaches*.
Table 1.2 provides a classification of the aforementioned multi-criteria models that have been applied to solve different decision-making problems in the energy sector, such as the renewable and sustainable energy, the renewable energy investments and the sustainable energy planning. This table has been derived from the main literature review studies on these topics (Abu-Taha, 2011; Strantzali and Aravossis 2016; Pohekar and Ramachandran, 2004; Mardani et al., 2015) to highlight the key contributions of MCDA methods in solving specific energy issues.

Table 1.2 Classification of MCDA methods by application area (Abu-Taha, 2011; Strantzali and Aravossis 2016; Pohekar and Ramachandran, 2004; Mardani et al., 2015)

Categories	MCDA method	Application Area	References
Value measurement methods	SAW	evaluation of new and renewable power plants	Afgan and Carvalho, 2002
		evaluation of commercial power supply technologies	Shakouri et al., 2014
		evaluation of natural gas systems	Afgan et al., 2007
	OWA	identification of the better siting for renewable energy systems	Aydin et al., 2013; Al-Yahyai et al., 2012
	MAUT	selection of energy projects	Golabi et al., 1981
		selection of energy resources	Pan et al., 2000
		study of the electric power system growth	Voropai and Ivanova, 2002
		assessment of the environmental effects of electric utilities	McDaniels, 1996
	AHP	energy policy problems	Toossi et al., 2013; Hämäläinen and Karjalainen, 1992; Poh and Ang, 1999; Sadeghi and Ameli, 2012; Kablan, 2004
		energy planning problems	Haddad et al., 2017; Lee et al., 2007; Lee et al., 2008
		assessment of power generation technologies and heating systems	Pilavachi et al., 2009; Chatzimouratidis and Pilavachi, 2009; Mohsen and Akash, 1997; Chatzimouratidis and Pilavachi, 2007; Chatzimouratidis and Pilavachi 2008
		selection of power plant location	Aras et al., 2004
		allocation of energy resources	Ramanathan and Ganesh, 1995; Ramanathan and Ganesh, 1993
	ANP	optimal fuel mix for sustainable power generation	Köne and Büke, 2007; Ulutaş, 2005
		investor's inclinations towards biomass power plants projects	Cannemi et al., 2014
		optimal recycling strategy in the solar energy industry	Shiue and Lin, 2012
		ranking renewable energy sources	Kabak and Dağdeviren, 2014
	MACBETH	compare feasibility of renewable energy projects	Burton and Hubacek, 2007
Reference level methods	TOPSIS	evaluation of power technologies	Lozano-Minguez et al., 2011; Boran et al., 2012

		evaluation of renewable resources	Doukas and Psarras, 2009
	VIKOR	select a renewable energy plan	San Cristóbal, 2011
		evaluate the feasibility of sustainable hydropower projects	Vučijak et al., 2013
	Goal Programming	resource allocation problems	Kambo et al., 1991
		select the optimal location for renewable power plants	Chang, 2015
	PROMETHEE	evaluation of renewable energy projects	Haralambopoulos and Polatidis, 2003; Tsoutsos et al., 2009
		optimal exploitation of geothermal resources	Goumas et al., 1999
		compare the sustainability of renewable energy technologies	Troldborg et al, 2014; Cavallaro, 2009
		evaluation the diffusion of future energy scenario	Diakoulaki and Karangelis, 2007; Madlener et al., 2007
Outranking methods	ELECTREE	selection of the best power generation project	Georgopoulou et al., 1997; Beccali et al., 2003
		selection of the most attractive energy source	Papadopoulos and Karagiannidis, 2008
		location of the thermal power plants and solar farm	Barda et al., 1990; Sánchez-Lozano et al., 2014; Jun et al., 2014
		ranking of a set of office buildings	Roulet et al., 2002
		sorting of energy efficiency initiatives	Neves et al., 2008
Other approaches	NAIADE	optimal scenario for natural gas systems and wind turbine technologies	Dinca et al., 2007; Cavallaro and Ciraolo, 2005
	PAIRS	evaluation of the competitiveness of residential energy heating systems	Alanne et al., 2007

The *uncertainty of data:* the energy decision-making problems are characterized by imprecision of data, fuzziness of individual judgements and vagueness of the parameters required. All these elements of uncertainty have to be taken into consideration by analysts both when a specific model is applied and when results are provided to the DM. For instance, evaluating alternatives on each criteria or eliciting weights over the whole set of attributes considered, is really a difficult task for the DM due to the high difficulty in quantifying its own preferences. Hence, two different MCDA techniques have been applied in the energy framework to handle with the data uncertainty issue: sensitivity analysis, fuzzy sets and fuzzy logic techniques.

- Sensitivity analysis: it consists of checking how the results of the model vary according to a single variation of input information, such as raw data or preference parameters that are provided by the DM. This tool, particularly suitable in ranking problems, highlights how the change of DM’s preferences on criteria weight may widely (or slightly) affect the final order of alternatives and lead therefore to the model instability (or stability) for that specific decision making problem. The main MCDA methods dealing with sensitivity analysis are the Stochastic Multi-Attribute Acceptability Analysis (SMAA models), the Data envelopment analysis (DEA) and ELECTRE IV. In ELECTRE methods for instance, the sensitivity analysis allows observing changes in preference, indifference and veto thresholds or evaluating the robustness for each outranking situation.

- Fuzzy sets and fuzzy logic techniques: are quantitative methodologies that enable to interpret qualitative information by numerical values. They own the advantage to convert the DM’s preferences, which are highly imprecise and expressed through linguistic variables, into a set of scores (weights) which make exact the final evaluation. In this way, it is possible to structure the problem hierarchically and to obtain highly accurate, transparent and realistic results from rough and approximate data. These techniques presented for the first time by Zadeh (1965) have been applied with other MCDA models to solve different decision-making problems in the energy sector. For instance, fuzzy analysis has been applied along with:

- MAUT: to compare the company performances in terms of sustainable supply chain (Erol et al., 2011), to develop an energy demand model for residential sector (Michalik et al., 1997);
- ANP: to evaluate the environmental impact of construction projects (Liu and Lai, 2009);
- AHP: to select the most appropriate renewable energy sources in the power generation, distributed and storage energy system (Ahmad and Tahar, 2014; Barin et al., 2009a; Barin et al., 2009b; Tasri and Susilawati, 2014), to evaluate the optimal tri-generation and heating system (Wang et al., 2008; Jaber et al., 2008);
- AHP and WIKOR: to identify the best energy policy and production site in Istanbul (Kaya and Kahraman, 2010);
- AHP and TOPSIS: to evaluate renewable energy alternatives in Turkey (Çolak and Kaya, 2017);
- TOPSIS: to rank and evaluate the environmental performance of energy supply system (Şengül et al., 2015; Awasthi et al., 2010), to select the facility location (Chu, 2002);
- PROMETHEE: to test and rank different geothermal energy exploitation systems (Goumas and Lygerou, 2000; Haralambopoulos and Polatidis, 2003), to assess the sustainability of production techniques (Geldermann et al., 2000);
- ELECTRE: to compare the fuzzy set methodology over the ELECTRE model to a real case of energy planning (Beccali et al., 1998), to assess the environmental effects of water resources based projects (Khodabakhshi and Jafari, 2010), to compare different energy options under the social and public safety viewpoint (Siskos and Hubert, 1983)

1.3.3 Literature review on MCDA models employed in firms' performance evaluation and credit risk assessment: filling the gaps and outlining the motivations

MCDA models have been widely applied also in studies dealing with firms' performance evaluation and credit risk assessment. The two notions are strictly related since through the investigation of the current company's performance it is possible to predict its future likelihood of success or failure (Psillaki et al., 2010).
Performance evaluation consists of appraising the efficiency and the efficacy of previously implemented strategies (Neely et al., 2002). The literature concerning this topic has been characterized by two main phases. In the first one, between the 1880s and the 1980s,

performance measures were directed to financial indicators based on accounting data, such as profitability, return on investment and productivity (Ghalayini and Noble, 1996). In the second one, as the market became more competitive (after the 1980s), it was realized that traditional financial measures presented several limitations in assessing a more strategic corporate condition and Performance Measurement Systems (PMSs) have been enriched of managerial components, able to improve the decision-making processes (Taticchi, 2008).

Thus, during years, several efforts have been made by the scientific community to guarantee the most appropriate performance evaluation models for enabling industrial practitioners to better understand an integrated assessment process. For instance the survey of De Toni and Tonchia (2001), classifies the PMSs models in five main typologies: hierarchical, balanced scorecard, frustum, internal-external performances and value chain models.

However, these conventional decision-making processes are no longer sufficient to consider several features simultaneously, which relate for instance to the financial or economic well-being as well as the market position, human capital, quality of goods produced and many other factors concerning the specific sector where the firm operate.

Multi-Criteria Decision Aid (MCDA) methods, thanks to their multi-dimensional nature and their capability to monitor several aspects concurrently, are instead suitable instruments to evaluate the complex structure of firms, which typically involves a set of conflicting criteria to assess their performances.

In the energy sector, the business evaluation analysis is even more relevant than in other fields, and the need for reliable models able to predict the corporate failure consistently and accurately is crucial. Just think to the recent cases of financial distresses occurred within the energy industry after deregulation policies, with their significant impacts on the economy of the country where the crash has taken place (Section 1.2.1.3).

Despite its great relevance in the modern economy, the available MCDA literature related to the performance evaluation of energy companies is not so wide and often limited to the analysis of the financial dimension. In the study of Eyüboglu and Çelik (2016), for instance, although authors suggest to monitor the performances of energy companies for their crucial importance in a given economy, they offer a ranking of firms based only on accounting measures, providing a reductive view for an exhaustive decision-making process. In this regard, the papers of Capece et al. (2013) and Guo et al. (2016), study the performance evaluation respectively of the Italian and Chinese energy companies through other perspectives, such as geographical position and top managers' background characteristics. Thus, the weakness detected in this stream of literature, is just to consider a single perspective at once.

To fill this gap, this thesis proposes the selection of a coherent and hierarchical set of criteria, specifically oriented towards energy industry assessment where, conventional financial criteria are considered together with other dimensions. Among these, sustainability, technical and market ones, have been identified to form the basis of a reliable model, addressed to several decision makers' purposes. The proposed family of criteria has been assessed on a set of listed companies operating in the energy sector, with the aim to provide a ranking of them in terms of performance.

On the methodological side, Hierarchy Stochastic Multi-Attribute Acceptability Analysis (HSMAA) (De Matteis et al., 2019) has been employed, as a suitable MCDA model simultaneously dealing with the hierarchical criteria structure and with the Decision Maker (DM)'s uncertainty on preference parameters, which has been considered simulating different scenarios. Indeed, a common feature of most real-life problems, independently of the context, is the plurality of different stakeholders (see Cinelli, 2017) as in the evaluation of the performance of the energy sector.

Credit risk, instead, is a kind of risk faced by lenders that arises from the declined refund of a granted loan under pre-specified terms and conditions. Because of its crucial importance in the banking system, credit risk assessment has been of central interest for many researchers.

In this regard, the literature review on credit risk evaluation has highlighted that methods mainly dealing with corporate failure prediction problems include usually statistical, econometric and machine learning techniques. For instance, the study of Balcaen and Ooghe (2006) provides a well-organized survey of the classical statistical modelling systems applied to business failure predictions of corporations throughout 35 years of studies. This paper identifies specifically four types of approaches with their main features and assumptions: univariate analysis, risk index models, multiple discriminant analysis (MDA) and conditional probability models.

Despite their extensive implementation, these methodologies present some specific issues related to the application of corporate failure prediction modelling and do not hold some significant attributes that analysts often require for scoring models, such as the ordinal risk grades and the monotonicity assumptions. The last requirement entails that if in a rating model an input variable for a given firm improves, then the probability of default should decrease. Both the aforementioned attributes fit well to multi-criteria decision aiding (MCDA) models, which have also the advantages of a high comprehensibility, easiness of application and ability to include the DM's preferences. These characteristics make these tools more efficient and powerful than traditional statistical techniques (Doumpos et al., 2002).

It is for all these reasons that multi-criteria models have been adopted to support a wide range of financial decisions, such as the portfolio selection, the choice of investments projects, the failure risk assessment of corporations (see Spronk et al., 2005 and Doumpos and Zopounidis, 2014 for literature reviews of MCDA on finance).

Moreover, multi-criteria analysis offers a variety of discrimination models (see Zopounidis and Doumpos, 2002a for a literature review of multi-criteria classification and sorting methods), which have been applied to handle with the credit risk assessment issue especially in financial and banking sector. Most of them make use of preference disaggregation approaches (Zopounidis and Doumpos, 1999; Doumpos and Pasiouras, 2005; Baourakis et al., 2009), goal programming (García et al., 2013), rough set theory (Slowinski and Zopounidis, 1995; Capotorti and Barbanera, 2012) outranking techniques (Doumpos and Zopounidis, 2011; Angilella and Mazzù, 2015; Angilella and Mazzù, 2019).

The *preference disaggregation approaches* are based on indirect elicitation of preference parameters. In the indirect elicitation, the DM is asked to provide preference information in terms of some pairwise comparisons on some criteria or reference alternatives. These MCDA models are widely used to tackle with several decision real problems since they require a less cognitive effort of the DM. The most known preference MCDA methodologies based on indirect elicitation are the Robust Ordinal Regression (ROR) (Greco et al., 2010) and the Stochastic Multi Attribute Acceptability Analysis (SMAA) methodologies (Lahdelma et al., 1998). For example, UTA method is a well-known MCDA method based on the ROR approach. In particular, the UTADIS methods are a variant of UTA methods, which are well suited for sorting problems. UTADIS models replicate accurately a predefined classification by building an additive utility function that is used then to estimate the global utility of each alternative. Finally, each additive utility function is compared to some thresholds, representing the lower and upper bounds of classes, which are estimated through linear program techniques.

In what follows, Table 1.3 highlights the strengths and the weaknesses of the main MCDA sorting models used in credit scoring and failure prediction problems.

Table 1.3 Pros and Cons of the main MCDA sorting models employed for credit scoring and failure prediction problems (Mousavi and Lin, 2020).

Method	Model	Reference	Pros	Cons
Preference disaggregation	UTADIS	Doumpos and Pasiouras, 2005	The estimation of the additive value function and the cut-off thresholds is performed through linear programming techniques. The additive value model that reproduce the predetermined classification of alternatives is developed as accurately as possible	The global DM's preferences are not perfectly represented by the model
	Evolutionary optimization	Doumpos, 2012	The methodology based on an evolutionary optimization process, is applicable with large dataset and it is particularly useful for modelling non-monotonic preferences.	A broad class of non-monotonic value functions is proposed, inferred directly from a set of decision examples
Outranking relation	ELECTRE TRI+SMAA methodology	Angilella and Mazzù, 2015	Through the SMAA procedure, it has been accounted for uncertainty and imprecision in the criteria weights, cutting level and data. Thus, the different points of view of credit officers are considered with regard to the importance of criteria	Due to the SMEs' lack of sufficient or reliable track records, the most useful approach for evaluating their creditworthiness is a rating based on experts' judgment.
	ELECTRE TRI + Evolutionary optimization	Doumpos and Zopounidis, 2011	Allows analyst to introduce the DM's preferences during the model building process and calibrate the model, by meeting the requirement posed by the risk management department of a credit institution. The DE algorithm optimizes the model fitting process	The assignment of the alternatives to the predefined categories is based on their comparison with the references profiles that have to be set by industry experts. For the huge amount of a-priori information needed to set the model, it can be applied specifically with members of a decision committee.
	ELECTRE TRI-nC	Doumpos and Figueira, 2019	The multiple characteristic profiles increase the robustness of the risk assignment for alternatives and decrease their deviations from external ratings. The robustness of the model is further enhanced by adding veto conditions.	The reference actions are defined depending on the preferences of the decision-maker and therefore, they are co-constructed during an intensive interaction process between the decision-maker and the analyst.
	MURAME	Corazza et al., 2016	Being based on the combination of ELECTRE TRI and PROMETHEE method, it allows, through three different stages, to: rank the firms according to their credit risk features, to sort them into creditworthiness classes, to compute the probabilities of migration over time from one class to another	If the model is built with few variables, it does not perform properly

	PROMCM	Hu and Chen, 2011	An overall preference index is defined using both concordance and discordance relations for ordinal sorting problems and the final classification depends on its net flow. Criteria weights, preferential parameters and cut off points, are automatically determined through the genetic algorithm based (GA-based) that increase its performance	GA parameter specifications are somewhat subjective
Fuzzy	Fuzzy rule-based classifiers	Gorzałczany and Rudziński, 2016	It involves and optimizes a trade-off between the accuracy and the interpretability requirements	The transparency and interpretability become limited when excessive numbers of complex rules are generated
	Fuzzy group decision making model	Yu et al., 2009	Intelligent agents are used in place of human experts to take decisions and formulate different opinions on a specified decision problem, reducing the bias of human experts in GDM. These opinions constitute the basis for formulating fuzzy opinions.	The classification accuracy used is affected by the overlap in the way the range of some evaluations results is split into various categories

In several credit risk assessment studies, some of the methods displayed in Table 1.3 have been compared to each other (Araz and Ozkarahan, 2005) and with traditional econometric tools such as discriminant, logit and probit analysis (Voulgaris et al., 2000; Zopounidis and Doumpos, 1999). All these studies agree in recognizing the higher efficiency of multi-criteria methods in comparison to the econometric ones in obtaining credit risk estimates (Doumpos and Zopounidis, 2002). Instead, a more controversial question is about which multi-criteria model is more efficient in corporate credit risk assessment, because of the significant link between the features of the context of application and the obtained results.
In literature, one of the most efficient multi-criteria discrimination model is the Multi-group Hierarchy Discrimination (M.H.DIS) technique elaborated by Zopounidis and Doumpos (2000). In comparison to other studies concerning the application of preference disaggregation approaches, (such as the family of UTADIS models), the performance of M.H.DIS is indeed not only superior for some real world cases, but also computationally less time-consuming, especially with respect to UTADIS II and UTADIS III (1 minute against several hours) (Zopounidis and Doumpos, 2000).
The following features emphasize the M.H.DIS model's main strengths:

- it is able to discriminate alternatives between two or more than two categories;
- it employs a hierarchical discrimination procedure to assign alternatives into classes. More specifically, the categories are discriminated progressively, starting by discriminating the most preferred alternatives (C_1) from all the alternatives of the remaining ones $\left(C_2, C_3, C_4, \dots, C_p\right)$ then proceeding to the discrimination between the alternatives of the next category (C_2) from all the alternatives of the remaining ones $\left(C_3, C_4, \dots, C_p\right)$ and so forth;
- his development process is based on three mathematical programming techniques, two linear programs (LP1, LP2) and a mixed-integer one (MIP), implemented at each stage of the hierarchical discrimination process to estimate the optimal pair of additive utility functions in terms of misclassification errors and clear distinction between categories. The first linear program (LP1) is employed to minimize the misclassification errors in terms of distance, the mixed integer program (MIP) is

performed then to minimize the number of misclassifications that could occur after the implementation of LP1 and the second linear program (LP2) is finally implemented to maximize the clarity of the discrimination after LP1 and MIP.

M.H.DIS model has been applied to several fields such as the banking system (Pasiouras et al., 2010; Spathis et al., 2004), the corporate sector (Doumpos et al., 2002; Kosmidou et al., 2002; Doumpos and Zopounidis, 1999) and the country analysis (Doumpos and Zopounidis, 2001; Doumpos et al., 2000).
However, to the best of our knowledge, the M.H.DIS model has never been employed to financial distress prediction of energy companies, despite their great importance for the entire economy.
Thus, thanks to its specific hierarchical procedure and optimization framework, the Multi-group Hierarchical Discrimination (M.H.DIS) model of Zopounidis and Doumpos (2000), has been selected among the wide range of MCDA sorting models to fill the aforementioned literature gap. More specifically, in this study, the M.H.DIS model has been applied on a dataset of European unlisted companies operating in the energy sector.
Following a five-fold cross validation procedure, it has been analyzed whether the model explains and replicates a two-group pre-defined classification of companies in the considered sample. Moreover, to provide a benchmark sorting procedure, the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) method has been performed then, as deeply discussed in Chapter 3.

1.4 The MCDA models applied in this study

In this Section, we provide some basic concepts used further in this thesis. More specifically, in Section 1.4.1 we present an overview of the Hierarchy Stochastic Multi-Attribute Acceptability Analysis (HSMAA), the multi-criteria model employed in the second Chapter. While, in Section 1.4.2 and Section 1.4.3 we describe respectively the main features of the Multi group Hierarchical Discrimination (M.H.DIS) and the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE II) that have been jointly implemented in Chapter 3.

1.4.1 Hierarchy Stochastic Multi-Attribute Acceptability analysis (HSMAA)

Hierarchy Stochastic Multi-Attribute Acceptability Analysis (HSMAA), firstly introduced in De Matteis et al. (2019), is an extension of the Stochastic Multi-Attribute Analysis (SMAA-2) (Lahdelma and Salminen, 2001) able to handle the imprecision relating to the criteria weights and/or alternatives from one side and the hierarchical structure of criteria from the other side.
Commonly in MCDA, Analytic Hierarchy Process (AHP) (Saaty, 2016) and Multi-Criteria Hierarchy Process (MCHP) (Corrente et al., 2012) have usually been applied to deal with the multi-level structure of criteria. Only recently, HSMAA model has been proposed to

manage the hierarchical criteria structure organised in macro-criteria, and sub-criteria, and the uncertainty with respect to the criteria weights.
In this study, Hierarchy Stochastic Multi Attribute Analysis (HSMAA) method has been applied to rank a set of listed companies operating in the energy sector based on their performance evaluation. In order to deal with the energy companies' performance assessment, the structure of criteria has been organized in three hierarchical levels (macro-criteria, criteria and sub-criteria, as better explained in Chapter 2). Thus, the application of HSMAA model, which is able to handle with a hierarchical structure of criteria and to take into account the space of fluctuations related to the imprecision on criteria weights, allows us to provide "more robust recommendation" on final rank results.
In this section, we introduce the HSMAA model using the following notation:

- $A = \{a_1, \dots, a_j, \dots, a_m\}$ is the set of finite alternatives;
- $G = \{g_1, \dots, g_i, \dots, g_n\}$ is the set of the macro-criteria at the first level;
- $Q_i = \{q_{i1}, \dots, q_{ik}, \dots, q_{is}\}$ is the set of sub-criteria at the second level, deriving from each macro-criterion g_i;
- $T_{ij} = \{t_{ik1}, \dots, t_{iky}, \dots, t_{ikr}\}$ is the set of elementary criteria at the third level, deriving from the criterion q_{ij}.

As in the traditional SMAA-2 model, HSMAA model captures the problem of imprecision on criteria weights and alternatives' evaluations through the probability distributions $f_W(w)$ and $f_X(\xi)$ related to the macro-criteria weights (W) and the alternatives' evaluations X, at which two further distributions $f_V(v), f_Z(z)$ are added, respectively, to the sub-criteria weights (V) and elementary criteria weights (Z), where:

- $W = \{(w_1, \dots, w_i, \dots, w_n) \in \mathbb{R}_+^n : w_1 + \dots + w_i + \dots + w_n = 1\}$ is the set of macro-criteria weights at the first level;
- $V = \{(v_{i1}, \dots, v_{ik}, \dots, v_{is}) \in \mathbb{R}_+^s : v_{i1} + \dots + v_{ik}, + \dots + v_{is} = 1,\ i = 1, 2, \dots, n\}$ is the set of sub-criteria weights at the second level;
- $Z = \{(z_{ik1}, \dots, z_{iky}, \dots, z_{ikr},) \in \mathbb{R}_+^r :\ z_{ik1}, + \dots + z_{iky}, + \dots + z_{ikr} = 1,\ i = 1, \dots, n,\ \ k = 1,2, \dots, s\}$ is the set of elementary criteria weights;
- X is the space of the alternatives' evaluations that can be taken by the elementary criteria $t_{iky} \in T_{ik}$ $(y = 1,2, \cdots, r)$.

Regardless of the issue analysed, one of the principal aspects in MCDA model is how to aggregate the evaluations of alternatives A on the set of criteria G, based on three different families acknowledged in literature: the value function (Keeney and Raiffa, 1993), the outranking relation (Roy, 2013) or the decision rules (Greco et al., 2001).
In our framework, the value function used to aggregate the alternatives' evaluations on the elementary criteria is the following weighted sum:

$$u(a_j, w, v_i, z_y) = \sum_{i=1}^{n} w_i \,.\, \sum_{k=1}^{s} v_{ik} \,.\, \sum_{y=1}^{r} z_{iky}\, t_{iky}(a_j) \quad (1)$$

with $w_i \in$ W, $v_{ik} \in V$ and $z_{iky} \in Z$.

The previous defined weighted sum gives a score to each alternative, which is used to evaluate the following indices as in SMAA-2.

Thus, HSMAA:

- introduces the ranking function relative to the alternative a_j:

$$rank(j, \xi, w, v, z) = 1 + \sum_{h \neq j} \rho\left(u(\xi_h, w, v_h, z_h) > u(\xi_j, w, v_j, z_j)\right), \quad (2)$$

  where $\rho\ (false) = 0$ and $\rho\ (true) = 1$,

- computes, for each alternative a_j, for each alternative's evaluation $\xi \in X$, and for each rank $r = 1, \dots, p$, the set of criteria weights for which alternative a_j assumes rank r:

$$W_j^r(\xi, v, z) = \{w \in W: rank(j, \xi, w, v, z) = r\}, \quad (3)$$

- evaluates the Rank Acceptability Index b_j^r (RAI), i.e. the probability that alternative a_j gets the r-th position, through the following formula:

$$b_j^r = \int_{w \in W_{j(\xi)}^r} fW(w) \int_{\xi \in X} fX(\xi) \int_{v \in V} fV(v) \int_{z \in Z} fZ(z)\, dz dv d\xi dw, \quad (4)$$

- estimates the Central Weight Vector (CWV) that is the barycentre of a set of criteria weights for which a_j is evaluated as the best alternative:

$$w_j^c = \frac{1}{b_j^1} \int_{\xi \in X} fX(\xi) \int_{w \in W_{j(\xi)}^1} fW(w) \int_{v \in V} fV(v) \int_{z \in Z} fZ(z)\, dz dv dw d\xi, \quad (5)$$

- assesses the Confidence Factor (CF), which is the relative measure expressing the probability of a given alternative a_j to be the best, considering the previous weights combination (CWV):

$$p_j^c = \int_{\substack{\xi \in X: u\left(\xi_j, w_j^c\right) \geq u\left(\xi_h, w_h^c\right) \\ \forall h = 1, \dots, i}} fX(\xi) d\,\xi, \quad (6)$$

- considers the Pairwise Winning Index (PWI) that provides the probability of the preference relation between two alternatives a_h and a_j according the formula:

$$p_{jh} = \int_{w \in W} f_W(w) \int_{v \in V} f_V(v) \int_{z \in Z} f_Z(z) \int_{\xi \in X: u(\xi_j, w) \geq u(\xi_h, w)} f_X(\xi) d\, \xi dz dv dw. \quad (7)$$

Moreover, the rank acceptability index has been used:

- to compute the upward and the downward cumulative rank acceptability indices (introduced in Angilella et al., 2016), represented respectively by the following two equations:

$$b_j^{\geq p} = \sum_{s=p}^{m} b_j^s \qquad \text{and} \qquad b_j^{\leq p} = \sum_{s=1}^{p} b_j^s \quad (8)$$

  where $b_j^{\geq p}$ represents the upward cumulative acceptability index, namely the frequency that a company a_j gets a rank position greater than p, and $b_j^{\leq p}$ the downward cumulative rank acceptability, i.e. the frequency that a company a_j gets a rank position lower than p;

- to define an uncertainty index using the Shannon entropy concept (presented in a multi-criteria decision context in Ciomek et al., 2017), able to measure the confidence for each alternative to be placed in a position j in the final rank according to the formula:

$$PRAI_j = -\frac{1}{n} \sum_{i=1}^{n} b_j^r(a_j) log_2 b_j^r(a_j) \quad (9)$$

Note that $PRAI_{\mathrm{j}}$ is minimal $(= 0)$ when there exists a unique alternative with b_j^r (RAI) $=$ 1 and thus there is no uncertainty for the alternative a_j to be placed in position j; while it is maximum $(= \frac{log_2 n}{n})$ when all the alternatives have the same probability $(b_j^r = \frac{1}{n})$ to be placed in position j. Summing up, $PRAI_{\mathrm{j}}$ belongs to the range $[0, \frac{log_2 n}{n}]$.

1.4.2 Multi-group Hierarchy Discrimination model (M.H.DIS)

The Multi-group Hierarchy Discrimination model (M.H.DIS) has been developed by Zopounidis and Doumpos (2000) and applied here to solve the sorting problem of the assignment of a given set of alternatives into predefined ordered classes (Chapter 3).
The following notation has been used:

- $A = \{a_1, \cdots a_j, \cdots, a_m\}$ is the set of finite alternatives;
- $G = \{g_1, \cdots g_{\mathrm{i}}, \cdots, g_n\}$ is the set of consistent criteria with an increasing or decreasing direction of preference order;
- a_{ji} indicates the evaluation of alternative j on criterion i;
- $\mathrm{C} = \{C_1 \succ \cdots \succ C_k \cdots \succ C_p\}$ is the set of p ordered categories from the best (or healthiest) C_1 to the worst (or riskiest) C_p.

Alternatives are evaluated on a set of criteria G representing the main aspects for distinguishing options between categories.
Moreover, for simplicity of computation, the model has been implemented only in the case in which criteria present an increasing preference direction, implying that the evaluation of an alternative on an attribute g_i that is negatively (positively) related to financial distress, increases its likelihood to be assigned to the best (worst) category.
Furthermore, M.H.DIS model is a credit risk assessment technique, such as discriminant, logit and probit analysis, that requires the application of two distinct samples: a basic sample (training set) to build a model able to reproduce the pre-specified classification as much as possible, and a holdout sample (test set) to validate and verify its generalization of application. Hence, also the following two subsets of A have to be considered in the building of M.H.DIS model:

- $\mathrm{B} = \{b_1, \cdots b_r, \cdots, b_s\}$ is the subset of alternatives composing the training sample, used for model development;
- $D = \{d_1, \cdots d_s, \cdots, d_t\}$ is the subset of alternatives composing the test sample, used for validation purposes with $B \cap D = \emptyset$.

Initially, the alternatives of the training sample are evaluated on the attributes in G and each of them is assigned to a pre-specified category C_k; once it is carried out, the model aims to sort companies into two categories in order to replicate, as much as possible, a given classification before model development. Then, the discriminating procedure is applied also to companies of test sample to classify them and validate the results.
In order to sort companies of training set, M.H.DIS model applies the following hierarchical technique. The procedure starts from stage $k = 1$ by considering the best category C_1 to which companies of training set (b_r) can belong. In $k = 1$, the model builds a pair of additive utility functions, of which formulas are provided below, to discriminate companies belonging to the healthiest category C_1 and companies belonging to the remaining riskier categories than C_1 (i.e. C_2 in our context):

$$U_1\big(\bar{g}(b_r)\big) = \sum_{i=1}^{n} h_1 u_{1i}\big(g_i(b_r)\big), \tag{10}$$

$$U_{\sim 1}\big(\bar{g}(b_\mathrm{r})\big) = \sum_{i=1}^{n} h_{\sim 1} u_{\sim 1i}\big(g_i(b_\mathrm{r})\big), \tag{11}$$

where $U_1\big(\bar{g}(b_\mathrm{r})\big) \in [0,1]$ and $U_{\sim 1}\big(\bar{g}(b_\mathrm{r})\big) \in [0,1]$ represent the two additive utility functions of each alternative b_r; $\bar{g}$ is the global evaluation of each alternative (b_r) on the whole set of criteria considered; $u_{1i}\big(g_i(b_\mathrm{r})\big)$ and $u_{\sim 1i}\big(g_i(b_\mathrm{r})\big)$ indicate the estimated two marginal utility functions with an increasing (or decreasing) preference direction according to each attribute g_i negatively (or positively) related to financial distress; h_1 and $h_{\sim 1}$ denote the weights of each criterion summing to one.

In stage $k = 1$, if the global score of the estimated additive utility function of healthiest category for alternative b_{r} , is higher than the global score of the estimated additive utility function of the riskiest categories, i.e. $U_1(\bar{g}(b_{\mathrm{r}})) \geq U_{\sim 1}(\bar{g}(b_{\mathrm{r}}))$, then b_{r} is classified to category C_1; otherwise if $U_1(\bar{g}(b_{\mathrm{r}})) \leq U_{\sim 1}(\bar{g}(b_{\mathrm{r}}))$, company b_{r} does not belong to class C_1 and the procedure will continue to stage $k = 2$. From stage 1, it has to be highlighted that if the strict inequality among the global scores of the estimated utility functions occurs $\left(U_1(\bar{g}(b_{\mathrm{r}})) > U_{\sim 1}(\bar{g}(b_{\mathrm{r}}))\right)$, then company b_{r} is classified correctly by the model; on the contrary if the two estimated additive utility functions are equal $\left(U_1(\bar{g}(b_{\mathrm{r}})) = U_{\sim 1}(\bar{g}(b_{\mathrm{r}}))\right)$, then the model misclassifies the company. The whole set of companies correctly or incorrectly classified in C_1 by the model, are excluded in next stages.

At stage $k = 2$, analogously the model builds another pair of additive utility functions to discriminate companies belonging to category C_2 from companies belonging to the remaining riskier categories than C_2 (i.e. $C_3, C_4, \cdots, C_p$). Similarly to stage 1, if $U_2(\bar{g}(b_{\mathrm{r}})) \geq U_{\sim 2}(\bar{g}(b_{\mathrm{r}}))$ or $U_2(\bar{g}(b_{\mathrm{r}})) \leq U_{\sim 2}(\bar{g}(b_{\mathrm{r}}))$, then company b_{r} is classified respectively into C_2 or $C_{\sim 2}$.

The same discriminating procedure continues until all companies of training sample have been classified into the ordered categories to replicate the pre-specified classification as much as possible. M.H.DIS model is also applied to companies of test sample in the same manner.

Figure 1.9 shows the hierarchical discrimination technique employed to perform the M.H.DIS model.

In order to generalize the hierarchical discriminating procedure to p categories, the expressions (1) and (2) are replaced with the following:

$$U_k(\bar{g}(b_r)) = \sum_{i=1}^{n} h_k u_{ki}(\bar{g}(b_r)), \tag{12}$$

$$U_{\sim k}(\bar{g}(b_{\mathrm{r}})) = \sum_{i=1}^{n} h_{\sim k} u_{\sim ki}(\bar{g}(b_{\mathrm{r}})) \tag{13}$$

Hence, the model will build as many pairs of additive utility functions as $p - 1$ classes to which companies have to be sorted.

Furthermore, to estimate optimally the additive utility functions of the model at each stage k, two mathematical programing techniques have been solved through a Matlab code: two linear programs (LP1 and LP2) and a mixed-integer program (MIP). The linear program LP1 has been implemented with the mixed-integer program MIP first, to minimize the misclassification costs of companies belonging to other categories than the pre-defined one; the second linear program LP2 has been performed then, to enhance the clarity of the obtained classification as an among-group variance maximization in discrimination analysis.

Further details on the assessment of the additive utility functions are provided in next Section.

1.4.2.1 Mathematical programming formulations to assess the additive utility functions in M.H.DIS model

M.H.DIS model employs two mathematical programming techniques to estimate optimally additive utility functions able to assign the considered companies into two categories: two linear programs (LP1 and LP2) and a mixed integer one (MIP). The first linear program LP1 is employed to determine a pair of utility functions able to reduce the misclassification errors of healthy companies into risky classes; the mixed integer one (MIP) is implemented then, to minimize the misclassification costs of companies sorted into different classes than the pre-specified ones; the second linear program (LP2) is developed last, to increase the accuracy results.

Table 1.4 shows the three mathematical programming problems solved through M.H.DIS model to assess the additive utility functions for sorting the companies of the sample.

Table 1.4 Mathematical programming problems solved by M.H.DIS model. Authors' elaboration

PROBLEM TO SOLVE	LP1: minimization of the misclassification error	MIP: minimization of the misclassification cost	LP2: maximization of the minimum distance
OBJECTIVE FUNCTION	$\min EC' = w_k\left(\frac{1}{N_k}\sum_{\forall\, b_r\in C_k} e_{kr}\right) + w_{\sim k}\left(\frac{1}{N_{\sim k}}\sum_{\forall b_r\in C_{\sim k}} e_{\sim kr}\right)$ where $e_{kr} = \max\{0, U_k(\bar{g}(b_r)) - U_{\sim k}(\bar{g}(b_r))\}$, $e_{\sim kr} = \max\{0, U_k(\bar{g}(b_r)) - U_{\sim k}(\bar{g}(b_r))\}$.	$\min EC = w_k\left(\frac{1}{N_k^{mis}}\sum_{r=1}^{N_k^{mis}} I_{kr}\right) + w_{\sim k}\left(\frac{1}{N_{\sim k}^{mis}}\sum_{r=1}^{N_{\sim k}^{mis}} I_{\sim kr}\right)$	$\max d = min\{d_1, d_2\}$ where $d_1 = min_{r=1,2,\cdots,N_K^{cor'}}\{U_k(\bar{g}(b_r)) - U_{\sim k}(\bar{g}(b_r))\}$, $d_2 = min_{r=1,2,\cdots,N_{\sim K}^{cor'}}\{U_{\sim k}(\bar{g}(b_r)) - U_k(\bar{g}(b_r))\}$
CONSTRAINTS:	s.t.	s.t.	s.t.
PREFERENCE		$\sum_{i=1}^{n} u_{ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) \geq s$, $b_r = 1,2,\cdots,N_k^{cor}$	$\sum_{i=1}^{n} u_{ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) - d \geq s$, $b_r = 1,2,\cdots,N_k^{cor'}$,
		$\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{ki}(g_i(b_r)) \geq s$, $b_r = 1,2,\cdots,N_{\sim k}^{cor}$,	$\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{ki}(g_i(b_r)) - d \geq s$, $b_r = 1,2,\cdots,N_{\sim k}^{cor'}$,
	$\sum_{i=1}^{n} u_{ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) + e_{kr} \geq s$ $\forall b_r \in C_k$	$\sum_{i=1}^{n} u_{ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) + I_{kr} \geq s$, $b_r = 1,2,\cdots,N_k^{mis}$,	$\sum_{i=1}^{n} u_{ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) \leq 0$, $b_r = 1,2,\cdots,N_k^{mis}$,
	$\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{ki}(g_i(b_r)) + e_{\sim kr} \geq s$ $\forall\, b_r \in C_{\sim k}$	$\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{ki}(g_i(b_r)) + I_{\sim kr} \geq s$, $b_r = 1,2,\cdots,N_{\sim k}^{mis}$,	$\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{ki}(g_i(b_r)) \leq 0$, $b_r = 1,2,\cdots,N_{\sim k}^{mis}$
NORMALIZATION	$\sum_{i=1}^{n} u_{ki}(g_i(b_{r*})) = 0$, $\sum_{i=1}^{n} u_{ki}(g_i(b_r^*)) = 1$, $\sum_{i=1}^{n} u_{\sim ki}(g_i(b_{r*})) = 1$, $\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r^*)) = 0$,	$\sum_{i=1}^{n} u_{ki}(g_i(b_{r*})) = 0$, $\sum_{i=1}^{n} u_{ki}(g_i(b_r^*)) = 1$, $\sum_{i=1}^{n} u_{\sim ki}(g_i(b_{r*})) = 1$, $\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r^*)) = 0$,	$\sum_{i=1}^{n} u_{ki}(g_i(b_{r*})) = 0$, $\sum_{i=1}^{n} u_{ki}(g_i(b_r^*)) = 1$, $\sum_{i=1}^{n} u_{\sim ki}(g_i(b_{r*})) = 1$, $\sum_{i=1}^{n} u_{\sim ki}(g_i(b_r^*)) = 0$,
MONOTONICITY	$u_{ki}(g_i(b_r))$ increasing function, $u_{\sim ki}(g_i(b_r))$ decreasing function, $u_{ki}(g_i(b_r)) \geq 0, u_{\sim ki}(g_i(b_r)) \geq 0$, $e_{kr} \geq 0, e_{\sim kr} \geq 0$.	$u_{ki}(g_i(b_r))$ increasing function, $u_{\sim ki}(g_i(b_r))$ decreasing function, $u_{ki}(g_i(b_r)) \geq 0, I_{kr}, I_{\sim kr}$ Integers.	$u_{ki}(g_i(b_r))$ increasing function, $u_{\sim ki}(g_i(b_r))$ decreasing function, $u_{ki}(g_i(b_r)) \geq 0, d \geq 0$.

The main aim of M.H.DIS model is to solve the problem of misclassification costs by minimizing the following function:

$$\min EC = w_k \left(\frac{1}{N_k} \sum_{\forall b_r \in C_k} I_{kr} \right) + w_{\sim k} \left(\frac{1}{N_{\sim k}} \sum_{\forall b_r \in C_{\sim k}} I_{\sim kr} \right) \tag{14}$$

where N_k and $N_{\sim k}$ represent the amount of companies belonging respectively to healthiest class C_k and the remaining riskiest classes than C_k (that is $C_{\sim k}$); I_{kr} and $I_{\sim kr}$ are two dichotomous variables that take value of 0 if company b_r is correctly assigned to class C_k ($C_{\sim k}$ for $I_{\sim kr}$) and 1 if the company is misclassified to class $C_{\sim k}$ (C_k for $I_{\sim kr}$); w_k and $w_{\sim k}$ are positive weights, and whose sum is one, that have to be chosen by the DM and depend on the misclassification cost and the a-priori default probability according to the formula: w_k=π_k MC_k and $w_{\sim k}$=$\pi_{\sim k}$ $MC_{\sim k}$. MC_k and $MC_{\sim k}$ are the misclassification costs related to the classification errors to sort companies of sample in other classes than the pre-specified ones (specifically MC_k is linked to the error of classify a company into $C_{\sim k}$ instead of $C_k$and $MC_{\sim k}$ is linked to the error of classifying a company in C_k instead of $C_{\sim k}$); while π_k and $\pi_{\sim k}$ indicate the ex-ante probability of b_r to belong respectively to category C_k or $C_{\sim k}$.

In this model w_k and $w_{\sim k}$ are set both equal to 0.5 for two reasons: first because the M.H.DIS problem is usually used to classify firms in two categories (the healthy and the distress class) where the $MC_{\sim 1} > MC_1$; secondly because the a-priori probability associated to failed companies is less than the active one (i.e. $\pi_{\sim 1} < \pi_1$), since the number of distressed companies is generally inferior than the healthy ones.

To minimize the equation above, a mixed integer program (MIP) has to be used. However, because of the huge number of integers I_{kr} and $I_{\sim kr}$ to compute in EC, it results a challenging procedure to implement as first stage. To overcome with this issue, the model introduces the following error function denoted with EC', to roughly estimate the previous EC. It is solved through the first linear program LP1 and Table 1.4 shows the constraints to solve this minimization problem.

$$\min EC' = w_k \left(\frac{1}{N_k} \sum_{\forall b_r \in C_k} e_{kr} \right) + w_{\sim k} \left(\frac{1}{N_{\sim k}} \sum_{\forall b_r \in C_{\sim k}} e_{\sim kr} \right) \tag{15}$$

with:

- $e_{kr} = \max\{0, U_k(\bar{g}_\iota(b_r)) - U_{\sim k}(\bar{g}_\iota(b_r))\}$, (16)

- $e_{\sim kr} = \max\{0, U_k(\bar{g}_\iota(b_r)) - U_{\sim k}(\bar{g}_\iota(b_r))\}$. (17)

e_{kr} and $e_{\sim kr}$ are positive real numbers that have been introduced in place of previous I_{kr} and $I_{\sim kr}$ to measure the intensity of classification errors in a more straightforward way. For instance if an alternative b_r belongs to C_k but the estimated pair of utility functions is such that $U_k(\overline{g_\iota}(b_r)) \leq U_{\sim k}(\overline{g_\iota}(b_r))$, then the classification error is $e_{kr} = \sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{ki}(g_i(b_r)) + s$; correspondingly if an alternative $b_r \notin C_k$ but additive utility functions satisfy the inequality $U_k(\overline{g_\iota}(b_r)) \geq U_{\sim k}(\overline{g_\iota}(b_r))$, then the classification error is $e_{kr} = \sum_{i=1}^{n} u_{ki}(g_i(b_r)) - \sum_{i=1}^{n} u_{\sim ki}(g_i(b_r)) + s$.

In these inequalities s is a negligible small value inserted into the model to comply with the strict inequality between the two additive utility functions $U_k(\overline{g_\iota}(b_r)) > U_{\sim k}(\overline{g_\iota}(b_r))$ and $U_{\sim k}(\overline{g_\iota}(b_r)) > U_k(\overline{g_\iota}(b_r))$; while $\overline{g_\iota}$ is the evaluation of the company b_r on the overall set of criteria considered in the analysis.

The implementation of LP1 gives us an initial pair of utility functions that minimize EC'; nevertheless, if this solution contains a classification error $e_{kr} > 0$, i.e. there is at least an alternative that is placed in a different class than the pre-specified one, it is possible to reduce the classification error of LP1 through the aforementioned mixed-integer program MIP.

Thus at stage 2, MIP is implemented by considering two sets of constraints: the first set is used to hold the companies classified correctly by LP1 (denoted with COR); otherwise, the second set is introduced to consider the companies misclassified by LP1 (denoted with MIS).

Once an optimal pair of utility functions has been found through LP1 and MP1 programs in terms of misclassification cost, the second aim of M.H.DIS model is to guarantee a high predictability to the obtained classification results, by finding those utility functions that clearly distinguish among firms belonging to different categories. In this regard, at stage 3 the second linear program LP2 is employed to maximize the minimum difference between the additive utility functions of companies classified correctly in previous stages ($LP1 + MIP$). Thus, analogously to MIP, LP2 is implemented by considering two set of constraints: the first set is used to hold the companies classified correctly by LP1 and MP1 (denoted with COR'); the second set is introduced to consider the companies misclassified by LP1 and MP1 (denoted with MIS').

The pair of utility functions obtained with LP2 program are the ones used for credit risk assessment of companies.

This procedure consisting in the resolution of three problems, LP1, MIP and LP2, stops when the model will build as many optimal pairs of additive utility functions as $\mathrm{p} - 1$ classes to which companies have to be sorted.

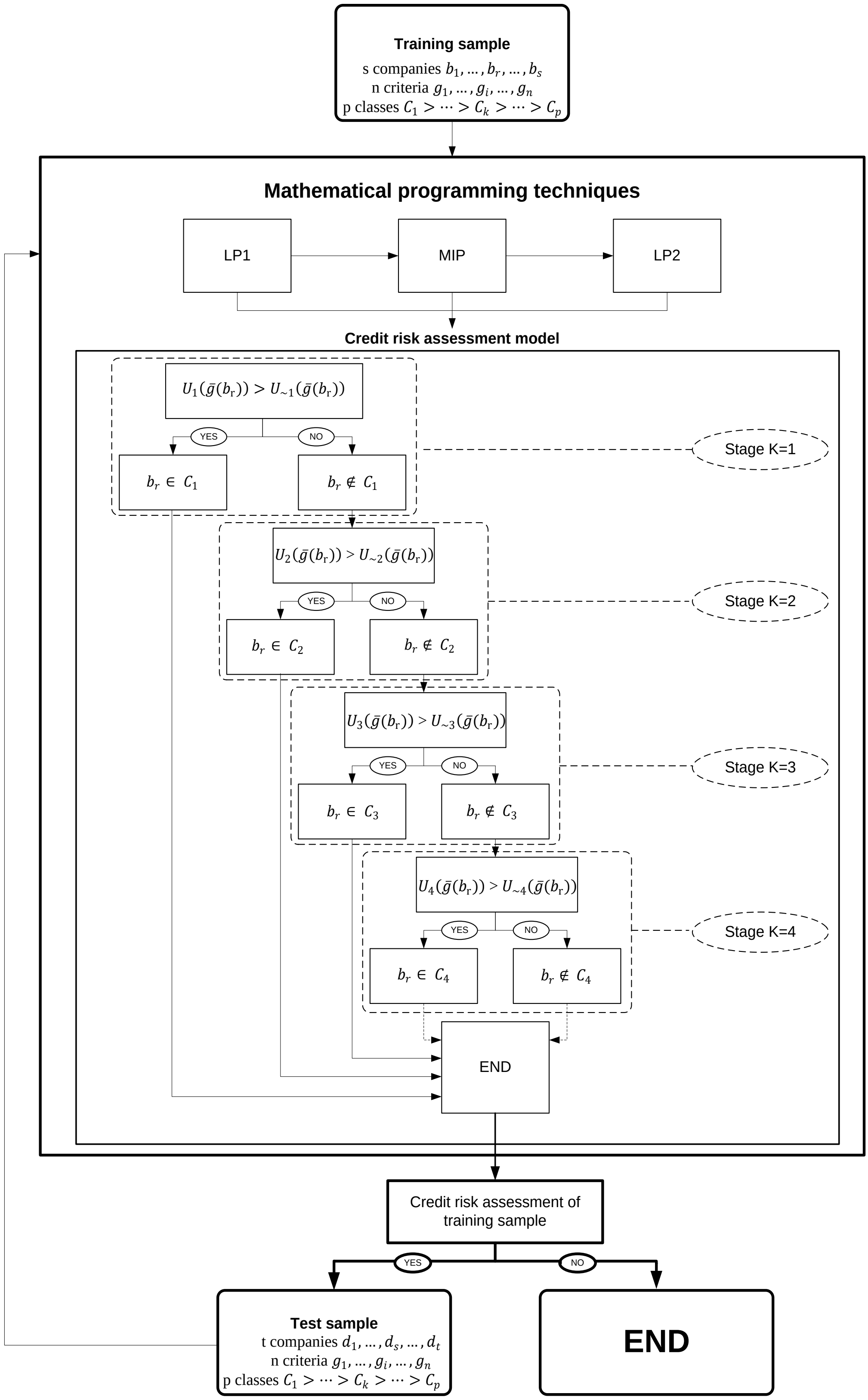


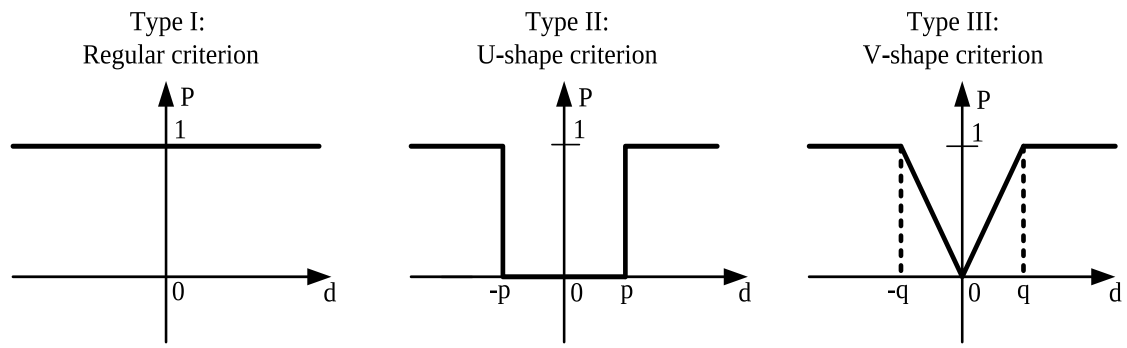
Figure 1.9 General scheme of model development in the M.H.DIS model. Authors' elaboration

1.4.3 Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE II)

PROMETHEE II is a multi-criteria method belonging to the family of PROMETHEE methods, that builds an overall composite indicator of alternatives on the basis of pairwise comparisons considering a set of criteria. PROMETHEE methods are widely used in Multiple Criteria Decision Aiding (see Brans and De Smet, 2016 for a state-of-the-art on the topic). There is a considerable number of PROMETHEE applications currently available for various fields. With respect to financial topics, PROMETHEE methods have been already successfully applied for example in banking (Mareschal and Brans, 1991 and Doumpos and Zopounidis, 2010), in asset evaluation (Albadvi et al., 2007), in bankruptcy prediction (Hu and Chen, 2011 and Mousavi and Lin, 2020), in portfolio selection (Vetschera and de Almeida, 2012), in country risk assessment (Doumpos and Zopounidis, 2001) and in performance assessment of microfinance institutions (Gaganis, 2016).

Among the different versions of PROMETHEE methods, PROMETHEE II is the most frequently applied one because it enables a decision maker (DM) to obtain a complete ranking of the alternatives. It is based on the preference function $P_i(a_j, a_h)$ representing the degree of preference of alternative a_j on a_h. $P_i(a_j, a_h)$ is a non-decreasing function of the difference $d_i = g_i(a_j) - g_i(a_h)$. In Mareschal, Brans and Vincke (1984), the multi-criteria methodology PROMETHEE II has been presented, considering six different types of preference functions: the regular criterion, the u-shape criterion, the v-shape criterion, the level criterion, the criterion with linear preference and indifference area and the Gaussian criterion.

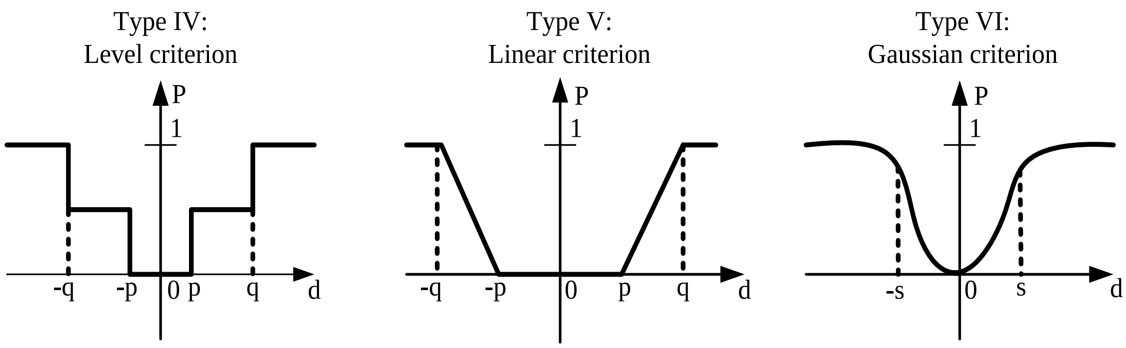
In this study, each preference function is employed to build a binary classification of companies which will be compared with the one provided by AMADEUS database. Moreover, the whole set of preference functions is used to observe how the classification made with PROMETHEE II method varies according the type of function considered (Figure 1.10).



$$P(d_i) = \begin{cases} 0, & if \quad d_i \leq 0 \\ 1, & if \quad d_i > 0 \end{cases}$$

$$P(d_i) \begin{cases} 0, & if \quad d_i \leq q_i \\ 1, & if \quad d_i > q_i \end{cases}$$

$$P(d_i) \begin{cases} 0, & if \quad d_i < 0 \\ \frac{d_i}{p_i}, & if \quad 0 \leq d_i \leq p_i \\ 1, & if \quad d_i > p_i \end{cases}$$



$$\mathrm{P}(d_i) = \begin{cases} 0, & if \quad d_i \leq q_i \\ \frac{1}{2}, & if \quad q_i < d_i < p_i \\ 1, & if \quad d_i \geq p_i \end{cases} \qquad P(d_i) = \begin{cases} 0, & if \quad d_i \leq q_i \\ \frac{d_i - q_i}{p_i - q_i}, & if \quad q_i < d_i \leq p_i \\ 1, & if \quad d_i > p_i \end{cases} \qquad P(d_i) \begin{cases} 0, & if \;\; d_i \leq 0 \\ 1 - e^{-\frac{d_i^2}{2 s_i{}^2}} & , if \;\; d_i > 0 \end{cases}$$

Figure 1.10 Types of preference functions $P(d_i)$. Authors' elaboration

Considering for each criterion g_i a weight w_i such that $w_i \geq 0$ and $\sum_{i=1}^{n} w_i = 1$, PROMETHEE II computes:

$$\pi(a_j, a_y) = \sum_{i=1}^{n} w_i \, P_i(a_j, a_y) \tag{18}$$

which represents the strength of preference of alternative a_j with respect to a_y on the basis of the whole set of criteria. Then PROMETHEE II compares each alternative a_j with the other alternatives by computing the positive and negative inflow of a_j, defined, respectively, as follows:

$$\Phi^{+}(a_j) = \frac{1}{m-1} \sum_{a_j \in \mathrm{A} \setminus \{a_y\}} \pi(a_j, a_y), \quad \text{and} \quad \Phi^{-}(a_j) = \frac{1}{m-1} \sum_{j \in \mathrm{A} \setminus \{a_y\}} \pi(a_y, a_j). \tag{19}$$

Finally, PROMETHEE II builds a net flow for each alternative by:

$$\Phi(a_j) = \Phi^{+}(a_j) - \Phi^{-}(a_j). \tag{20}$$

PROMETHEE II provides a complete preorder on A ranking the alternatives from the best to the worst. The net flow takes values in the range $[-1{,}1]$; if $\Phi(a_j) \simeq 1$, then a_i is almost strictly preferred over all alternative, while if $\Phi(a_j) \simeq -1$, then a_j is almost strictly preferred by all the alternatives.

In Chapter 3, the following assumptions have been considered:

- the weights of criteria have been simulated using a hit and run procedure (see Smith, 1984) with 10,000 scenarios similarly to SMAA-PROMETHEE method (Corrente et al., 2014) but without providing preference information of Decision Maker on the parameters involved and without estimating the SMAA indices;

under each scenario the net flow of each company has been evaluated and the average net flow of each company has been computed for all the scenarios;

- the user constant s_i of the Gaussian criterion, has to be determined on the basis of a rule of thumb: $s_i = \frac{p_i+q_i}{2} > 0$, where for each $g_i \in \mathrm{G}$, p_i and q_i are, respectively, the preference and indifference thresholds;
- as in Rogers and Bruen (1998), for each $g_i \in \mathrm{G}$ we have assumed p_i and q_i constant, computed as follows: $p_i = \frac{2}{3}\,r_i$ and $q_i = \frac{1}{6}\,r_i$ with $r_i = |\max(g_i) - \min(g_i)|$.

Chapter 2

Performance assessment of energy companies employing Hierarchy Stochastic Multi-Attribute Acceptability Analysis[4]

In this chapter we analyses the development of a performance assessment model for the most important listed companies operating in the energy sector, using a dataset obtained merging different sources. The construction of the model is based on a multiple criteria decision aid (MCDA) approach considering various indicators. The multidimensional nature of the topic in this study requires the definition of a hierarchical structure of criteria, which has been aggregated into a composite index to obtain a final ranking for the energy companies under investigation. To handle with a hierarchical criteria structure and to take into account the space of fluctuations related to the imprecision on criteria weights, we employ the Hierarchy Stochastic Multi-Attribute Analysis (HSMAA). Thus, the proposed model is able to evaluate the performances of energy companies under different uncertainty scenarios. The results indicate that the first and last positions are quite robust in all considered scenarios, while the rankings relative to the intermediate positions vary widely by the chosen set of weights, exemplifying the need to rank companies based on multiple sets of criteria weights.

2.1 Background

Nowadays, energy sector appears highly concentrated and characterized by the frequent creation of large corporate groups, in which the principal aim is the extension of the area in which public utilities are delivered also compliant with environmental requirements (Jamasb and Pollitt 2005). In this context, investment programmes play a significant role to foster the development of energy companies and a thorough analysis of the firm's health status is needful to make decisions concerning the optimization of capital allocation.

Thus, for its relevant implications in the public and private sectors, the attention of researchers has focused on the performance evaluation of energy companies, becoming a significant field of study.

Stakeholders require consistent methods to detect the best alternative within the multifaceted setting of the energy system performance, dealing with energy security, energy equity and

[4] This study has been published in the journal of Operational Research: Silvia Angilella, Maria Rosaria Pappalardo (2020). *Performance assessment of energy companies employing Hierarchy Stochastic Multi-Attribute Acceptability Analysis*. Springer Journal. DOI: 10.1007/s12351-020-00567-5. The current work is a combined effort of the two authors. However, Maria Rosaria Pappalardo contributed in conceptualization, implementation, data search and curation, writing; Silvia Angilella contributed in conceptualization and supervision.

environmental sustainability policies as acknowledged also by the Energy Trilemma index of the World Energy Council (2017), assessed for each country's energy market (Song et al., 2017). Energy security concerns an effective management system of primary supply from domestic and external sources, energy equity is related to the energy access and affordability, while environmental sustainability deals with the achievement of the supply and demand side efficiencies and the development of energy supply from renewable sources.

Thus, in this context, a multidimensional analysis is necessary, and Multi Criteria Decision Aid (MCDA) methods appear as the most suitable tools to assess the integrated structure of firms, which typically entails a family of conflicting criteria.

Several studies deal with the implementations of MCDA methods in the energy sector (Section 1.3.2). However, as suggested in Section 1.3.3, the available MCDA literature based on energy companies' performance evaluation is narrow and restricted to the financial aspects of the business (see for example Eyüboglu and Çelik, 2016). This gives a partial perspective for making proper decision-making process, and other dimensions need to be considered along with the financial aspect.

For these reasons, this study aims to select a coherent and hierarchical set of criteria, which highlight the link with the performances enhancement of firms operating in the energy sector. Hence, additional criteria, such as sustainability, technical and market criteria, widely implemented in similar sector studies (Section 1.3.2), have been added to the traditional financial ones, giving more reliability to the decision-making process addressed to several purposes. The proposed family of criteria has been assessed on a set of twenty worldwide listed energy companies, for providing a ranking of them based on their performances.

Moreover, the Hierarchy Stochastic Multi-Attribute Acceptability Analysis (HSMAA) (firstly, introduced in De Matteis et al., 2019) has been employed here, to handle with a structure of criteria organized hierarchically and with the Decision Maker (DM)'s uncertainty on preference parameters, which has been considered simulating different scenarios.

The results of the employed HSMAA model show that the first and last positions of the considered companies are quite robust in all considered scenarios, while the rankings relative to the intermediate positions vary widely by the chosen set of weights, exemplifying the need to rank companies based on multiple sets of criteria weights.

The goals of this study are twofold: on one hand investors will have the advantage to evaluate, as quickly and efficiently as possible, their capital allocation process among various investment opportunities on the energy sector; on the other hand business leaders and policy makers will use the proposed method to check the strengths and the weaknesses of the considered energy companies, identifying then potential energy-policy actions to enhance their overall performances in the future. To this purpose, market criteria as well as indicators about sustainability and technical features of energy companies have been selected and added to the traditional financial variables.

The chapter is organized as follows. The next section provides a literature review of SMAA based models applied on the energy management and of the macro-criteria used to evaluate the energy companies. Section 2.3 describes the data and the family of criteria. In Section

2.4, the proposed methodology is implemented in a real decision problem, considering twenty worldwide listed energy companies. Section 2.5 presents and discusses the obtained results. Finally, conclusions and policy implications are presented in Section 2.6.

2.2 Literature review

One important question arises from the decision-making process for the performance assessment of energy companies: *How it is possible to manage simultaneously a large set of conflictual criteria and different DMs' preference parameters?*

One branch of multi-criteria decision aid (MCDA) models, which helps to solve this important issue, is the Stochastic Multi Attribute Analysis (SMAA), which has been introduced firstly by Lahdelma et al. (1998) to handle with uncertainty on the alternatives' evaluations and/or weights. Furthermore, SMAA methods evaluate some indices through Monte Carlo simulations, supporting a sensitivity analysis on the decision-making process.

The original SMAA method has been extended to SMAA-2 (Lahdelma and Salminen 2001) for ranking purposes and to SMAA-O (Lahdelma et al., 2003) to deal simultaneously with ordinal and cardinal criteria. Moreover, SMAA method has been applied in addition to conventional MCDA methods such as the Data Envelopment Analysis (DEA) (Lahdelma and Salminen, 2006), the PROMETHEE method (Corrente et al., 2014) and the Choquet integral preference model (Angilella et al., 2015) under the hierarchical structure of criteria with a Non Additive Robust Ordinal Regression (NAROR) (Angilella et al., 2016a; Angilella et al., 2016). SMAA methodologies have been successfully implemented in various fields (environmental, health-care, business and financial management) and more related to our concern, they have been employed also in the energy management (see the recent literature review of Pelissari et al., 2019) which suggests that papers on this topic represent the 20% of total papers applying SMAA methods. More specifically, this study has identified sixteen papers, which are listed in Table 2.1, according to the SMAA methodology used.

Table 2.1 Studies using SMAA methodologies for the energy management (Pelissari et al., 2019).

SMAA methods	References	Models used jointly with SMAA	Problem statement to tackle	Main findings	Criteria	Sub-Criteria
SMAA	Loikkanen et al. (2017)	-	To extend traditional benefit-cost analysis by considering criterion of soft attractiveness	Evaluate sustainable technologies to build a large office building in Finland	Attractiveness	Evaluated by experts on a qualitative scale
					Economic	Internal rate of return
					Improvement of the energy efficiency	Improvement in the E-score
					Environmental	CO_2 reduction
	Jung et al. (2016)	-	Analyse the robustness of the respondents' preference rankings in a survey	Analyse the social acceptance of renewables technologies for building in Finland	Perceived reliability	
					Investment costs	
					Payback time	
					National incentives	
	Song et al. (2017)	-	Determine a holistic ranking scheme through the rank acceptability indices and the holistic	Measure country energy performance via energy trilemma index	Energy security	Management of primary energy supply from domestic and external sources, reliability of energy infrastructures, ability of energy companies to meet current and future demand.
					Energy equity	Accessibility and affordability of energy supply across the population

			acceptability indices		Environ. sustainability	supply and demand energy efficiency, development of renewable and low carbon energy supply
SMAA-2	Vishnupriyan and Manohara (2018)	AHP and BWM	Implement a sensitivity analysis and compare the results with AHP and BWM	Evaluate the RES for upgrading and existing power system in India	Technical dimension	PV Capacity factor, Renewable fraction
					Economic dimension	ROI, Payback period, Initial cost, COE
					Environ. dimension	Emissions
	Wang et al. (2017)	SMAA-O	Handle the uncertainties of ordinal criteria measurements when mapping the ordinal scales	Evaluate the combined district heating system	Economy	Net heating cost
					Technology	Reliability, regulation convenience, maturity
					Environment	NO_x, SO_2, PM_{10}, CO_2
					Energy	Energy efficacy, energy utilization policy
	Wang et al. (2015)	-	Handle the uncertainties in criteria evaluations and weighting through the Feasible weight space	Evaluate combined heat and power units	Technical dimension	Electrical output, power to heat ratio
					Economic dimension	Installation cost, maintenance cost, electricity cost, heat cost
					Environ. dimension	CO_2 production, footprint
	Rahman et al. (2013)	SMAA-O	Treat mixed ordinal and cardinal measurements for criteria	Evaluate choices for sustainable rural electrification projects	Technical dimension	Capacity utilization factor, compatibility with future capacity expansion, compatibility with existing infrastructure, Availability of local skills and resources , Weather and climate condition dependence, Annual resource availability duration
					Economic dimension	Capital cost, Annual operation and maintenance costs , Lifespan of the system, Learning rate, Current market share, Dependence on fossil fuel
					Social dimension	Public and political acceptance, Scope for local employment, Public awareness and willingness, Conflict with other applications
					Environ. dimension	Lifecycle, GHG emissions, Local environmental impact
					Policy/regulation dimension	Land requirement and acquisition, Emphasis on use of local resources, Opportunity for private participation, Tax incentives, Degree of local ownership, Interference with other utilities
	Kirppu et al. (2018)	-	Deal with highly conflicting experts preferences	Evaluate production technologies only based on carbon-neutral heat	Costs	Investments costs, levelized costs of heat
					Technical	Availability, storability, flexibility, maturity
					Environmental	Space requirements, logistics, CO_2 emissions, other emissions
	Mendecka et al. (2020)	Data reconcilia tion approach	Consider different and individual uncertainty of the criteria preferences and to adjust the random vector of weights	Evaluate biodiesel production technologies	Energy	Cumulative energy consumption
					Environmental	Global warming potential
					Economic	Investment and operating cost
					Social	Human health
	Rahman et al. (2016)	LEAP model	Examine the preferences of different policy elements that are not available	Evaluate energy policy elements in Bangladesh	Technical dimension	Capacity utilization factor, compatibility with future capacity expansion, compatibility with existing infrastructure, Availability of local skills and resources, Weather and climate condition dependence, Annual resource availability duration
					Economic dimension	Capital cost, Annual operation and maintenance costs , Lifespan of the system, Learning rate, Current market share, Dependence on fossil fuel
					Social dimension	Public and political acceptance, Scope for local employment, Public awareness and willingness, Conflict with other applications
					Environ. dimension	Lifecycle GHG emissions, Local environmental impact
					Policy/regulation dimension	Land requirement and acquisition, Emphasis on use of local resources , Opportunity for private participation, Tax incentives, Degree of local ownership, Interference with other utilities
	Wang et al. (2018)	SMAA-O	Deal with quantitative and qualitative criteria	Evaluate district heating systems	Economy	Tot. costs per floor area
					Environment	NO_x, SO_2, CO, CO_2, other
					Energy	Technical merit, mentality effects, heating charge
	Kontu et al. (2015)	Hierarchi cal model	Handle simultaneously with a hierarchy of criteria and sub-criteria, ordinal and	Evaluate heating choices for a new sustainable residential area	Economic	Investment costs, operating costs
					Environmental	Climate impact, particulate emissions
					Social	Domestic, promotes new technologies, popularity, competing energy providers
					Technology	technical solutions are flexible, reliability

			uncertain cardinal information and imprecise preference information		Usability	provides meaningful activity, easy to acquire, care-free, easy to use, requires little space and his unobtrusive
SMAA-2	Lahdelma et al. (2006)	Multivariate Gaussian distribution	Treat the criteria uncertainties and their independencies	Support the strategic decision of an electricity retailer in the deregulated European electric. market	Long term profit	
					Short term profit	
	Lahdelma et al. (2009)				Market share	
					Green share	
SMAA	Dias et al. (2018)	ELECTRE TRI	Determine approximately robust classifications of energy policies	Sort and rank energy policies of smart grids in Brazil	Environ. and human health	
					Technol. Infrastructure	
					Security of supply	
					Electricity markets	
					Financial benefit to agents	
					Benefit to country	
					Feasibility and adoption	
SMAA	Tylock et al. (2012)	Revision of the Algorithm 2	Constraint weight ranges and facilitate DMs to express the weights in qualitative terms	Identify the best choice for energy technologies in terms of investment decision	Fossil fuel savings	
					Economic payback period	
					Energy independence	
					Personnel requirements	

All the studies have the characteristic to use conflictual criteria, involving all those aspects that are expected to affect the specific issue under investigation. The selection of the most appropriate criteria is an important aspect in whatever decision-making problem, becoming more evident in performance evaluation of energy companies; however, in this respect, the literature appears poor and inadequate.

Consequently, it is important to enrich the existing literature mainly based on financial measures (Altman, 1968; Beaver, 1966), adding some specific features of energy companies taken from studies of sustainability energy assessment applying MCDA methods and chosen for their possible implications in terms of performance evaluations (Weber et al., 2008). Therefore, beyond the financial indicators, three macro-criteria have been also considered: sustainability, technical and market.

Sustainability measures the behaviour of each group with respect to the surrounding environmental structure, emphasizing the concept of “green sustainability”.

Most studies on companies from different sectors examine the relationship between environmental and financial performance (Edwards, 2014; Klassen and McLaughlin, 1996) and some of these find a positive impact of green practices (e.g. pollution avoidance, reducing raw materials use) on competitive outcomes (e.g. product quality, company innovativeness) (Rusinko, 2007). This relationship becomes more evident for energy companies, since they can be simultaneously producers and distributors of energy and thus of pollutants.

Moreover, according to their green policies, companies are able to attract more stakeholders’ investments, enhancing their competitive advantage (Shrivastava, 1995).

Technical macro-criteria are referred generally to internal company features. Several papers emphasize the importance of technical characteristics inside the evaluation process. They affect the equilibrium values of the firm’s productivity, the profitability and the stock price, enhancing companies’ business profits (Alam and Sickles, 1998). A firm needs specific

technical elements to be efficient, to provide a reliable quality of service, to ensure future developments increasing its market shares.
Moreover, it is widely acknowledged that market orientation contributes to enhance significant companies' achievements in terms of firm's financial dimensions as well as external market price (Ramaswami et al., 2009). In this sense, the existence of a large gap between firm's market value and financial results arising from financial statements has been emphasized, due to not full adequacy of the balance sheet data with the technological improvement, competition or deregulation of companies' lifecycle.
Renewed variables associated to market criteria are required in the analysis, since liberalization process and green energy policies have been increased over the last decades. Thus, recent economic studies intensify their interest towards "non-financial variables" that have the power to be more discriminating than traditional financial ratios. Some studies identify these variables with product quality, customer satisfaction and market share (Banker et al., 2000), some others with sales volume and market development (Sarkar et al., 2001). However, all of them strongly agree that market share has a positive relationship with business profitability even if inconsistent in magnitude (Prescott et al., 1986).

2.3 Data

2.3.1 Data collection and alternatives

The sample considered for implementing the HSMAA method is composed of twenty European and American energy listed companies whose data have been collected by merging different sources. Initially, a set of European companies have been drawn from the Amadeus database of Van Dijk (2010), based on the two-digit NACE code 35 used as filter which covers the main industrial sectors in the energy sector. Within the NACE code 35, we have selected specifically the code 351, indicating electricity, gas, steam and air conditioning supply sector, articulated in the electricity production, transmission, distribution and trade segments. Among the listed companies operating in the energy supply chain, only those located in Europe have been selected.
Then, all those companies mainly involved in only one sector (such as the distribution of electricity, the renewable power production, the trading sector, the industrial plant management) have been excluded from the original sample, as well as those with unavailable public sustainability report or drawn up in a language other than English, Italian or French. Finally, other European and American companies have been added to the original sample, selecting those that contribute significantly to the gross national power production. The first ones have been chosen from the "Annual Report on the state of services and on the regulatory activities" published by Arera in 2018; the second ones have been selected among the main competitors of the most important European energy companies. Thus, the final sample is composed of twenty worldwide energy listed companies mainly operating in the gas and electricity market. Table 2.2 shows how the examined companies are distributed per country.

Table 2.2 Energy companies in the final sample distributed per country.

ENERGY COMPANIES	COUNTRY	ACRONYM
ENEL SPA	ITALY	BIT:ENEL
ENI	ITALY	BIT:ENI
EDISON SPA	ITALY	BIT: EDNR
A2A SPA	ITALY	BIT: A2A
IREN SPA	ITALY	BIT:IRE
ACEA SPA	ITALY	BIT:ACE
GRUPPO HERA	ITALY	BIT:HER
ELECTICITE' DE FRANCE	FRANCE	ENXTPA
ENGIE SA	FRANCE	ENXTPA:ENGIE
E.ON SE	GERMANY	DB:EOAN
SSE PLC	UK	LSE:SSE
DRAX GROUP PLC	UK	LSE:DRX
RWE	GERMANY	DB:RWE
EXELON CORPORATION	USA	NYSE:EXC
AMEREN	USA	NYSE:AEE
DTE ENERGY COMPANY	USA	NYSE:DTE
XCEL ENERGY INC	USA	NasdaqGS:XEL
DUKE ENERGY CORPORATION	USA	WBAG:DUKE
IBERDROLA	SPAIN	BME:IBE
ENDESA	SPAIN	BME:ELE

Each company is organized in business units of different nature, such as electricity generation and trading, service facilities, environment, trade, smart city, e-solutions, which have the common feature to operate predominantly in the same activity sectors: the production of electricity and the distribution of electricity and gas.
The performance matrix has been constructed by merging the following data sources:

- Compustat database, to compute the financial ratios;
- the sustainability reports, the consolidated balance sheets and the specific group's website, to handle respectively with environmental and technical criteria;
- Arera Annual Report (2018) and U.S. Energy Information Administration (EIA), State Electricity Profiles (2017) to deal with the market criteria.

All the data have been collected in 2017, the latest fiscal year for which data are fully available.

2.3.2 Family of criteria

In this section, we describe the hierarchical structure of criteria used in the analysis of the performance of the considered energy companies in the selected sample. The examined variables involve financial, environmental, technical and market dimensions of the energy companies' performance assessment. Specifically, in this study four macro-criteria are considered: financial, sustainability, technical and market. These criteria have been further decomposed into more detailed sub-criteria as follows:

1) **Financial**. The first macro-criterion considered to evaluate the performance of energy companies is the financial one. Financial ratios have been frequently used by several researchers to assess corporate firm's performance (see among others Altman, 1968; Beaver, 1966), including also the energy sector (Eyüboglu and Çelik, 2016). Analysts have provided many attempts to sort financial ratios into four or five categories, to examine better the specific aspects, which have a significant impact on energy firm's

performances. Usually, these aspects are identified with profitability, turnover, solvency, liquidity and leverage.

In this study, we monitor such dimensions, using Return on Asset (ROA), Total Asset Turnover ratio (TAT), Total Liabilities to Net Worth ratio (TLNW), Current Ratio (CR), and the Debt Ratio (DR) as measures, respectively, of profitability, turnover, solvency, liquidity and leverage.

Table 2.3 presents the correlation coefficients between the variables under consideration. From Table 2.3, it can be observed that most of the correlations are moderate, ranging below 0.4, except for the high correlation of ROA with Debt Ratio (greater than 0.6), which has been eliminated from the original set of elementary criteria referred to the financial macro-criteria.

Table 2.3 Pearson correlation coefficients among financial criteria. Sources: Statistical Software Stata

Variables	ROA	TAT	TLNW	CR	DR
ROA	1.000				
TAT	-0.107	1.000			
TLNW	-0.083	-0.241	1.000		
CR	-0.373	0.383	-0.008	1.000	
DR	0.640*	-0.347	0.031	-0.258	1.000

* shows significance at the .05 level

More in detail, to avoid inconsistency issues, profitability and turnover have been grouped into *efficiency criteria*, while solvency and liquidity into *indebtedness criteria*. Thus, the financial macro-criterion is split into two sub-criteria: efficiency and indebtedness. Moreover, the efficiency sub-criteria have been further decomposed in Return on Asset and Total Asset Turnover, while Total Liabilities to Net Worth and Current Ratio descend from indebtedness criteria. A brief description of the financial elementary criteria is provided below.

Efficiency criteria:

- *Return on asset (ROA)* is the ratio between the current year's net income and the value of all company's assets in the same period, chosen among a broad range of profitability ratios, for its frequent use in the energy sector (Doumpos et al., 2017);
- *Total asset turnover (TAT)* is measured as ratio between company's revenue and total asset, chosen considering the multi-criteria analysis of Babic and Plazibat (1998) on the enterprises' ranking.

Indebtedness criteria:

- *Total liabilities to net worth (TLNW)* has been computed as the total liabilities over the net worth (the difference between assets and liabilities) to provide to lenders and investors, a crucial indicator of the firm's indebtedness level;
- *Current ratio (CR)* is the ratio between the current assets and the current liabilities. The higher the ratio, the greater the liquidity position. Optimal values for current ratios differ according to the specific sectors in which the companies operate. Among

the common liquidity ratios, Current Ratio has been chosen, since it is a good measure of liquidity criteria also in energy sector (Eyüboglu and Çelik, 2016) and it represents the firm's ability to cover debts over the next 12 months.

2) **Sustainability** is the second macro-criterion considered. It is split into three sub-criteria: environmental, economic, social. Moreover, at the third level carbonic intensity index and morbidity indicator descend from the environmental criteria, while sustainable resources indicator and employment indicator descend respectively from economic and social criteria.
These elementary criteria, generally obtained from companies' sustainable or integrated report, measure the environmental, human and social externalities.
In this analysis, the "triple bottom line" approach has been followed, since it is based on the sustainable development concept. It is often used by many organizations, to evaluate their sustainability performance in a broader environmental, economic and social perspective. Hereafter, sustainability sub-criteria are described more in detail.

Environmental criteria refer to negative externalities produced by power plants in a given environment. Generally, they have been used to evaluate the impact that the production of energy can generate on surrounding environment, through the reduction or the increase of the pollutant emissions. However, the use of electricity also causes damage to human health, natural ecosystem and other non-environmental externalities like employment and security, which will be "paid" by future generations.
In this study, environmental criterion has been further decomposed into two elementary criteria:

- *Carbonic Intensity index (CO_2_Emissions)* represents the specific amount of CO_2 emissions derived from thermal generation, simple and combined, over the total production of electricity and heat (gCO_2/KWh) (La Rovere et al., 2010; U.S. Energy Information Administration Glossary, 2012). It is always used together with other Greenhouse gas emissions (GHG) and waste production, as measures of environmental externalities.
- *Morbidity indicator (Morbidity)* is given by the ratio between the amounts of NO_x emissions expressed in tons and the total annual energy produced by the power plant (tNO_x/MWh). In this study, it has been used to measure the adverse health effects of energy production, following the approach of Afgan and Carvalho (2008).

Economic criteria are always considered in MCDA studies addressed to the energy companies, to evaluate the sustainability of electrical energy generation technologies. Generally, companies that want to survive for a longer period and gain a competitive advantage, base their policies on two elements: "green resources", i.e. new and renewable energy sources (such as hydropower, biomass, wind, solar) and "sustainable investments", namely corporate investments addressed to environmental, ethical and social aspects.

In this study, the economic criteria have been assessed only with a *sustainable resource indicator*, since the data on sustainable investments are not available for all the considered alternatives:

- *Sustainable resources indicator (Sust_Res)* is the percentage contribution of renewable energy resources (RER) as defined before to the total amount of energy production (%) (Štreimikienė et al., 2016).

Social criteria represent the third pillar of Sustainability Development and generally refer to personal resources such as skills, education, and employment. For long time, social sustainability has been neglected in reports, for its difficulty of quantification in terms of economic and environmental impact. Only recently social reputation and firms' performance relationship attracted the attention among academics. Some attempts to build social indicators through the Global Reporting Initiative (an international corporation that helps organizations understand and communicate their sustainability report in a clear and comparable way) and MCDA models, highlight the importance of this criterion in the evaluation process (see GRI- Global Reporting Initiative, 2002 for further details).
A literature review on MCDA in sustainability energy decision-making (Wang et al., 2009), stresses how social sustainability continues to reflect qualitative criteria; instead other studies prefer to employ quantitative indicators such as the job indicators, social acceptability, visual impact and health effects on the surrounding population (Barros et al., 2015; Maxim, 2014). Among these several and various quantitative indicators, a few studies aim to create hybrid indicators by merging the social with the political aspects (Kahraman et al., 2009); others deal only with social indicators (La Rovere et al., 2010); other ones add to the traditional job creation indicators, specific social sub-indicators (Jovanović et al., 2009).
In this analysis, the social criteria have been assessed with the following indicator, obtained by merging the approach of La Rovere et al. (2010) and Barros et al. (2015):

- *Employment indicator (Employment)* is computed as the amount of full-time permanent employee divided by the electrical energy production (full-time person-years/GWh) (Maxim, 2014).

3) **Technical.** It is the third macro-criterion considered in this analysis. It is further decomposed into two criteria of the second level: *technical efficiency and technical capacity*, and from each of them some elementary criteria of third level has been identified: energy loss indicator, customer satisfaction index and network density indicator descending from the *technical efficiency criterion*; electrical factor capacity and demand indicator descending from *technical capacity criterion*.
Again, specific indicators generally obtained from companies' sustainable, integrated report or companies' website, measure these elementary criteria.
Technical efficiency and technical capacity criteria clearly represent the features of the technology linked to power source and to production capabilities.

Technical efficiency indicates the effectiveness with which a firm produces the output, given a set of inputs. In the electrical production process, this measure expresses the amount of energy within raw materials converted into output, such as electricity and heat (Maxim, 2014).

In this study, *technical efficiency* has been assessed using the following elementary criteria:

- *Energy loss indicator (Energy_loss)* is a percentage value obtained from the difference between the theoretical efficiency, 100%, and the specific efficiency score of each company. The efficiency score is calculated as the ratio between the total production of electrical energy measured in GWh and the equivalent amount of energy associated to the raw materials (i.e. gas, coal, oil and others) used in the electricity production process, converted in GWh (Maxim, 2014).
- *Customer Satisfaction Index (CSI)* represents the satisfaction perceived by the customer from the quality of goods and services provided by a company, expressed as percentage. Data on CSI have been taken from the Sustainability Reports of energy companies, which gather them annually by means of different survey methods. One of these survey practises is the so-called CATI methodology (Computer Aided Telephone Interview), in which data on customer satisfaction are collected through a telephone interview of 15 minutes on a sample of householders and then evaluated on an increasing numerical scale (see for further details of CSI computation, Hera Group. Consolidated non-financial report, 2017).
- *Network density indicator (EG_Density)* is given by the ratio between the total volume of electricity and gas delivered per unit of network length (GWh/km) and it measures the economies of density of a company i.e. the expansion in the existing service areas where further network is not necessary (Jamasb et al., 2012).

Technical capacity indicates the firms' ability to make the maximum electrical energy production by using its installations. It was employed in multi-criteria decision aid studies related to sustainability assessment or expansion of electrical generation technologies (Maxim, 2014).
The *technical capacity* is measured by:

- *Electrical factor capacity (E_factor)* is the percentage ratio between the net produced electrical energy per year and the maximum electrical energy that could be obtained exploiting the maximum power plant capacity in the same period, i.e. the total installed power, multiplied by the total amount of hours in one year (Wang et al., 2009);
- *Demand indicator (EG_demand)* is the total volume of electricity and gas delivered by the company in a year over the total number of customers, expressed in GWh/person (Farsi et al., 2007).

4) Market. The fourth macro-criterion considered in this analysis is the market one. It is split into three criteria of the second level: *market share*, *investment opportunity* and *country profile* further decomposed into three elementary criteria, specifically market share, price to book value and trilemma index.

Data on market share have been taken from different sources: Arera Annual Report for Italian companies (2018); U.S. Energy Information Administration (EIA), total retail sales (2017) for American companies; Iberian Data Flyer (2017) for Spanish companies and Ofgem Data Portal for UK companies (2017). Data on price to book value and on trilemma index have been obtained from, respectively, Compustat database and the report published annually by the world energy council (2017) website.

To the best of our knowledge, one of the most significant attempts to consider market criterion in the energy sector, is the paper of Doumpos et al. (2017). They measure the country effects on firms' performance assessment using macroeconomic environmental variables, countries' energy markets characteristics and firm's specific attributes. Such indicators highlight how energy companies are affected by the status of the economic and national institutional context in which companies produce, distribute or sell their products.

In this study, the following three market elementary criteria have been considered:

- *Absolute market share (MS):* is the ratio between the company's electricity sales and the total electricity sales of companies operating in a certain country. It is a representative measure of the company's market position in comparison to its competitors producing similar products, i.e. its market power.

  Absolute market share has been used in this analysis instead of the relative one, since the considered companies belong to the same sector (see Szymanski et al., 1993 for further details of calculation).
- *Price to book ratio (P/B)* is computed as the market share price over the book value per share.

  Market share price is obtained here by looking at the average value among the high, low and close share price in the market at the end of 2017; book value per share is obtained from the balance sheet data as ratio between the difference of total assets and total liabilities and the number of shares outstanding.

  It measures how good a company is evaluated on market in comparison with its book value; thus, it is a good indicator for DMs that are looking for the best potential investment.
- *Energy Trilemma index (ETI)* is an official indicator published annually by the World Energy Council (2017) to rank the energy performance of different countries with respect to three dimensions: energy security, energy equity and environmental sustainability (Song et al., 2017).

  Energy security refers to the ability to provide a safe and reliable energy system; Energy equity denotes the level of accessibility and affordability across the population and Environmental sustainability represents the efficiency and the development of green resources within the energy system.

For each country, WEC establishes separate values on single dimensions and then compute a composite indicator (ETI) expressed in a balance score, to give a global ranking of all countries. The higher the values in all three dimensions, the better will be the balance score and consequently the final ranking of the country.
In this study, ETI has been employed for its great ability to enclose in a unique balance score, elements of different nature such as economic and social factors, institutional elements, public and private actors, resources, demand and supply behaviour, allowing to introduce a comprehensive country effect inside our decision model.
For our purpose, ETI has been used in the performance matrix with numerical values in place of the balance score to facilitate the comparison among alternatives and the normalization process. Therefore, for each country of the considered companies' average value from the three aforementioned dimensions has been calculated and then applied to each company located in the same considered country.

The whole hierarchy of criteria, which has been displayed in Figure 2.1, is composed at the first level of four macro-criteria, at the second level of ten criteria and at the third level of sixteen elementary criteria.
Table 2.4 lists all the elementary criteria and reports the corresponding units of measures, preference direction, abbreviations and data sources.

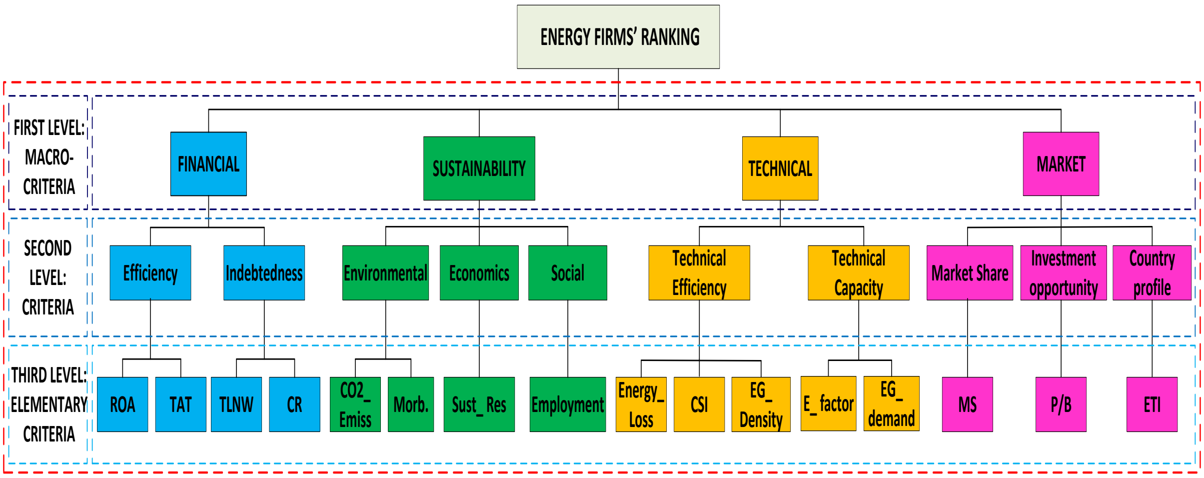


Figure 2.1 Hierarchical structure of criteria

Table 2.4 Description of the variables

Elementary criteria	Acronym	Definition	Unit of measure	Pref. Direc.
Return on Asset	ROA	Net Income/Total asset	%	max
Total asset turnover	TAT	Revenue/Total assets	%	max
Total liabilities to net worth	TLNW	Total liabilities/Net worth	%	min
Current ratio	CR	Current assets/ Current liabilities	%	max
Carbonic Intensity index	CO_2_Emis	CO_2 emissions from thermal generation/Net energy Production	gCO_2/KWh	min
Morbidity indicator	Morb	NO_x emissions/Energy production	tNO_x/GWh	min
Sustainable resources indicator	Sust_Res	Contribution of RER (hydropower, biomass, geothermal, wind, solar…)/Total energy production	%	max
Employment indicator	Employment	Full time permanent employee/Electricity production	person-years/GWh	max
Energy loss indicator	Energy_loss	100% - Efficiency score (electricity production /equivalent amount of energy associated to the row materials)	%	min
Customer satisfaction index	CSI	Percentage quality measure of good and services	%	max
Network density indicator	EG_Density	Tot. volume of electricity and gas delivered/tot. network length	GWh/km	max
Electrical factor capacity	E_factor	Net electricity production/Total installed power * 8640 hours	%	max
Demand indicator	EG_demand	Tot. volume of electricity and gas sold/Tot. number of customers	GWh/person	min
Absolute Market share	MS	Company's energy sales / Market's electricity sales	%	max
Price to book ratio	P/B	Market share price /Book value per share	%	max
Energy Trilemma Index	ETI	Average value between energy security-energy equity-environmental sustainability for a given country	n.	min

2.4 The methodology: HSMAA

In a Multi Criteria Decision Aiding (MCDA) problem there is a finite set of alternatives $A = \{a_1, \dots, a_k, \dots, a_m\}$, which are evaluated on a consistent set of criteria $G = \{g_1, g_2, \dots, g_n\}$.
In this study, the alternatives are twenty worldwide listed companies operating in the energy sector, mainly in the gas and electricity segment. Each alternative $a_k \in$ A is assessed on a hierarchical criteria structure composed of three levels: macro-criteria, criteria and elementary criteria, as shown in Figure 2.1.
In this study, we rank these companies based on their performance evaluations, from the best to the worst. Moreover, since the structure of criteria is organized in the three aforementioned levels, Hierarchy Stochastic Multi Attribute Analysis (HSMAA) (De Matteis et al., 2019) is adopted to provide a "more robust recommendation" on final rank results.
The detailed description of this methodology is presented in Section 1.4.1.
Moreover, from a computational point of view, in this study the proposed HSMAA method shares the following elements with the methodology presented in De Matteis et al. (2019):

- the use of Monte Carlo Simulation in calculating the multidimensional integral for rank acceptability index computation;
- the elimination of the probability distribution on alternatives $f_X(\xi)$, for the availability of a specific value on each criterion taken from the companies' balance sheet data or their sustainability report.

However, our model differs from HSMAA of De Matteis et al. (2019) for the implementation of the Hit and Run (HAR) technique (Smith, 1984; Tervonen and Lahdelma, 2007) in place of the uniform distribution, to sample the set of weights. In particular, HAR sampling procedure has been applied respectively on weights of the macro-criteria and sub-criteria. Otherwise, inside the same node the weights have been divided equally among the elementary criteria. The stopping rule used for the HAR sampling procedure is the maximum number of iterations equal to 10,000 meaningful to obtain robust results (Tervonen et al., 2013).

Within HSMAA we shall consider the following two different cases:

- **Case (1).** HSMAA is performed without DM's preference on the macro-criteria weights;
- **Case (2).** The analyst simulates the possibility that the DM can express a preference on macro-criteria weights, preferring for example the financial to the sustainability and the technical to the market macro-criteria (translated into the following constraints $w_1 > w_2$ or $w_3 > w_4$) and so on. Simulating a decision process, six-preference information on the criteria weights have been taken into consideration and presented in Table 2.5.

For the sake of uniformity, we call the first case also first scenario; while the six-preference information relative to case (2) are renamed scenarios from second to the seventh.
Table 2.5 summarizes the all scenarios with the corresponding preference information.

Table 2.5 The considered scenarios

Cases	**Scenarios**	**DM's preferences on macro-criteria weights**
Case (1)	Scenario 1	no preference information on macro-criteria
Case (2)	Scenario 2	$w_1>w_4$ and $w_2>w_3$
	Scenario 3	$w_1>w_2$ and $w_3>w_4$
	Scenario 4	$w_1>w_3$ and $w_2>w_4$
	Scenario 5	$w_2>w_1$ and $w_4>w_3$
	Scenario 6	$w_3>w_1$ and $w_4>w_2$
	Scenario 7	$w_4>w_1$ and $w_3>w_2$
macro-criteria	1 = financial; 2 = sustainability; 3 = technical; 4 = market	

Consequently, in each case HSMAA gives as output:

- **Case (1)** One probability distribution for the alternatives' ranking (rank acceptability indices);
- **Case (2)** Six probability distributions for the alternatives' ranking (rank acceptability indices).

Finally, to get more insights in the problem at hand, HSMAA has been also implemented with respect to each macro-criterion: financial, sustainability, technical, market, obtaining four probability distributions for the alternatives' ranking.

2.5 Results and discussions

2.5.1 Ranking of energy companies' performances

Criteria evaluations of the twenty energy-listed corporations considered are reported in Table 2.6.

Table 2.6 Performance matrix. Authors' elaboration.

ALTERNATIVES		**MACRO-CRITERIA**	**FINANCIAL RATIO**				**SUSTAINABILITY**			
		Elementary criteria	ROA	TAT	TLNW	CR	CO2_Emis	Morb.	Sust_Res	Employment
		Unit of measure	%	%	%	%	g CO2/KWh	t NOx/GWh	%	person- years/GWh
		Pref. direction	max	max	min	max	min	min	max	max
ENERGY COMPANIES		COUNTRY								
1	ENEL SPA	ITALY	3.80	46.69	198.39	90.05	411	0.81	6.56	0.24
2	ENI	ITALY	2.70	58.23	139.04	148.08	393	0.11	0.09	0.90
3	EDISON SPA	ITALY	-0.30	85.11	66.37	119.81	314	0.21	16.00	0.23
4	A2A SPA	ITALY	4.40	56.19	230.20	130.77	419	0.16	25.00	0.54
5	IREN SPA	ITALY	3.40	43.67	216.05	138.49	366	0.06	86.00	0.50
6	ACEA SPA	ITALY	2.90	36.37	305.02	100.18	424	0.21	65.13	4.84
7	GRUPPO HERA	ITALY	3.50	63.87	224.72	109.31	527	0.43	67.50	4.29
8	EDF	FRANCE	0.90	23.87	458.20	144.09	82	0.10	10.17	0.24
9	ENGIE SA	FRANCE	1.90	39.68	256.60	105.34	363	0.16	23.10	0.25
10	E.ON SE	GERMANY	2.00	67.58	734.10	103.44	308	0.39	29.30	0.11
11	SSE PLC	UK	4.80	121.4	281.30	112.44	304	0.21	30.30	0.69
12	DRAX GROUP	UK	-2.00	104.7	104.50	143.40	297	0.72	65.00	0.12
13	RWE	GERMANY	0.30	21.25	714.20	115.13	670	0.41	5.22	0.28
14	EXELON CORP.	USA	2.60	28.74	262.80	110.17	488	0.90	15.00	0.16
15	AMEREN	USA	3.60	22.78	254.10	54.83	729	0.38	4.49	0.20
16	DTE ENERGY	USA	3.20	37.34	238.00	109.57	707	0.53	8.73	0.24
17	XCEL ENERGY	USA	3.10	26.32	275.60	72.72	458	0.33	27.00	0.11
18	DUKE ENERGY	USA	2.70	16.81	230.40	67.72	478	0.25	5.00	0.13
19	IBERDROLA	SPAGNA	1.90	28.24	159.00	82.50	187	0.26	41.00	0.24
20	ENDESA	SPAGNA	3.90	63.01	236.20	73.39	439	1.07	4.38	0.17

ALTERNATIVES		**MACRO-CRITERIA**	**TECHNICAL**					**MARKET**		
		Elementary criteria	Energy_loss	CSI	EG_Density	E_factor	EG_demand	MS	P/B	ETI
		Unit of measure	%	%	GWh/Km	%	GWh/person	%	%	n.
		Pref. direction	min	max	max	max	min	max	max	min
ENERGY COMPANIES		COUNTRY								
1	ENEL SPA	ITALY	40.54	93.75	0.20	34.06	0.006	25.00	1.35	21.66
2	ENI	ITALY	55.63	86.70	0.30	55.21	0.101	5.70	1.01	21.66
3	EDISON SPA	ITALY	43.33	95.80	0.75	35.86	0.079	5.20	0.87	21.66
4	A2A SPA	ITALY	35.53	90.60	1.44	20.78	0.010	2.70	1.57	21.66
5	IREN SPA	ITALY	56.25	92.00	1.14	36.81	0.027	3.00	1.4	21.66
6	ACEA SPA	ITALY	63.26	89.60	0.35	32.26	0.050	1.60	1.69	21.66
7	GRUPPO HERA	ITALY	73.30	69.00	1.00	53.69	0.017	3.60	1.61	21.66
8	EDF	FRANCE	63.13	71.00	0.28	51.98	0.019	68.00	0.66	14.66
9	ENGIE SA	FRANCE	56.40	83.00	1.16	51.98	0.047	11.00	0.86	14.66
10	E.ON SE	GERMANY	28.35	70.00	0.39	26,00	0.011	11.60	15.27	20.33
11	SSE PLC	UK	20.96	76.00	0.90	28.59	0.002	14.00	2.58	16.66
12	DRAX GROUP	UK	59.03	84.00	0,00	26.89	0.028	10.00	0.67	16.66
13	RWE	GERMANY	46.55	75.00	0.54	54.08	0.023	16.00	2.04	20.33
14	EXELON CORP.	USA	72.30	79.00	7.25	64.27	0.042	5.69	1.31	35.66
15	AMEREN	USA	24.77	74.00	0.81	41.89	0.040	2.07	1.93	35.66
16	DTE ENERGY	USA	27.80	71.90	1.59	39.09	0.057	1.20	2.09	35.66
17	XCEL ENERGY	USA	31.00	72.30	0.55	66.16	0.048	2.87	2.12	35.66
18	DUKE ENERGY	USA	58.74	76.00	0.78	48.32	0.042	6.78	1.43	35.66
19	IBERDROLA	SPAGNA	34.82	78.00	0.25	32.88	0.012	22.00	1.14	22.66
20	ENDESA	SPAGNA	29.91	73.00	0.37	38.44	0.014	29.00	2.34	22.66

Data Source: Compustat Database, Sustainability report, annual report, integrated report, companies website, Arera, U.S. EIA Total retail sales, Iberian Data Flyer, Ofgem Data portal, World Energy Council Trilemma Index

In order to get recommendations to DMs as robust as possible, the ranking of the energy companies considered was made employing the HSMAA, presented in the above section. Before implementing the proposed methodology, we perform a normalization procedure on the criteria evaluations of each company.

Normalization procedure is necessary since it allows the transformation of raw data into comparable measurement scales.

Many normalization methods are reported in literature (Joint Research Centre of the European Commission, 2008). Usually they are clustered in:

- data driven and expert-driven;
- internal and external.

Data driven methods are based on statistical elements of the dataset and include the standardization, the min-max and the target approach; while expert-driven methods consist for instance of the value theory methodology based on inputs provided by experts and a value function elicited from specialists or DMs (Geneletti and Ferretti, 2015).

Moreover, normalization methods can be classified into internal or external according to whether they are dependent or independent from the raw dataset with a reference point fixed externally or internally to the dataset (Laurent and Hauschild, 2015).

Although until now, it does not exist a specific rule of thumb to select a normalization method over another, each of them is characterized by proper advantages and disadvantages. Therefore, the final choice depends on a combination of theoretical framework and data properties (Joint Research Centre of the European Commission, 2008).

In this study, we have applied specifically the min-max normalization method since it is the most used when an additive aggregation function is employed as the weighted sum and no direct or indirect inputs are provided by experts or DMs (see Gasser et al., 2020 for a detailed analysis and comparison of normalization methods).

Specifically, the two equations displayed below, have been employed according to the preference direction of each elementary criterion, respectively, to maximize or to minimize:

$$\overline{g}_i(a_k) = \frac{g_i(a_k) - min_i}{max_i - min_i}; \tag{21}$$

$$\overline{g}_i(a_k) = \frac{max_i - g_i(a_k)}{max_i - min_i}; \tag{22}$$

where $\overline{g}_i(a_k)$ is the value after the normalization, $g_i(a_k)$ is the evaluation of the alternative a_k on the elementary criterion g_i, min_i and max_i are, respectively, the minimum and the maximum values that alternative a_k has on criterion g_i.

Min-max normalization method being based on the bounded scale $[0, 1]$ presents the advantages to provide an easy comparison among the alternatives and to not be affected by the number of over/under performances. However, it has the disadvantages to not maintain the ratios between the performances and to be strongly affected by outliers (Carrino, 2017).

To overcome the issue that outliers can have a strong impact on the normalized values, data were trimmed. The outliers were identified with the Interquartile Range method (IRQ), by simply verifying one of the following inequalities (Gasser et al., 2020):

$$g_i(a_k) < Q_1 - 1.5(Q_3 - Q_1) \quad \text{or} \quad g_i(a_k) > Q_3 + 1.5(Q_3 - Q_1) \tag{23}$$

Then, data were trimmed to the maximum or minimum values that are not outliers.
Table 2.7 reports data trimmed to the maximum and minimum values, respectively, in yellow and orange.

Table 2.7 Performance matrix with the outliers trimmed to the maximum and minimum values. Authors' elaboration.

ALTERNATIVES		MACRO-CRITERIA	FINANCIAL RATIO				SUSTAINABILITY			
		Elementary criteria	ROA	TAT	TLNW	CR	CO2_Emis	Morb.	Sust_Res	Employment
		Unit of measure	%	%	%	%	gCO_2/KWh	tNO_x/GWh	%	person- years/GWh
		Pref. direction	max	max	min	max	min	min	max	max
ENERGY COMPANIES		COUNTRY								
1	ENEL SPA	ITALY	3.80	46.69	198.39	90.05	411	0.81	6.56	0.24
2	ENI	ITALY	2.70	58.23	139.04	148.08	393	0.11	0.09	0.90
3	EDISON SPA	ITALY	-0.30	85.11	139.04	119.81	314	0.21	16.00	0.23
4	A2A SPA	ITALY	4.40	56.19	230.20	130.77	419	0.16	25.00	0.54
5	IREN SPA	ITALY	3.40	43.67	216.05	138.49	366	0.06	67.50	0.50
6	ACEA SPA	ITALY	2.90	36.37	305.02	100.18	424	0.21	65.13	0.90
7	GRUPPO HERA	ITALY	3.50	63.87	224.72	109.31	527	0.43	67.50	0.90
8	EDF	FRANCE	0.90	23.87	305.02	144.09	82	0.1	10.17	0.24
9	ENGIE SA	FRANCE	1.90	39.68	256.60	105.34	363	0.16	23.10	0.25
10	E.ON SE	GERMANY	2.00	67.58	305.02	103.44	308	0.39	29.30	0.11
11	SSE PLC	UK	4.80	104.70	281.30	112.44	304	0.21	30.30	0.69
12	DRAX GROUP	UK	-0.30	104.70	139.04	143.40	297	0.72	65.00	0.12
13	RWE	GERMANY	0.30	21.25	305.02	115.13	670	0.41	5.22	0.28
14	EXELON CORP.	USA	2.60	28.74	262.80	110.17	488	0.81	15.00	0.16
15	AMEREN	USA	3.60	22.78	254.10	54.83	729	0.38	4.49	0.20
16	DTE ENERGY	USA	3.20	37.34	238.00	109.57	707	0.53	8.73	0.24
17	XCEL ENERGY	USA	3.10	26.32	275.60	72.72	458	0.337	27.00	0.11
18	DUKE ENERGY	USA	2.70	16.81	230.40	67.72	478	0.255	5.00	0.13
19	IBERDROLA	SPAGNA	1.90	28.24	159.00	82.50	187	0.261	41.00	0.24
20	ENDESA	SPAGNA	3.90	63.01	236.20	73.39	439	0.06	4.38	0.17
		max	4.80	104.70	305.02	148.08	729.00	0.81	67.50	0.896
		min	-0.30	16.81	139.04	54.83	82.00	0.06	0.09	0.110

ALTERNATIVES		MACRO-CRITERIA	TECHNICAL					MARKET		
		Elementary criteria	Energy_loss	CSI	EG_Density	E_factor	EG_demand	MS	P/B	ETI
		Unit of measure	%	%	GWh/Km	%	GWh/person	%	%	n.
		Pref. direction	min	max	max	max	min	max	max	min
ENERGY COMPANIES		COUNTRY								
1	ENEL SPA	ITALY	41	93.75	0.20	34.06	0.006	25.00	1.35	21.66
2	ENI	ITALY	56	86.70	0.30	55.21	0.080	5.70	1.01	21.66
3	EDISON SPA	ITALY	43	95.80	0.75	35.86	0.079	5.20	0.87	21.66
4	A2A SPA	ITALY	36	90.60	1.45	20.78	0.011	2.70	1.57	21.66
5	IREN SPA	ITALY	56.25	92.00	1.14	36.81	0.027	3.00	1.40	21.66
6	ACEA SPA	ITALY	63	89.60	0.35	32.26	0.050	1.60	1.69	21.66
7	GRUPPO HERA	ITALY	73.30	69.00	1.00	53.69	0.018	3.60	1.61	21.66
8	EDF	FRANCE	63	71.00	0.29	51.98	0.019	29	0.66	14.66
9	ENGIE SA	FRANCE	56	83.00	1.17	51.98	0.047	11	0.86	14.66
10	E.ON SE	GERMANY	28	70.00	0.39	26.00	0.011	11.60	2.58	20.33
11	SSE PLC	UK	20.96	76.00	0.90	28.59	0.003	14	2.58	16.66
12	DRAX GROUP	UK	59	84.00	0.00	26.89	0.028	10	0.67	16.66
13	RWE	GERMANY	47	75.00	0.54	54.08	0.023	16	2.04	20.33
14	EXELON CORP.	USA	72	79.00	1.59	64.27	0.043	5.69	1.31	22.66
15	AMEREN	USA	24.77	74.00	0.81	41.89	0.040	2.07	1.93	22.66
16	DTE ENERGY	USA	27.80	71.90	1.59	39.09	0.057	1.20	2.09	22.66
17	XCEL ENERGY	USA	31	72.30	0.55	66.16	0.048	2.87	2.12	22.66
18	DUKE ENERGY	USA	59	76.00	0.78	48.32	0.043	6.78	1.43	22.66
19	IBERDROLA	SPAGNA	35	78.00	0.25	32.88	0.013	22	1.14	22.66
20	ENDESA	SPAGNA	30	73.00	0.37	38.44	0.014	29.00	2.34	22.66
		max	73.30	95.80	1.59	66.16	0.08	29.00	2.58	22.66
		min	20.96	69.00	0.00	20.78	0.00	1.20	0.66	14.66

The next step to evaluate the companies' performances is to aggregate the normalized dataset.

In this study, the weighted sum (eq.(1)) has been used as value function to aggregate the alternatives' evaluations on the elementary criteria (Section 1.4.1).
In literature, several aggregation functions are known (see Langhans et al., 2014 and De Condorcet, 2014 for an exhaustive description of them) and the selection procedure for one or another, affects the whole assessment process according to their specific value and trade-off properties (Langhans et al., 2014).
The additive function is one of the most common aggregation functions used in MCDA studies (Keeney and Raiffa, 1976) and it is characterized by a full level of compensation. It is suitable when the preference values of the decision maker are linear. This means that criteria with low performances can be fully compensated by criteria with high performances, without changing his/her own preferences.
In many real-world cases, however, the aggregation functions based on partial compensation (geometric, harmonic, minimum) are preferred to the full one, since they represent better the DMs' preferences (Gasser et al., 2020). Nevertheless, they are not recommended when the lowest normalized values are negative or equal to 0, as in our case. Moreover, since the additive function can simply take into consideration different weights to aggregate values and the main aim of this study is to consider different scenarios according the DM's preferences (Table 2.5), we have decided to use the linear weighted sum.
Hence, Table 2.8 and Figure 2.2 show, respectively, the summary statistics and the boxplot of the scores obtained by employing the considered methodology:

- Max is the maximum value of the scores obtained considering the 10,000 vectors of criteria weights;
- Min is the minimum value of the scores obtained considering the 10,000 vectors of criteria weights;
- Utility is the value of the scores that an alternative obtains on average;
- Skewness is a measure of the asymmetry of the probability distribution of the scores about its mean;
- Volatility is the standard deviations of the scores.

Table 2.8 Summary Statistics in case (1)

ALTERNATIVES		MAX	MIN	UTILITY	MODE	MEDIAN	SKEW.	VOLATILITY
a_1	ENEL SPA	0.8072	0.1280	0.4328	0.1280	0.4421	-0.1899	0.1106
a_2	ENI	0.9844	0.0885	0.4675	0.0885	0.4512	0.4040	0.1548
a_3	EDISON SPA	0.8330	0.1283	0.3817	0.1283	0.3783	0.2562	0.1224
a_4	A2A SPA	0.7865	0.1222	0.5046	0.1222	0.5105	-0.3923	0.1106
a_5	IREN SPA	0.9455	0.1219	0.5353	0.1219	0.5514	-0.3273	0.1295
a_6	ACEA SPA	0.9794	0.0713	0.4500	0.0713	0.4295	0.5446	0.1501
a_7	GRUPPO HERA	0.9877	0.1113	0.5285	0.1113	0.5290	0.0861	0.1462
a_8	EDF	0.9806	0.0534	0.4673	0.0534	0.4585	0.2313	0.1767
a_9	ENGIE SA	0.8735	0.1499	0.4544	0.1499	0.4520	0.4705	0.0866
a_{10}	E.ON SE	0.9051	0.0603	0.4323	0.0603	0.4290	0.4728	0.1008
a_{11}	SSE PLC	0.9907	0.3897	0.6653	0.3897	0.6584	0.3886	0.0899
a_{12}	DRAX GROUP PLC	0.9606	0.1029	0.4721	0.1029	0.4539	0.5124	0.1295
a_{13}	RWE	0.7050	0.0945	0.3640	0.0945	0.3536	0.3371	0.1108
a_{14}	EXELON CORP.	0.6909	0.0457	0.3197	0.0457	0.3125	0.4001	0.1059
a_{15}	AMEREN	0.6009	0.0313	0.2917	0.0313	0.2859	0.1901	0.0979
a_{16}	DTE ENERGY COMP.	0.6833	0.0186	0.3427	0.0186	0.3456	0.0174	0.1089
a_{17}	XCEL ENERGY	0.6977	0.0172	0.3549	0.0172	0.3621	-0.0675	0.1134
a_{18}	DUKE ENERGY CORP.	0.5259	0.0289	0.2865	0.0289	0.2911	-0.1496	0.0819
a_{19}	IBERDROLA	0.7489	0.0620	0.4453	0.0620	0.4528	-0.3309	0.1129
a_{20}	ENDESA	0.9614	0.0708	0.4783	0.0708	0.4812	8,2742	0.1456

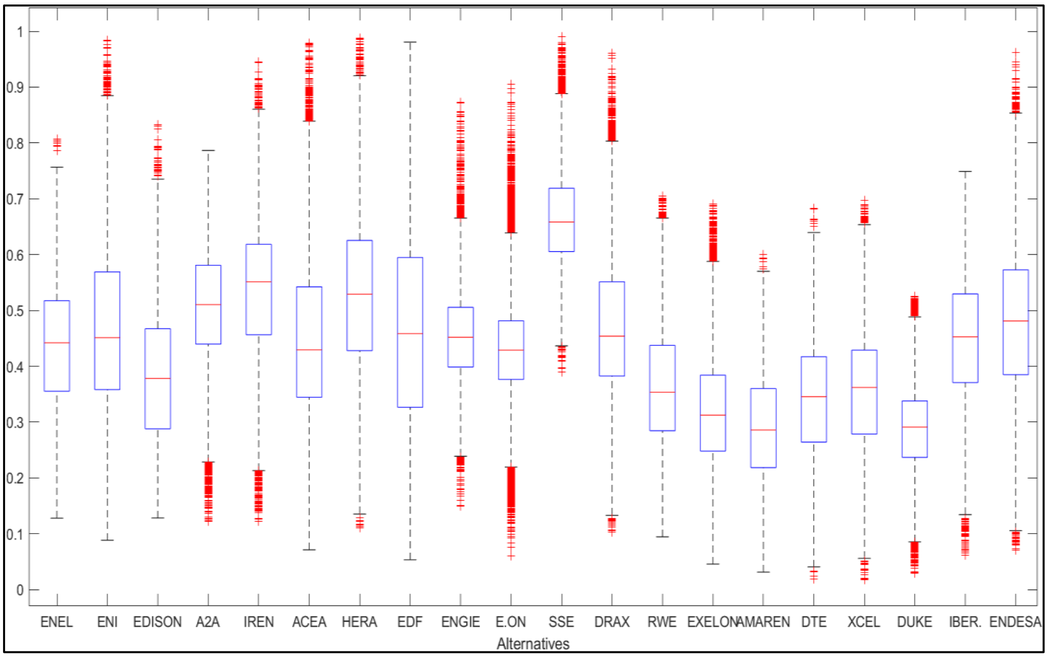


Figure 2.2 Boxplot of the alternatives' score in case (1).

At the end of all iterations, SMAA indices have been computed (Tervonen and Lahdelma, 2007); specifically the rank acceptability index (RAI), the central weight vector (CWV), the confidence factor (CF), and the pairwise winning indices (PWI), which are commented in the next section.

Moreover, Table 2.9 shows the rank acceptability index for case (1) and Figure 2.3 displays the probability distribution of each company arising from rank acceptability index, highlighting the interval of rank positions. More in detail, the value of the highest frequency of each company for a given position is represented by the peak of the probability distribution, while the downward rank acceptability indices are indicated in Figure 2.4 as line chart.

Moreover, Table 2.10 displays the results of the Shannon entropy index computed for cases (1) and (2) and with respect to each macro-criterion.

The overall results obtained in cases (1) and (2) are contained in the Appendix A.

Specifically, Table A-1 and Table A-2 show, respectively, the rank acceptability index and the downward cumulative rank acceptability index in case (1) and case (2), assembling all scenarios (from the first to the seventh). Instead, Figure 2.5 displays the probability distribution arising from Table A-1, in order to observe each company's trend arising simultaneously from all scenarios.

Rank acceptability indices are presented in Table A-3 , Table A-4, Table A-5 and Table A-6 in the Appendix A, with respect to the financial, sustainability, technical and market macro-criterion, respectively.

2.5.1.1 Case (1)

Case (1) is an uncertainty scenario in which the DM has not a precise system of preferences on criteria weights assigned to every macro-criterion.

Looking at the first scenario of Table A-2 in the Appendix A, we can observe that AMEREN can be considered as the best energy company because $b_{\leq 2}^{15} = 41.95\%$. It is also confirmed from Table 2.9, since it is the corporation with the highest probability (23.70%) to get the first position in the ranking, followed by DUKE ENERGY CORPORATION (19.66%) and RWE (11.10%). Furthermore, DUKE ENERGY CORPORATION and EXELON CORPORATION are two of the best companies, since $b_{\leq 5}^{18} = 84.47\%$ and $b_{\leq 5}^{14} = 58.36\%$ meaning that their ranks are stable for the first five positions (see Table A-2).
Otherwise, from Table 2.9 it is possible to notice that SSE PLC presents the highest probability (46.08%) to be placed in the last position of the final ranking followed by EDF (13.04%) confirmed by the downward rank acceptability index ($b_{\leq 19}^{11}$, $b_{\leq 19}^{8}$ are respectively about 50% and 80%, see Figure 2.4). These trends are more evident by looking at the graphs in Figure 2.3, illustrating the companies' probability distribution among rank positions. Indeed, AMEREN and DUKE ENERGY CORPORATION display a decreasing probability distribution with rank position, showing a null probability from the 17th position to the last one for the first company and from the 12th position to the last one for the second company; EXELON and RWE have the same decreasing trends as AMAREN and DUKE ENERGY CORPORATION, but less evident. Instead, SSE PLC and EDF show a very low and constant probability distribution up to the central positions, increasing abruptly towards the last positions.
Generally, it is possible to classify companies into three groups according to the rank position: top positions (from the 1st to the 7th position), intermediate positions (from the 8th to the 14th position), and last positions (from the 15th to the 20th position). For the sake of clarity, this threefold classification has been displayed respectively with green, yellow and red colour, by considering a RAI greater than 0.06. Hence, the first group includes AMAREN, DUKE ENERGY, EXELON, RWE, DTE ENERGY, XCEL ENERGY; the second group is composed by ENGIE SA, E.ON SE, ENEL, EDISON SPA; some companies such as A2A SPA, ENDESA, IBERDROLA can be classified between the second and the third ones; finally the third group contains clearly, IREN SPA, ENI, ACEA SPA, GRUPPO HERA, DRAX GROUP, EDF and SSE PLC.

Table 2.9 Case (1) "First Scenario": Rank acceptability indices

ALTERNATIVES\RANK		b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
a_1	ENEL SPA	0	0.0011	0.0073	0.0288	0.0474	0.0608	0.0667	0.0656	0.0853	0.0680
a_2	ENI	0.0154	0.0449	0.0407	0.0411	0.0416	0.0357	0.0438	0.0446	0.0414	0.0464
a_3	EDISON SPA	0.0988	0.0423	0.0433	0.0505	0.0398	0.0601	0.0636	0.0701	0.0834	0.0958
a_4	A2A SPA	0	0	0	0.0006	0.0059	0.0142	0.0321	0.0392	0.0403	0.0462
a_5	IREN SPA	0	0	0.0001	0.0011	0.0024	0.0068	0.0133	0.0231	0.0354	0.0506
a_6	ACEA SPA	0.0554	0.0538	0.0547	0.0490	0.0443	0.0556	0.0497	0.0547	0.0467	0.0460
a_7	GRUPPO HERA	0.0091	0.0121	0.0062	0.0125	0.0177	0.0178	0.0292	0.0297	0.0378	0.0466
a_8	EDF	0.0963	0.0573	0.0380	0.0319	0.0276	0.0276	0.0319	0.0322	0.0339	0.0435
a_9	ENGIE SA	0.0010	0.0049	0.0071	0.0174	0.0225	0.0283	0.0399	0.0677	0.0838	0.0954
a_{10}	E.ON SE	0.0007	0.0039	0.0169	0.0323	0.0459	0.0648	0.0745	0.0935	0.0927	0.0804
a_{11}	SSE PLC	0	0	0	0	0	0	0	0.0003	0.0024	0.0055
a_{12}	DRAX GROUP	0.0169	0.0282	0.0301	0.0402	0.0375	0.0371	0.0453	0.0479	0.0416	0.0398
a_{13}	RWE	0.1110	0.0735	0.0604	0.0696	0.0738	0.0718	0.0618	0.0638	0.0541	0.0482
a_{14}	EXELON CORP.	0.0781	0.1090	0.1431	0.1259	0.1275	0.1046	0.0826	0.0586	0.0466	0.0301
a_{15}	AMEREN	0.2370	0.1825	0.1417	0.1127	0.0718	0.0558	0.0438	0.0373	0.0241	0.0203
a_{16}	DTE ENERGY	0.0725	0.0883	0.0949	0.0750	0.1016	0.0888	0.0784	0.0742	0.0578	0.0556
a_{17}	XCEL ENERGY	0.0084	0.0875	0.0829	0.1248	0.1042	0.1047	0.0906	0.0651	0.0520	0.0518
a_{18}	DUKE ENERGY	0.1966	0.1990	0.2033	0.1297	0.1161	0.0707	0.0388	0.0248	0.0135	0.0039
a_{19}	IBERDROLA	0.0028	0.0089	0.0182	0.0395	0.0359	0.0496	0.0524	0.0526	0.0635	0.0597
a_{20}	ENDESA	0	0.0028	0.0111	0.0174	0.0365	0.0452	0.0616	0.0550	0.0637	0.0662

ALTERNATIVES\RANK		b_{11}	b_{12}	b_{13}	b_{14}	b_{15}	b_{16}	b_{17}	b_{18}	b_{19}	b_{20}
a_1	ENEL SPA	0.0725	0.0740	0.0814	0.0658	0.0738	0.0687	0.0683	0.0524	0.0102	0.0019
a_2	ENI	0.0641	0.0443	0.0484	0.0519	0.0682	0.0658	0.0561	0.0606	0.0695	0.0755
a_3	EDISON SPA	0.0693	0.0631	0.0537	0.0495	0.0316	0.0290	0.0319	0.0234	0.0008	0
a_4	A2A SPA	0.0634	0.0640	0.0819	0.1057	0.1223	0.1013	0.0687	0.0639	0.1132	0.0371
a_5	IREN SPA	0.0450	0.0468	0.0568	0.0621	0.0823	0.1125	0.1210	0.1677	0.1028	0.0702
a_6	ACEA SPA	0.0401	0.0439	0.0422	0.0403	0.0484	0.0551	0.0764	0.0705	0.0586	0.0146
a_7	GRUPPO HERA	0.0497	0.0512	0.0523	0.0576	0.0744	0.0734	0.0912	0.0962	0.1194	0.1159
a_8	EDF	0.0415	0.0443	0.0431	0.0463	0.0364	0.0407	0.0416	0.0663	0.0892	0.1304
a_9	ENGIE SA	0.1081	0.0993	0.1004	0.0869	0.0597	0.0461	0.0347	0.0541	0.0386	0.0041
a_{10}	E.ON SE	0.0723	0.0695	0.0825	0.0654	0.0503	0.0480	0.0253	0.0379	0.0432	0
a_{11}	SSE PLC	0.0089	0.0125	0.0159	0.0205	0.0371	0.0630	0.0945	0.1138	0.1648	0.4608
a_{12}	DRAX GROUP	0.0431	0.0762	0.0579	0.0725	0.0679	0.0668	0.1025	0.0460	0.0609	0.0416
a_{13}	RWE	0.0468	0.0340	0.0388	0.0440	0.0531	0.0381	0.0367	0.0160	0.0042	0.0003
a_{14}	EXELON CORP.	0.0224	0.0190	0.0121	0.0095	0.0088	0.0078	0.0078	0.0038	0.0017	0.0010
a_{15}	AMEREN	0.0202	0.0185	0.0206	0.0127	0.0009	0.0001	0	0	0	0
a_{16}	DTE ENERGY	0.0496	0.0352	0.0257	0.0216	0.0287	0.0281	0.0197	0.0042	0.0001	0
a_{17}	XCEL ENERGY	0.0443	0.0536	0.0374	0.0242	0.0241	0.0259	0.0135	0.0040	0.0010	0
a_{18}	DUKE ENERGY	0.0036	0	0	0	0	0	0	0	0	0
a_{19}	IBERDROLA	0.0676	0.0926	0.0912	0.0949	0.0851	0.0826	0.0653	0.0307	0.0068	0.0001
a_{20}	ENDESA	0.0675	0.0580	0.0577	0.0686	0.0469	0.0470	0.0448	0.0885	0.1150	0.0465

RAI>0.06 in Top positions (1st group)	RAI>0.06 in Intermediate positions (2nd group)	RAI>0.06 in Last positions (3rd group)

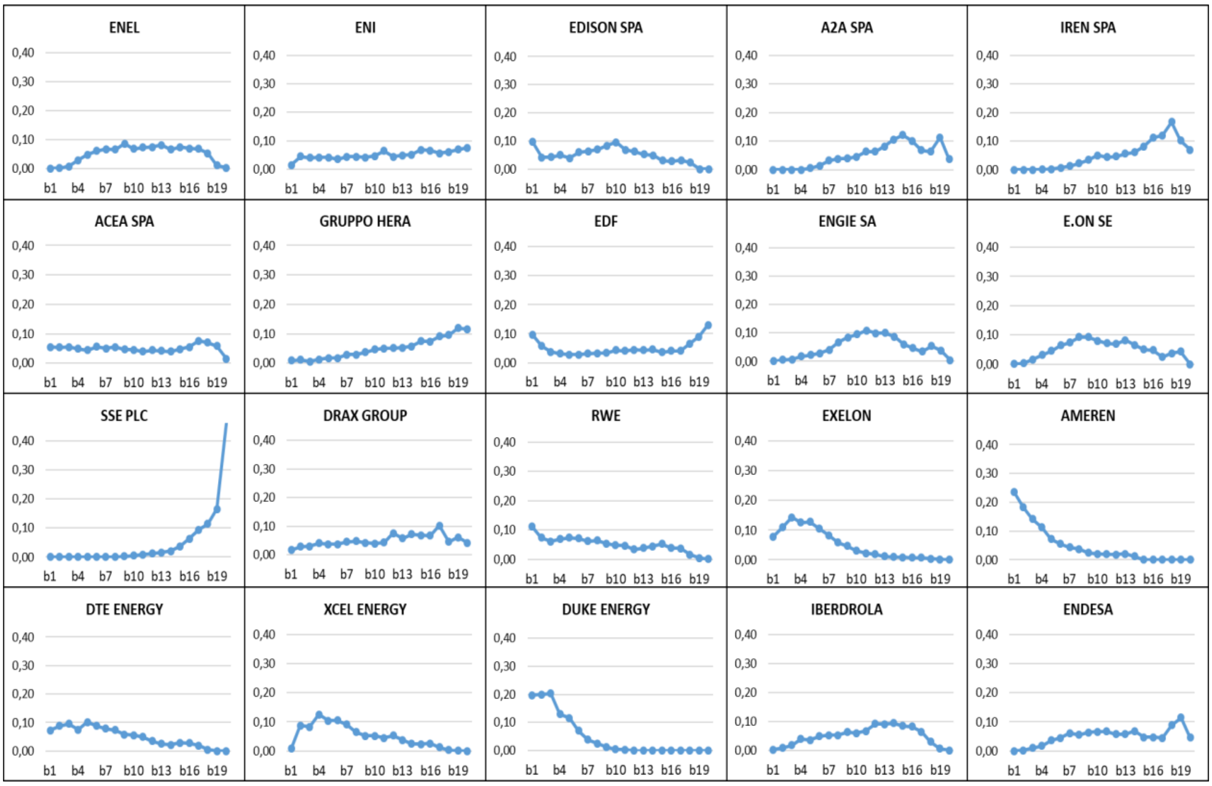


Figure 2.3 Case (1) “First Scenario”: Rank acceptability indices probability distributions. Authors ‘elaboration.

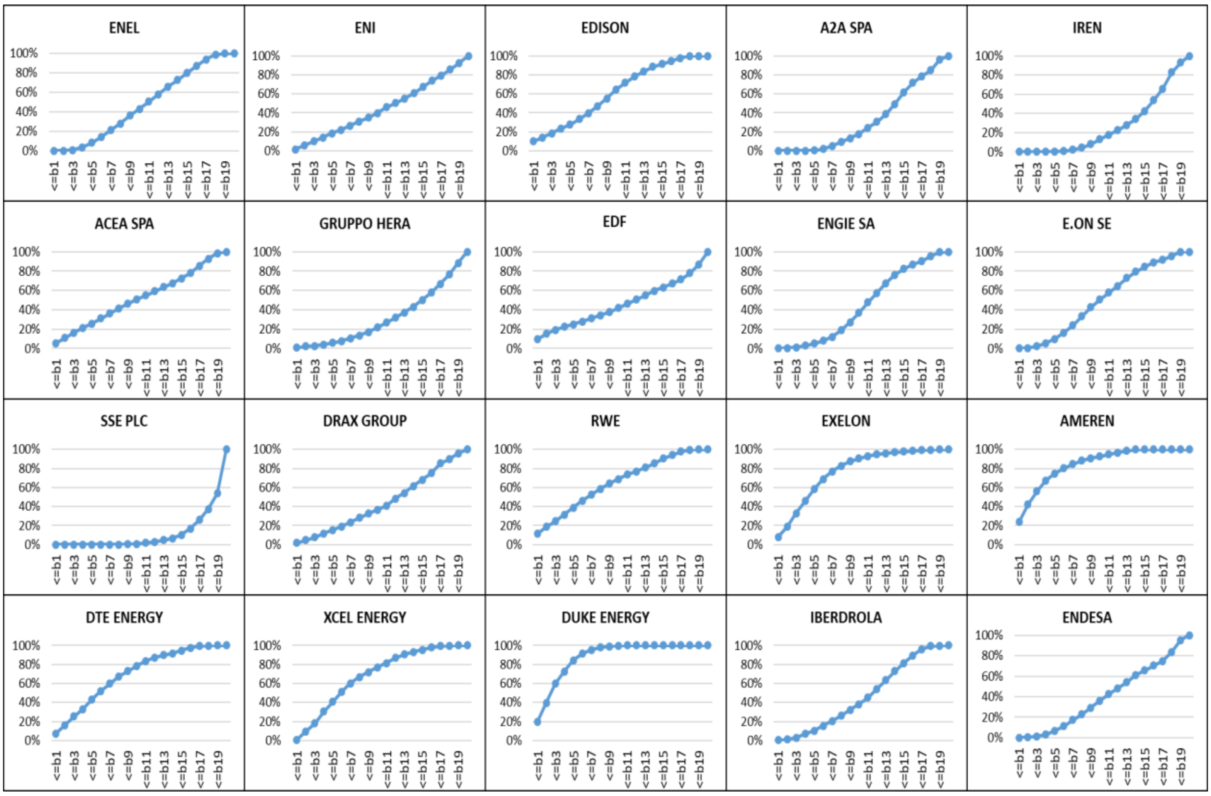


Figure 2.4 Case (1) Downward cumulative rank acceptability indices as line chart.

2.5.1.2 Case (2)

Case (2) is performed on the overall set of macro-criteria, considering the DM's preference information as shown in Table 2.5.

As explained in Section 2.4, six probability distributions of rankings (rank acceptability index) are obtained from this case. Looking at Table A-2 in Appendix A that summarizes the downward cumulative rank acceptability indices evaluated within cases (1) and (2) (from the first to the seventh scenario), we can observe that AMEREN is considered the company with the highest probability to get the first position in "second, third and fourth scenarios" since $b_{\le 2}^{15}$ vary among 38.02% and 55.04%. This is confirmed by Table A-1in which the rank acceptability index of AMEREN for the first position is 38.99%, 26.10% and 38.36%, respectively, for the second, third and fourth scenarios.

Otherwise, DUKE ENERGY CORPORATION is the company with the highest probability to get the first position in the fifth scenario (23.67%), while EDISON in the sixth (22.74%) and seventh scenarios (23.31%).

The company with the highest probability to be placed in the last position of the ranking is SSE PLC for "all the considered scenarios" where $b_{\le 19}^{11}$ vary between about 40% and 60%, followed by ENI and EDF, respectively, in the "second, third and fourth scenarios" (slightly above 80%) and in the "fifth, sixth and seventh scenarios" (slightly above 70%, see Figure 2.4).

2.5.2 Further comments on the results

Comparison of rank acceptability indices probability distributions deriving from all different scenarios of cases (1) and (2) is shown in Table A-1 and Figure 2.5

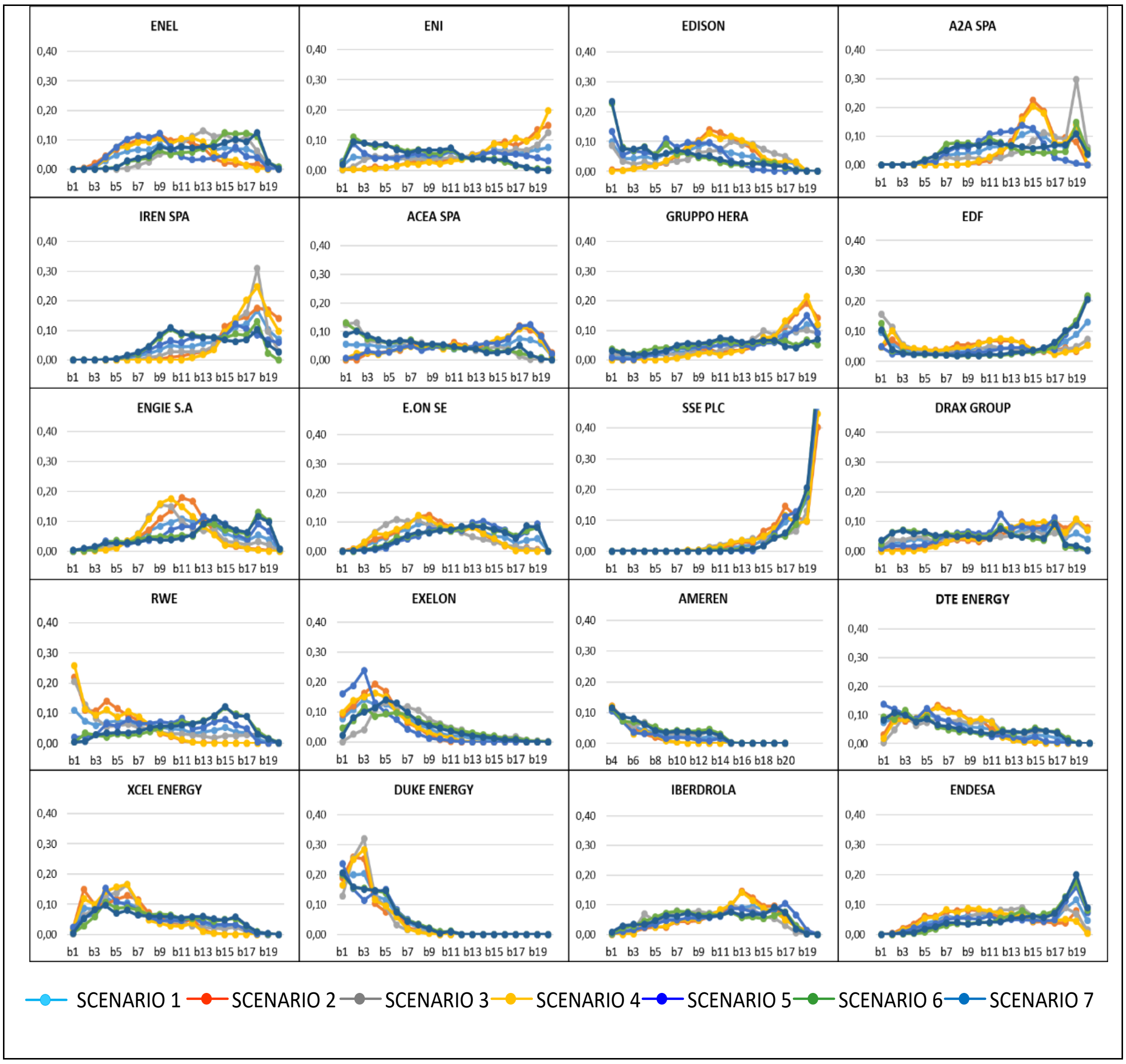


Figure 2.5 Cases (1) and (2) “From first to Seventh Scenario”: Rank acceptability indices. Authors’ elaboration

Two important findings arise from these cases.

Firstly, by looking at Figure 2.5 , cases (1) and (2) provide the same global pattern on the rank acceptability indices probability distributions for half of the considered companies, regardless of the scenario and thus of DM’s preferences we are dealing with. This result is evident for companies like IREN SPA, GRUPPO HERA, EDF, SSE PLC, EXELON, AMEREN, XCEL ENERGY, DUKE ENERGY, IBERDROLA, ENDESA, confirming generally that DM’s preferences do not affect the final ranking results.

Secondly, from the results of cases (1) and (2), it emerges a diversified picture among countries. American companies like EXELON, AMEREN, DTE ENERGY, XCEL ENERGY, DUKE ENERGY, show the highest probability to be placed in the first positions

(1-7). Instead, European energy companies display two results: a high probability to be placed in the worst rank positions (17-20) for SSE PLC, EDF and ENI; and a diversified trend, according the scenario under consideration, for most of Italian and German companies (ENEL, EDISON, A2A SPA, ACEA SPA, ENGIE SA, E.ON SE, DRAX GROUP, RWE).
Moreover, HSMAA has been implemented by considering each single dimension (financial, sustainability, technical and market) at a time, to provide useful insights into the evaluation process and to give a perspective at each node of the hierarchy of the criteria.
Table A-3 , Table A-4, Table A-5 and Table A-6 in the Appendix A, present the rank acceptability indices considering singularly each macro-criterion.
The outcomes obtained from this last implementation of HSMAA, are different from the previous ones of cases (1) and (2). Indeed, the companies with the highest probability to arrive first are RWE (60.61%) and EXELON CORPORATION (almost 40%), respectively, on the financial and the sustainability macro-criteria, EDISON (39.21% and 40.70%) on both the technical and the market macro-criteria. Otherwise, the energy corporation with the highest probability to be the worsts are ENI (54.12%), ACEA SPA (37.45%), A2A SPA (54.32%) and EDF (38.98%), respectively, on the financial, sustainability, technical and market macro-criteria.
Finally, the Shannon entropy ($PRAI_k$) has been computed on data trimmed for case (1), case (2) and at each dimension and shown in Table 2.10. It represents a valuable mathematical tool in decision-making problems to measure the uncertainty degree of an information or an event (Lofti and Fallahnejad, 2010). In such cases as our, where uncertainty is expressed by a probability distribution, Shannon entropy can be useful to specify the quality and the clarity of evidence for each alternative to be placed in a certain rank position (Yin et al., 2018; Xiao, 2019). Hence, the importance of $PRAI_k$ to be added to the other aforementioned indices of this analysis and to be computed according to the formula (9) presented in Section 1.4.1.
Thus, by looking at Table 2.10 it results that $0 < PRAI_k < \frac{log_2 20}{20} = 0.21609$, while the average values of $PRAI_k$ computed for cases (1) and (2) highlight how the alternative's uncertainty to be assigned in a given rank position k is higher than in the case where the performance evaluation is assessed on each macro-criterion. Therefore, alternatives' uncertainty is wider among different scenarios than at each single macro-criterion

Table 2.10 Shannon entropy computed on data trimmed for case (1), case (2) and at each dimension. Authors' elaboration.

Shannon entropy											
Cases	**Case (1)**	**Case (2)**						**HSMAA implementation on each macro-criterion**			
Scenarios	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**	**Scenario 6**	**Scenario 7**				
Criteria	**All criteria**	**All criteria**	**All criteria**	**All criteria**	**All criteria**	**All criteria**	**All criteria**	**Financial**	**Sustainability**	**Technical**	**Market**
$\mathbf{b_1}$	0.15532	0.11830	0.13506	0.11460	0.14674	0.15293	0.15069	0.04836	0.11224	0.08777	0.11058
$\mathbf{b_2}$	0.169845	0.145912	0.160121	0.144753	0.153872	0.172029	0.174470	0.08181	0.148948	0.086440	0.15467
$\mathbf{b_3}$	0.175190	0.160649	0.166035	0.152889	0.163250	0.177410	0.181018	0.11482	0.142515	0.114543	0.17509
$\mathbf{b_4}$	0.189609	0.175662	0.185842	0.173852	0.184147	0.185790	0.185276	0.12355	0.144631	0.112341	0.17953
$\mathbf{b_5}$	0.195534	0.181891	0.189643	0.179907	0.191837	0.194653	0.193301	0.12058	0.133250	0.144464	0.17243
$\mathbf{b_6}$	0.201853	0.188141	0.191925	0.185808	0.200093	0.203041	0.202872	0.14864	0.149805	0.107330	0.17846
$\mathbf{b_7}$	0.206998	0.193707	0.198101	0.193954	0.206134	0.206918	0.208358	0.14077	0.164764	0.136196	0.18390
$\mathbf{b_8}$	0.208114	0.194965	0.200595	0.194348	0.207004	0.208949	0.209850	0.11990	0.169296	0.149769	0.18304
$\mathbf{b_9}$	0.207089	0.192278	0.200896	0.189293	0.203926	0.208906	0.208048	0.13667	0.161081	0.126856	0.18049
$\mathbf{b_{10}}$	0.206450	0.189060	0.202416	0.187114	0.204256	0.207487	0.206240	0.14863	0.137747	0.148709	0.18817
$\mathbf{b_{11}}$	0.206489	0.186206	0.205234	0.189401	0.202278	0.207496	0.206085	0.08091	0.152988	0.135739	0.16972
$\mathbf{b_{12}}$	0.204978	0.189987	0.203381	0.190979	0.196600	0.204972	0.204163	0.12639	0.113827	0.132387	0.16764
$\mathbf{b_{13}}$	0.203847	0.189383	0.204283	0.188336	0.194732	0.205409	0.204502	0.08010	0.155814	0.133887	0.17371
$\mathbf{b_{14}}$	0.202372	0.185709	0.203158	0.186694	0.192851	0.203904	0.202003	0.12640	0.140258	0.137671	0.16598
$\mathbf{b_{15}}$	0.200525	0.176280	0.200208	0.180332	0.194333	0.200438	0.200337	0.14466	0.140614	0.110119	0.15126
$\mathbf{b_{16}}$	0.200222	0.174819	0.197356	0.177573	0.194257	0.200633	0.200987	0.12782	0.138296	0.140805	0.14886
$\mathbf{b_{17}}$	0.196172	0.172802	0.190342	0.167471	0.186918	0.197569	0.200060	0.10684	0.106454	0.144013	0.14576
$\mathbf{b_{18}}$	0.187864	0.169767	0.169041	0.158273	0.178079	0.183074	0.180664	0.11264	0.123832	0.151502	0.12836
$\mathbf{b_{19}}$	0.173636	0.157988	0.156657	0.153344	0.160554	0.159787	0.159759	0.07171	0.098618	0.142019	0.11873
$\mathbf{b_{20}}$	0.126781	0.122312	0.115055	0.113989	0.107928	0.092707	0.099174	0.04975	0.107489	0.072477	0.08344
min	0.126781	0.118308	0.115055	0.113989	0.107928	0.092707	0.099174	0.04836	0.098618	0.072477	0.08344
max	0.208114	0.194965	0.205234	0.194348	0.207004	0.208949	0.209850	0.14864	0.169296	0.151502	0.18817
mean	0.190945	0.173291	0.183768	0.171146	0.183490	0.188705	0.188893	0.11055	0.137124	0.125752	0.15799

2.6 Conclusions and policy implications

In this chapter, we have ranked twenty European and American listed corporations operating in the energy sector based on their performance. We have employed the HSMAA method, an extension of SMAA-2, to handle simultaneously with a hierarchical structure of criteria and Decision Maker's uncertainty on the preference model parameters. The literature on firm's performance evaluation has been enriched with the introduction of more specific energy criteria along three dimensions: sustainability, technical and the market criteria in addition to the usual financial ones. Among these, one of the most important are the market criteria, which provide a good measure of the market profile in which the energy company is located, giving more exhaustiveness and reliability to the analysis of this complex sector. Moreover, to test the robustness of the ranking results, several uncertainty scenarios, which translate the DM's preferences, have been considered. More specifically, two cases have been analysed, obtaining in total seven different scenarios, fully described in the previous Section.

Two important findings derive from these cases. Firstly, cases (1) and (2), provide on half of the considered companies almost the same results on the rank acceptability indices distributions, regardless the DM's preferences on criteria weights. Secondly, a diversified picture among countries; American companies show the highest probability to be placed in the first positions (1-7), while European energy companies either get the worst rank positions (17-19) or display a trend varying according to the scenario under consideration.

Therefore, in between bottom and top positions, we find that many companies' rankings vary widely by the chosen set of criteria weights, exemplifying the need to rank companies based on multiple sets of criteria weights.

Moreover, by implementing HSMAA on each single dimension at a time (financial, sustainability, technical and market), it gives different results than the previous ones, according to the DM's perspective focused on a given macro-criterion or another.

The methodology employed in this analysis is undoubtedly useful for all categories of stakeholders dealing with firm's performance evaluation, such as investors, business leaders, and policy makers, for two kinds of reasons.

Firstly, stakeholders can use cases (1) and (2) in their decision-making process, for examining several perspectives simultaneously. In particular, potential investors can direct their investment decisions more safely, taking into account all the most important aspects affecting the firm's performance evaluation of energy companies. Instead, business leaders and policy makers can use this method to check strengths and weaknesses of companies' performances within a given country, evaluating also the possible differences of implementation of energy policies among countries. Indeed, the ranking stability reached by some companies on uncertainty scenarios, give deep insights into their performances. The companies ranked in the first positions, whatever uncertainty scenario is considered, are good companies from all of the hierarchical structure criteria point of view: financial, sustainability, technical and market. Therefore, for these companies, any sort of policy intervention is needed to enhance their performances and to guarantee reliable services to customers. Similarly, the same considerations can be done for the companies in the last positions. In this case, policy makers can detect which companies are not wealthy on the whole set of criteria and may cause problems to customers, for example in the erogation of energy services. In this regard, the policy intervention is needful to ensure the continuity of the services.

Instead, for the companies which are unstable in the rankings under the different scenarios, it can be useful for policy makers to analyse the scenarios in which a company has a good/bad position to emphasize its strengths and weaknesses and consequently to implement proper energy policies. For example, under the fifth scenario, where sustainability criteria are considered more important than financial criteria and market criteria are more important than technical criteria, the best two companies (with a downward cumulative rank acceptability index on the first five positions slightly more than 80%) are Exelon and Ameren. Their strengths are on the sustainability and market criteria; otherwise, their weaknesses are on technical and financial criteria. For these companies it would be advisable to preserve their potential on low levels of pollutants emissions and high rates of renewable energy resources employed in the production as well as their strong price to book ratio and to act with policies able to reinforce their technical inefficiency or the perception that customers have on the quality of delivered services. The companies involved in this study belong to different countries and it is difficult to consider a unique energy policy, which regard all the companies in the sample. For the sake of simplicity, we limit the analysis to European context considering, among different energy policies, one important document i.e

the EU Energy Roadmap for 2050 (EU Commission, 2011), which addresses three principal objectives: sustainability, competitiveness and energy security. Moreover, the EU Energy Roadmap illustrates alternative development paths with respect to different scenarios followed by companies of European energy system, to reduce greenhouse gas emissions by 2050. The scenarios change in terms of energy sources and technologies, level of demand, reduction of technologies. It is worthy to note that the objectives of the EU Energy RoadMap are in line with the framework of criteria selected in this study. For this reason, it could be useful in the future to implement the methodology employed in different years to test if the scenarios considered by the Energy Roadmap can affect the companies in terms of overall performance of the European companies.
Secondly, stakeholders can use HSMAA on each dimension to consider one perspective at once. For instance, potential investors may be interested in focusing one dimension that is the most viable for its own capital allocation purposes, achieving different solutions according the single criteria under observation. Instead, policy makers, by looking at one criteria at time, can understand if there are substantial differences among countries and formulate new energy policies based on each macro-criterion. They can have a wide range of options: expansive fiscal policies for financial aspect; financial subsidies for countries, which adopt clean technologies and contain greenhouse gases emissions for environmental perspective; significant infrastructure investments to reduce waste on the grid and transmission networks for technical elements; important actions to give reliability and affordability improvement to energy systems for market criteria.
Understanding the general situation in which a country is, will be useful to formulate and then implement new energy policies to address towards those companies that are in the lowest positions of the final ranking, like the European ones.
While our study focuses only on the performance evaluation of energy companies, it is conceivable that the adoption of this methodology could be implemented in other sectors, but it is crucial to consider the adequate set of criteria it thinks can affect the performance evaluation of the companies operating in that specific sector.
We hope this study motivates future research on the implementation of MCDA models to assess the performance of companies taking into account also other perspectives than the single financial one.
Moreover, it is worthy to notice that the employed method HSMAA has some limitations since it considers criteria with a monotone direction of preference even if this aspect is commonly shared by several multicriteria methods. Indeed, it is acknowledged in literature that some criteria have not a monotone direction of preference (see Doumpos, 2012) as for example the criterion Electrical factor capacity considered in the real life problem of this study. For example, it is clear that 80% is better than 20% (too much capacity sitting idle), but 100% is not better than 80%, meaning that the company cannot keep up with an increase in demand.
Another limitation of the employed methodology is the selected method to normalize and aggregate the data, which can be affected respectively by the presence of outliers and by the full compensation level. With regard to the normalization method, here, the issue of the

outliers has been overcome by trimming the data, while the implicit trade-offs problem could arise by changing the min-max normalization method with another one (Carrino, 2017 and Gasser et al., 2019). Whereas, with regard to the aggregation of data, the main problem of the additive approach is the unenforceability to the real-world cases that might be solved by applying partial compensation based methods with normalization approaches including only positive values different from zero.

Chapter 3

Assessment of a failure prediction model in the energy sector: a multicriteria discrimination approach with PROMETHEE based classification[5]

In this chapter we presents the implementation of a non-parametric multiple criteria decision aiding (MCDA) model, the Multi-group Hierarchy Discrimination (M.H.DIS) model, with the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), on a dataset of 114 European unlisted companies operating in the energy sector.
Firstly, the M.H.DIS model has been developed following a five-fold cross validation procedure to analyze whether the model explains and replicates a two-group pre-defined classification of companies in the considered sample, provided by Bureau van Dijk's Amadeus database. Since the M.H.DIS method achieves a quite limited satisfactory accuracy in predicting the considered Amadeus classification in the holdout sample, the PROMETHEE method has been performed then to provide a benchmark sorting procedure useful for comparison purposes.
The analysis indicates that in terms of average accuracy, M.H.DIS model development with the PROMETHEE based classification provides consistently better results compared to the one obtained with the Amadeus classification in the majority of combinations, which have been built with the financial variables covering the main firm's dimensions such as profitability, financial structure, liquidity and turnover.

3.1 Background

In last decades, some energy companies faced severe financial soundness issues due to flawed risk management actions of banks and deregulation processes introduced in the European energy industry on December 1996. For instance, the recent directives implemented to liberalize the European electricity sector, outlined in Section 1.2.1.1, were aimed to lower consumers' prices and to create a more competitive context (Kočenda and Čábelka, 1998; Meyer, 2003). However, for the specific features of the energy sector such as the large infrastructure costs and the economic difficulties to replicate the transmission lines, the wholesale prices of energy market remained significantly high and their associated

[5] This study is currently under review in the journal of "Expert Systems with Applications". The present work is a combined effort of the two authors: Silvia Angilella and Maria Rosaria Pappalardo. However, Maria Rosaria Pappalardo contributed in conceptualization, data searching and analysis, writing; Silvia Angilella contributed in conceptualization and supervision.

sales volume low. Hence, several financial distresses have occurred within the energy sector. Various case studies across the world give examples of energy companies being challenged by deregulation processes (see Section 1.2.1.3 for a detailed description of energy companies' failures). These failures generated serious effects on the economy of a country, which have been promptly faced by governments' interventions, such as large expenses on the whole country's economy where the crash has taken place.

In order to prevent possible macro-economic effects, the monitoring of energy companies' financial performances is crucial.

In this regard, after deregulation processes, several studies have been mainly focused on the issue of assessing market (Denton et al., 2003), financial (Bjorgan, 1999) and price risk (Dahlgren et al., 2003). Despite the relevance of the topic, few studies have been specifically devoted to credit risk assessment of companies operating in this sector; the only one is the work of Silva and Pereira (2014) that assesses the credit risk of thirty renewable energy companies sited in Portugal employing a traditional linear regression model.

The corporate failure prediction models mainly employed in literature, concern the traditional statistical, econometric and machine learning techniques. However, as highlighted in Section 1.3.3, these techniques lack of specific features that current experts increasingly require, such as the ordinal risk grades and the monotonicity assumptions, which instead fit well in multi-criteria decision aiding (MCDA) models. All these attributes along with their transparency, simplicity of use and incorporation of DM's preferences, make these models more effective than traditional ones.

For these reasons, and for their wide implementations to the issues of credit risk assessment in different fields such as banking, corporate and country analysis, the purpose of this chapter is to develop a Multi-criteria decision aiding (MCDA) model for credit risk analysis of a set of European unlisted companies operating in the energy sector.

As detected in Section 1.3.3, since one of the most efficient multi-criteria discrimination model is the Multi-group Hierarchy Discrimination (M.H.DIS) technique elaborated by Zopounidis and Doumpos (2000), this chapter aims to apply this method to a balanced sample of 114 active and inactive energy companies for up to four years prior the financial distress occurred. In order to observe whether a pre-defined classification of companies in two categories, active and inactive ones, provided by Bureau van Dijk's Amadeus database is well replicated by the model, a five-fold cross validation has been performed on companies of the sample.

Despite what we expect, the average accuracy rate of the M.H.DIS model developed on Amadeus classification is not quite satisfactory in the holdout sample of the analysis. Therefore, in this study we consider a further well-known multicriteria decision aid model, the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE II) (presented for the first time in Mareschal et al., 1984), on which a classification of firms in the sample is based. Such classification acts as benchmark sorting on which to compare the accuracy of the discrimination model.

To deal with this aim, we identify first six financial ratios that in our analysis result the most powerful in highly discriminating between the two categories of companies. Then, they have

been considered in all the possible combinations of subsets of three criteria and employed in turn in the building of PROMETHEE II classification first and M.H.DIS model development then.
Thus, the contribution of this study is fourfold:

- we address the literature gap in multicriteria sorting models (Section 1.3.3), enriching applications of the M.H.DIS model also on credit risk assessment of energy companies;
- we extend the M.H.DIS model development with a well-established multicriteria outranking model, the PROMETHEE II method, to provide a benchmark sorting procedure to compare with the pre-defined classification given by Amadeus database;
- we suggest a novel use of the proposed discrimination model to support the credit risk assessment process for firms lacking of a synthetic judgment provided by credit rating agencies (CRAs);
- we provide a more consistent and robust discrimination model in terms of average and overall accuracy rate. The robustness is examined over time, under different combinations of financial variables, under different preference functions employed for PROMETHEE classification and simulating the criteria weights in different scenarios.

The rest of the chapter is organized as follows. Section 3.2 presents the data used in the analysis and the sampling procedure. Section 3.3 discusses about the building of M.H.DIS model starting from a three steps selection procedure of the most predictive variables in discriminating between active and inactive companies. Section 3.4 shows the results of the M.H.DIS model in terms of accuracy for the AMADEUS classification, whereas Section 3.5 develops a specific classification of companies according the PROMETHEE II method for comparison purposes. Section 3.6 summarizes the main findings. Section 3.7 concludes the study and discusses some future directions of research.

3.2 Data collection

The first step to develop a risk assessment model is the selection of the firms' sample. The primary source for the collection was the database of Bureau van Dijk's Amadeus. We have looked for unlisted companies with the NACE code 35 used as filter, which covers the main industrial sectors in the energy sector. Within the NACE code 35, we have chosen specifically the code 351, indicating electricity, gas, steam and air conditioning supply sector, articulated in the electricity production, transmission, distribution and trade segments. Among the unlisted companies operating in the energy supply chain, only those located in the 28 countries of the European Union, with active and inactive status, have been selected. An inactive company is defined by Amadeus like the one that is in liquidation, bankruptcy or dissolved (merger, take-over, demerger). Thus, the original sample consists of 219 inactive companies and 5736 active companies that has been further cleaned up of all missing values also in relation to the identified events of financial distress spanning the period 2013-2018 chosen in this study. Hence, inactive and active companies have been reduced respectively to 57 and 1551. Then a stratified resampling method, consisting of deriving the same number of failed and non-failed firms by matching them to the inactive ones of the same size, has been applied to the original sample, to avoid problems of inconsistent parameter estimation and under-valuate misclassification error rate that may arise with an unbalanced sample (Stanghellini, 2009). According to a careful screening process, the 1551 active companies have been classified into four groups (large, medium, small and micro-companies) with respect to their size, which is traditionally measured by three parameters: number of employees, annual revenues and annual assets. The four groups have been labelled as follows: Large (1), Medium (2), Small (3) and Micro (4). Thus, the number of active companies, denoted as $Active_j$ with $j \in \{1,2,3,4\}$, and belonging to each category, has been reduced by applying the following formula:

$$Active_j = Tot.\ Inactive \cdot \left(\frac{n_j}{Tot.\ Active}\right), \tag{24}$$

with n_j denoting the number of large, medium, small and micro active companies, $Tot. Inactive$ and $Tot. Active$ indicating, respectively, the total number of inactive and active companies.

Thus, the final sample constructed through the above procedure involves 28 countries and consists of 114 unlisted European energy companies.

Table 3.1 shows the balanced sample classified into inactive and active companies obtained after the stratified resampling method of 1551 active companies, whereas Table B-1 in the Appendix B displays the set of 114 Energy companies distributed per country.

Table 3.1 Balanced sample after the stratified resampling method. Authors' elaboration

	SIZE OF COMPANIES				
STATUS OF ENERGY COMPANIES	LARGE	MEDIUM	SMALL	MICRO	TOTAL
INACTIVE	28	8	17	4	**57**
ACTIVE	827	635	83	6	**1551**
ACTIVE AFTER RESAMPLING METHOD	30.392	23.336	3.050	0.220	57
ACTIVE_j	30	23	3	1	**57**

Moreover, a five-fold cross-validation has been performed in order to eliminate the problem of small sample and to develop the model adequately. Thus, the final balanced sample consisting of 114 energy companies has been split, in a random way, into five mutually exclusive folds of equal size composed respectively of training and test set in the proportion of 80% and 20%. Each fold contains a training set of 92 companies to fit the model and a test set of 22 companies for validation purposes. The average accuracy rate over all the five folds is the cross-validated accuracy rate.

3.3 M.H.DIS model building

The Multi-group Hierarchy Discrimination model (M.H.DIS) of Zopounidis and Doumpos (2000) has been applied here to solve the sorting problem of the assignment of the selected energy companies into predefined ordered classes.
We recall briefly the basic notation used in this model and detailed described in Section 1.4.2:

- $A = \{a_1, \cdots a_j, \cdots, a_m\}$ is the set of finite alternatives;
- $G = \{g_1, \cdots g_\mathrm{i}, \cdots, g_n\}$ is the set of consistent criteria with an increasing or decreasing direction of preference order;
- a_{ji} is the evaluation of alternative j on criterion i;
- $\mathrm{C} = \{C_1 \succ \cdots \succ C_k \cdots \succ C_p\}$ is the set of p ordered categories from the best (or healthiest) C_1 to the worst (or riskiest) C_p;
- $\mathrm{B} = \{b_1, \cdots b_r, \cdots, b_s\}$ is the subset of alternatives A composing the training sample, used for model development;
- $D = \{d_1, \cdots d_s, \cdots, d_t\}$ is the subset of alternatives composing the test sample, used for validation purposes with $B \cap D = \emptyset$.

In order to sort companies of training set, M.H.DIS model applies the following hierarchical technique. At stage $k = 1$ the procedure considers the best category C_1 to which companies of training set (b_r) can belong and a pair of additive utility functions are built by the model to discriminate companies belonging to the healthiest category C_1 and companies belonging to the remaining riskier categories than C_1 (i.e. C_2 in our context). At this stage if the global score of the estimated additive utility function of healthiest category for alternative b_r, is higher than the global score of the estimated additive utility function of the riskiest categories, then b_r is classified to category C_1; otherwise company b_r does not belong to class C_1 and the procedure will continue to stage $k = 2$ analogously. The model will build as many pairs of additive utility functions as $p - 1$ classes to which companies have to be sorted (see Section 1.4.2 and Section 1.4.2.1 for a full description of the M.H.DIS model development).

Thus, once the final sample has been balanced (Table 3.1), the development of credit risk assessment model requires a careful selection of predictor variables able to well discriminate among active and inactive companies. In the next section, a literature review of independent variables most widely employed in failure prediction models is discussed, whereas Section 3.3.2 involves a careful screening in three steps, able to detect variables with a high explanatory and discriminating power between active and inactive companies.

3.3.1 Independent variables selection: literature review in failure prediction models

A large growing body of literature on failure prediction models based on Financial Ratios (FRs) is available for their easiness of assessment from the financial statements (Altman, 1968; Beaver, 1966; Ohlson, 1980). Usually, the employed FRs have been grouped according to the main firms' dimensions such as profitability, financial structure, liquidity, solvency, turnover and activity, which provide insights on how companies' internal aspects affect their risk of failure.

Generally, scholars have adopted a wide range of predictor variables in numerous scientific research studies; however, analytical predictive models have to comply with a tradeoff: a limited set of predictors to fit the model, able to represent all relevant information without creating overlapping, together with a low over-fitting on the training sample and a high performance on the test sample.

For these reasons, a careful screening process has to be performed to provide more accuracy in the distress prediction model.

This section deals with one of the initial steps in the development of a failure prediction model: the selection of the most predictive variables that could have a strong effect on the output (Saltelli et al., 2010; Saltelli et al., 2004). It consists of the review of the distress prediction literature with special attention to the most predictive variables employed in the energy sector (see for a literature review of FRs on failure prediction models: Xu et al., 2019; Liang et al., 2016; Du Jardin, 2016). Table 3.2 shows the set of 42 FRs derived from the literature review, which are classified according to six firms' dimensions, together with their acronyms and definitions. The list includes also other FRs measuring the company size, because some scholars suggest that dimensional difference among companies is a key factor affecting the company's default probability. To this aim, we include two other variables widely used in literature, namely total assets and total sales revenue as proxies for the firm size (Al-Khazali and Zoubi, 2005). Variables denoted with * have been eliminated from Table 3.2 because of abridgement of the information provided by the financial statements of Amadeus. Then the total number of FRs used for subsequent analysis has been reduced to 37.

Table 3.2 Financial ratios derived from literature review of failure prediction models.

FINANCIAL RATIOS (FRs)			
Acronym	**Variables**	**Definition**	**Tot.**
	PROFITABILITY		
EBIT_TA	EBIT/tot. assets	Ebit/tot. assets	
LTDR	Long-term debt ratio	Long-term debt/tot. assets	
OP_MARG	Operating margin	EBIT/net sales	
PROF_MARG	Profit margin	Net income/net sales	
ROE	ROE	Net income/stareholders' equity	
ROA	ROA	Net income/ tot. assets	11
ROCE	ROCE	EBIT/(currents assets-current liabilities)	
EBIT_EQ	EBIT/shareholder funds	EBIT/shareholder funds	
EBITDA_TA	EBITDA/tot. assets	EBITDA/tot. assets	
CF_TA	Cash flow/tot. assets	Cash flow/tot. assets	
CF_EQ	Cash flow to equity	Cash flow/shareholders' equity	
	FINANCIAL STRUCTURE		
EQ_RATIO	Equity ratio	Tot. equity/ tot. assets	
FAT	Fixed asset turnover	Net sales/ fixed assets	
*IC	*Interest coverage	*EBIT/interest expense	
TD_TA	Tot. debts/ tot. assets	(long-term debt + current liabilities)/tot. assets	7
LTD_EP	Long-term debt/ shareholder funds	Long-term debt/shareholder funds	
NOWC	Net op. work. capital/ tot. assets	(current assets-current liabilities)/tot. assets	
TD_EQ	Tot. debt/shareholder funds	(long-term debt + current liabilities)/shareholder funds	
	LIQUIDITY		
CA_TA	Current assets/tot. assets	Current assets/tot. assets	
CR	Current ratio	Current asset/current liabilities	
DR	Debt ratio	Total liabilities/tot. assets	
WC_TA	Working capital/total assets	Working capital/tot. assets	
CASH_CL	Cash/current liability	Cash/current liability	
CASH_TA	Cash/tot. assets	Cash/tot. assets	10
CL_TA	Current liability/tot. assets	Current liability/ tot. assets	
TLTA*	One if total liabilities exceeds tot. assets, zero otherwise	One if total liabilities exceeds tot. assets, zero otherwise	
CASH_CA	Cash/current assets	Cash/current assets	
CF_CL	Cash flow/current liabilities	Cash flow/current liabilities	
	SOLVENCY		
FE_EBITDA	Financial expenses/EBITDA	Financial expenses/EBITDA	
FE_NI	Financial expenses/net income	Financial expenses/net income	3
FE_TA	Financial expenses/tot. assets	Financial expenses/tot. assets	
	TURNOVER		
CL_TS	Current liabilities/tot. sales	Current liabilities/tot. sales	
CA_TS	Current assets/tot. sales	Current assets / tot. sales	4
*NAT	*Net asset turnover	*Net sales/tot. assets	
WC_TS	Work. Capital/tot. sales	Work. Capital/tot. sales	
	ACTIVITY/GROWTH		
CF_NS	Cash flow/sales	Cash flow/sales	
GROW_TA	Growth ratio of tot. assets	(tot assets/tot. assets t-1)-1	4
EBITDA_TS	EBITDA/tot. sales	EBITDA/tot. sales	
*NI_GROW	*Net income growth	*$(Ni_t – NI_{t-1})/(\lvert NI_t\rvert + \lvert NI_{t-1}\rvert)$, NI_t : latest net income	
	OTHERS		
*ORPE	*Operating revenue per employee	*Operating revenue/n.employee	
TA	Tot. assets	Tot. assets	3
SALES	Tot. sales revenue	Tot. sales revenue	
	Total FRs		**42**

Moreover, for each firm, financial data have been collected for up to four years prior the financial distress occurred due to limited data availability on Amadeus Database and, for the sake of simplification in the final results, they have been indicated with year-1, year-2, year-3, year-4. For instance, for a firm that faced financial distress in 2014, the collected financial data span the period 2013-2010 in which 2013 represents the year before its financial distress (year-1), corresponding also to the last year of available information on Amadeus database, and years 2010-2011-2012 represent respectively the year-2, year-3 and year-4 before the company's financial distress. Since the last available data cover a period between 2013 and 2018, the current sample actually covers the period 2013-2018.

Thus, each variable of Table 3.2 has been considered throughout four years' time span and their selection, implemented only on the training sample, has been performed with the following stages:

(1) A discriminatory power analysis of the 37 FRs through the information value for the four years considered;
(2) The t-test t has been applied on the selected variables of the previous stage;
(3) A correlation analysis has been also performed to eliminate the issue of overlapping information measuring the same characteristics.

3.3.2 Independent variables selection: Information value, t-test and correlation analysis

The sample identification of the variables over the four years considered with the highest explanatory relationship with the credit risk is composed of the three aforementioned steps that we discuss in detail in this section.

Stage 1. Information Value (IV) has been often used in credit scoring model as benchmark value to distinguish variables with no or weak predictive power, useless for credit risk modelling, from those with medium or high predictive power, decisive in increasing the accuracy of the final model (see Yap et al., 2011 and Nikolic et al., 2013 for its application). Information Value is computed according to the following formula:

$$IV_i = \sum_{j=1}^{m} \left(\left(active_j - inactive_j \right) \cdot WOE_j \right), \tag{25}$$

where IV_i is the information value of variable i under consideration, m is the total number of companies in the sample, $active_j$ and $inactive_j$ represent respectively the proportion of active and inactive companies for the variable i over m, j is the index relative to the company to evaluate and WOE is the weight of evidence, calculated with the formula:

$$WOE_j = ln\left(\frac{active_j}{inactive_j}\right). \tag{26}$$

Moreover, in order to determine if the predictive power of independent variables is poor, medium or high with respect to company's creditworthiness, the thresholds values, as determined by Siddipi (2012), have been computed (see Table 3.3).

Table 3.3 The predictive value of IV according to Siddipi (2012) interpretation.

Predictive value	***IV***
useless for prediction	$<0,05$
weak predictor	$0,05<IV<0,01$
medium predictor	$0,01<IV<0,25$
strong predictor	$0,25<IV<0,50$
suspicious or too good to be true	$IV>0,50$

With respect to the previous analysis, three variables have been eliminated from information value analysis because of their null or weak predictive power ($IV < 0.1$) in financial distress modelling in at least three years, namely: TD_EQ, CL_TA and FE_TA; otherwise variables in which the information value is predictive in at least two or three years, have been retained for stage 2, together with those variables in which IV is predictive in all the considered years.

Stage 2. In this step, another useful discriminatory power indicator, the t-test, has been applied on the remaining 34 variables obtained at stage 1, in order to analyze which variables well discriminate on average between failed and not-failed companies. A p-value less than 10% has been considered as confidence interval to define high predictive variables in failure prediction model; otherwise, predictors with a not significant p-value for at least three years have been removed for a further analysis. In this stage, it results that only the following eight variables have been selected: ROA, EBITDA_TA and CF_TA regarding the profitability dimension; EQ_RATIO and TD_TA the financial structure; CA_TA and DR the liquidity condition and CA_TS the turnover aspect.
From stage 2, it is worthy to notice that solvency and activity categories have not predictive power in determining the failure of companies operating in the energy sector as well as the size variables, introduced in this analysis to consider the difference among companies in terms of dimensions. This last result contradicts some credit scoring studies conducted in other sectors, suggesting the significant impact of firm's size on the future companies' probability to fail.

Stage 3. Finally, a pairwise correlation analysis has been implemented on the eight variables selected in the previous step for each year of observation (year-1, year-2, year-3 year-4), to eliminate the potential issue of overlapping information leading to the high overfitting on training sample and low performance on test sample. A correlation coefficient greater or equal than |0.5| suggests a high correlation strength between each pair of variables. over all the considered years.
Table 3.4 presents the results of the correlation analysis from which it is observed that the CF_TA and DR are highly correlated with at least two other variables over all the considered years.

Table 3.4 Pearson correlation coefficients among financial variables selected in stage 2 for all periods considered. Source: Statistical Software Stata

	Year-1							
	ROA	EBITDA_TA	CF_TA	EQ_RATIO	TD_TA	CA_TA	DR	CA_TS
ROA	1							
EBITDA_TA	-0.1373	1						
CF_TA	0.6866*	-0.1062	1					
EQ_RATIO	0.4342	0.0957	0.5831*	1				
TD_TA	-0.4037	-0.0832	-0.5880*	-0.8448*	1			
CA_TA	-0.2821	0.0911	-0.4155	-0.3310	0.3829	1		
DR	-0.4342	-0.0957	-0.5831*	-1.0000*	0.8448*	0.3310	1	
CA_TS	-0.1349	-0.0509	-0.0930	-0.0541	0.0769	-0.0138	0.0541	1
	Year-2							
ROA	1							
EBITDA_TA	0.5359*	1						
CF_TA	0.6122*	0.9467*	1					
EQ_RATIO	0.2671	0.4566	0.5365*	1				
TD_TA	-0.2010	-0.1583	-0.1930	-0.6910*	1			
CA_TA	-0.0634	-0.2232	-0.2177	-0.2874	0.3823	1		
DR	-0.2671	-0.4566	-0.5365	-1.0000*	0.6910*	0.2874	1	
CA_TS	-0.0765	-0.0976	-0.0736	-0.0064	0.0417	-0.0030	0.0064	1

Year-3								
ROA	1							
EBITDA_TA	0.7513*	1						
CF_TA	0.4590	0.3496	1					
EQ_RATIO	0.3317	0.2121	0.1847	1				
TD_TA	-0.2110	-0.2373	-0.1039	-0.7014*	1			
CA_TA	-0.0261	-0.2426	0.0565	-0.2217	0.3151	1		
DR	-0.3317	-0.2121	-0.1847	-1.0000*	0.7014*	0.2217	1	
CA_TS	-0.0853	-0.2223	-0.0859	-0.0931	0.0329	-0.0225	0.0931	1
Year-4								
ROA	1							
EBITDA_TA	0.7554*	1						
CF_TA	0.9081*	0.8129*	1					
EQ_RATIO	0.2990	0.1106	0.3160	1				
TD_TA	-0.1754	-0.1331	-0.2141	-0.6974*	1			
CA_TA	0.0763	-0.1142	-0.1651	-0.1774	0.2130	1		
DR	-0.2990	-0.1106	-0.3160	-1.0000*	0.6974*	0.1774	1	
CA_TS	-0.1677	-0.2333	-0.1812	-0.1117	0.0738	-0.0245	0.1117	1

* correlation coefficient ≥ $|0.50|$

CF_TA and DR have been removed from further considerations in the analysis to avoid multi-collinearity problems with the development of M.H.DIS model.
Thus, after performing the examined three steps procedure, six Financial Ratios have been retained covering different aspects of firms' main features related to profitability (ROA and EBITDA_TA), financial structure (EQ_RATIO and TD_TA), liquidity (CA_TA) and turnover (CA_TS).
Table B-2 in the Appendix B summarizes the results obtained from the previous steps.
In what follows, we apply the M.H.DIS method using the selected variables, summarized in Table 3.5, as evaluation criteria.

Table 3.5 List of the six financial variables selected through the three steps procedure. Authors' elaboration

Acronym	Variables	Category	Preference direction
ROA	ROA	profitability	max
EBITDA_TA	EBITDA/tot. assets	profitability	max
EQ_RATIO	Equity ratio	financial structure	max
TD_TA	Tot. debts/tot. assets	financial structure	min
CA_TS	Current assets/tot. sales	turnover	min
CA_TA	Current assets/tot. assets	liquidity	max

3.4 M.H.DIS model development and main results

The M.H.DIS model proposed by Zopounidis and Doumpos (2000) has been developed through the following steps.
Initially, a performance matrix has been built in order to organize the dataset in alternatives and criteria; the companies of the full sample constitute alternatives, whereas the six financial ratios selected with the explained three steps procedure, are the criteria under which alternatives are evaluated.
Then criteria with a non-increasing preference direction, such as TD_TA and CA_TS, have been aligned to the criteria with an increasing preference direction, by multiplying the evaluation of alternatives with respect to these criteria for -1, and possible outliers have been smoothed through a data trimmed procedure. In this regard, outliers have been identified with the Interquartile Range method (IRQ), by verifying one of the following inequalities (Gasser et al., 2020):

$$g_i(a_j) < \mathrm{Q}_1 - 1.5\,(Q_3 - Q_1) \quad \text{or} \quad g_i(a_j) > \mathrm{Q}_1 + 1.5\,(Q_3 - Q_1). \qquad (27)$$

Once data have been trimmed to the maximum or minimum values that are not outliers, a five-fold cross validation has been applied to the full sample for year-1. Thus for year-1, the training set of each fold has been used for model development and the test set of each fold has been used for validation purposes.

Moreover, because of the lack for the suitable synthetic judgments released by credit rating agencies (CRAs) for unlisted European energy companies, in this study we consider the classification provided by Amadeus database annually, that sorts companies into two categories: active and inactive ones.

Because of this two-class classification, the M.H.DIS method provides a pair of utility functions in one stage.

In the first stage, the companies belonging to C_1 are distinguished from the remaining firms of the other class and two additive utility functions are built according to the two mathematical programming techniques described in Section 1.4.2.1: the first one $\left(U_1\left(\bar{g}(b_r)\right) = \sum_{i=1}^{n} h_1 u_{1i}\left(g_i(b_r)\right)\right)$, for C_1 and the second one $\left(U_{\sim 1}\left(\bar{g}(b_\mathrm{r})\right) = \sum_{i=1}^{n} h_{\sim 1} u_{\sim 1i}\left(g_i(b_\mathrm{r})\right)\right)$ for the riskier class than C_1 (i.e. C_2). If the global utility function on the first class is greater than the second utility function ($U_1 > U_{\sim 1}$), then the company is classified into C_1; otherwise it belongs to C_2.

Table 3.6 presents the set of weights of the financial ratios in the two global utility functions computed (h_1 and $h_{\sim 1}$). The results indicate that EBITDA_TA and CA_TA are the most significant criteria in discriminating companies of class C_1 from companies of class C_2.

Table 3.6 Financial ratios weights in the utility function developed through M.H.DIS model.

FRs	h_{1i}(%)	$h_{\sim 1i}$(%)
ROA	13.57	50.54
EBITDA_TA	42.79	4.69
EQ_RATIO	8.21	2.22
TD_TA	10.69	13.34
CA_TA	23.55	7.29
CA_TS	1.17	21.88

Finally, Table 3.7 and Table 3.8 display the classification results of the discriminating model applied for year-1, year-2, year-3 and year-4 on the average of five folds assessed respectively for training and test set. More specifically, Table 3.7 shows the classification results in terms of companies belonging to each class, correctly or incorrectly predicted by the model. Whereas Table 3.8 shows the results in terms of average and overall accuracy rate.

It is important to point out that according to the confusion matrix it is possible to provide the following definitions:

- True Positive (TP): the number of correctly classified companies belonging to class C_1; i.e. companies that according to the Amadeus classification belong to C_1 and are classified by the model to the same class C_1;
- True Negative (TN): the number of correctly classified companies belonging to class C_2, i.e. companies that according to the Amadeus classification belong to C_2 and are classified by the model to the same class C_2;

- False Positive (FP): the number of active companies misclassified as inactive (Type I error); i.e. companies that according to the Amadeus classification belong to C_1 and are classified by the model to C_2;
- False Negative (FN): the number of inactive companies misclassified as active (Type II error), i.e. companies that according to the Amadeus classification belong to C_2 and are classified by the model to C_1.

Moreover, TP and TN, i.e. the companies correctly classified by the model, are located in the main diagonal of the confusion matrix; while FP and FN, i.e. the companies misclassified by the model, are located outside the main diagonal of the matrix. To be more precise, in Table 3.7 we have denoted the aforementioned acronyms with apices.

The main results of Table 3.7 suggest that on average the M.H.DIS model developed for year-1 estimates correctly 75 companies on training set $(41\,TP + 35\,TN)$, and 15 companies on test set $(8\,TP + 7\,TN)$. Similarly, for year-2 on average the model estimates correctly 73 companies on training set $(37\,TP + 36\,TN)$, and 15 companies on test set $(8\,TP + 7\,TN)$. As expected, the number of companies correctly predicted by the model decreases in year-3 and year-4 in both training and test set.

Moreover, the results of the model can be read with respect to the accuracy rate. The two most important measures are: the overall and the average accuracy rate.

- Average accuracy rate (ACA): is the average of each accuracy per class. It is computed as $\left(\frac{TP}{TP+FP} + \frac{TN}{TN+FN}\right)/classes$;

- Overall accuracy rate (OCA): is the number of correctly predicted companies over the total companies to predict. It is computed as $\frac{TP+TN}{TP+FP+TN+FN}$.

Hence, from Table 3.8 it is worth to note that on average the model developed for year-1 estimates correctly the 83.36% (OCA) of companies of training set and less than the 70% of companies for the test set (OCA 68.18%). This trend decreases with years, by reaching an overall accuracy rate of 56.36% for year-4. This result confirms what we expect, namely that on average the model estimates better companies where data are collected more recently than where data are collected from the past. The reason is quite intuitive since the predefined classification provided by Amadeus is more likelihood to be affected by the last balance sheet data (year-1) than the previous ones (year-2, year-3, year-4).

Furthermore, the overall classification accuracy for year-1, in both training and test sample, is not quite satisfactory compared to other studies on M.H.DIS model applications. Indeed here, on average the M.H.DIS model classifies correctly 83.26% companies of basic sample and 68.18% of holdout sample against the percentage range of [100, 93.18] and [75.11, 69] respectively for training and test set of other similar studies in other sectors (Kosmidou et al., 2002; Doumpos and Zopounidis, 1999; Kosmidou et al., 2004).

Table 3.7 Classification results of M.H.DIS model in terms of companies belonging to each class for year-1, year-2, year-3, year-4 (average over 5-fold cross-validation for training and test set). Source: Matlab Software

M.H.DIS MODEL ESTIMATED WITH AMADEUS CLASSIFICATION												
TRAINING SET												
PREDEFINED CLASSIFICATION	Companies belonging to each class											
	Year-1			Year-2			Year-3			Year-4		
	C_1	C_2	Tot	C_1	C_2	Tot	C_1	C_2	Tot	C_1	C_2	Tot
C_1	41 **(TP)**	5 **(FP)**	46	37 **(TP)**	9 **(FP)**	46	40 **(TP)**	6 **(FP)**	46	37 **(TP)**	9 **(FP)**	46
C_2	11 **(FN)**	35 **(TN)**	46	10 **(FN)**	36 **(TN)**	46	16 **(FN)**	30 **(TN)**	46	13 **(FN)**	33 **(TN)**	46
Tot			92			92			92			92
TEST SET												
PREDEFINED CLASSIFICATION	Companies belonging to each class											
	Year-1			Year-2			Year-3			Year-4		
	C_1	C_2	Tot	C_1	C_2	Tot	C_1	C_2	Tot	C_1	C_2	Tot
C_1	8 **(TP)**	3 **(FP)**	11	8 **(TP)**	3 **(FP)**	11	8 **(TP)**	3 **(FP)**	11	7 **(TP)**	4 **(FP)**	11
C_2	4 **(FN)**	7 **(TN)**	11	4 **(FN)**	7 **(TN)**	11	6 **(FN)**	5 **(TN)**	11	6 **(FN)**	5 **(TN)**	11
Tot			22			22			22			22

(TP)-True Positive; (TN)-True Negative; (FN)-False Negative; (FP)-False Positive

Table 3.8 Classification results of M.H.DIS model in terms of Average and Overall accuracy rate for year-1, year-2, year-3, year-4 (average over 5-fold cross-validation for training and test set). Source: Matlab Software

M.H.DIS MODEL ESTIMATED WITH AMADEUS CLASSIFICATION								
TRAINING SET								
PREDEFINED CLASSIFICATION	Accuracy (%)							
	Year-1		Year-2		Year-3		Year-4	
	C_1	C_2	C_1	C_2	C_1	C_2	C_1	C_2
C_1	89.95	10.05	80.37	19.63	87.43	12,57	81.22	18.77
C_2	23.36	76.64	21.21	78.79	34.57	65.43	29.46	70.53
Average accuracy (%)	83.29		79.58		76.43		75.87	
Overall accuracy (%)	83.26		79.56		76.31		75.86	
TEST SET								
PREDEFINED CLASSIFICATION	Accuracy (%)							
	Year-1		Year-2		Year-3		Year-4	
	C_1	C_2	C_1	C_2	C_1	C_2	C_1	C_2
C_1	75.65	24.35	68.44	31.56	72.19	27.81	64.70	35.29
C_2	38.12	61.88	35.83	64.17	57.35	42.65	52.09	47.90
Average accuracy (%)	68.77		66.31		57.42		56.30	
Overall accuracy (%)	68.18		66.36		57.27		56.36	

It has to be pointed out that this not fully satisfactory result of M.H.DIS model might depend on the rough classification provided by Amadeus database rather than the one provided by credit rating agencies (CRAs). Indeed these latter usually provide an objective synthetic credit rating for each company that is surely more reliable than the one provided by Amadeus for applying the M.H.DIS model. Unfortunately, this type of information is not provided here since the original database is composed by unlisted companies. Hence, the PROMETHEE II model, an acknowledged MCDA model, has been further implemented on the same dataset, to realize whether the original balanced classification provided by Amadeus database, could vary with the application of this model.

3.5 PROMETHEE based classification

To overcome the issue that the M.H.DIS model also in the most recent year-1 does not achieve highly satisfactory results in the holdout sample and for comparison purposes, another two-class assignment of the energy companies in the considered sample has been built on the basis of a well-known multi-criteria decision aid model, the PROMETHEE II method.

PROMETHEE II method has been applied in this study, to provide a benchmark sorting procedure on which to compare the classification provided by Amadeus database. Although there are other PROMETHEE methods specifically developed for solving sorting problems, such as PROMETHEE TRI and PROMSORT, the PROMETHEE II method has been selected here for several practical reasons.

From one side PROMETHEE TRI and PROMSORT present some important limits in terms of inputs needed for implementing the model. Both models indeed, require two important inputs to introduce: the reference alternatives and the limit profiles. Thus, a priori definition of these elements generates great constraints for practical applications, since it needs the assessment of industry experts. Although in PROMSORT model, the issue to have pre-defined reference alternatives can be can be tackled with PROMETHEE I method (Araz and Ozkarahan, 2007), in PROMETHEE TRI such issue is still present (Figueira et al., 2004). Moreover, the PROMETHEE TRI model presents also the disadvantages to use only single criterion net flows as inputs rather than outranking relation between alternatives, giving back also not perfectly ordered categories.

From the other side PROMETHEE II method presents some advantages in comparison to the aforementioned models, such as its easiness of implementation, its wide practical applications also to credit scoring models (Hu and Chen, 2011; Mousavi and Lin, 2020) and its feature to provide a complete ranking of alternatives.

To implement PROMETHEE II method, firstly, from the six financial variables selected in previous stage, we have built all the subsets composed of three criteria i.e. $C_{6,3} = 20$. Then, for each subset we have considered its complement, forming a pair of disjoint subsets denoted as follows:

$$\mathcal{P} = (\mathrm{F}, \mathrm{F}^{\mathrm{c}}) \ \forall F \subset G \text{ formed of three variables.} \quad (28)$$

However, the twenty pairs of subsets composed of three criteria (denoted with $\mathcal{P}$) have been reduced to eight, according to the following rules:

(1) If $\mathcal{P}$ is composed of subsets of criteria with a high pairwise correlation ($> |0.5|$) then such pair has been removed. For example, in our sample the couples of criteria ROA and EBITDA_TA, EQ_RATIO and TD_TA show a high pairwise correlation (see Table 3.4);

(2) If $\mathcal{P}$ is composed of subsets of at least two criteria belonging to the same dimension, i.e. profitability, financial structure, liquidity or turnover, then it has been eliminated. Since the considered dimensions are four, according to the above rule every subset (and its complement) related to each $\mathcal{P}$ is composed of three criteria representing three different company's aspects.

Applying these rules, eight of the twenty pairs have been retained. To achieve clarity in notation, we denote each of the eight pairs with a numerical label, i.e. $\mathcal{P}_{\mathrm{h}} = (F_h, F_h^c)$ with $h \in \{1, 2, \cdots, 8\}$.

Table 3.9 displays the eight pairs considered listing the three criteria for each subset and its complement. The three criteria (or financial variables) belonging to each set $F_h \in \mathcal{P}_{\mathrm{h}}$ have been used in PROMETHEE II as evaluation criteria on which companies' classification is based, whereas the remaining three ones belonging to its relative complement $F_h^c \in \mathcal{P}_{\mathrm{h}}$, have been employed as evaluation criteria of M.H.DIS model development with respect to both the AMADEUS and PROMETHEE based classification.

Table 3.9 Pairs ($\mathcal{P}$) considered in our analysis. Authors' elaboration.

	Criteria employed	
	F_h PROMETHEE II Classification	F_h^c M.H.DIS Model development
$\mathcal{P}_1$	ROA EQ_RATIO CA_TS	EBITDA_TA TD_TA CA_TA
$\mathcal{P}_2$	ROA EQ_RATIO CA_TA	EBITDA_TA TD_TA CA_TS
$\mathcal{P}_3$	ROA TD_TA CA_TS	EBITDA_TA TD_TA CA_TA
$\mathcal{P}_4$	ROA TD_TA CA_TA	EBITDA_TA EQ_RATIO CA_TS
$\mathcal{P}_5$	EBITDA_TA EQ_RATIO CA_TS	ROA TD_TA CA_TA
$\mathcal{P}_6$	EBITDA_TA EQ_RATIO CA_TA	ROA TD_TA CA_TS
$\mathcal{P}_7$	EBITDA_TA TD_TA CA_TS	ROA EQ_RATIO CA_TA
$\mathcal{P}_8$	EBITDA_TA TD_TA CA_TA	ROA EQ_RATIO CA_TS

This procedure has several advantages. Firstly, only those criteria that well discriminate companies' dimensions are used to sort energy firms into classes, giving an increasing consistency to the PROMETHEE based companies' classification than the one collected from the AMADEUS database.

Secondly, by considering F_h^c, relative to each $\mathcal{P}_{\mathrm{h}}$, it is possible to develop the M.H.DIS model on the PROMETHEE based classification, which represents a benchmark to compare the classification performances of AMADEUS based classification in terms of overall accuracy.

Thirdly, taking into account all the considered subsets of three criteria (F_h^c with $h \in \{1, 2, \cdots, 8\}$), it is highlighted how the overall accuracy varies according to the pair considered, acting as robustness check if M.H.DIS model built with PROMETHEE classification achieves higher results than the ones obtained with AMADEUS classification for most of the pairs.

PROMETHEE II, being founded on six types of preference functions, can potentially yield a different companies' classification according to the preference function used; if the obtained classification does not vary very much, then the model is quite consistent regardless the preference function used, representing a further element of robustness.

Finally, by simulating different scenarios for criteria weights, we performed a robustness analysis also with respect to the assessment of the PROMETHEE evaluation of each company and consequently on its assignment to a class.

3.6 Results and discussions of M.H.DIS model developed on the PROMETHEE based classification

In this section, we discuss the results of the M.H.DIS model developed respectively with AMADEUS and PROMETHEE based classification, which we will build before applying the multicriteria discrimination model. To deal with this aim, once data have been trimmed and criteria with a non-increasing preference direction have been aligned to the ones with an increasing preference function as explained in Section 3.4, PROMETHEE II method has been applied with respect to the three criteria belonging to F_h of each $\mathcal{P}_{\mathrm{h}}$ (Table 3.9, 2nd column) by considering the six type preference functions described in Section 2.2. For each Preference Function (PF), alternative (a_j) and set of three criteria ($F_h \in \mathcal{P}_{\mathrm{h}}$), we obtain a net flow $\Phi(a_j) \in [-1,1]$ that allows to rank alternatives from the best to the worst. In order to classify companies into two categories, the healthiest (C_1) and the riskiest class (C_2), we employ the median of the net flow of the all alternatives as a cut-off limiting the two classes. The choice of the median as cut-off threshold has been performed here, since it allows us to distribute equally the alternatives' net scores between the two considered categories. In this framework, the six preference functions of PROMETHEE II have been considered for each set of criteria $F_h \in \mathcal{P}_{\mathrm{h}}$ with $h \in \{1, 2, \cdots, 8\}$. Thus, we get in total forty-eight classifications of companies obtained multiplying the eight subsets (F_h) considered (see Table 3.9) by six type preference functions. Hence, the achieved classifications might differ each other according to the preference function and the set of criteria F_h considered. However, it has to be pointed out that the majority of preference functions (in at least four of the six type functions) classify companies in the same manner. In this regard, Table 3.10 shows the classification of companies into the healthiest and riskiest class according to the majority of the preference functions, with their relative and cumulative frequency for each combination.

Table 3.10 Companies' classification according to the most preference functions employed in PROMETHEE II. Authors' elaboration.

	Classification of companies according to the majority of preference functions			
	Class	Number of companies	Relative frequency (%)	Cumulative frequency (%)
F_1^c	1	72	63.16	-
	2	40	35.09	63.16
	not perfectly determined by most of PF	2	1.75	98.25
	total	114	100	100
F_2^c	1	45	39.47	-
	2	65	57.01	39.47
	not perfectly determined by most of PF	4	3.50	96.49
	total	114	100	100
F_3^c	1	82	71.92	-
	2	30	26.31	71.92
	not perfectly determined by most of PF	2	1.75	98.24
	total	114	100	100

F_4^c	1 2 not perfectly determined by most of PF total	58 55 1 114	50.87 48.24 0.87 100	- 50.87 99.12 100
F_5^c	1 2 not perfectly determined by most of PF total	83 29 2 114	72.8 25.43 1.75 100	- 72.80 98.24 100
F_6^c	1 2 not perfectly determined by most of PF total	70 43 1 114	61.40 37.71 0.87 100	- 61.40 99.12 100
F_7^c	1 2 not perfectly determined by most of PF total	90 22 2 114	78.94 19.29 1.75 100	- 78.94 98.24 100
F_8^c	1 2 not perfectly determined by most of PF total	80 30 4 114	70.17 26.31 3.50 100	- 70.17 96.49 100

Two main elements can be observed from Table 3.10:

(1) the significant difference between the classification obtained with the PROMETHEE method and the one provided by AMADEUS database;
(2) the robustness of the PROMETHEE II method to sort companies.

With regard to the first point, PROMETHEE model classifies, in six of the eight combinations ($\mathrm{F_h^c}$ with $h = 1, 3, 5, 6, 7$ and 8), most of companies as healthiest with a relative frequency that ranges between 61.40% and 78.94%; on the contrary AMADEUS based classification is equally distributed among the two classes (see Table 3.1).
With regard to the second point, PROMETHEE based method represents a robust tool to sort companies, since in each combination the majority of the preference functions (in at least four of the six type functions) provides a consistent classification regardless of the preference function employed. Moreover, those companies for which most preference functions are not able to determine with a strict preference the membership to healthiest or riskiest class, are limited to very few cases (from one to four companies).
Table 3.12 presents the main results of M.H.DIS model for year-1, developed respectively for AMADEUS and PROMETHEE based classification. Furthermore, in order to compare the efficiency of the discrimination model on two different rating settings, different performance indicators are needed. Among the most widely applied to assess the performance of credit rating models (Sobehart and Keenan, 2001; Keenan and Sobehart, 1999; Engelmann et al., 2003; Tinoco and Wilson, 2013) there are:

- *Cumulative Accuracy Profiles (CAP)*: is a graphical representation of two CAP curves that help to visualize the global performance of a model to discriminate two groups. However, to plot these curves it is necessary that companies have to be ranked by risk score. Random models display a curve coincident with the main diagonal of the graph; while perfect models show a line steeper to the left and closer to the point (0, 1);

- *Sensitivity (SENS)*: is a measure of how well a model identifies True Positive. It is given by the number of non-defaulted companies evaluated correctly by the model (TP), over the total number of non-defaulted companies ($TP + FP$);
- *Specificity (SPEC)*: is a measure of how well a model identifies True Negatives. It is computed by the number of defaulted companies evaluated correctly by the model (TN) over the total number of defaulted companies ($TN + FN$);
- *Classification Accuracy (CA)*: it is a single summary measure that examines whether a company is classified correctly by the model without considering the magnitude of misclassification. It can be distinguished into average and overall accuracy rate (ACA and OCA);
- *Receiver Operating Characteristic (ROC)*: it is a graphical plot similar to the CAP that provides a sketch of rating scores' distribution for active and inactive companies (Fawcett, 2006). However, it presents results that are more intuitive than CAP. The rating model's performance is the better when the ROC curve is steeper to the left and closer to the point (0, 1);
- *Area Under the Receiver Operating Characteristic curve (AUROC)*: it is the summary statistic of the ROC curve and it is a standard measure for the predictive accuracy of the model. It represents the likelihood that an active company will obtain a higher credit score compared to an inactive company, by measuring the area between the curve and the diagonal of the Lorenz curve (Fawcett, 2006). AUROC values range between 0-1. The model assumes a value equal to 0.5 whether it is random or lacks discriminative power; while it takes a value equal to 1 whether it perfectly discriminates among groups. Generally, models takes values between 0.5 and 1;
- *Gini Coefficient (GINI)*: it is widely used to assess the predictive accuracy of training and test set (Altman et al., 2010). It is easy to interpret and compute since it derives from AUROC, but differs for computing the full area below the curve. Hence, following the approach of Altman et al. (2020), it can be computed as $(2 * AUROC) - 1$. A Gini coefficient greater than 0.5 can be considered satisfactory;
- *Kolmogorov-Smirnov distance (KSD)*: it measures the maximum vertical deviation between two cumulative distributions functions. It has been mainly used to evaluate the predictive accuracy of USA rating systems jointly with other performance indicators (Andersen, 2007). Acceptable values of KS range between $[20\%, 70\%]$; if values are higher than 70%, the model is too good to be true (Mays, 2004);
- *F1_Score:* is one of the most used indicators for machine learning applications not only for a binary classification, but also for multiple classification. It is a weighted harmonic mean of Recall and Precision test (Powers, 2015). Recall is the Sensitivity, while Precision is the Specificity.

In this Chapter, the six performance indicators of Table 3.11 have been selected from the previous list to compare the discriminating performance of M.H.DIS model developed respectively with Amadeus and PROMETHEE based classification. More specifically,

following the approach of Doumpos et al. (2016), we have selected only those measures deriving from the main elements of confusion matrix (TP, TN, FP, FN) (Section 3.4) and endowed of higher computational intelligibility than graphical. Thus, performance indicators such as CAP, RO, KSD have been discarded because of their high graphic evidence; conversely SENS, SPEC, ACA, OCA, AUROC and Gini coefficient have been retained for their high quantitative evidence. Gini coefficient, in particular, has been included among these measures to check the consistency of the other performance indicators involved into the efficiency analysis.
In Table 3.12, performance indicators with respect to each preference function, used to develop M.H.DIS model with PROMETHEE-based classification, that are lower than the ones obtained with AMADEUS, are denoted with asterisk (*).

Table 3.11 Performance indicators used to evaluate the efficiency of M.H.DIS model. Authors' elaboration.

Performance Indicators				
Acronym	Indicator's name	Formula	Value (%)	Pref. direction
SENS	Sensitivity	$\frac{TP}{TP+FP}$	[0-100]	max
SPEC	Specificity	$\frac{TN}{TN+FN}$	[0-100]	max
ACA	Average accuracy	$\frac{SENS+SPEC}{classes}$	[0-100]	max
OCA	Overall accuracy	$\frac{TP+TN}{TP+FP+TN+FN}$	[0-100]	max
AUROC	Area under the receiving operating characteristic	$\frac{1}{2}*\left(\frac{TP}{TP+FN}+\frac{TN}{TN+FP}\right)$	[50-100]	max
GINI	Gini coefficient	$(2*AUROC)-1$	[-100; 100]	max

Table 3.12 Results of M.H.DIS model for year-1 developed for AMADEUS and PROMETHEE classification (average over 5-fold cross-validation for training and test set).

	Criteria employed		TRAINING AND TEST SET	M.H.DIS MODEL							
				YEAR-1							
						PROMETHEE CLASSIFICATION					
	F_h PROMETHEE II	F_h^c M.H.DIS Model Development		PERFORMANCE INDICATORS	AMADEUS CLASSIFICATION	REGULAR	U-SHAPE	V-SHAPE	LEVEL	LINEAR	GAUSSIAN
				SENS	86.00	94.79	94.56	92.46	95.50	86.76	86.76
				SPEC	66.64	73.56	80.31	81.45	81.31	83.74	83.74
	ROA	EBITDA_TA	TRAINING SET	ACA	76.32	84.17	87.43	86.95	88.40	85.25	85.25
				OCA	76.30	85.00	88.91	88.48	90.43	86.09	86.09
				AUROC	77.64	86.57	89.34	87.97	90.93	79.99	79.99
	EQ_RATIO	TD_TA		GINI	55.28	73.14	78.68	75.94	81.87	59.98	59.98
$\mathcal{P}_1$				SENS	70.62	84.21	87.64	87.06	87.26	82.93	82.93
				SPEC	50.77	65.51	73.50	72.78	72.00	72.29	72.29
	CA_TS	CA_TA	TEST SET	ACA	60.70	74.86	80.57	79.92	79.63	77.61	77.61
				OCA	60.91	74.55	80.91	80.00	80.00	79.09	79.09
				AUROC	61.01	75.43	81.48	79.96	80.25	72.21	72.21
				GINI	22.01	50.86	62.95	59.91	60.50	44.42	44.42
				SENS	86.86	86.42*	82.33*	87.05	85.65*	84.54*	87.96
				SPEC	68.39	74.97	73.79	72.81	68.12*	71.61	66.90*
	ROA	EBITDA_TA	TRAINING SET	ACA	77.63	80.69	78.06	79.93	76.89*	78.07	77.43*
				OCA	77.61	81.09	77.61	78.70	75.00*	76.31*	73.91*
				AUROC	78.68	81.37	77.97*	79.18	76.12*	76.12*	74.78*
	EQ_RATIO	TD_TA		GINI	57.36	62.73	55.94*	58.37	52.25*	52.23*	49.56*
$\mathcal{P}_2$				SENS	76.60	72.59*	63.07*	84.27	70.55*	71.31*	74.98*
				SPEC	61.17	66.24	63.99	68.64	56.81*	57.31*	58.14*
	CA_TA	CA_TS	TEST SET	ACA	68.89	69.42	63.53*	76.46	63.68*	64.31*	66.56*
				OCA	69.09	69.09	62.73*	74.55	62.73*	61.82*	64.55*
				AUROC	69.23	70.05	64.08*	75.96	63.51*	63.28*	65.80*
				GINI	38.47	40.10	28.16*	51.92	27.02*	26.56*	31.60*
				SENS	79.73	94.92	93.36	86.09	89.03	90.14	90.37

				SPEC	69.19	83.69	84.60	91.78	92.31	95.54	95.99
	ROA	EBITDA_TA	TRAINING SET	ACA	74.46	89.31	88.98	88.94	90.67	92.84	93.18
				OCA	74.56	90.00	90.00	87.61	90.00	91.09	91.52
				AUROC	75.38	90.73	90.15	83.66	87.09	83.79	85.83
	TD_TA	TD_TA		GINI	50.75	81.46	80.30	67.31	74.17	67.57	71.66
$\mathcal{P}_3$				SENS	69.34	87.70	90.08	77.41	77.22	82.97	86.60
				SPEC	55.92	73.53	65.29	68.00	74.79	79.29	80.29
	CA_TS	CA_TA	TEST SET	ACA	62.63	80.61	77.68	72.71	76.00	81.13	83.44
				OCA	61.82	81.82	81.82	73.64	75.46	80.91	83.80
				AUROC	62.95	81.72	83.29	68.90	71.41	73.32	79.24
				GINI	25.90	63.45	66.57	37.80	42.82	46.64	58.47
				SENS	86.46	93.77	88.63	85.56*	83.25*	68.54*	67.96*
				SPEC	68.87	80.32	74.79	80.38	76.77	81.11	79.71
	ROA	EBITDA_TA	TRAINING SET	ACA	77.67	87.05	81.71	82.97	80.01	74.83*	73.84*
				OCA	77.61	87.82	81.52	83.04	80.00	75.44*	74.13*
				AUROC	78.51	88.67	82.27	83.17	80.61	77.27*	76.45*
	TD_TA	EQ_RATIO		GINI	57.03	77.35	64.55	66.35	61.23	54.55*	52.89*
$\mathcal{P}_4$				SENS	80.08	87.65	81.13	77.46*	77.68*	55.43*	58.89*
				SPEC	52.84	67.00	64.18	70.99	68.62	64.38	60.51
	CA_TA	CA_TS	TEST SET	ACA	66.46	77.33	72.66	74.22	73.15	59.91*	59.70*
				OCA	66.36	78.18	71.82	74.55	73.64	60.00*	60.00*
				AUROC	67.65	78.96	73.40	74.66	73.26	60.16*	59.78*
				GINI	35.30	57.93	46.80	49.32	46.53	20.31*	19.55*
				SENS	89.81	88.12*	81.17*	84.33*	84.33*	80.24*	77.28*
				SPEC	60.52	84.60	95.31	90.23	90.23	87.43	89.41
	EBITDA_TA	ROA	TRAINING SET	ACA	75.16	86.36	88.24	87.28	87.28	83.83	83.34
				OCA	75.22	86.52	85.65	85.87	85.87	82.17	80.00
				AUROC	78.52	86.62	83.98	81.70	81.70	78.51*	77.10*
	EQ_RATIO	TD_TA		GINI	57.05	73.25	67.97	63.40	63.40	57.01*	54.21*
$\mathcal{P}_5$				SENS	75.09	80.47	75.25	79.85	79.85	78.97	73.72*
				SPEC	48.43	72.37	82.43	82.38	76.67	72.14	75.00
	CA_TS	CA_TA	TEST SET	ACA	61.76	76.42	78.84	81.12	78.26	75.56	74.36
				OCA	61.82	76.36	77.27	79.09	77.27	73.64	71.82
				AUROC	63.60	76.27	74.48	76.07	73.42	73.75	61.93*
				GINI	27.20	52.54	48.95	52.15	46.84	47.51	23.86*
				SENS	88.12	93.90	92.05	84.35*	86.09*	85.64*	84.22*
				SPEC	73.08	81.44	86.73	88.38	85.78	83.74	87.54
	EBITDA_TA	ROA	TRAINING SET	ACA	80.60	87.67	89.39	86.37	85.93	84.69	85.88
				OCA	80.65	88.91	89.78	85.87	85.87	85.00	85.43
				AUROC	81.62	89.37	90.35	82.60	85.43	85.36	85.77
	EQ_RATIO	TD_TA		GINI	63.25	78.74	80.71	65.20	70.85	70.72	71.55
$\mathcal{P}_6$				SENS	75.09	79.35	78.35	69.25*	73.19*	72.32*	68.30*
				SPEC	56.42	67.33	75.56	71.91	65.50	70.86	66.19
	CA_TA	CA_TS	TEST SET	ACA	65.76	73.34	76.95	70.58	69.35	71.59	67.25
				OCA	65.46	74.55	76.37	70.00	70.91	69.09	67.27
				AUROC	66.54	73.40	77.06	69.24	67.82	70.62	66.16*
				GINI	33.07	46.81	54.13	38.49	35.65	41.23	32.33*
				SENS	90.13	89.81	82.32*	86.81	87.33	90.82	90.82
				SPEC	57.41	83.19	91.59	87.93	86.70	82.11	82.11
	EBITDA_TA	ROA	TRAINING SET	ACA	73.77	86.50	86.96	87.37	87.01	86.46	86.46
				OCA	73.91	86.96	85.22	87.17	87.39	89.35	89.35
				AUROC	78.62	86.91	83.31	80.67	80.90	80.57	80.57
	TD_TA	EQ_RATIO		GINI	57.25	73.83	66.62	61.34	61.81	61.14	61.14
$\mathcal{P}_7$				SENS	76.34	78.54	76.04*	79.67	80.99	85.53	85.53
				SPEC	48.69	73.27	78.09	65.71	68.43	52.38	52.38
	CA_TS	CA_TA	TEST SET	ACA	62.51	75.90	77.07	72.69	74.71	68.95	68.95
				OCA	61.82	75.45	75.45	74.54	76.36	79.09	79.09
				AUROC	65.82	76.56	74.30	70.26	70.80	65.40*	65.40*
				GINI	31.64	53.13	48.60	40.51	41.61	30.80*	30.80*
				SENS	92.15	92.16	94.14	88.19*	88.89*	89.44*	89.50*
				SPEC	65.82	72.94	78.38	84.61	86.12	92.57	93.78
	EBITDA_TA	ROA	TRAINING SET	ACA	78.99	82.55	86.26	86.40	87.51	91.01	91.64
				OCA	78.91	85.65	88.26	87.17	88.26	90.22	90.44
				AUROC	81.12	84.91	88.48	84.17	83.88	85.73	84.66
	TD_TA	EQ_RATIO		GINI	62.23	69.81	76.95	68.35	67.76	71.45	69.31
$\mathcal{P}_8$				SENS	82.21	85.90	85.38	84.88	84.57	87.81	86.27
				SPEC	55.84	60.33	67.12	59.52	59.05	70.09	74.21
	CA_TA	CA_TS	TEST SET	ACA	69.03	73.12	76.25	72.20	71.81	78.95	80.24
				OCA	69.09	77.27	78.18	78.18	79.09	83.64	82.73
				AUROC	71.09	74.99	78.45	73.85	75.49	78.42	79.07
				GINI	42.18	49.97	56.90	47.70	50.99	56.84	58.15

Data on performance indicators are expressed in percentage.

The results clearly show that the discrimination power of M.H.DIS model developed with PROMETHEE based classification is higher than the one obtained with AMADEUS classification, in most of the combinations of criteria relative to subsets $\mathrm{F}_{\mathrm{h}}^{\mathrm{c}}$ with $h = 1, 3, 5, 6, 7$ and 8 for both training and test sample. In these combinations the specificity, the average and the overall accuracy rate of M.H.DIS with PROMETHEE based classification are strictly higher than the ones obtained with AMADEUS classification, regardless the preference function used to develop the PROMETHEE model. Instead, the combinations of criteria relative to subsets $\mathrm{F}_{\mathrm{h}}^{\mathrm{c}}$ with $h = 2$ and 4 do not achieve the same high-performance results especially with regard to the test set.

However, it is observed that in no combination, the performance indicators relative to the AMADEUS classification achieve the maximum value as with PROMETHEE-based classification, but they take an intermediate value within the range of possible six values obtained according to the different preference functions employed in PROMETHEE classification. In other words, it exists at least one or more preference functions also for the less performing combinations 2 and 4, in which the M.H.DIS model performed with PROMETHEE-based classification, gives an accuracy rate that is higher than the one achieved with AMADEUS classification.

Moreover, the combinations of criteria relative to subsets $\mathrm{F}_{\mathrm{h}}^{\mathrm{c}}$ with $h = 1, 3, 5, 6, 7$ and 8 with the highest accuracy rate present some important common features:

- the PROMETHEE-based classification, on which M.H.DIS is developed, is not equally distributed among the two classes, but is more concentrated on the healthiest companies, with a relative frequency ranging between 61.40% and 78.94%;
- the M.H.DIS model is developed by using at least two of the financial variables with a higher weight in discriminating between categories (see Table 3.5) such as: EBITDA_TA, CA_TA and ROA, with the only exception of the combination of criteria referred to $\mathrm{F}_{6}^{\mathrm{c}}$;
- three of the performance indicators, i.e. Sensitivity, Auroc and Gini coefficient, computed for the M.H.DIS model developed with PROMETHEE based classification achieve the lowest results whenever the preference function employed is more complex such as the level, the linear and Gaussian criterion (see PROMETHEE classification in the combinations of criteria relative to subsets $\mathrm{F}_{\mathrm{h}}^{\mathrm{c}}$ with $h = 1, 3, 5, 6, 7$ and 8).

On the contrary, combinations of criteria relative to subsets $\mathrm{F}_{2}^{\mathrm{c}}$ and $\mathrm{F}_{4}^{\mathrm{c}}$ achieve a quite limited accuracy rate and share the following common aspects:

- a PROMETHEE-based classification more equally distributed among categories of companies, such as the AMADEUS classification, with a relative frequency ranging between 39.47% and 50.87%;
- the M.H.DIS model is developed on financial variables with a lower weight in discriminating between categories (see Table 3.5) such as: EQ_RATIO, TD_TA and CA_TS;
- most of the performance indicators (including also the average and the overall accuracy rate) computed for the M.H.DIS model developed with PROMETHEE based classification achieve the lowest results whenever the preference function employed is more complex such as for the level, the linear and Gaussian ones.

Finally, to prove the robustness of M.H.DIS model developed in PROMETHEE-based classification with respect to the AMADEUS one, M.H.DIS model developed for year-1 has been also applied to the training and test sample for year-2, year-3, year-4.

For the sake of simplification, in Table 3.13 the performances of two models have been presented in terms of average and overall accuracy rate. Moreover, only the minimum and maximum values of M.H.DIS model with PROMETHEE based classification, attained considering the six-preference functions on the average of 5-fold cross-validation, have been displayed.

Table 3.13 Results of M.H.DIS model for year-1, year-2, year-3, year-4, developed for AMADEUS and PROMETHEE-based classification (average over 5-fold cross-validation for training and test set).

		M.H.DIS MODEL												
		YEAR-1				YEAR-2			YEAR-3			YEAR-4		
	TRAINING AND TEST SET	PERF. INDICATORS	AMADEUS CLASSIF.	PROMETHEE CLASSIF.		AMADEUS CLASSIF.	PROMETHEE CLASSIF.		AMADEUS CLASSIF.	PROMETHEE CLASSIF.		AMADEUS CLASSIF.	PROMETHEE CLASSIF.	
				MIN	MAX		MIN	MAX		MIN	MAX		MIN	MAX
$\mathcal{P}_1$	TRAINING SET	ACA	76.32	84.17	88.40	73.23	79.45	84.00	69.79	76.80	82.61	69.07	76.65	84.59
		OCA	76.30	85.00	90.43	73.26	79.35	86.52	69.78	79.35	83.04	69.13	72.17	85.22
	TEST SET	ACA	60.70	74.86	80.57	63.88	62.66*	70.38	58.09	62.71	71.94	58.40	62.84	71.62
		OCA	60.91	74.55	80.91	63.64	68.18	71.82	58.18	67.27	72.73	58.18	64.54	72.73
$\mathcal{P}_2$	TRAINING SET	ACA	77.63	76.89*	80.69	76.65	78.00	84.33	73.97	74.30	83.70	72.11	71.19*	83.61
		OCA	77.61	73.91*	81.09	76.74	76.30*	84.57	73.91	70.65*	84.13	72.17	66.96*	83.91
	TEST SET	ACA	68.89	63.53*	76.46	63.57	62.13*	70.49	60.95	62.32	75.34	60.40	54.60*	71.21
		OCA	69.09	61.82*	74.55	62.73	61.82*	70.91	60.91	60.00*	75.46	60.00	51.82*	71.82
$\mathcal{P}_3$	TRAINING SET	ACA	74.46	88.94	93.18	73.33	83.85	87.19	67.95	75.81	81.63	69.59	76.46	81.80
		OCA	74.56	87.61	91.52	73.26	82.17	86.52	68.04	75.22	81.52	69.78	71.96	81.52
	TEST SET	ACA	62.63	72.71	83.44	61.80	68.18	83.95	58.62	59.49	75.38	58.57	64.03	70.75
		OCA	61.82	73.64	83.80	60.91	70.00	81.82	58.18	61.82	76.36	57.27	63.64	70.91
$\mathcal{P}_4$	TRAINING SET	ACA	77.67	73.84*	87.05	77.51	74.26*	84.40	73.89	71.35*	82.93	74.32	72.12*	81.25
		OCA	77.61	74.13*	87.82	77.61	75.00*	84.54	73.91	71.30*	82.61	74.35	72.17*	80.65
	TEST SET	ACA	66.46	59.70*	77.33	63.98	64.28	75.82	60.44	53.00*	73.43	63.71	60.11*	72.90
		OCA	66.36	60.00*	78.18	62.73	63.64	75.46	60.00	52.73*	74.55	63.64	60.00*	72.73
$\mathcal{P}_5$	TRAINING SET	ACA	75.16	83.34	88.24	72.61	75.34	81.45	65.76	71.28	78.24	70.04	74.58	78.81
		OCA	75.22	80.00	86.52	72.61	75.65	80.87	65.65	75.87	79.56	70.00	73.48	78.70
	TEST SET	ACA	61.76	74.36	81.12	66.08	68.50	77.47	55.55	55.33*	65.44	57.63	57.22*	64.97
		OCA	61.82	71.82	79.09	65.45	65.45	74.54	55.45	60.00	66.36	58.18	60.91	67.27
$\mathcal{P}_6$	TRAINING SET	ACA	80.60	84.69	89.39	73.13	82.78	87.16	72.57	78.41	86.09	74.90	80.86	86.68
		OCA	80.65	85.00	89.78	73.26	83.04	87.17	72.39	78.91	86.09	74.78	81.96	86.52
	TEST SET	ACA	65.76	67.25	76.95	57.44	67.70	72.01	56.94	68.33	76.47	60.88	68.17	79.79
		OCA	65.46	67.27	76.37	56.36	66.37	71.82	57.27	67.27	75.46	60.91	70.00	80.00
$\mathcal{P}_7$	TRAINING SET	ACA	73.77	86.46	87.37	68.45	75.68	80.49	64.71	69.07	75.44	72.67	72.07*	79.39
		OCA	73.91	85.22	89.35	68.48	73.26	79.13	64.78	70.44	76.09	72.61	68.91*	78.70
	TEST SET	ACA	62.51	68.95	77.07	55.65	64.75	76.66	58.96	57.56*	67.13	61.10	52.12*	66.90
		OCA	61.82	74.54	79.09	54.55	63.64	74.55	58.18	63.64	67.27	60.91	54.55*	65.45
$\mathcal{P}_8$	TRAINING SET	ACA	78.99	82.55	91.64	72.01	78.05	86.49	72.86	74.80	80.13	74.20	74.37	85.28
		OCA	78.91	85.65	90.44	72.17	73.48	82.61	72.83	73.70	78.70	74.13	73.70*	81.31
	TEST SET	ACA	69.03	71.81	80.24	60.25	65.99	72.04	59.73	63.62	70.53	61.91	61.28*	76.59
		OCA	69.09	77.27	83.64	58.18	64.55	73.64	59.09	67.27	72.73	61.82	63.64	73.64

Data on average and overall accuracy are expressed in percentage.

According to the obtained results, the average and the overall accuracy rates decrease in years prior the financial distress, underlying that the model becomes less efficient with years in replicating a pre-specified classification. This trend is more evident in M.H.DIS model developed with AMADEUS classification than the one obtained with PROMETHEE method, especially for pairs $\mathcal{P}_2$ and $\mathcal{P}_3$.

Moreover, the higher performances of M.H.DIS model developed with PROMETHEE-based classification in terms of accuracy rate is generally confirmed in the same previous combinations of criteria referred to subsets $\mathrm{F}_{\mathrm{h}}^{\mathrm{c}}$ with $h = 1, 3, 5, 6, 7$ and 8. Indeed, in these last combinations ACA and OCA of M.H.DIS model performed with PROMETHEE-based classification are always higher than the one achieved with AMADEUS classification, regardless the preference functions used except for the ACA of the following test set: $\mathcal{P}_1$ for year-2; $\mathcal{P}_5$ for year-3, year-4; and $\mathcal{P}_8$ for year-4.

Similarly, in combinations $\mathcal{P}_2$ and $\mathcal{P}_4$, the M.H.DIS model built on AMADEUS database, displays an ACA and OCA that are within intervals of the minimum and maximum value

attained through the multi-criteria discrimination model built with PROMETHEE method also for year-2, year-3, year-4, confirming the results obtained in year-1.
Unclear case is combination $\mathcal{P}_7$, where the results of year-4 are opposite to year-1. Specifically, the discrimination model performed with AMADEUS classification achieves in this last year, an accuracy rate that is higher than the minimum accuracy value obtained with PROMETHEE based classification in both training and test set, but never higher than its maximum, giving however robustness to the PROMETHEE method in classifying companies also for previous years to financial distress.

3.7 Conclusions

In light of the recent flawed risk management actions of banks and deregulation processes introduced in the European energy industry on December 1996, the development and use of more reliable and accurate failure prediction models is becoming of major importance for energy companies, in order to prevent financial repercussions that could be catastrophic for the economy of a country.
While several statistical techniques are widely employed to deal with the issue of companies' credit risk assessment, multicriteria models are often preferred to them thanks to their high comprehensibility, easiness of application and ability to incorporate the DM's preferences.
Thus, this study employs one of the most efficient multi-criteria failure prediction models, the Multi-group Hierarchy Discrimination (M.H.DIS) technique elaborated by Zopounidis and Doumpos (2000). It has been applied on a balanced sample of 114 active and inactive European unlisted energy companies for up to four years prior the financial distress occurred. Moreover, in order to avoid the issue of small sample and to develop the model adequately, a five-fold cross validation has been performed to analyze whether the pre-specified classification of companies provided by Amadeus database is well replicated by the model.
Since the M.H.DIS method achieves a quite limited satisfactory accuracy in predicting the considered Amadeus classification in the holdout sample (68.18%), the PROMETHEE method has been performed then to provide a benchmark sorting procedure useful for comparison purposes. Thus, the six financial variables, previously selected to implement the M.H.DIS model with Amadeus based classification, have been considered in eight combinations and employed in turn in subsets of three criteria in the building of PROMETHEE classification first and M.H.DIS model development then.
Through this twofold application of M.H.DIS model, respectively with Amadeus and PROMETHEE classification, it has been possible:

- to observe if the classification built on PROMETHEE method differs from the one provided by Amadeus, acting as a benchmark sorting procedure;
- to compare the results of M.H.DIS model developed with Amadeus and PROMETHEE classification in terms of accuracy rate.

Consequently, the role of M.H.DIS model in this study is not to provide a final classification of companies into classes but to verify which of these two different classifications, inserted as input in the model, are better replicated by the model on the basis of different performance indicators (Table 3.11).

The evidences provided in this study highlight the robustness of M.H.DIS model developed with PROMETHEE based classification as consequence of the following three main results:

(1) by considering all possible combinations of more powerful financial variables in well distinguishing the two classes, the discrimination power of M.H.DIS model developed with PROMETHEE based classification in year-1 is higher than the one obtained with AMADEUS classification on six of the eight pairs $\mathcal{P}_\mathrm{h}$ with $h = 1, 3, 5, 6, 7$ and 8 for training and test set;

(2) by taking into account the whole set of preference functions to build a PROMETHEE based classification, it is worthy to note that PROMETHEE model represents a robust tool to sort companies into categories since the majority of preference functions classify companies into the same healthiest and riskiest class. Moreover, the results of the M.H.DIS model developed with PROMETHEE based classification show a higher performance in terms of accuracy rate than AMADEUS one, regardless of the preference function used. Indeed, in all combinations, the performance indicators relative to AMADEUS based classification are never higher than the maximum accuracy value achieved with the six preference functions used in PROMETHEE based classification;

(3) by simulating the weights of criteria in 10,000 different scenarios with the hit and run procedure, the final PROMETHEE based classification handles with the DM's uncertainty on criteria weights providing a more robust assessment of the companies' classification. This is further confirmed by the fact that cases with the highest accuracy rate ($\mathcal{P}_\mathrm{h}$ with $h = 1, 3, 5, 6, 7$ and 8) share common features such as: the not equally sample distribution between the two classes with a concentration in favor of class C_1, the attainment of the lowest performance results where the preference functions is more complex (level, linear or Gaussian criterion), the development of the M.H.DIS model on at least two financial variables with a greater weight in discriminating between class C_1 and C_2 (Table 3.6).

Moreover, if on the one side the efficiency of the M.H.DIS model decreases with years (year-2, year-3, year-4), on the other side, the robustness of PROMETHEE based classification against the AMADEUS one is further confirmed in the same aforementioned combinations ($\mathcal{P}_\mathrm{h}$ with $h = 1, 3, 5, 6, 7$ and 8) and regardless of the preference function employed, even for years before financial distress occurred. Indeed, similarly to year-1, in all combinations of year-2, year-3 and year-4, the average and the overall accuracy rate of M.H.DIS model developed with AMADEUS based classification never exceed the maximum accuracy value obtained with the six preference functions employed in PROMETHEE based classification, taking otherwise an intermediate value within the range of possible six accuracy values.

Therefore, the noteworthy results obtained in this study show that PROMETHEE based classification, used jointly with M.H.DIS model, enhances the performances of the discrimination model specifically for credit risk assessment of energy companies. More generally, this approach is recommended in two cases:

- whenever the M.H.DIS model developed with a pre-specified classification give results not fully satisfactory in terms of overall accuracy;
- whenever the sample under consideration is composed by alternatives for which the credit rating are not provided by credit rating agencies (CRAs) as in the case of unlisted or small and medium-sized enterprises (SMEs), even if a support to the credit risk assessment process is relevant also in this case.

Chapter 4

Concluding remarks

In this thesis, we employed three different Multi criteria Decision Aid (MCDA) models to address two research issues related to the energy sector: the performance evaluation and the credit risk assessment of energy companies.

In Chapter 1, we highlighted the great importance of the energy industry for the modern economy and the recent effects of deregulation policies on energy markets (Section 1.2.1.2). Among the various consequences caused by liberalization directives, the failures of energy companies were the most crucial in terms of government interventions and public expenditures (Section 1.2.1.3). Thus, a constant monitoring of energy companies' financial performances is fundamental as well as reliable credit risk assessment models able to predict corporate failure consistently and accurately. MCDA models helped to reach these aims thanks to their easiness of application and multi-faceted nature.

With regard to the first issue, the evaluation of energy companies, it was emphasized that the available literature review on this topic is limited to the analysis of financial dimension (Section 1.3.3). To fill this research gap, the first aim of this thesis was to evaluate the complex structure of energy companies under several conflictual criteria.

Thus, Chapter 2 proposed the performance assessment of a set of twenty listed energy companies under different criteria and uncertainty scenarios.

More specifically, first we selected a coherent family of criteria to take into account all those dimensions that could affect the performances of the companies operating in this field (Section 2.3.2).

The literature on firm's performance evaluation has been enriched with the introduction of more specific energy criteria such as the sustainability, the technical and the market dimension, widely implemented in similar sector studies. They represented the crucial viewpoints that different decision makers have to analyze, in order to make decisions in line with their own purposes. Among these, the market criteria were definitely the most crucial one, since it determined a good measure of the market profile in which the company is located and therefore it gave more exhaustiveness and reliability to the analysis of this complex sector.

Then the aforementioned four criteria have been structured hierarchically to provide a full assessment of each company expressed through a composite index (Section 2.4). Finally, we ranked the energy firms based on their performances (Section 2.5.1).

In order to make the final result as robust as possible, different DM's uncertainty parameters, reflecting the DM's preferences, have been considered simulating seven different scenarios.

On the methodological side, the Hierarchy Stochastic Multi Attribute Acceptability Analysis (HSMAA) elaborated by (De Matteis et al., 2019) was selected in this study as the most suitable model for energy companies' performance assessment. Indeed, for its ability to handle simultaneously with a structure of criteria organized hierarchically and with the DMs'

uncertainties on preference parameters, used to simulate different scenarios, it provided us more robust recommendation on final rank results than other MCDA models dealing with similar multi-level structure of criteria, such as the AHP model.
The main findings of this research confirmed the reliability, the flexibility, and the usefulness of this model.
This model is reliable because first and last positions of the considered energy companies are quite robust in all the considered scenario, while the rankings relative to the intermediate positions varied widely by the chosen set of weights, exemplifying the need to rank companies based on multiple set of criteria weights.
This model is flexible because it is easily adaptable to different stakeholders' needs. Depending on whether they are interested into performing a complete or a partial companies' evaluation based respectively on the whole set of criteria (case (1) and (2)) or on a single point of view, this model allows stakeholders to make the most appropriate strategic choice.
This model is useful for the significant policy implications that it determines. Indeed, it is aimed at all categories of stakeholders dealing with the firm performance evaluation, such as investors, business leaders and policymakers, representing a reliable support tool for their strategic decisions. Potential investors can use the results of case (1) and case (2) to make their investment decision-making process more safely; while the results on singular criteria if they are more interested, for instance, to evaluate the financial performances only. Business leaders and policymakers can use case (1) and case (2) to check the strengths and the weaknesses of companies' performances within a country; while the results on singular criteria to implement specific strategies, such as expansive fiscal policies or infrastructural investments if the companies performed badly under the financial or the economic perspective respectively.
However, the ranking stability reached by some companies on uncertainty scenarios, gave deep insights into their performances. Companies ranked in the first positions, regardless the scenario under consideration, were generally considered good companies and thus suitable for investment decisions (for investors) or to provide a benchmark to strive for (for policymakers). In this case, any sort of policy intervention is needed to improve their performances and to guarantee reliable services. Similarly, for companies ranked in the worst positions, regardless the scenario under consideration, they are generally considered not wealthy on the whole set of criteria and therefore policy interventions have to be guaranteed to ensure the continuity of the services to customers. Whereas, companies that are unstable in the ranking under different scenarios, it could be useful for police makers to analyze in which scenario the companies performed good/bad to highlight its strengths or weaknesses and therefore to implement proper energy policies that increase their performances.
The second main issue emerged throughout this thesis, is represented by the serious episodes of energy companies' failures occurred after liberalization policies. These generated serious economic losses as well as power outages that forced governments to intervene in order to straighten out the severely compromised situation. Thus it has been emphasized how proper

risk assessment model are needed in order to predict energy companies failures accurately and in advance.
The literature on failure prediction is reached of credit risk models and it mainly includes statistical, econometric and machine learning techniques. However, these methods did not hold some significant features that analysts often requires to have, such as the ordinal risk grade and the monotonicity assumption.
The thesis showed that MCDA models appear as the most suitable tools also to deal with this problem since they are comprehensible, easy to apply and include different DM's preferences.
In section 1.3.3, it has been highlighted how different MCDA models have been employed to solve sorting problems in credit risk assessment. Among the most applied ones, methods based on preference disaggregation functions, such as the M.H.DIS and the entire family of UTADIS model; methods based on outranking techniques, such as the ELECTRE TRI and its extensions and methods based on the rough set theory.
Among these, M.H.DIS model has proven to be one of the most efficient discrimination methods for sorting problems. Its main strengths are the ability to discriminate among two or more than two categories, the progressive discrimination procedure on which it is based, the three different mathematical programming techniques used to estimate the "optimal" pair of additive utility functions and the computational speed.
Despite its wide implementation on several fields, such as the banking sector, the corporate sector and the country analysis, the M.H.DIS model has never been applied to the energy sector to predict the financial distress of energy companies.
Thus, for the great relevance that the energy sector has for the entire economy, the aim of Chapter 3 was to fill the aforementioned research gap by applying the M.H.DIS model elaborated by Zopounidis et Doumpos (2000), on a sample of 114 European unlisted energy companies. To avoid biased results arising from a small sample, the M.H.DIS model was developed following a five-fold cross validation procedure to analyze if the model explained and replicated a two groups pre-defined classification of companies into two classes, provided by Amadeus database.
Since M.H.DIS model achieved a quite limited satisfactory accuracy in predicting the considered Amadeus classification in the test set, compared to similar M.H.DIS applications in other sectors (Section 3.4), the second aim of Chapter 3 was to provide a benchmark sorting procedure on which to compare the initial classification inserted in the model.
In this regard, it has been pointed out that this balanced classification of companies into two categories, was rough since it derived from the Amadeus database rather than credit rating agencies (CRAs). Indeed these latter usually provide an objective synthetic credit rating for each company that is surely more reliable than the one provided by Amadeus for applying the M.H.DIS model. In this study, since unlisted companies composed the original sample, CRAs did not provide objective ratings and therefore the doubt about the roughness of companies' classification provided by Amadeus database, has been confirmed by the not fully satisfactory results obtained by the application of the M.H.DIS model with Amadeus database.

In order to overcome this issue, in Chapter 3 the PROMETHEE 2 method has been employed on the same dataset, to realize whether the original balanced classification (Amadeus) could vary with the application of a well acknowledged MCDA model (Section 3.5).
In this study PROMETHEE II has been employed to a classification problem, despite it was a specifically developed method for ranking problems. In this regard, it has been pointed out that this choice has depended by different reasons. Firstly, the very limited literature related on PROMETHEE TRI and PROMSORT, the main PROMETHEE models used specifically for classification issues, has demonstrated their weakness especially for practical applications. Secondly, their important limits in terms of inputs needed for implementing the specific sorting model that had to be fix a priori by industry experts. Thirdly, the advantages of PROMETHEE II methods in terms of easiness of implementation, spread of applications for credit scoring models and complete ranking of alternatives. Thus, through the obtained net score, it was possible to define the median value of all alternatives and to fix it as cut-off level to limit the two classes.
By applying a robustness analysis with any possible combination of preference functions and the six criteria endowed of high highest discrimination power in well discriminating between the two categories of companies, PROMETHEE II method has returned an unbalanced classification of companies more shifted towards active companies for most of combinations (Table 3.10). Only two combinations of criteria (F_2^c and F_4^c) resulted to be more balanced among the two classes. Thus, our presumption about the roughness of Amadeus database was correct.
The evidences provided in this study highlighted the robustness of M.H.DIS model developed with PROMETHEE based classification through the following main results:

- the discriminatory power of M.H.DIS model developed with PROMETHEE based classification in year-1 was higher than the one obtained with AMADEUS classification for six out of eight combinations for both training and test set;
- in all combinations, the performance indicators relative to AMADEUS based classification was never higher than the maximum accuracy value achieved with the six preference functions used in PROMETHEE based classification;
- the final PROMETHEE based classification handles with the DM's uncertainty on criteria weights by applying the Hit and Run sampling procedure on weights;
- the discriminatory power of M.H.DIS model developed with PROMETHEE based classification was higher than the one developed with Amadeus classification also for previous years (year-2,-3,-4), in the same combinations (P_h with $h = 1,3,5,6,7,8$) and the average and overall accuracy rate never exceed the maximum accuracy value obtained with the six preference functions employed in M.H.DIS with PROMETHEE based classification.

Therefore, Chapter 3 showed that:

- M.H.DIS used jointly with PROMETHEE II methods enhances the performances of the discrimination model specifically for credit risk assessment of energy companies

- this approach is recommended for cases in which either the M.H.DIS model developed with a pre-specified classification gives results not fully satisfactory in terms of accuracy rate or whenever the sample to assess is composed of alternatives for which the CRAs does not provide an objective rating such as unlisted companies or small and middle enterprises.

Finally, we envisage some possible directions for future research. These directions have been collected according to their relevance to the main chapters of this thesis. With regard to Chapter 2:

- <u>Related to the dataset</u>: in this study, we evaluated the performance of twenty European and American energy listed companies. For future directions of research it could be interesting to implement the HSMAA model on an extended data set of alternatives, in order to observe how the inclusion of other energy listed companies located in other countries, could affect the rank stability of the initial alternatives considered;
- <u>Related to the set of criteria</u>: in this thesis, we performed the assessment of energy companies based on a hierarchical set of four criteria: sustainability, economic, technical and market criteria. Potential future directions of research related to the set of criteria could focus on two main directions:

- *include new sub-criteria among the pre-existent ones*: for instance to consider measures that look at the life-cycle implications (LCA) among the environmental criteria, measures that look to the energy reliability (SAIDI) among the technical criteria and measure that look to the ability to deliver secure energy (EAPI) among the market criteria.

  LCA is a tool, widely applied in practice, to evaluate the environmental impact and resources used during the power plant’s life cycle, from raw material extraction to waste management. However, it is a time-consuming procedure since it requires several data to collect and several phases to perform (Finnveden et al., 2009). In order to include LCA as future direction, the Graph-Based Model proposed by Yu et al., 2015 could be performed in our analysis, since it allows to simplify its traditional time-consuming procedure and to check the potential changes that could be realized in the final evaluation of alternatives. In this way, it can be carried out what is defined environmental burden shifting approach (Yu et al., 2015).

  SAIDI is the acronym of System Average Interruption Duration index and represents the ratio between the total duration of customer interruption over the total number of customers served. Since it represents a measure of energy reliability for electricity distribution, it could affect the performance of energy companies.

  EAPI stands for global Energy Architecture Performance Index and it is a composite index created by the collaboration between the World Economic Forum and Accenture to benchmark the performance of national energy systems and compare nations based on energy access and security, environmental sustainability, economic growth and development (Mundial, 2017). For future developments, it could be interesting to understand how EAPI index could vary among companies located in different countries, and therefore how it could affect the entire energy companies' performances;

- *extend the original set of criteria with new ones*: for instance to include also qualitative criteria, such as internal attributes of corporate governance, in the decision making process. In this regard, some empirical studies demonstrate that qualitative criteria are positively related to the financial performance of companies. Examples of possible qualitative criteria considered for future analysis could be: board size, outside directors, managerial ownership, ownership concentration, managerial skills and qualifications of the considered companies (Sheikh et al., 2013). Their inclusions into the list of criteria could lead to revise the HSMAA into the AHP model as suitable MCDA model for its ability to handle simultaneously with a structure of criteria organized hierarchically and to manage qualitative and quantitative data;

- <u>Related to the stakeholders' preferences elicitation</u>: in this study, HSMAA was performed with and without the DM's preferences on macro-criteria weights. In particular, in case (2) we indirectly elicited six different preferences on macro-criteria weights, reaching in total seven different scenarios. A possible future direction of research could consist of taking into consideration different stakeholders' preference information directly through questionnaires or the deck of card method (DCM) if information is not necessarily complete and imprecise. A suitable method to collect and manage this last type of information is ELECTRE (Figueira and Roy, 2002);
- <u>Related to the period considered:</u> in this study, we collected data for 2017, the latest fiscal year for which data are fully available. Future researches could be devoted to analyse data in other periods, to take into account the significant events occurred in the European energy market, such as the liberalization process of 1996 and test simultaneously the principal European policy implications;
- <u>Related to the MCDA model applied:</u> in this study, we performed the HSMAA model to handle simultaneously with a hierarchical criteria structure and uncertainties of DMs. More specifically, we employed the min-max procedure to normalize indicators that generated problems with outliers. To overcome the issue of outliers without using the IRQ method (Gasser et al., 2020), future researches could focus on the application of other multi-criteria methods, such as the ELECTRE III methods, for its ability to deal with inaccurate, imprecise and uncertainty of data. The main aim of this application is to highlight how final companies' rank changes according to the Multi-criteria method employed, without normalize the criteria evaluations;
- <u>Related to the robustness:</u> in this study, we tested the robustness of the ranking results with several uncertainty scenarios, which translate the DM's preferences. A possible future direction related to the robustness, could be implemented by considering several combinations of normalization methods (such as the min-max approach, the standardization and the distance to a reference country, specifically useful for environmental issues) and aggregation approaches (such as the geometric, harmonic, minimum, median, Condorcet method, the mixed, the reverse and mixed). In this way,

the obtained ranking results could be compared each other, giving more reliability to the analysis. Moreover, the DMs could identify their final rank position with more confidence and successful strategies could be implemented to reach the alternative with the best performance.

While future research could extend the proposed methodology of Chapter 3:

- Related to variables: in this study, we employed only financial variables to evaluate the creditworthiness of energy companies. Future researches could be devoted to investigate whether soft variables, such as management, market and macro-economic variables, could affect the creditworthiness of energy companies or could improve the predictive accuracy of the distress model.
  Moreover, it might be interesting to consider the multidimensional nature of the energy companies' assessment that requires the definition of a hierarchical structure of criteria including elements such as the environmental, the technical and the market criteria, to observe whether the accuracy of the two combined models performed on this evaluation could increase against externally assigned ratings;
- Related to the dataset: in this study, unlisted European energy companies composed the sample and the lack of synthetic rating judgement provided by CRAs has been highlighted for this sample. Therefore, a possible future direction could consider a set of alternatives composed by listed energy companies in order to compare the results obtained through our proposed methodology, i.e. the combination of M.H.DIS and PROMETHEE II model, and the M.H.DIS developed with the pre-defined classification issued by credit rating agencies (CRAs). In this way, it could be possible to observe which of two classifications is better replicated by the discrimination model.

Appendix A

Table A-1 Cases (1) and (2) “From first to Seventh Scenario”: Rank acceptability indices (All the data are expressed in percent)

ALTERNATIVES		RANKS/ SCENARIO	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
a_1	ENEL SPA	SCEN. 1	0	0.0011	0.0073	0.0288	0.0474	0.0608	0.0667	0.0656	0.0853	0.0680
		SCEN. 2	0	0.0027	0.0201	0.0446	0.0679	0.0854	0.0978	0.0950	0.1184	0.0968
		SCEN. 3	0	0	0	0	0.0001	0.0018	0.0127	0.0247	0.0506	0.0571
		SCEN. 4	0	0.0010	0.0057	0.0363	0.0736	0.0757	0.0901	0.0933	0.1045	0.0865
		SCEN. 5	0	0.0015	0.0079	0.0415	0.0743	0.1019	0.1137	0.1069	0.1212	0.0770
		SCEN. 6	0	0	0	0.0020	0.0066	0.0248	0.0326	0.0386	0.0635	0.0500
		SCEN. 7	0	0	0	0.0009	0.0049	0.0280	0.0369	0.0459	0.0773	0.0676
a_2	ENI	SCEN. 1	0.0154	0.0449	0.0407	0.0411	0.0416	0.0357	0.0438	0.0446	0.0414	0.0464
		SCEN. 2	0.0054	0.0030	0.0048	0.0125	0.0094	0.0150	0.0256	0.0291	0.0282	0.0289
		SCEN. 3	0.0009	0.0120	0.0359	0.0462	0.0433	0.0463	0.0359	0.0384	0.0336	0.0396
		SCEN. 4	0.0040	0.0034	0.0056	0.0067	0.0091	0.0147	0.0222	0.0207	0.0284	0.0217
		SCEN. 5	0.0293	0.0886	0.0568	0.0402	0.0423	0.0407	0.0507	0.0551	0.0495	0.0513
		SCEN. 6	0.0240	0.1111	0.0897	0.0793	0.0842	0.0754	0.0624	0.0690	0.0582	0.0559
		SCEN. 7	0.0191	0.0953	0.0897	0.0863	0.0846	0.0688	0.0568	0.0664	0.0666	0.0673
a_3	EDISON SPA	SCEN. 1	0.0988	0.0423	0.0433	0.0505	0.0398	0.0601	0.0636	0.0701	0.0834	0.0958
		SCEN. 2	0.0043	0.0033	0.0099	0.0158	0.0196	0.0279	0.0528	0.0838	0.1022	0.1390
		SCEN. 3	0.0859	0.0342	0.0239	0.0312	0.0248	0.0299	0.0338	0.0398	0.0635	0.0681
		SCEN. 4	0	0.0023	0.0085	0.0151	0.0185	0.0354	0.0563	0.0779	0.0989	0.1273
		SCEN. 5	0.1332	0.0553	0.0689	0.0632	0.0561	0.1082	0.0801	0.0968	0.0943	0.0962
		SCEN. 6	0.2274	0.0800	0.0704	0.0820	0.0560	0.0898	0.0575	0.0608	0.0464	0.0457
		SCEN. 7	0.2331	0.0761	0.0735	0.0814	0.0508	0.0596	0.0706	0.0652	0.0520	0.0516
a_4	A2A SPA	SCEN. 1	0	0	0	0.0006	0.0059	0.0142	0.0321	0.0392	0.0403	0.0462
		SCEN. 2	0	0	0	0	0	0	0	0.0001	0.0033	0.0105
		SCEN. 3	0	0	0	0.0001	0.0040	0.0205	0.0276	0.0211	0.0269	0.0219
		SCEN. 4	0	0	0	0	0	0	0.0008	0.0013	0.0046	0.0148
		SCEN. 5	0	0	0	0.0025	0.0122	0.0135	0.0429	0.0619	0.0580	0.0825
		SCEN. 6	0	0	0	0.0025	0.0193	0.0305	0.0732	0.0768	0.0761	0.0688
		SCEN. 7	0	0	0	0.0026	0.0175	0.0325	0.0512	0.0675	0.0680	0.0682
a_5	IREN SPA	SCEN. 1	0	0	0.0001	0.0011	0.0024	0.0068	0.0133	0.0231	0.0354	0.0506
		SCEN. 2	0	0	0	0	0	0	0	0.0001	0.0044	0.0095
		SCEN. 3	0	0	0	0	0	0.0002	0.0020	0.0098	0.0135	0.0293
		SCEN. 4	0	0	0	0	0	0	0	0	0	0
		SCEN. 5	0	0.0006	0.0003	0.0022	0.0044	0.0119	0.0197	0.0354	0.0517	0.0658
		SCEN. 6	0	0.0002	0.0003	0.0019	0.0038	0.0150	0.0212	0.0456	0.0752	0.1053
		SCEN. 7	0	0	0.0002	0.0024	0.0049	0.0164	0.0263	0.0460	0.0844	0.1091
a_6	ACEA SPA	SCEN. 1	0.0554	0.0538	0.0547	0.0490	0.0443	0.0556	0.0497	0.0547	0.0467	0.0460
		SCEN. 2	0	0.0016	0.0240	0.0249	0.0311	0.0351	0.0574	0.0405	0.0505	0.0444
		SCEN. 3	0.1247	0.1312	0.0684	0.0639	0.0613	0.0596	0.0660	0.0599	0.0541	0.0450
		SCEN. 4	0.0054	0.0237	0.0264	0.0204	0.0295	0.0382	0.0481	0.0450	0.0512	0.0388
		SCEN. 5	0.0067	0.0113	0.0325	0.0243	0.0293	0.0421	0.0505	0.0342	0.0453	0.0455
		SCEN. 6	0.1308	0.1040	0.0744	0.0705	0.0600	0.0661	0.0705	0.0527	0.0525	0.0481
		SCEN. 7	0.0898	0.1012	0.0871	0.0719	0.0614	0.0699	0.0663	0.0559	0.0566	0.0541
a_7	GRUPPO HERA	SCEN. 1	0.0091	0.0121	0.0062	0.0125	0.0177	0.0178	0.0292	0.0297	0.0378	0.0466
		SCEN. 2	0	0	0.0003	0.0013	0.0008	0.0022	0.0104	0.0222	0.0309	0.0371
		SCEN. 3	0.0173	0.0210	0.0170	0.0151	0.0225	0.0217	0.0175	0.0228	0.0273	0.0251
		SCEN. 4	0	0	0	0.0024	0.0015	0.0035	0.0071	0.0130	0.0219	0.0268
		SCEN. 5	0.0082	0.0033	0.0036	0.0154	0.0190	0.0303	0.0401	0.0413	0.0447	0.0454
		SCEN. 6	0.0377	0.0266	0.0193	0.0302	0.0405	0.0427	0.0419	0.0456	0.0543	0.0556
		SCEN. 7	0.0324	0.0249	0.0199	0.0207	0.0267	0.0319	0.0503	0.0566	0.0551	0.0609
a_8	EDF	SCEN. 1	0.0963	0.0573	0.0380	0.0319	0.0276	0.0276	0.0319	0.0322	0.0339	0.0435
		SCEN. 2	0.0465	0.0723	0.0454	0.0416	0.0409	0.0364	0.0393	0.0543	0.0537	0.0612
		SCEN. 3	0.1566	0.1134	0.0553	0.0417	0.0334	0.0358	0.0346	0.0295	0.0266	0.0397
		SCEN. 4	0.0479	0.1021	0.0509	0.0429	0.0405	0.0345	0.0404	0.0446	0.0432	0.0584
		SCEN. 5	0.0484	0.0250	0.0254	0.0232	0.0255	0.0220	0.0216	0.0272	0.0306	0.0308
		SCEN. 6	0.1264	0.0344	0.0315	0.0223	0.0228	0.0218	0.0219	0.0182	0.0195	0.0192
		SCEN. 7	0.1044	0.0399	0.0268	0.0235	0.0248	0.0229	0.0219	0.0186	0.0213	0.0193
a_9	ENGIE SA	SCEN. 1	0.0010	0.0049	0.0071	0.0174	0.0225	0.0283	0.0399	0.0677	0.0838	0.0954
		SCEN. 2	0.0007	0.0035	0.0060	0.0103	0.0129	0.0307	0.0476	0.0710	0.1091	0.1356
		SCEN. 3	0	0.0001	0.0038	0.0128	0.0183	0.0340	0.0581	0.1155	0.1554	0.1492
		SCEN. 4	0	0	0.0019	0.0042	0.0106	0.0336	0.0557	0.1083	0.1588	0.1752
		SCEN. 5	0	0.0016	0.0049	0.0346	0.0287	0.0235	0.0315	0.0369	0.0458	0.0715
		SCEN. 6	0	0.0022	0.0062	0.0281	0.0359	0.0298	0.0392	0.0470	0.0488	0.0477
		SCEN. 7	0.0029	0.0095	0.0156	0.0279	0.0279	0.0273	0.0298	0.0410	0.0369	0.0380

a_{10}	**E.ON SE**	**SCEN. 1**	0.0007	0.0039	0.0169	0.0323	0.0459	0.0648	0.0745	0.0935	0.0927	0.0804
		SCEN. 2	0.0011	0.0080	0.0212	0.0423	0.0506	0.0650	0.0944	0.1186	0.1237	0.1006
		SCEN. 3	0.0001	0.0040	0.0305	0.0654	0.0922	0.1091	0.1018	0.1080	0.0872	0.0862
		SCEN. 4	0.0005	0.0048	0.0307	0.0620	0.0566	0.0750	0.0869	0.1228	0.1097	0.0875
		SCEN. 5	0	0.0002	0.0026	0.0053	0.0107	0.0321	0.0418	0.0515	0.0757	0.0762
		SCEN. 6	0	0.0002	0.0048	0.0121	0.0210	0.0473	0.0488	0.0631	0.0651	0.0768
		SCEN. 7	0	0.0014	0.0040	0.0069	0.0184	0.0335	0.0541	0.0651	0.0631	0.0711
a_{11}	**SSE PLC**	**SCEN. 1**	0	0	0	0	0	0	0	0.0003	0.0024	0.0055
		SCEN. 2	0	0	0	0	0	0	0	0.0001	0.0012	0.0029
		SCEN. 3	0	0	0	0	0	0	0	0.0018	0.0030	0.0138
		SCEN. 4	0	0	0	0	0	0	0	0.0042	0.0027	0.0098
		SCEN. 5	0	0	0	0	0	0	0	0	0	0
		SCEN. 6	0	0	0	0	0	0	0	0	0	0.0037
		SCEN. 7	0	0	0	0	0	0	0	0	0	0
a_{12}	**DRAX GROUP PLC**	**SCEN. 1**	0.0169	0.0282	0.0301	0.0402	0.0375	0.0371	0.0453	0.0479	0.0416	0.0398
		SCEN. 2	0.0025	0.0040	0.0058	0.0093	0.0161	0.0281	0.0290	0.0395	0.0369	0.0331
		SCEN. 3	0.0134	0.0387	0.0373	0.0475	0.0479	0.0315	0.0432	0.0435	0.0494	0.0388
		SCEN. 4	0.0002	0.0002	0.0003	0.0010	0.0057	0.0153	0.0295	0.0445	0.0429	0.0385
		SCEN. 5	0.0089	0.0185	0.0175	0.0169	0.0218	0.0338	0.0550	0.0610	0.0657	0.0586
		SCEN. 6	0.0247	0.0637	0.0715	0.0675	0.0620	0.0458	0.0592	0.0562	0.0586	0.0479
		SCEN. 7	0.0363	0.0616	0.0698	0.0586	0.0654	0.0528	0.0557	0.0487	0.0536	0.0446
a_{13}	**RWE**	**SCEN. 1**	0.1110	0.0735	0.0604	0.0696	0.0738	0.0718	0.0618	0.0638	0.0541	0.0482
		SCEN. 2	0.2200	0.1109	0.1080	0.1412	0.1158	0.0931	0.0774	0.0585	0.0330	0.0232
		SCEN. 3	0.2062	0.1293	0.0829	0.0558	0.0588	0.0636	0.0528	0.0493	0.0372	0.0317
		SCEN. 4	0.2587	0.1137	0.0942	0.1115	0.0870	0.1054	0.0888	0.0622	0.0361	0.0253
		SCEN. 5	0.0208	0.0230	0.0296	0.0652	0.0584	0.0789	0.0664	0.0662	0.0719	0.0660
		SCEN. 6	0.0039	0.0346	0.0283	0.0213	0.0321	0.0268	0.0303	0.0399	0.0510	0.0595
		SCEN. 7	0.0040	0.0070	0.0281	0.0348	0.0366	0.0355	0.0410	0.0514	0.0575	0.0566
a_{14}	**EXELON CORP.**	**SCEN. 1**	0.0781	0.1090	0.1431	0.1259	0.1275	0.1046	0.0826	0.0586	0.0466	0.0301
		SCEN. 2	0.0917	0.1214	0.1632	0.1941	0.1704	0.1114	0.0649	0.0480	0.0235	0.0092
		SCEN. 3	0.0010	0.0266	0.0421	0.1106	0.1329	0.1162	0.1181	0.1063	0.0769	0.0621
		SCEN. 4	0.0993	0.1382	0.1522	0.1647	0.1506	0.1004	0.0713	0.0490	0.0320	0.0218
		SCEN. 5	0.1624	0.1885	0.2392	0.1318	0.1002	0.0757	0.0436	0.0271	0.0131	0.0102
		SCEN. 6	0.0469	0.0713	0.1195	0.0872	0.0942	0.0992	0.0911	0.0780	0.0615	0.0580
		SCEN. 7	0.0225	0.0828	0.1002	0.1149	0.1418	0.1306	0.0995	0.0687	0.0559	0.0466
a_{15}	**AMEREN**	**SCEN. 1**	0.2370	0.1825	0.1417	0.1127	0.0718	0.0558	0.0438	0.0373	0.0241	0.0203
		SCEN. 2	0.3899	0.1605	0.1316	0.1218	0.0806	0.0471	0.0318	0.0202	0.0101	0.0044
		SCEN. 3	0.2610	0.1192	0.0809	0.1081	0.0778	0.0561	0.0691	0.0508	0.0332	0.0303
		SCEN. 4	0.3836	0.1638	0.1409	0.1203	0.0767	0.0311	0.0388	0.0292	0.0091	0.0040
		SCEN. 5	0.1826	0.2458	0.2017	0.1061	0.0715	0.0355	0.0324	0.0321	0.0156	0.0213
		SCEN. 6	0.0768	0.1790	0.1255	0.1143	0.0741	0.0699	0.0651	0.0537	0.0376	0.0430
		SCEN. 7	0.1225	0.1436	0.1344	0.1162	0.0873	0.0808	0.0631	0.0426	0.0360	0.0386
a_{16}	**DTE ENERGY COMP.**	**SCEN. 1**	0.0725	0.0883	0.0949	0.0750	0.1016	0.0888	0.0784	0.0742	0.0578	0.0556
		SCEN. 2	0.0299	0.0940	0.0784	0.0808	0.1060	0.1333	0.1154	0.1073	0.0806	0.0813
		SCEN. 3	0.0026	0.0473	0.0994	0.0634	0.0742	0.0853	0.0783	0.0799	0.0706	0.0746
		SCEN. 4	0.0173	0.0776	0.0838	0.0890	0.1083	0.1259	0.1094	0.1028	0.0784	0.0868
		SCEN. 5	0.1371	0.1195	0.1043	0.0856	0.1227	0.0857	0.0795	0.0619	0.0433	0.0363
		SCEN. 6	0.0929	0.0841	0.1161	0.0778	0.0954	0.0575	0.0477	0.0422	0.0407	0.0317
		SCEN. 7	0.0818	0.1081	0.0995	0.0756	0.0854	0.0647	0.0587	0.0502	0.0431	0.0384
a_{17}	**XCEL ENERGY**	**SCEN. 1**	0.0084	0.0875	0.0829	0.1248	0.1042	0.1047	0.0906	0.0651	0.0520	0.0518
		SCEN. 2	0.0179	0.1485	0.0990	0.0999	0.1165	0.1283	0.1151	0.0717	0.0549	0.0395
		SCEN. 3	0.0025	0.0627	0.0848	0.1290	0.1381	0.1649	0.0981	0.0587	0.0454	0.0437
		SCEN. 4	0.0184	0.1185	0.0988	0.1422	0.1563	0.1663	0.1080	0.0480	0.0362	0.0285
		SCEN. 5	0.0237	0.0548	0.0671	0.1531	0.1096	0.0978	0.0813	0.0580	0.0460	0.0467
		SCEN. 6	0.0043	0.0286	0.0586	0.1071	0.0866	0.0891	0.0815	0.0648	0.0668	0.0649
		SCEN. 7	0.0039	0.0520	0.0821	0.0963	0.0696	0.0805	0.0635	0.0605	0.0598	0.0600
a_{18}	**DUKE ENERGY CORP.**	**SCEN. 1**	0.1966	0.1990	0.2033	0.1297	0.1161	0.0707	0.0388	0.0248	0.0135	0.0039
		SCEN. 2	0.1891	0.2590	0.2524	0.1030	0.0753	0.0754	0.0230	0.0159	0.0067	0.0002
		SCEN. 3	0.1278	0.2552	0.3193	0.1322	0.0930	0.0323	0.0150	0.0140	0.0097	0.0015
		SCEN. 4	0.1647	0.2504	0.2832	0.1154	0.0952	0.0595	0.0182	0.0098	0.0036	0
		SCEN. 5	0.2367	0.1518	0.1140	0.1422	0.1505	0.0829	0.0505	0.0344	0.0190	0.0091
		SCEN. 6	0.2000	0.1577	0.1541	0.1466	0.1390	0.0773	0.0474	0.0346	0.0224	0.0091
		SCEN. 7	0.2055	0.1589	0.1513	0.1467	0.1457	0.0746	0.0450	0.0323	0.0200	0.0039
a_{19}	**IBERDROLA**	**SCEN. 1**	0.0028	0.0089	0.0182	0.0395	0.0359	0.0496	0.0524	0.0526	0.0635	0.0597
		SCEN. 2	0.0010	0.0041	0.0093	0.0219	0.0247	0.0251	0.0430	0.0444	0.0467	0.0614
		SCEN. 3	0	0.0051	0.0145	0.0690	0.0489	0.0550	0.0790	0.0738	0.0788	0.0709
		SCEN. 4	0	0.0001	0.0010	0.0401	0.0252	0.0279	0.0457	0.0516	0.0499	0.0635
		SCEN. 5	0.0020	0.0100	0.0153	0.0250	0.0327	0.0472	0.0481	0.0568	0.0551	0.0580
		SCEN. 6	0.0042	0.0223	0.0285	0.0445	0.0587	0.0725	0.0783	0.0766	0.0662	0.0677
		SCEN. 7	0.0084	0.0285	0.0340	0.0345	0.0466	0.0638	0.0620	0.0727	0.0632	0.0599
a_{20}	**ENDESA**	**SCEN. 1**	0	0.0028	0.0111	0.0174	0.0365	0.0452	0.0616	0.0550	0.0637	0.0662
		SCEN. 2	0	0.0032	0.0206	0.0347	0.0614	0.0605	0.0751	0.0797	0.0820	0.0812
		SCEN. 3	0	0	0.0040	0.0080	0.0285	0.0362	0.0564	0.0524	0.0571	0.0714

		SCEN. 4	0	0.0002	0.0159	0.0258	0.0551	0.0576	0.0827	0.0718	0.0879	0.0848
		SCEN. 5	0	0.0007	0.0084	0.0217	0.0301	0.0363	0.0506	0.0553	0.0535	0.0516
		SCEN. 6	0	0	0.0013	0.0028	0.0078	0.0187	0.0302	0.0366	0.0356	0.0414
		SCEN. 7	0	0.0010	0.0041	0.0065	0.0184	0.0260	0.0386	0.0404	0.0340	0.0395

ALTERNATIVES		**RANKS/ SCENARIO**	$\mathbf{b_{11}}$	$\mathbf{b_{12}}$	$\mathbf{b_{13}}$	$\mathbf{b_{14}}$	$\mathbf{b_{15}}$	$\mathbf{b_{16}}$	$\mathbf{b_{17}}$	$\mathbf{b_{18}}$	$\mathbf{b_{19}}$	$\mathbf{b_{20}}$
$\mathbf{a_1}$	**ENEL SPA**	**SCEN. 1**	0.0725	0.0740	0.0814	0.0658	0.0738	0.0687	0.0683	0.0524	0.0102	0.0019
		SCEN. 2	0.1030	0.0880	0.0723	0.0361	0.0205	0.0192	0.0148	0.0163	0.0010	0.0001
		SCEN. 3	0.0866	0.1110	0.1310	0.1114	0.1190	0.0967	0.1117	0.0610	0.0195	0.0051
		SCEN. 4	0.1030	0.1064	0.0925	0.0568	0.0328	0.0298	0.0120	0	0	0
		SCEN. 5	0.0430	0.0327	0.0348	0.0386	0.0474	0.0738	0.0421	0.0392	0.0024	0.0001
		SCEN. 6	0.0557	0.0582	0.0708	0.0885	0.1237	0.1198	0.1225	0.1112	0.0243	0.0072
		SCEN. 7	0.0769	0.0717	0.0766	0.0771	0.0900	0.1021	0.0925	0.1251	0.0243	0.0022
$\mathbf{a_2}$	**ENI**	**SCEN. 1**	0.0641	0.0443	0.0484	0.0519	0.0682	0.0658	0.0561	0.0606	0.0695	0.0755
		SCEN. 2	0.0365	0.0419	0.0532	0.0591	0.0891	0.0938	0.0820	0.0996	0.1344	0.1485
		SCEN. 3	0.0437	0.0428	0.0513	0.0585	0.0633	0.0613	0.0695	0.0672	0.0849	0.1254
		SCEN. 4	0.0301	0.0360	0.0499	0.0587	0.0891	0.0837	0.1073	0.0961	0.1150	0.1976
		SCEN. 5	0.0662	0.0442	0.0415	0.0545	0.0606	0.0527	0.0542	0.0482	0.0414	0.0320
		SCEN. 6	0.0713	0.0416	0.0386	0.0386	0.0388	0.0278	0.0160	0.0093	0.0054	0.0034
		SCEN. 7	0.0737	0.0466	0.0374	0.0390	0.0345	0.0380	0.0183	0.0100	0.0016	0
$\mathbf{a_3}$	**EDISON SPA**	**SCEN. 1**	0.0693	0.0631	0.0537	0.0495	0.0316	0.0290	0.0319	0.0234	0.0008	0
		SCEN. 2	0.1286	0.1096	0.0942	0.0749	0.0390	0.0290	0.0344	0.0313	0.0004	0
		SCEN. 3	0.0708	0.1002	0.0894	0.0917	0.0744	0.0601	0.0506	0.0251	0.0026	0
		SCEN. 4	0.1096	0.1166	0.1040	0.0877	0.0446	0.0325	0.0319	0.0324	0.0005	0
		SCEN. 5	0.0746	0.0355	0.0239	0.0076	0.0040	0.0017	0.0003	0.0001	0	0
		SCEN. 6	0.0304	0.0224	0.0224	0.0284	0.0323	0.0283	0.0129	0.0058	0.0011	0
		SCEN. 7	0.0393	0.0295	0.0268	0.0260	0.0247	0.0177	0.0180	0.0024	0.0017	0
$\mathbf{a_4}$	**A2A SPA**	**SCEN. 1**	0.0634	0.0640	0.0819	0.1057	0.1223	0.1013	0.0687	0.0639	0.1132	0.0371
		SCEN. 2	0.0168	0.0403	0.0810	0.1674	0.2248	0.1871	0.0933	0.0945	0.0796	0.0013
		SCEN. 3	0.0230	0.0250	0.0399	0.0501	0.0840	0.1130	0.0978	0.0871	0.2964	0.0616
		SCEN. 4	0.0272	0.0494	0.0695	0.1566	0.2048	0.1795	0.0762	0.0759	0.1393	0.0001
		SCEN. 5	0.1082	0.1138	0.1184	0.1372	0.1273	0.0741	0.0250	0.0168	0.0057	0
		SCEN. 6	0.0921	0.0780	0.0607	0.0451	0.0455	0.0420	0.0449	0.0457	0.1484	0.0504
		SCEN. 7	0.0780	0.0737	0.0685	0.0633	0.0574	0.0632	0.0700	0.0707	0.1088	0.0389
$\mathbf{a_5}$	**IREN SPA**	**SCEN. 1**	0.0450	0.0468	0.0568	0.0621	0.0823	0.1125	0.1210	0.1677	0.1028	0.0702
		SCEN. 2	0.0134	0.0216	0.0278	0.0427	0.1128	0.1359	0.1466	0.1762	0.1687	0.1403
		SCEN. 3	0.0288	0.0278	0.0309	0.0492	0.0779	0.1347	0.1600	0.3096	0.0971	0.0292
		SCEN. 4	0.0005	0.0086	0.0188	0.0347	0.0951	0.1396	0.2020	0.2466	0.1575	0.0966
		SCEN. 5	0.0594	0.0769	0.0756	0.0748	0.0821	0.1214	0.1051	0.0847	0.0681	0.0599
		SCEN. 6	0.0859	0.0869	0.0797	0.0758	0.0758	0.0884	0.0841	0.1310	0.0238	0.0001
		SCEN. 7	0.0904	0.0819	0.0773	0.0771	0.0677	0.0632	0.0693	0.1034	0.0536	0.0264
$\mathbf{a_6}$	**ACEA SPA**	**SCEN. 1**	0.0401	0.0439	0.0422	0.0403	0.0484	0.0551	0.0764	0.0705	0.0586	0.0146
		SCEN. 2	0.0617	0.0500	0.0419	0.0567	0.0613	0.0807	0.1201	0.1054	0.0874	0.0253
		SCEN. 3	0.0431	0.0438	0.0346	0.0392	0.0493	0.0389	0.0146	0.0024	0	0
		SCEN. 4	0.0541	0.0461	0.0482	0.0588	0.0733	0.0810	0.1091	0.1190	0.0717	0.0120
		SCEN. 5	0.0422	0.0419	0.0536	0.0583	0.0593	0.0749	0.1190	0.1242	0.0840	0.0209
		SCEN. 6	0.0404	0.0406	0.0384	0.0359	0.0299	0.0332	0.0260	0.0175	0.0085	0
		SCEN. 7	0.0470	0.0397	0.0391	0.0260	0.0267	0.0312	0.0516	0.0191	0.0052	0.0002
$\mathbf{a_7}$	**GRUPPO HERA**	**SCEN. 1**	0.0497	0.0512	0.0523	0.0576	0.0744	0.0734	0.0912	0.0962	0.1194	0.1159
		SCEN. 2	0.0241	0.0325	0.0329	0.0452	0.0704	0.0819	0.1128	0.1597	0.1926	0.1427
		SCEN. 3	0.0316	0.0440	0.0529	0.0701	0.0988	0.0859	0.1192	0.0982	0.1011	0.0909
		SCEN. 4	0.0178	0.0271	0.0353	0.0552	0.0764	0.0797	0.1321	0.1654	0.2140	0.1208
		SCEN. 5	0.0524	0.0545	0.0491	0.0440	0.0574	0.0593	0.0818	0.1086	0.1499	0.0917
		SCEN. 6	0.0669	0.0612	0.0564	0.0576	0.0633	0.0648	0.0649	0.0499	0.0687	0.0519
		SCEN. 7	0.0743	0.0708	0.0593	0.0631	0.0666	0.0674	0.0464	0.0424	0.0600	0.0703
$\mathbf{a_8}$	**EDF**	**SCEN. 1**	0.0415	0.0443	0.0431	0.0463	0.0364	0.0407	0.0416	0.0663	0.0892	0.1304
		SCEN. 2	0.0684	0.0678	0.0684	0.0632	0.0371	0.0336	0.0374	0.0445	0.0331	0.0549
		SCEN. 3	0.0516	0.0435	0.0426	0.0320	0.0305	0.0350	0.0361	0.0402	0.0491	0.0728
		SCEN. 4	0.0688	0.0745	0.0718	0.0599	0.0383	0.0375	0.0225	0.0316	0.0365	0.0532
		SCEN. 5	0.0339	0.0422	0.0464	0.0453	0.0341	0.0458	0.0397	0.0901	0.1300	0.2128
		SCEN. 6	0.0213	0.0204	0.0242	0.0302	0.0303	0.0366	0.0502	0.0987	0.1341	0.2160
		SCEN. 7	0.0232	0.0229	0.0293	0.0297	0.0365	0.0442	0.0631	0.1016	0.1204	0.2057
$\mathbf{a_9}$	**ENGIE SA**	**SCEN. 1**	0.1081	0.0993	0.1004	0.0869	0.0597	0.0461	0.0347	0.0541	0.0386	0.0041
		SCEN. 2	0.1781	0.1677	0.1036	0.0664	0.0214	0.0158	0.0099	0.0063	0.0034	0
		SCEN. 3	0.1004	0.0749	0.0683	0.0717	0.0332	0.0292	0.0215	0.0315	0.0219	0.0002
		SCEN. 4	0.1487	0.1159	0.0825	0.0536	0.0206	0.0193	0.0084	0.0026	0.0001	0
		SCEN. 5	0.0811	0.0825	0.1152	0.0924	0.0910	0.0561	0.0395	0.0908	0.0663	0.0061
		SCEN. 6	0.0532	0.0515	0.0887	0.0902	0.0716	0.0649	0.0574	0.1303	0.1013	0.0060
		SCEN. 7	0.0425	0.0548	0.0918	0.1114	0.0878	0.0703	0.0632	0.1151	0.0979	0.0084
$\mathbf{a_{10}}$	**E.ON SE**	**SCEN. 1**	0.0723	0.0695	0.0825	0.0654	0.0503	0.0480	0.0253	0.0379	0.0432	0
		SCEN. 2	0.0831	0.0659	0.0866	0.0599	0.0341	0.0191	0.0091	0.0115	0.0052	0

		SCEN. 3	0.0785	0.0643	0.0495	0.0411	0.0311	0.0217	0.0156	0.0096	0.0041	0
		SCEN. 4	0.0840	0.0706	0.0813	0.0603	0.0427	0.0215	0.0023	0.0007	0.0001	0
		SCEN. 5	0.0696	0.0709	0.0974	0.1028	0.0860	0.0732	0.0431	0.0671	0.0938	0
		SCEN. 6	0.0680	0.0773	0.0882	0.0859	0.0683	0.0688	0.0525	0.0699	0.0819	0
		SCEN. 7	0.0738	0.0846	0.0855	0.0833	0.0760	0.0642	0.0456	0.0871	0.0823	0
$\mathbf{a_{11}}$	**SSE PLC**	**SCEN. 1**	0.0089	0.0125	0.0159	0.0205	0.0371	0.0630	0.0945	0.1138	0.1648	0.4608
		SCEN. 2	0.0086	0.0228	0.0309	0.0290	0.0655	0.0821	0.1463	0.1120	0.0969	0.4017
		SCEN. 3	0.0201	0.0289	0.0352	0.0403	0.0401	0.0436	0.0531	0.0657	0.1301	0.5243
		SCEN. 4	0.0145	0.0285	0.0348	0.0350	0.0482	0.0726	0.1158	0.0904	0.0980	0.4455
		SCEN. 5	0	0.0009	0.0013	0.0023	0.0207	0.0578	0.1135	0.1278	0.1757	0.5000
		SCEN. 6	0.0045	0.0036	0.0093	0.0074	0.0176	0.0500	0.0482	0.0870	0.1924	0.5763
		SCEN. 7	0	0.0010	0.0046	0.0065	0.0182	0.0429	0.0589	0.1100	0.2058	0.5521
$\mathbf{a_{12}}$	**DRAX GROUP PLC**	**SCEN. 1**	0.0431	0.0762	0.0579	0.0725	0.0679	0.0668	0.1025	0.0460	0.0609	0.0416
		SCEN. 2	0.0437	0.0558	0.0691	0.0982	0.0839	0.0823	0.1014	0.0754	0.1062	0.0797
		SCEN. 3	0.0442	0.0489	0.0523	0.0551	0.0718	0.0538	0.0622	0.0521	0.0994	0.0690
		SCEN. 4	0.0497	0.0776	0.0805	0.0935	0.0947	0.0987	0.0849	0.0626	0.1091	0.0706
		SCEN. 5	0.0605	0.1242	0.0770	0.0847	0.0758	0.0797	0.1120	0.0164	0.0098	0.0022
		SCEN. 6	0.0510	0.0844	0.0567	0.0493	0.0423	0.0369	0.0934	0.0141	0.0113	0.0035
		SCEN. 7	0.0435	0.0762	0.0536	0.0468	0.0516	0.0435	0.0924	0.0224	0.0183	0.0046
$\mathbf{a_{13}}$	**RWE**	**SCEN. 1**	0.0468	0.0340	0.0388	0.0440	0.0531	0.0381	0.0367	0.0160	0.0042	0.0003
		SCEN. 2	0.0104	0.0041	0.0023	0.0021	0	0	0	0	0	0
		SCEN. 3	0.0317	0.0271	0.0250	0.0188	0.0258	0.0251	0.0288	0.0324	0.0150	0.0027
		SCEN. 4	0.0128	0.0040	0.0002	0.0001	0	0	0	0	0	0
		SCEN. 5	0.0829	0.0485	0.0540	0.0725	0.0793	0.0610	0.0497	0.0051	0.0006	0
		SCEN. 6	0.0718	0.0661	0.0763	0.0893	0.1194	0.0979	0.0893	0.0419	0.0175	0.0028
		SCEN. 7	0.0609	0.0659	0.0727	0.0927	0.1231	0.0918	0.0906	0.0320	0.0156	0.0022
$\mathbf{a_{14}}$	**EXELON CORP.**	**SCEN. 1**	0.0224	0.0190	0.0121	0.0095	0.0088	0.0078	0.0078	0.0038	0.0017	0.0010
		SCEN. 2	0.0020	0.0002	0	0	0	0	0	0	0	0
		SCEN. 3	0.0481	0.0403	0.0282	0.0218	0.0202	0.0153	0.0183	0.0072	0.0045	0.0033
		SCEN. 4	0.0151	0.0040	0.0012	0.0002	0	0	0	0	0	0
		SCEN. 5	0.0058	0.0023	0.0001	0	0	0	0	0	0	0
		SCEN. 6	0.0447	0.0370	0.0312	0.0243	0.0200	0.0125	0.0137	0.0063	0.0027	0.0007
		SCEN. 7	0.0370	0.0287	0.0212	0.0172	0.0137	0.0079	0.0080	0.0015	0.0008	0.0005
$\mathbf{a_{15}}$	**AMEREN**	**SCEN. 1**	0.0202	0.0185	0.0206	0.0127	0.0009	0.0001	0	0	0	0
		SCEN. 2	0.0009	0.0006	0.0005	0	0	0	0	0	0	0
		SCEN. 3	0.0285	0.0266	0.0387	0.0174	0.0018	0.0003	0.0002	0	0	0
		SCEN. 4	0.0015	0.0008	0.0002	0	0	0	0	0	0	0
		SCEN. 5	0.0176	0.0113	0.0090	0.0169	0.0006	0	0	0	0	0
		SCEN. 6	0.0396	0.0407	0.0461	0.0309	0.0033	0.0004	0	0	0	0
		SCEN. 7	0.0380	0.0330	0.0366	0.0245	0.0026	0.0002	0	0	0	0
$\mathbf{a_{16}}$	**DTE ENERGY COMP.**	**SCEN. 1**	0.0496	0.0352	0.0257	0.0216	0.0287	0.0281	0.0197	0.0042	0.0001	0
		SCEN. 2	0.0485	0.0235	0.0112	0.0052	0.0037	0.0005	0.0004	0	0	0
		SCEN. 3	0.0779	0.0370	0.0409	0.0355	0.0394	0.0434	0.0371	0.0128	0.0004	0
		SCEN. 4	0.0741	0.0220	0.0113	0.0048	0.0069	0.0013	0.0003	0	0	0
		SCEN. 5	0.0251	0.0277	0.0225	0.0122	0.0234	0.0066	0.0048	0.0018	0	0
		SCEN. 6	0.0341	0.0470	0.0353	0.0406	0.0544	0.0430	0.0422	0.0170	0.0003	0
		SCEN. 7	0.0334	0.0416	0.0414	0.0386	0.0483	0.0440	0.0378	0.0091	0.0003	0
$\mathbf{a_{17}}$	**XCEL ENERGY**	**SCEN. 1**	0.0443	0.0536	0.0374	0.0242	0.0241	0.0259	0.0135	0.0040	0.0010	0
		SCEN. 2	0.0373	0.0514	0.0152	0.0048	0	0	0	0	0	0
		SCEN. 3	0.0411	0.0286	0.0239	0.0219	0.0182	0.0248	0.0095	0.0029	0.0012	0
		SCEN. 4	0.0277	0.0373	0.0092	0.0044	0.0002	0	0	0	0	0
		SCEN. 5	0.0452	0.0562	0.0430	0.0325	0.0340	0.0327	0.0172	0.0011	0	0
		SCEN. 6	0.0541	0.0523	0.0563	0.0432	0.0498	0.0524	0.0282	0.0089	0.0025	0
		SCEN. 7	0.0545	0.0587	0.0593	0.0520	0.0472	0.0592	0.0301	0.0078	0.0029	0.0001
$\mathbf{a_{18}}$	**DUKE ENERGY CORP.**	**SCEN. 1**	0.0036	0	0	0	0	0	0	0	0	0
		SCEN. 2	0	0	0	0	0	0	0	0	0	0
		SCEN. 3	0	0	0	0	0	0	0	0	0	0
		SCEN. 4	0	0	0	0	0	0	0	0	0	0
		SCEN. 5	0.0088	0.0001	0	0	0	0	0	0	0	0
		SCEN. 6	0.0114	0.0004	0	0	0	0	0	0	0	0
		SCEN. 7	0.0105	0	0	0	0	0	0	0	0	0
$\mathbf{a_{19}}$	**IBERDROLA**	**SCEN. 1**	0.0676	0.0926	0.0912	0.0949	0.0851	0.0826	0.0653	0.0307	0.0068	0.0001
		SCEN. 2	0.0657	0.0977	0.1466	0.1235	0.0948	0.0959	0.0534	0.0282	0.0125	0.0001
		SCEN. 3	0.0796	0.1035	0.0833	0.0842	0.0599	0.0542	0.0310	0.0060	0.0033	0
		SCEN. 4	0.0836	0.1024	0.1425	0.1148	0.0877	0.0760	0.0492	0.0253	0.0132	0.0003
		SCEN. 5	0.0615	0.0874	0.0867	0.0744	0.0698	0.0840	0.1052	0.0661	0.0142	0.0005
		SCEN. 6	0.0651	0.0757	0.0569	0.0588	0.0538	0.0639	0.0760	0.0288	0.0015	0
		SCEN. 7	0.0636	0.0760	0.0652	0.0687	0.0657	0.0928	0.0741	0.0185	0.0018	0
$\mathbf{a_{20}}$	**ENDESA**	**SCEN. 1**	0.0675	0.0580	0.0577	0.0686	0.0469	0.0470	0.0448	0.0885	0.1150	0.0465
		SCEN. 2	0.0692	0.0586	0.0623	0.0656	0.0416	0.0431	0.0381	0.0391	0.0786	0.0054
		SCEN. 3	0.0707	0.0818	0.0821	0.0900	0.0613	0.0630	0.0632	0.0890	0.0694	0.0155
		SCEN. 4	0.0772	0.0722	0.0663	0.0649	0.0446	0.0473	0.0460	0.0514	0.0450	0.0033
		SCEN. 5	0.0620	0.0463	0.0505	0.0490	0.0472	0.0452	0.0478	0.1119	0.1581	0.0738

		SCEN. 6	0.0385	0.0547	0.0638	0.0800	0.0599	0.0684	0.0776	0.1267	0.1743	0.0817
		SCEN. 7	0.0413	0.0425	0.0538	0.0570	0.0617	0.0562	0.0701	0.1218	0.1987	0.0884

Table A-2 Cases (1) and (2) “From first to Seventh Scenario”: Downward cumulative rank acceptability indices (All the data are expressed in percent).

SCENARIO 1										
RANK/ ALTERN.	$\mathbf{a_1}$ **ENEL SPA**	$\mathbf{a_2}$ **ENI**	$\mathbf{a_3}$ **EDISON SPA**	$\mathbf{a_4}$ **A2A SPA**	$\mathbf{a_5}$ **IREN SPA**	$\mathbf{a_6}$ **ACEA SPA**	$\mathbf{a_7}$ **GRUPPO HERA**	$\mathbf{a_8}$ **EDF**	$\mathbf{a_9}$ **ENGIE SA**	$\mathbf{a_{10}}$ **E.ON SE**
$\le b_1$	0.00	1.54	9.88	0.00	0.00	5.54	0.91	9.63	0.10	0.07
$\le b_2$	0.11	6.03	14.11	0.00	0.00	10.92	2.12	15.36	0.59	0.46
$\le b_3$	0.84	10.10	18.44	0.00	0.01	16.39	2.74	19.16	1.30	2.15
$\le b_4$	3.72	14.21	23.49	0.06	0.12	21.29	3.99	22.35	3.04	5.38
$\le b_5$	8.46	18.37	27.47	0.65	0.36	25.72	5.76	25.11	5.29	9.97
RANK/ ALTERN.	$\mathbf{a_{11}}$ **SSE PLC**	$\mathbf{a_{12}}$ **DRAX GROUP**	$\mathbf{a_{13}}$ **RWE**	$\mathbf{a_{14}}$ **EXELON**	$\mathbf{a_{15}}$ **AMEREN**	$\mathbf{a_{16}}$ **DTE ENERGY**	$\mathbf{a_{17}}$ **XCEL ENERGY**	$\mathbf{a_{18}}$ **DUKE ENERGY**	$\mathbf{a_{19}}$ **IBERDROLA**	$\mathbf{a_{20}}$ **ENDESA**
$\le b_1$	0.00	1.69	11.10	7.81	23.70	7.25	0.84	19.66	0.28	0.00
$\le b_2$	0.00	4.51	18.45	18.71	41.95	16.08	9.59	39.56	1.17	0.28
$\le b_3$	0.00	7.52	24.49	33.02	56.12	25.57	17.88	59.89	2.99	1.39
$\le b_4$	0.00	11.54	31.45	45.61	67.39	33.07	30.36	72.86	6.94	3.13
$\le b_5$	0.00	15.29	38.83	58.36	74.57	43.23	40.78	84.47	10.53	6.78
SCENARIO 2										
RANK/ ALTERN.	$\mathbf{a_1}$ **ENEL SPA**	$\mathbf{a_2}$ **ENI**	$\mathbf{a_3}$ **EDISON SPA**	$\mathbf{a_4}$ **A2A SPA**	$\mathbf{a_5}$ **IREN SPA**	$\mathbf{a_6}$ **ACEA SPA**	$\mathbf{a_7}$ **GRUPPO HERA**	$\mathbf{a_8}$ **EDF**	$\mathbf{a_9}$ **ENGIE SA**	$\mathbf{a_{10}}$ **E.ON SE**
$\le b_1$	0.00	0.54	0.43	0	0	0	0	4.65	0.07	0.11
$\le b_2$	0.27	0.84	0.76	0	0	0.16	0.00	11.88	0.42	0.91
$\le b_3$	2.28	1.32	1.75	0	0	2.56	0.03	16.42	1.02	3.03
$\le b_4$	6.74	2.57	3.33	0	0	5.05	0.16	20.58	2.05	7.26
$\le b_5$	13.53	3.51	5.29	0	0	8.16	0.24	24.67	3.34	12.32
RANK/ ALTERN.	$\mathbf{a_{11}}$ **SSE PLC**	$\mathbf{a_{12}}$ **DRAX GROUP**	$\mathbf{a_{13}}$ **RWE**	$\mathbf{a_{14}}$ **EXELON**	$\mathbf{a_{15}}$ **AMEREN**	$\mathbf{a_{16}}$ **DTE ENERGY**	$\mathbf{a_{17}}$ **XCEL ENERGY**	$\mathbf{a_{18}}$ **DUKE ENERGY**	$\mathbf{a_{19}}$ **IBERDROLA**	$\mathbf{a_{20}}$ **ENDESA**
$\le b_1$	0	0.25	22.00	9.17	38.99	2.99	1.79	18.91	0.10	0
$\le b_2$	0	0.65	33.09	21.31	55.04	12.39	16.64	44.81	0.51	0.32
$\le b_3$	0	1.23	43.89	37.63	68.20	20.23	26.54	70.05	1.44	2.38
$\le b_4$	0	2.16	58.01	57.04	80.38	28.31	36.53	80.35	3.63	5.85
$\le b_5$	0	3.77	69.59	74.08	88.44	38.91	48.18	87.88	6.10	11.99
SCENARIO 3										
RANK/ ALTERN.	$\mathbf{a_1}$ **ENEL SPA**	$\mathbf{a_2}$ **ENI**	$\mathbf{a_3}$ **EDISON SPA**	$\mathbf{a_4}$ **A2A SPA**	$\mathbf{a_5}$ **IREN SPA**	$\mathbf{a_6}$ **ACEA SPA**	$\mathbf{a_7}$ **GRUPPO HERA**	$\mathbf{a_8}$ **EDF**	$\mathbf{a_9}$ **ENGIE SA**	$\mathbf{a_{10}}$ **E.ON SE**
$\le b_1$	0	0.09	8.59	0	0	12.47	1.73	15.66	0	0.01
$\le b_2$	0	1.29	12.01	0	0	25.59	3.83	27.00	0.01	0.41
$\le b_3$	0	4.88	14.40	0	0	32.43	5.53	32.53	0.39	3.46
$\le b_4$	0	9.50	17.52	0.01	0	38.82	7.04	36.70	1.67	10.00
$\le b_5$	0.01	13.83	20.00	0.41	0	44.95	9.29	40.04	3.50	19.22
RANK/ ALTERN.	$\mathbf{a_{11}}$ **SSE PLC**	$\mathbf{a_{12}}$ **DRAX GROUP**	$\mathbf{a_{13}}$ **RWE**	$\mathbf{a_{14}}$ **EXELON**	$\mathbf{a_{15}}$ **AMEREN**	$\mathbf{a_{16}}$ **DTE ENERGY**	$\mathbf{a_{17}}$ **XCEL ENERGY**	$\mathbf{a_{18}}$ **DUKE ENERGY**	$\mathbf{a_{19}}$ **IBERDROLA**	$\mathbf{a_{20}}$ **ENDESA**
$\le b_1$	0	1.34	20.62	0.10	26.10	0.26	0.25	12.78	0	0
$\le b_2$	0	5.21	33.55	2.76	38.02	4.99	6.52	38.30	0.51	0.00
$\le b_3$	0	8.94	41.84	6.97	46.11	14.93	15.00	70.23	1.96	0
$\le b_4$	0	13.69	47.42	18.03	56.92	21.27	27.90	83.45	8.86	1.20
$\le b_5$	0	18.48	53.30	31.32	64.70	28.69	41.71	92.75	13.75	4.05
SCENARIO 4										
RANK/ ALTERN.	$\mathbf{a_1}$ **ENEL SPA**	$\mathbf{a_2}$ **ENI**	$\mathbf{a_3}$ **EDISON SPA**	$\mathbf{a_4}$ **A2A SPA**	$\mathbf{a_5}$ **IREN SPA**	$\mathbf{a_6}$ **ACEA SPA**	$\mathbf{a_7}$ **GRUPPO HERA**	$\mathbf{a_8}$ **EDF**	$\mathbf{a_9}$ **ENGIE SA**	$\mathbf{a_{10}}$ **E.ON SE**
$\le b_1$	0	0.40	0	0	0	0.54	0	4.79	0	0.05
$\le b_2$	0.10	0.74	0.23	0	0	2.91	0	15.00	0	0.53
$\le b_3$	0.67	1.30	1.08	0	0	5.55	0	20.09	0.19	3.60
$\le b_4$	4.30	1.97	2.59	0	0	7.59	0.24	24.38	0.61	9.80
$\le b_5$	11.66	2.88	4.44	0	0	10.54	0.39	28.43	1.67	15.46
RANK/ ALTERN.	$\mathbf{a_{11}}$ **SSE PLC**	$\mathbf{a_{12}}$ **DRAX GROUP**	$\mathbf{a_{13}}$ **RWE**	$\mathbf{a_{14}}$ **EXELON**	$\mathbf{a_{15}}$ **AMEREN**	$\mathbf{a_{16}}$ **DTE ENERGY**	$\mathbf{a_{17}}$ **XCEL ENERGY**	$\mathbf{a_{18}}$ **DUKE ENERGY**	$\mathbf{a_{19}}$ **IBERDROLA**	$\mathbf{a_{20}}$ **ENDESA**
$\le b_1$	0	0.02	25.87	9.93	38.36	1.73	1.84	16.47	0	0
$\le b_2$	0	0.04	37.24	23.75	54.74	9.49	13.69	41.51	0.01	0.02
$\le b_3$	0	0.07	46.66	38.97	68.83	17.87	23.57	69.83	0.11	1.61
$\le b_4$	0	0.17	57.81	55.44	80.86	26.77	37.79	81.37	4.12	4.19
$\le b_5$	0	0.74	66.51	70.50	88.53	37.60	53.42	90.89	6.64	9.70

SCENARIO 5										
RANK/ ALTERN.	a_1 ENEL SPA	a_2 ENI	a_3 EDISON SPA	a_4 A2A SPA	a_5 IREN SPA	a_6 ACEA SPA	a_7 GRUPPO HERA	a_8 EDF	a_9 ENGIE SA	a_{10} E.ON SE
$\leq b_1$	0	2.93	13.32	0	0	0.67	0.82	4.84	0	0
$\leq b_2$	0.15	11.79	18.85	0	0.06	1.80	1.15	7.34	0.16	0.02
$\leq b_3$	0.94	17.47	25.74	0.00	0.09	5.05	1.51	9.88	0.65	0.28
$\leq b_4$	5.09	21.49	32.06	0.25	0.31	7.48	3.05	12.20	4.11	0.81
$\leq b_5$	12.52	25.72	37.67	1.47	0.75	10.41	4.95	14.75	6.98	1.88
RANK/ ALTERN.	a_{11} SSE PLC	a_{12} DRAX GROUP	a_{13} RWE	a_{14} EXELON	a_{15} AMEREN	a_{16} DTE ENERGY	a_{17} XCEL ENERGY	a_{18} DUKE ENERGY	a_{19} IBERDROLA	a_{20} ENDESA
$\leq b_1$	0	0.89	2.08	16.24	18.26	13.71	2.37	23.67	0.20	0
$\leq b_2$	0	2.74	4.38	35.09	42.84	25.66	7.85	38.85	1.20	0.07
$\leq b_3$	0	4.49	7.34	59.01	63.01	36.09	14.56	50.25	2.73	0.91
$\leq b_4$	0	6.18	13.86	72.19	73.62	44.65	29.87	64.47	5.23	3.08
$\leq b_5$	0	8.36	19.70	82.21	80.77	56.92	40.83	79.52	8.50	6.09

SCENARIO 6										
RANK/ ALTERN.	a_1 ENEL SPA	a_2 ENI	a_3 EDISON SPA	a_4 A2A SPA	a_5 IREN SPA	a_6 ACEA SPA	a_7 GRUPPO HERA	a_8 EDF	a_9 ENGIE SA	a_{10} E.ON SE
$\leq b_1$	0	2.40	22.74	0	0	13.08	3.77	12.64	0.00	0.00
$\leq b_2$	0	13.51	30.74	0	0.02	23.48	6.43	16.08	0.22	0.02
$\leq b_3$	0	22.48	37.78	0	0.05	30.92	8.36	19.23	0.84	0.50
$\leq b_4$	0.20	30.41	45.98	0.25	0.24	37.97	11.38	21.46	3.65	1.71
$\leq b_5$	0.86	38.83	51.58	2.18	0.62	43.97	15.43	23.74	7.24	3.81
RANK/ ALTERN.	a_{11} SSE PLC	a_{12} DRAX GROUP	a_{13} RWE	a_{14} EXELON	a_{15} AMEREN	a_{16} DTE ENERGY	a_{17} XCEL ENERGY	a_{18} DUKE ENERGY	a_{19} IBERDROLA	a_{20} ENDESA
$\leq b_1$	0.00	2.47	0.39	4.69	7.68	9.29	0.43	20.00	0.42	0
$\leq b_2$	0.00	8.84	3.85	11.82	25.58	17.70	3.29	35.77	2.65	0
$\leq b_3$	0.00	15.99	6.68	23.77	38.13	29.31	9.15	51.18	5.50	0.13
$\leq b_4$	0.00	22.74	8.81	32.49	49.56	37.09	19.86	65.84	9.95	0.41
$\leq b_5$	0.00	28.94	12.02	41.91	56.97	46.63	28.52	79.74	15.82	1.19

SCENARIO 7										
RANK/ ALTERN.	a_1 ENEL SPA	a_2 ENI	a_3 EDISON SPA	a_4 A2A SPA	a_5 IREN SPA	a_6 ACEA SPA	a_7 GRUPPO HERA	a_8 EDF	a_9 ENGIE SA	a_{10} E.ON SE
$\leq b_1$	0	1.91	23.31	0	0	8.98	3.24	10.44	0.29	0.00
$\leq b_2$	0	11.44	30.92	0	0	19.10	5.73	14.43	1.24	0.14
$\leq b_3$	0	20.41	38.27	0	0.02	27.81	7.72	17.11	2.80	0.54
$\leq b_4$	0.09	29.04	46.41	0.26	0.26	35.00	9.79	19.46	5.59	1.23
$\leq b_5$	0.58	37.50	51.49	2.01	0.75	41.14	12.46	21.94	8.38	3.07
RANK/ ALTERN.	a_{11} SSE PLC	a_{12} DRAX GROUP	a_{13} RWE	a_{14} EXELON	a_{15} AMEREN	a_{16} DTE ENERGY	a_{17} XCEL ENERGY	a_{18} DUKE ENERGY	a_{19} IBERDROLA	a_{20} ENDESA
$\leq b_1$	0	3.63	0.40	2.25	12.25	8.18	0.39	23.89	0.84	0
$\leq b_2$	0	9.79	1.10	10.53	26.61	18.99	5.59	40.60	3.69	0.10
$\leq b_3$	0	16.77	3.91	20.55	40.05	28.94	13.80	53.70	7.09	0.51
$\leq b_4$	0	22.63	7.39	32.04	51.67	36.50	23.43	67.51	10.54	1.16
$\leq b_5$	0	29.17	11.05	46.22	60.40	45.04	30.39	80.21	15.20	3.00

Table A-3 Rank acceptability indices on Financial macro-criterion

ALTERNATIVES\RANK		b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}
a_1	ENEL SPA	0	0	0	0	0	0	0	0	0	0
a_2	ENI	0	0	0	0	0	0	0	0	0	0
a_3	EDISON SPA	0	0	0	0	0	0	0	0.1295	0.0314	0.1149
a_4	A2A SPA	0	0	0	0	0	0	0	0	0	0
a_5	IREN SPA	0	0	0	0	0	0	0	0	0	0
a_6	ACEA SPA	0	0	0.2828	0.0701	0.1232	0.1452	0.0124	0.0060	0.1994	0.1609
a_7	GRUPPO HERA	0	0	0	0	0	0	0	0	0	0
a_8	EDF	0	0.4536	0.0101	0.0029	0.0573	0.0562	0.0875	0.0011	0.0218	0.1036
a_9	ENGIE SA	0	0	0	0	0.2625	0.0756	0.1794	0.3339	0.1486	0
a_{10}	E.ON SE	0	0	0	0.2289	0.0038	0.1872	0.0626	0.0143	0.0546	0.1576
a_{11}	SSE PLC	0	0	0	0	0	0	0	0.1466	0.0135	0.0458
a_{12}	DRAX GROUP PLC	0	0	0	0	0	0	0	0	0	0
a_{13}	RWE	0.6061	0.0168	0.0943	0.0539	0.0039	0.1203	0.1047	0	0	0
a_{14}	EXELON CORP.	0	0	0	0	0	0.2416	0.0524	0.1981	0.3114	0.1965
a_{15}	AMEREN	0.3939	0.1146	0.0102	0.0147	0.1407	0.0160	0.0159	0.1645	0.1295	0
a_{16}	DTE ENERGY COMP.	0	0	0	0	0	0	0	0	0	0.0152
a_{17}	XCEL ENERGY	0	0.3903	0.1460	0.1559	0.0453	0.0209	0.2416	0	0	0
a_{18}	DUKE ENERGY CORP.	0	0.0247	0.3184	0.3040	0.3452	0.0077	0	0	0	0
a_{19}	IBERDROLA	0	0	0.1382	0.1696	0.0181	0.0246	0.0158	0.0051	0.0772	0.1083
a_{20}	ENDESA	0	0	0	0	0	0.1047	0.2277	9.0000e-04	0.0126	0.0972

	ALTERNATIVES\RANK	b_{11}	b_{12}	b_{13}	b_{14}	b_{15}	b_{16}	b_{17}	b_{18}	b_{19}	b_{20}
a_{1}	ENEL SPA	0	0	0.6578	0.0962	0.0556	0.1904	0	0	0	0
a_{2}	ENI	0	0	0	0	0.1904	0.0893	0.0144	0.0735	0.0912	0.5412
a_{3}	EDISON SPA	0.0068	0.1190	0.0041	0.0617	0.0305	0.0484	0.0079	0.4458	0	0
a_{4}	A2A SPA	0	0	0	0	0	0.3904	0.1911	0.0509	0.3676	0
a_{5}	IREN SPA	0	0	0.1512	0.2034	0.1500	0.1050	0.3904	0	0	0
a_{6}	ACEA SPA	0	0	0	0	0	0	0	0	0	0
a_{7}	GRUPPO HERA	0	0	0	0.3985	0.1603	0.1127	0.2791	0.0494	0	0
a_{8}	EDF	0.2059	0	0	0	0	0	0	0	0	0
a_{9}	ENGIE SA	0	0	0	0	0	0	0	0	0	0
a_{10}	E.ON SE	0.0084	0.1931	0.0895	0	0	0	0	0	0	0
a_{11}	SSE PLC	0.0651	0.0430	0.0083	0.0444	0.0720	0.0150	0.0053	0.0652	0.0170	0.4588
a_{12}	DRAX GROUP PLC	0	0.0895	0.0714	0.0851	0.0598	0.0227	0.0768	0.0705	0.5242	0
a_{13}	RWE	0	0	0	0	0	0	0	0	0	0
a_{14}	EXELON CORP.	0	0	0	0	0	0	0	0	0	0
a_{15}	AMEREN	0	0	0	0	0	0	0	0	0	0
a_{16}	DTE ENERGY COMP.	0.6341	0.3507	0	0	0	0	0	0	0	0
a_{17}	XCEL ENERGY	0	0	0	0	0	0	0	0	0	0
a_{18}	DUKE ENERGY CORP.	0	0	0	0	0	0	0	0	0	0
a_{19}	IBERDROLA	0.0471	0.0820	0.0119	0.0695	0.2326	0	0	0	0	0
a_{20}	ENDESA	0.0326	0.1227	0.0058	0.0412	0.0488	0.0261	0.0350	0.2447	0	0

Table A-4 Rank acceptability indices on Sustainability macro-criterion

ALTERNATIVES\RANK		b_{1}	b_{2}	b_{3}	b_{4}	b_{5}	b_{6}	b_{7}	b_{8}	b_{9}	b_{10}
a_{1}	ENEL SPA	0	0.1573	0.3220	0.2167	0.1014	0.0511	0.0493	0.0519	0.0465	0.0038
a_{2}	ENI	0.0309	0.0067	0.0045	0.0087	0.0151	0.0155	0.0658	0.0687	0.0313	0.0301
a_{3}	EDISON SPA	0	0	0	0	0	0	0	0.0201	0.1774	0.3479
a_{4}	A2A SPA	0	0	0	0	0	0	0	0	0	0
a_{5}	IREN SPA	0	0	0	0	0	0	0	0	0	0
a_{6}	ACEA SPA	0	0	0	0	0	0	0	0	0	0
a_{7}	GRUPPO HERA	0	0	0	0	0	0	0.0471	0.0112	0.0329	0.0278
a_{8}	EDF	0	0	0	0	0	0	0.0288	0.1371	0.0994	0.0604
a_{9}	ENGIE SA	0	0	0	0	0	0	0	0	0	0
a_{10}	E.ON SE	0	0.0300	0.0340	0.0391	0.0175	0.0266	0.0191	0.0498	0.2882	0.1439
a_{11}	SSE PLC	0	0	0	0	0	0	0	0	0	0
a_{12}	DRAX GROUP PLC	0.0067	0.0336	0.0227	0.0238	0.0513	0.1696	0.0331	0.0578	0.0209	0.0456
a_{13}	RWE	0	0.0307	0.0621	0.1240	0.4277	0.0731	0.0644	0.0211	0.0681	0.0499
a_{14}	EXELON CORP.	0.3917	0.0822	0.0477	0.1119	0.1368	0.0259	0.0835	0.0689	0.0514	0
a_{15}	AMEREN	0.2324	0.1504	0.2192	0.2863	0.0124	0.0611	0.0382	0	0	0
a_{16}	DTE ENERGY COMP.	0.0977	0.2881	0.1190	0.0781	0.0685	0.1480	0.0877	0.0789	0.0247	0.0093
a_{17}	XCEL ENERGY	0.0435	0.0446	0.0425	0.0171	0.0290	0.0498	0.2494	0.1929	0.0578	0.0907
a_{18}	DUKE ENERGY CORP.	0.1916	0.0762	0.0543	0.0571	0.1069	0.2906	0.0447	0.1256	0.0530	0
a_{19}	IBERDROLA	0	0	0	0	0	0	0	0	0	0
a_{20}	ENDESA	0.0055	0.1002	0.0720	0.0372	0.0334	0.0887	0.1889	0.1160	0.0484	0.1906

ALTERNATIVES\RANK		b_{11}	b_{12}	b_{13}	b_{14}	b_{15}	b_{16}	b_{17}	b_{18}	b_{19}	b_{20}
a_{1}	ENEL SPA	0	0	0	0	0	0	0	0	0	0
a_{2}	ENI	0.0318	0.0214	0.0717	0.0251	0.0438	0.1244	0.0396	0.1737	0.0909	0.1003
a_{3}	EDISON SPA	0.3122	0.0620	0.0248	0.0326	0.0215	0.0015	0	0	0	0
a_{4}	A2A SPA	0.0244	0.0933	0.1392	0.3292	0.3531	0.0608	0	0	0	0
a_{5}	IREN SPA	0	0	0	0	0.0608	0.2134	0.0446	0.2825	0.1675	0.2312
a_{6}	ACEA SPA	0.0218	0.0071	0.0032	0.0043	0.0240	0.0268	0.0295	0.0722	0.4366	0.3745
a_{7}	GRUPPO HERA	0.0125	0.0084	0.0219	0.0179	0.0346	0.0195	0.0436	0.2699	0.2664	0.1863
a_{8}	EDF	0.1168	0.0494	0.0855	0.1596	0.0400	0.0237	0.0340	0.0218	0.0358	0.1077
a_{9}	ENGIE SA	0.1414	0.5907	0.1893	0.0326	0.0381	0.0079	0	0	0	0
a_{10}	E.ON SE	0.1262	0.0217	0.1027	0.1012	0	0	0	0	0	0
a_{11}	SSE PLC	0	0	0	0.0036	0.2256	0.2079	0.4928	0.0701	0	0
a_{12}	DRAX GROUP PLC	0.0299	0.0236	0.0706	0.0548	0.0290	0.0629	0.2641	0	0	0
a_{13}	RWE	0.0259	0.0180	0.0086	0.0264	0	0	0	0	0	0
a_{14}	EXELON CORP.	0	0	0	0	0	0	0	0	0	0
a_{15}	AMEREN	0	0	0	0	0	0	0	0	0	0
a_{16}	DTE ENERGY COMP.	0	0	0	0	0	0	0	0	0	0
a_{17}	XCEL ENERGY	0.0794	0.0715	0.0318	0	0	0	0	0	0	0
a_{18}	DUKE ENERGY CORP.	0	0	0	0	0	0	0	0	0	0
a_{19}	IBERDROLA	0.0107	0.0138	0.2348	0.2034	0.1217	0.2512	0.0518	0.1098	0.0028	0
a_{20}	ENDESA	0.0670	0.0191	0.0159	0.0093	0.0078	0	0	0	0	0

Table A-5 Rank acceptability indices on Technical macro-criterion

ALTERNATIVES\RANK		$\mathbf{b_1}$	$\mathbf{b_2}$	$\mathbf{b_3}$	$\mathbf{b_4}$	$\mathbf{b_5}$	$\mathbf{b_6}$	$\mathbf{b_7}$	$\mathbf{b_8}$	$\mathbf{b_9}$	$\mathbf{b_{10}}$
$\mathbf{a_1}$	ENEL SPA	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_2}$	ENI	0	0	0.1785	0.4330	0.0595	0.1085	0.0135	0.2070	0	0
$\mathbf{a_3}$	EDISON SPA	0.3921	0.0195	0.0330	0.0607	0.0061	0.0004	0.0212	0.0239	0.0185	0.0114
$\mathbf{a_4}$	A2A SPA	0	0	0	0	0	0.2157	0.0228	0.0277	0.0526	0.0332
$\mathbf{a_5}$	IREN SPA	0	0	0	0	0	0	0	0	0.1746	0.0964
$\mathbf{a_6}$	ACEA SPA	0.0561	0.5278	0.0524	0.0780	0.0983	0.0140	0.1734	0	0	0
$\mathbf{a_7}$	GRUPPO HERA	0	0.2661	0.0976	0.0248	0.0318	0.0136	0.0331	0.0392	0.0122	0.0167
$\mathbf{a_8}$	EDF	0.3540	0.0621	0.0277	0.0509	0.0096	0.0030	0.0417	0.0219	0.0066	0.0418
$\mathbf{a_9}$	ENGIE SA	0	0	0	0	0	0	0	0	0	0.0287
$\mathbf{a_{10}}$	E.ON SE	0	0	0	0	0.0915	0.4480	0.2868	0.1737	0	0
$\mathbf{a_{11}}$	SSE PLC	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{12}}$	DRAX GROUP PLC	0.1978	0.1245	0.4116	0.0427	0.2234	0	0	0	0	0
$\mathbf{a_{13}}$	RWE	0	0	0	0	0.1874	0.0118	0.0078	0.1165	0.0321	0.0576
$\mathbf{a_{14}}$	EXELON CORP.	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{15}}$	AMEREN	0	0	0	0	0	0	0.2363	0.1763	0.0099	0.0424
$\mathbf{a_{16}}$	DTE ENERGY COMP.	0	0	0.1992	0.0242	0.1808	0.0154	0.0314	0.0214	0.0092	0.0225
$\mathbf{a_{17}}$	XCEL ENERGY	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{18}}$	DUKE ENERGY CORP.	0	0	0	0.2857	0.1116	0.1696	0.1320	0.0349	0.0916	0.1746
$\mathbf{a_{19}}$	IBERDROLA	0	0	0	0	0	0	0	0.1575	0.3113	0.2602
$\mathbf{a_{20}}$	ENDESA	0	0	0	0	0	0	0	0	0.2814	0.2145

ALTERNATIVES\RANK		$\mathbf{b_{11}}$	$\mathbf{b_{12}}$	$\mathbf{b_{13}}$	$\mathbf{b_{14}}$	$\mathbf{b_{15}}$	$\mathbf{b_{16}}$	$\mathbf{b_{17}}$	$\mathbf{b_{18}}$	$\mathbf{b_{19}}$	$\mathbf{b_{20}}$
$\mathbf{a_1}$	ENEL SPA	0	0	0	0	0.6198	0.0903	0.2210	0.0584	0.0105	0
$\mathbf{a_2}$	ENI	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_3}$	EDISON SPA	0.0254	0.0143	0.0129	0.0030	0.0453	0.0536	0.0240	0.0113	0.2234	0
$\mathbf{a_4}$	A2A SPA	0.0058	0.0065	0.0047	0.0293	0.0269	0.0085	0.0036	0.0001	0.0194	0.5432
$\mathbf{a_5}$	IREN SPA	0.0856	0.0166	0.0395	0.0435	0.0219	0.0461	0.2572	0.1197	0.0989	0
$\mathbf{a_6}$	ACEA SPA	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_7}$	GRUPPO HERA	0.0146	0.0194	0.0182	0.0144	0.0248	0.0116	0.0571	0.0380	0.0212	0.2456
$\mathbf{a_8}$	EDF	0.0042	0.0033	0.0042	0.0400	0.0215	0.1114	0.0658	0.0959	0.0344	0
$\mathbf{a_9}$	ENGIE SA	0.1863	0.2159	0.3727	0.1873	0.0091	0	0	0	0	0
$\mathbf{a_{10}}$	E.ON SE	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{11}}$	SSE PLC	0	0	0.2393	0.0897	0.0445	0.3004	0.0379	0.1148	0.1734	0
$\mathbf{a_{12}}$	DRAX GROUP PLC	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{13}}$	RWE	0.0437	0.0075	0.0307	0.0487	0.0310	0.0100	0.0051	0.1350	0.2751	0
$\mathbf{a_{14}}$	EXELON CORP.	0	0.3343	0.0164	0.0069	0.0438	0.0744	0.1492	0.1030	0.0608	0.2112
$\mathbf{a_{15}}$	AMEREN	0.0380	0.1319	0.0764	0.2888	0	0	0	0	0	0
$\mathbf{a_{16}}$	DTE ENERGY COMP.	0.0194	0.0121	0.0295	0.0041	0.0294	0.0532	0.0671	0.2594	0.0217	0
$\mathbf{a_{17}}$	XCEL ENERGY	0.3878	0.0166	0.0305	0.0050	0.0820	0.2405	0.1120	0.0644	0.0612	0
$\mathbf{a_{18}}$	DUKE ENERGY CORP.	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{19}}$	IBERDROLA	0.1024	0.1686	0	0	0	0	0	0	0	0
$\mathbf{a_{20}}$	ENDESA	0.0868	0.0530	0.1250	0.2393	0	0	0	0	0	0

Table A-6 Rank acceptability indices on Market macro-criterion

ALTERNATIVES\RANK		$\mathbf{b_1}$	$\mathbf{b_2}$	$\mathbf{b_3}$	$\mathbf{b_4}$	$\mathbf{b_5}$	$\mathbf{b_6}$	$\mathbf{b_7}$	$\mathbf{b_8}$	$\mathbf{b_9}$	$\mathbf{b_{10}}$
$\mathbf{a_1}$	ENEL SPA	0	0	0	0	0	0.0257	0.0392	0.0608	0.0212	0.0631
$\mathbf{a_2}$	ENI	0	0.2364	0.1625	0.0690	0.0947	0.0163	0.0326	0.0486	0.0893	0.1089
$\mathbf{a_3}$	EDISON SPA	0.4070	0.1038	0.0559	0.0394	0.0200	0.0472	0.0327	0.1295	0.0680	0.0776
$\mathbf{a_4}$	A2A SPA	0	0	0.0057	0.0865	0.1652	0.0985	0.1331	0.1268	0.0988	0.1156
$\mathbf{a_5}$	IREN SPA	0	0.0433	0.0745	0.0969	0.1292	0.2090	0.1477	0.1429	0.0878	0.0592
$\mathbf{a_6}$	ACEA SPA	0.0489	0.0720	0.0718	0.0759	0.0348	0.0808	0.0556	0.0656	0.0589	0.0716
$\mathbf{a_7}$	GRUPPO HERA	0	0	0	0	0	0.0133	0.1655	0.1203	0.2074	0.1340
$\mathbf{a_8}$	EDF	0.0036	0.0323	0.0274	0.0207	0.0390	0.0161	0.0149	0.0063	0.0148	0.0064
$\mathbf{a_9}$	ENGIE SA	0	0	0.0222	0.1007	0.0338	0.0252	0.0156	0.0161	0.0155	0.0263
$\mathbf{a_{10}}$	E.ON SE	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{11}}$	SSE PLC	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{12}}$	DRAX GROUP PLC	0.1017	0.0717	0.0641	0.0284	0.0162	0.0158	0.0154	0.0160	0.0118	0.0193
$\mathbf{a_{13}}$	RWE	0	0	0	0	0	0	0	0	0	0
$\mathbf{a_{14}}$	EXELON CORP.	0.1058	0.0786	0.1286	0.1931	0.0908	0.1000	0.1115	0.0588	0.0743	0.0585
$\mathbf{a_{15}}$	AMEREN	0.0042	0.2328	0.1180	0.0495	0.0380	0.0589	0.0461	0.0417	0.0384	0.0479
$\mathbf{a_{16}}$	DTE ENERGY COMP.	0.2786	0.0334	0.0223	0.0416	0.0509	0.0255	0.0321	0.0262	0.0300	0.0446
$\mathbf{a_{17}}$	XCEL ENERGY	0	0	0.1279	0.0824	0.0545	0.0864	0.0224	0.0372	0.0310	0.0486
$\mathbf{a_{18}}$	DUKE ENERGY CORP.	0	0.0539	0.0632	0.0722	0.1903	0.0612	0.0573	0.0779	0.1257	0.0972
$\mathbf{a_{19}}$	IBERDROLA	0.0502	0.0418	0.0559	0.0437	0.0426	0.1201	0.0313	0.0225	0.0175	0.0175
$\mathbf{a_{20}}$	ENDESA	0	0	0	0	0	0	0.0470	0.0028	0.0096	0.0037

ALTERNATIVES\RANK		b_{11}	b_{12}	b_{13}	b_{14}	b_{15}	b_{16}	b_{17}	b_{18}	b_{19}	b_{20}
a_1	ENEL SPA	0.0304	0.0256	0.1258	0.1473	0.0927	0.1001	0.0533	0.2045	0.0103	0
a_2	ENI	0.1173	0.0122	0.0122	0	0	0	0	0	0	0
a_3	EDISON SPA	0.0099	0.0090	0	0	0	0	0	0	0	0
a_4	A2A SPA	0.1442	0.0256	0	0	0	0	0	0	0	0
a_5	IREN SPA	0.0095	0	0	0	0	0	0	0	0	0
a_6	ACEA SPA	0.0956	0.0809	0.1581	0.0295	0	0	0	0	0	0
a_7	GRUPPO HERA	0.1449	0.1704	0.0442	0	0	0	0	0	0	0
a_8	EDF	0.0154	0.0175	0.0176	0.0117	0.0526	0.0375	0.0365	0.0673	0.1726	0.3898
a_9	ENGIE SA	0.0128	0.0221	0.1557	0.0814	0.0519	0.0426	0.0417	0.1033	0.2102	0.0229
a_{10}	E.ON SE	0	0.0898	0.0881	0.1387	0.0890	0.1414	0.0775	0.1505	0.2250	0
a_{11}	SSE PLC	0	0	0	0	0.0727	0.0689	0.0679	0.2426	0.1847	0.3632
a_{12}	DRAX GROUP PLC	0.0162	0.1907	0.0799	0.0485	0.0396	0.0313	0.2334	0	0	0
a_{13}	RWE	0	0	0.0103	0.0906	0.3123	0.2968	0.2686	0.0214	0	0
a_{14}	EXELON CORP.	0	0	0	0	0	0	0	0	0	0
a_{15}	AMEREN	0.0714	0.0413	0.0396	0.1722	0	0	0	0	0	0
a_{16}	DTE ENERGY COMP.	0.0521	0.0867	0.0427	0.0341	0.1795	0.0197	0	0	0	0
a_{17}	XCEL ENERGY	0.0614	0.0584	0.1005	0.0463	0.0321	0.1804	0.0305	0	0	0
a_{18}	DUKE ENERGY CORP.	0.1944	0.0067	0	0	0	0	0	0	0	0
a_{19}	IBERDROLA	0.0198	0.1615	0.0642	0.1023	0.0393	0.0350	0.1348	0	0	0
a_{20}	ENDESA	0.0047	0.0016	0.0611	0.0974	0.0383	0.0463	0.0558	0.2104	0.1972	0.2241

Appendix B

Table B-1 Energy companies in the final balanced sample after the stratified resampling method distributed per country. Authors' elaboration

COUNTRY	ELECTRIC COMPANIES			
	ACTIVE	Relative frequency	**INACTIVE**	Relative frequency
GERMANY	STADTWERKE BONN GMBH (SWB) STADTWERKE WEIßENBURG GMBH STADTWERKE PRENZLAU GMBH STADTWERKE SCHWEINFURT GMBH STADTWERKE GREIFSWALD GESELLSCHAFT MIT BESCHRÄNKTER HAFTUNG ENERGIEVERSORGUNG SEHNDE GMBH ENERGIEEINKAUFS- UND -HANDELSGESELLSCHAFT MECKLENBURG-VORPOMMERN MBH STADTWERKE EBERBACH STADTWERKE HUSUM GMBH STADTWERKE WERL GMBH STADTWERKE ERDING GMBH	19.30%	EEV BIOENERGIE GMBH & CO. KG OVAG ENERGIE AG MT-BIOMETHAN GMBH	5.26%
SPAIN	SUN EUROPEAN INVESTMENTS EOLICO OLIVILLO SA. MOLINOS DEL EBRO SA CONTOURGLOBAL LA RIOJA SL EVOLUCION 2000 SOCIEDAD LIMITADA. M TORRES DESARROLLOS ENERGETICOS SL SOLYNOVA VALVERDON SL BIO OILS ENERGY SA TECNOHUERTAS SA GRANSOLAR DESARROLLO Y CONSTRUCCION SL.	15.79%	SIBERIA SOLAR SL SERRA DO MONCOSO-CAMBAS SL X-ELIO REAL ESTATE ENERGY SL. ALTEN POZOHONDO SOCIEDAD LIMITADA PARQUE SOLAR LA ROBLA SL ALTEN ALANGE SL AUDAX ENERGIA SA PLANSOFOL SL	8.77%
ITALY	C.V.A. VENTO S.R.L. SOCIETA' ELETTRICA IN MORBEGNO SOCIETA' COOPERATIVA PER AZIONI EOLICA SANTOMENNA S.R.L. ERMES GAS & POWER SOCIETA' A RESPONSABILITA' LIMITATA SOCIETA' ENERGIE RINNOVABILI 1 SOCIETA' PER AZIONI ENOMONDO S.R.L. AGSM ENERGIA S.P.A. ORSA MAGGIORE PV S.R.L. ALPERIA VIPOWER SPA ENERGIA UNO S.R.L. TG MASSERIA GIORGINI S.R.L. IMPIANTO ALPHA S.R.L. OTTANA SOLAR POWER S.P.A.	22.80%	EVIVA S.P.A. IN LIQUIDAZIONE ELECTRA ITALIA S.P.A. ENERGHE S.P.A. TRADECOM S.P.A E.S.TR.A. ELETTRICITA' S.P.A. AEVV ENERGIE S.R.L. ENERGIA E TERRITORIO – SRL AZIENDA ENERGETICA VALTELLINA VALCHIAVENNA S.P.A. AP ENERGIA S.R.L. - IN LIQUIDAZIONE ESPERIA SOCIETA' PER AZIONI IN LIQUDAZIONE HOLDING FORTORE ENERGIA S.R.L. LINEA RETI E IMPIANTI S.R.L. UNIPOWER ITALIA S.R.L. GENERAL POWER S.R.L. IN LIQUIDAZIONE HELIOS ITA 3 S.R.L. SOLAR ENERGY ITALIA 7 SRL EMMECIDUE S.R.L. IN LIQUIDAZIONE VENUSIA SRL PARCO EOLICO GIRIFALCO S.R.L. VARSI FOTOVOLTAICO SRL GREENSOURCE S.P.A. S5 SRL EN & EN - ENERGIE PER ENERGIA S.R.L. EF AUGUSTA S.R.L. VILLA CASTELLI WIND S.R.L. IDREG-PIEMONTE - S.P.A. ITALBREVETTI SOCIETA' A RESPONSABILITA' LIMITATA STS SOCIETA' TERMOELETTRICA SEDRINA S.R.L SUNSHIRE S.R.L. FILOVERDE S.P.A.	52.63%
FRANCE	CENTRALE EOLIENNE DE PRODUCTION D'ENERGIE DE HAUT CHEMIN EWZ PARC EOLIEN EPINETTE ELICIO VENT D'OUEST	5.26%	ENGIE NUCLEAR DEVELOPMENT FORCES HYDRAULIQUES DE MEUSE LA COMPAGNIE DU VENT ALBIOMA CARAIBES	7.01%
SWEDEN	KRISTINEHAMNS ELNÄT AB SKÅNSKA ENERGI NÄT AKTIEBOLAG HÄRRYDA ENERGI AKTIEBOLAG AB BORLÄNGE ENERGI ELNÄT	7.01%		0%
FINLAND	VOIMAPATO OY PARIKKALAN VALO OY LAPPEENRANNAN ENERGIAVERKOT OY	5.26%		0%
GREECE	GREEK ENVIRONMENTAL & ENERGY NETWORK A.E. ΗΡΩΝ ΘΕΡΜΟΗΛΕΚΤΡΙΚΗ Α.Ε.	3.50%		0%
DANMARK	VESTJYSKE NET 60 KV A/S GRINDSTED EL- OG VARMEVÆRK A.M.B.A	3.50%		0%
ROMANIA	OET ROMANIA LTD BULGARIA SUCURSALA BUCURESTI SOCIETATEA DE DISTRIBUŢIE A ENERGIEI ELECTRICE TRANSILVANIA SUD.	3.50%	SOCIETATEA COMERCIALA DE PRODUCERE A ENERGIEI ELECTRICE SI TERMICE "TERMOELECTRICA"	1.75%

PORTUGAL	TEJO ENERGIA - PRODUÇÃO E DISTRIBUIÇÃO DE ENERGIA ELÉCTRICA, S.A. BIOELÉCTRICA DA FOZ, S.A.	3.50%		0%
BULGARIA	ТОПЛОФИКАЦИЯ РУСЕ ЕАД ЕЛЕКТРОЕНЕРГИЕН СИСТЕМЕН ОПЕРАТОР ЕАД	3.50%	ТОПЛОФИКАЦИЯ ПЕТРИЧ ЕАД ЕНЕРГИЙНА ФИНАНСОВА ГРУПА АД	3.50%
BELGIUM	ESSENT BELGIUM	1.75%	INTERCOMMUNALE MAATSCHAPPIJ VOOR ENERGIEVOORZIENING ANTWERPEN	1.75%
SLOVENIA	ELEKTRO MARIBOR, PODJETJE ZA DISTRIBUCIJO ELEKTRIČNE ENERGIJE, D.D.	1.75%		0%
LATVIA	AUGSTSPRIEGUMA TĪKLS AS	1.75%		0%
POLAND	EOLOS POLSKA SP. Z O.O.	1.75%	PARK WIATROWY TYCHOWO SP. Z O.O. PARK WIATROWY NOWY STAW SP. Z O.O.	3.50%
HUNGARY		0%	VEOLIA SZOLGÁLTATÓ KÖZPONT MAGYARORSZÁG KFT MISTRAL ENERGETIKA VILLAMOSENERGIA-TERMELŐ KFT KAPTÁR SZÉLERŐMŰ KERESKEDELMI ÉS SZOLGÁLTATÓ KFT MVM ÉSZAK-BUDAI KOGENERÁCIÓS FŰTŐERŐMŰ KFT	7.01%
CZECHIA		0%	MORAVIA GREEN POWER S.R.O.	1.75%
SLOVAKIA		0%	LUMIUS SLOVAKIA, S.R.O. V LIKVIDÁCII	1.75%

Table B-2 Stages performed to select independent variables of the sample introduced in the failure prediction model. Authors' elaboration.

INDEPENDENT VARIABLES (FRs)	Stage 1				Stage 2		Stage 3
PROFITABILITY	Year	*IV* Value	Predictive power		t-test p value	Predictive power	Correlation analysis
EBIT_TA	-1	0.7226	SUSPICIOUS	S	0.4934	NS	NS
	-2	0.4472	STRONG	S	0.0123	S	NS
	-3	0.1583	MEDIUM	S	0.1536	NS	NS
	-4	0.4165	STRONG	S	0.4381	NS	NS
LTDR	-1	0.4621	STRONG	S	0.1904	NS	NS
	-2	0.2118	MEDIUM	S	0.4909	NS	NS
	-3	0.1907	MEDIUM	S	0.6455	NS	NS
	-4	0.0825	WEAK	NS	0.8063	NS	NS
OP_MARG	-1	0.8934	SUSPICIOUS	S	0.2695	NS	NS
	-2	0.2635	STRONG	S	0.0219	S	NS
	-3	0.097	WEAK	NS	0.4368	NS	NS
	-4	0.3002	STRONG	S	0.1694	NS	NS
PROF_MARG	-1	1.0343	SUSPICIOUS	S	0.0223	S	NS
	-2	0.4354	STRONG	S	0.0284	S	NS
	-3	0.2902	STRONG	S	0.4255	NS	NS
	-4	0.324	STRONG	S	0.1405	NS	NS
ROE	-1	0.6102	SUSPICIOUS	S	0.0223	S	NS
	-2	0.2479	MEDIUM	S	0.7253	NS	NS
	-3	0.2014	MEDIUM	S	0.683	NS	NS
	-4	0.0961	WEAK	NS	0.2315	NS	NS
ROA	-1	1.0723	SUSPICIOUS	S	0.0018	S	S
	-2	0.4323	STRONG	S	0.0088	S	S
	-3	0.2449	MEDIUM	S	0.0717	S	S
	-4	0.4779	STRONG	S	0.05	S	S
ROCE	-1	0.8736	SUSPICIOUS	S	0.1202	NS	NS
	-2	0.4537	STRONG	S	0.1502	NS	NS
	-3	0.128	MEDIUM	S	0.9242	NS	NS
	-4	0.2545	STRONG	S	0.9431	NS	NS
EBIT_EQ	-1	0.4227	STRONG	S	0.6235	NS	NS
	-2	0.3912	STRONG	S	0.3479	NS	NS
	-3	0.3932	STRONG	S	0.2048	NS	NS
	-4	0.2014	MEDIUM	S	0.2434	NS	NS
EBITDA_TA	-1	0.4583	STRONG	S	0.448	NS	S
	-2	0.7929	SUSPICIOUS	S	0.0053	S	S
	-3	0.5576	SUSPICIOUS	S	0.0275	S	S
	-4	0.5049	SUSPICIOUS	S	0.049	S	S
CF_TA	-1	0.769	SUSPICIOUS	S	0.0012	S	NS
	-2	0.6866	SUSPICIOUS	S	0.007	S	NS
	-3	0.5734	SUSPICIOUS	S	0.659	NS	NS
	-4	0.7187	SUSPICIOUS	S	0.0008	S	NS
CF_EQ	-1	0.4227	STRONG	S	0.0877	S	NS
	-2	0.3981	STRONG	S	0.3296	NS	NS
	-3	0.2279	MEDIUM	S	0.271	NS	NS
	-4	0.3912	STRONG	S	0.2598	NS	NS
FINANCIAL STRUCTURE							
EQ_RATIO	-1	0.4235	STRONG	S	0.0023	S	S
	-2	0.5111	SUSPICIOUS	S	0.0131	S	S
	-3	0.459	STRONG	S	0.0229	S	S
	-4	0.3624	STRONG	S	0.0747	S	S
FAT	-1	0.1932	MEDIUM	S	0.23	NS	NS
	-2	0.1875	MEDIUM	S	0.5129	NS	NS
	-3	0.1586	MEDIUM	S	0.7108	NS	NS
	-4	0.2236	MEDIUM	S	0.8005	NS	NS

TD_TA	-1	0.4185	STRONG	S	0.0007	S	S
	-2	0.5272	SUSPICIOUS	S	0.0022	S	S
	-3	0.0035	USELESS	NS	0.0071	S	S
	-4	0.4218	STRONG	S	0.0051	S	S
LTD_EQ	-1	0.6287	SUSPICIOUS	S	0.0488	S	NS
	-2	0.2837	STRONG	S	0.227	NS	NS
	-3	0.3403	STRONG	S	0.2849	NS	NS
	-4	0.0828	WEAK	NS	0.487	NS	NS
NOWC	-1	0.9949	SUSPICIOUS	S	0.0006	S	NS
	-2	0.244	MEDIUM	S	0.0267	S	NS
	-3	0.1328	MEDIUM	S	0.2129	NS	NS
	-4	0.1017	MEDIUM	S	0.1974	NS	NS
TD_EQ	-1	0.2479	MEDIUM	S	NS	NS	NS
	-2	0	USELESS	NS	NS	NS	NS
	-3	0	USELESS	NS	NS	NS	NS
	-4	0.0946	WEAK	NS	NS	NS	NS
LIQUIDITY							
CA_TA	-1	0.1946	MEDIUM	S	0.0798	S	S
	-2	0.2994	STRONG	S	0.0467	S	S
	-3	0.2646	STRONG	S	0.0494	S	S
	-4	0.024	USELESS	NS	0.1674	NS	S
CR	-1	0.5679	SUSPICIOUS	S	0.4555	NS	NS
	-2	0.1948	MEDIUM	S	0.3666	NS	NS
	-3	0.0887	WEAK	NS	0.1555	NS	NS
	-4	0.2882	STRONG	S	0.4258	NS	NS
DR	-1	0.4235	STRONG	S	0.0023	S	NS
	-2	0.5111	SUSPICIOUS	S	0.0131	S	NS
	-3	0.459	STRONG	S	0.0229	S	NS
	-4	0.3624	STRONG	S	0.0747	S	NS
WC_TA	-1	0.5326	SUSPICIOUS	S	0.0175	S	NS
	-2	0.5181	SUSPICIOUS	S	0.0526	S	NS
	-3	0.128	MEDIUM	S	0.8698	NS	NS
	-4	0.3182	STRONG	S	0.3793	NS	NS
CASH_CL	-1	0.5987	SUSPICIOUS	S	0.009	S	NS
	-2	0.3538	STRONG	S	0.0206	S	NS
	-3	0.2226	MEDIUM	S	0.2166	NS	NS
	-4	0.3615	STRONG	S	0.5139	NS	NS
CASH_TA	-1	0.3164	STRONG	S	0.1324	NS	NS
	-2	0.1141	MEDIUM	S	0.1524	NS	NS
	-3	0.1137	MEDIUM	S	0.1594	NS	NS
	-4	0.123	MEDIUM	S	0.8282	NS	NS
CL_TA	-1	0.0035	USELESS	NS	NS	NS	NS
	-2	0.0035	USELESS	NS	NS	NS	NS
	-3	0.0946	WEAK	NS	NS	NS	NS
	-4	0.0065	USELESS	NS	NS	NS	NS
CASH_CA	-1	0.3685	STRONG	S	0.0073	S	NS
	-2	0.2922	STRONG	S	0.0478	S	NS
	-3	0.1981	MEDIUM	S	0.1055	NS	NS
	-4	0.1999	MEDIUM	S	0.4105	NS	NS
CF_CL	-1	1.0513	SUSPICIOUS	S	0.1834	NS	NS
	-2	1.1251	SUSPICIOUS	S	0.2161	NS	NS
	-3	0.6668	SUSPICIOUS	S	0.4845	NS	NS
	-4	0.6798	SUSPICIOUS	S	0.1408	NS	NS
SOLVENCY							
FE_EBITDA	-1	0.6828	SUSPICIOUS	S	0.4209	NS	NS
	-2	0.5668	SUSPICIOUS	S	0.796	NS	NS
	-3	0.0946	WEAK	NS	0.0106	S	NS
	-4	0.2036	MEDIUM	S	0.1563	NS	NS
FE_NI	-1	0.9736	SUSPICIOUS	S	0.4022	NS	NS
	-2	0.2189	MEDIUM	S	0.8175	NS	NS
	-3	0.038	USELESS	NS	0.1887	NS	NS
	-4	0.5069	SUSPICIOUS	S	0.0711	NS	NS
FE_TA	-1	0.0957	WEAK	NS	NS	NS	NS
	-2	0.0329	USELESS	NS	NS	NS	NS
	-3	0.0329	USELESS	NS	NS	NS	NS
	-4	0.0946	WEAK	NS	NS	NS	NS
TURNOVER							
CA_TS	-1	0.0325	USELESS	NS	0.0271	S	S
	-2	0.4823	STRONG	S	0.0146	S	S
	-3	0.4127	STRONG	S	0.0444	S	S
	-4	0.1295	MEDIUM	S	0.1626	NS	S
CL_TS	-1	0.0035	USELESS	NS	0.0748	S	NS
	-2	0.4745	STRONG	S	0.1159	NS	NS
	-3	0.3306	STRONG	S	0.0663	S	NS
	-4	0.3152	STRONG	S	0.2084	NS	NS
WC_TS	-1	0.5606	SUSPICIOUS	S	0.6022	NS	NS
	-2	0.1321	MEDIUM	S	0.7	NS	NS
	-3	0.1292	MEDIUM	S	0.2822	NS	NS
	-4	0.2479	MEDIUM	S	0.3865	NS	NS

ACTIVITY							
CF_NS	-1	0.6786	SUSPICIOUS	S	0.3012	NS	NS
	-2	0.7162	SUSPICIOUS	S	0.03	S	NS
	-3	0.3497	STRONG	S	0.455	NS	NS
	-4	0.3488	STRONG	S	0.5297	NS	NS
GROW_TA	-1	0.4537	STRONG	S	0.51	NS	NS
	-2	0.5116	SUSPICIOUS	S	0.9802	NS	NS
	-3	0.0387	USELESS	NS	0.3038	NS	NS
	-4	0.0961	WEAK	NS	0.5249	NS	NS
EBITDA_TS	-1	0.2189	MEDIUM	S	0.1205	NS	NS
	-2	0.5168	SUSPICIOUS	S	0.0653	S	NS
	-3	0.2806	STRONG	S	0.5821	NS	NS
	-4	0.2871	STRONG	S	0.2843	NS	NS
SIZE							
TA	-1	0.1802	MEDIUM	S	0.2417	NS	NS
	-2	0.1318	MEDIUM	S	0.2944	NS	NS
	-3	0.1069	MEDIUM	S	0.3636	NS	NS
	-4	0.1009	MEDIUM	S	0.323	NS	NS
SALES	-1	0.2152	MEDIUM	S	0.5979	NS	NS
	-2	0.2719	STRONG	S	0.9897	NS	NS
	-3	0.2236	MEDIUM	S	0.7313	NS	NS
	-4	0.2776	STRONG	S	0.8508	NS	NS

References

Abu-Taha, R. (2011). Multi-criteria applications in renewable energy analysis: A literature review. In 2011 Proceedings of PICMET'11: Technology Management in the Energy Smart World (PICMET) (pp. 1-8). IEEE.

Afgan, N. H., & Carvalho, M. G. (2002). Multi-criteria assessment of new and renewable energy power plants. Energy, 27(8), 739-755.

Afgan, N. H., Carvalho, M. G. (2008). Sustainability assessment of a hybrid energy system. Energy Policy, 36 (8), 2903-2910.

Afgan, N. H., Pilavachi, P. A., & Carvalho, M. G. (2007). Multi-criteria evaluation of natural gas resources. Energy Policy, 35(1), 704-713.

Ahmad, S., & Tahar, R. M. (2014). Selection of renewable energy sources for sustainable development of electricity generation system using analytic hierarchy process: A case of Malaysia. Renewable energy, 63, 458-466.

Alam IMS, Sickles RC. (1998). The relationship between stock market returns and technical efficiency innovations: evidence from the US airline industry. Journal of Productivity Analysis, 9: 35–51.

Alanne, K., Salo, A., Saari, A., & Gustafsson, S. I. (2007). Multi-criteria evaluation of residential energy supply systems. Energy and buildings, 39(12), 1218-1226.

Albadvi, A., Chaharsooghi, S. K. and Esfahanipour, A. (2007). Decision making in stock trading: An application of PROMETHEE. European Journal of Operational Research 177(2), 673 – 683.

Al-Khazali, O. M., & Zoubi, T. A. (2005). Empirical testing of different alternative proxy measures for firm size. Journal of Applied Business Research (JABR), 21(3).

Altman E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The journal of Finance, 23 (4), 589-609

Altman, E.I., Sabato, G., Wilson, N. The value of non-financial information in small and medium-sized enterprise risk management. The Journal of Credit Risk, 6 (2010), pp. 1-33

Al-Yahyai, S., Charabi, Y., Gastli, A., & Al-Badi, A. (2012). Wind farm land suitability indexing using multi-criteria analysis. Renewable Energy, 44, 80-87.

Angilella, S., & Mazzù, S. (2015). The financing of innovative SMEs: A multicriteria credit rating model. European Journal of Operational Research, 244(2), 540-554.

Angilella, S., & Mazzù, S. (2019). A credit risk model with an automatic override for innovative small and medium-sized enterprises. Journal of the Operational Research Society, 70(10), 1784-1800.

Angilella, S., Bottero, M., Corrente, S., Ferretti, V., Greco, S., & Lami, I. M. (2016). Non Additive Robust Ordinal Regression for urban and territorial planning: an application for siting an urban waste landfill. Annals of Operations Research, 245(1-2), 427-456.

Angilella, S., Corrente, S., & Greco, S. (2015). Stochastic multiobjective acceptability analysis for the Choquet integral preference model and the scale construction problem. European Journal of Operational Research, 240(1), 172-182.

Angilella, S., Corrente, S., Greco, S., & Słowiński, R. (2016a). Robust Ordinal Regression and Stochastic Multiobjective Acceptability Analysis in multiple criteria hierarchy process for the Choquet integral preference model. Omega, 63, 154-169.

Antunes, C. H., Martins, A. G., & Springer. (2014). Multi-objective optimization and multi-criteria decision analysis in the energy sector. Multiple Criteria Decision Analysis.

APEC Energy Working Group (2013). Energy Performance Evaluation Methodology Development and Promotion in APEC Economies. Final report 2012. APEC#213-RE-01.6

Aras, H., Erdoğmuş, Ş., & Koç, E. (2004). Multi-criteria selection for a wind observation station location using analytic hierarchy process. Renewable energy, 29(8), 1383-1392.

Araz, C., & Ozkarahan, I. (2005, July). A multicriteria sorting procedure for financial classification problems: The case of business failure risk assessment. In International Conference on Intelligent Data Engineering and Automated Learning (pp. 563-570). Springer, Berlin, Heidelberg.

Araz, C., & Ozkarahan, I. (2007). Supplier evaluation and management system for strategic sourcing based on a new multicriteria sorting procedure. International journal of production economics, 106(2), 585-606.

Ardiyok, S. (2008). California energy crisis and critics of Turkish electricity deregulation process. Available at SSRN 1305208.

Arera. Relazione annuale (2018). Indagine annuale sui settori regolati 2017, vol. 2, 101 (https://www.arera.it/it/relaz_ann/18/18.htm)

Atmaca, E., & Basar, H. B. (2012). Evaluation of power plants in Turkey using Analytic Network Process (ANP). Energy, 44(1), 555-563.

Awasthi, A., & Chauhan, S. S. (2011). Using AHP and Dempster–Shafer theory for evaluating sustainable transport solutions. Environmental Modelling & Software, 26(6), 787-796.

Awasthi, A., Chauhan, S. S., & Goyal, S. K. (2010). A fuzzy multicriteria approach for evaluating environmental performance of suppliers. International Journal of Production Economics, 126(2), 370-378.

Aydin, N. Y., Kentel, E., & Duzgun, H. S. (2013). GIS-based site selection methodology for hybrid renewable energy systems: A case study from western Turkey. Energy conversion and management, 70, 90-106.

Babic, Z., & Plazibat, N. (1998). Ranking of enterprises based on multicriterial analysis. International journal of production economics, 56, 29-35.

Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems. The British Accounting Review, 38(1), 63-93.

Banker, R. D., Potter, G., & Srinivasan, D. (2000). An empirical investigation of an incentive plan that includes nonfinancial performance measures. The accounting review, 75 (1), 65-92.

Baourakis, G., Conisescu, M., Van Dijk, G., Pardalos, P. M., & Zopounidis, C. (2009). A multicriteria approach for rating the credit risk of financial institutions. Computational Management Science, 6(3), 347-356.

Barda, O. H., Dupuis, J., & Lencioni, P. (1990). Multicriteria location of thermal power plants. European Journal of Operational Research, 45(2-3), 332-346.

Barin, A., Canha, L. N., Abaide, A. D. R., Magnago, K. F., & Wottrich, B. (2009a). Multi-criteria analysis of the operation of renewable energy sources taking as basis the AHP method and fuzzy logic concerning distributed generation systems. The Online Journal on Electronics and Electrical Engineering, 1(1), 52-57.

Barin, A., Canha, L. N., da Rosa Abaide, A., & Magnago, K. F. (2009b). Selection of storage energy technologies in a power quality scenario—the AHP and the fuzzy logic. In 2009 35th Annual Conference of IEEE Industrial Electronics (pp. 3615-3620). IEEE.

Barros, J. J. C., Coira, M. L., De la Cruz López, M. P., & del Caño Gochi, A. (2015). Assessing the global sustainability of different electricity generation systems. Energy, 89, 473-489.

Beaver, W. H. (1966). Financial ratios as predictors of failure. Journal of accounting research, 71-111.

Beccali, M., Cellura, M., & Ardente, D. (1998). Decision making in energy planning: the ELECTRE multicriteria analysis approach compared to a FUZZY-SETS methodology. Energy Conversion and Management, 39(16-18), 1869-1881.

Beccali, M., Cellura, M., & Mistretta, M. (2003). Decision-making in energy planning. Application of the Electre method at regional level for the diffusion of renewable energy technology. Renewable energy, 28(13), 2063-2087.

Belton, V., & Stewart, T. (2002). Multiple criteria decision analysis: an integrated approach. Springer Science & Business Media.

Bjorgan, R., Liu, C. C., & Lawarree, J. (1999). Financial risk management in a competitive electricity market. IEEE Transactions on power systems, 14(4), 1285-1291.

Boran, F. E., Boran, K., & Menlik, T. (2012). The evaluation of renewable energy technologies for electricity generation in Turkey using intuitionistic fuzzy TOPSIS. Energy Sources, Part B: Economics, Planning, and Policy, 7(1), 81-90.

Bouyssou, D. (1990). Building criteria: a prerequisite for MCDA. In Readings in multiple criteria decision aid (pp. 58-80). Springer, Berlin, Heidelberg.

Brans, J. P., & De Smet, Y. (2016). PROMETHEE methods. In Multiple criteria decision analysis (pp. 187-219). Springer, New York, NY.

Burton, J., & Hubacek, K. (2007). Is small beautiful? A multicriteria assessment of small-scale energy technology applications in local governments. Energy policy, 35(12), 6402-6412.

Cannemi, M., García-Melón, M., Aragonés-Beltrán, P., & Gómez-Navarro, T. (2014). Modeling decision making as a support tool for policy making on renewable energy development. Energy policy, 67, 127-137.

Capece, G., Di Pillo, F., & Levialdi, N. (2013). The performance assessment of energy companies. APCBEE procedia, 5, 265-270.

Capotorti, A., & Barbanera, E. (2012). Credit scoring analysis using a fuzzy probabilistic rough set model. Computational Statistics & Data Analysis, 56(4), 981-994.

Carrino, L. (2017). The role of normalisation in building composite indicators. Rationale and consequences of different strategies, applied to social inclusion. In Complexity in Society: From Indicators Construction to their Synthesis (pp. 251-289). Springer, Cham.

Cavallaro, F. (2009). Multi-criteria decision aid to assess concentrated solar thermal technologies. Renewable Energy, 34(7), 1678-1685.

Cavallaro, F., & Ciraolo, L. (2005). A multicriteria approach to evaluate wind energy plants on an Italian island. *Energy policy*, *33*(2), 235-244.

Chang, C. T. (2015). Multi-choice goal programming model for the optimal location of renewable energy facilities. Renewable and Sustainable Energy Reviews, 41, 379-389.

Chatzimouratidis, A. I., & Pilavachi, P. A. (2007). Objective and subjective evaluation of power plants and their non-radioactive emissions using the analytic hierarchy process. Energy policy, 35(8), 4027-4038.

Chatzimouratidis, A. I., & Pilavachi, P. A. (2008). Multicriteria evaluation of power plants impact on the living standard using the analytic hierarchy process. Energy policy, 36(3), 1074-1089.

Chatzimouratidis, A. I., & Pilavachi, P. A. (2009). Technological, economic and sustainability evaluation of power plants using the Analytic Hierarchy Process. Energy policy, 37(3), 778-787.

Chen, H. H., Kang, H. Y., & Lee, A. H. (2010). Strategic selection of suitable projects for hybrid solar-wind power generation systems. Renewable and Sustainable Energy Reviews, 14(1), 413-421.

Cheymetova, V. A., & Scherbakov, V. V. (2017). Methodological approaches to managerial efficiency evaluation of organization. Espacios, 38(48), 8-8

Choudhary, D., & Shankar, R. (2012). An STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: A case study from India. Energy, 42(1), 510-521.

Chu, T. C. (2002). Facility location selection using fuzzy TOPSIS under group decisions. International journal of uncertainty, fuzziness and knowledge-based systems, 10(06), 687-701.

Cinelli, M. (2017). The art of supporting decision-making. Exchanges. The Interdisciplinary Research Journal, 4(2), 298-308

Cinelli, M., Kadziński, M., Gonzalez, M., & Słowiński, R. (2020). How to Support the Application of Multiple Criteria Decision Analysis? Let Us Start with a Comprehensive Taxonomy. Omega, 102261.

Ciomek, K., Kadziński, M., & Tervonen, T. (2017). Heuristics for selecting pair-wise elicitation questions in multiple criteria choice problems. European Journal of Operational Research, 262(2), 693-707.

Çolak, M., & Kaya, İ. (2017). Prioritization of renewable energy alternatives by using an integrated fuzzy MCDM model: A real case application for Turkey. Renewable and sustainable energy reviews, 80, 840-853.

Compustat Database from S&P Global Market Intelligence, S&P Capital IQ (https://www.capitaliq.com) |Accessed 13 June 2019.

Corazza, M., Funari, S., & Gusso, R. (2016). Creditworthiness evaluation of Italian SMEs at the beginning of the 2007–2008 crisis: An MCDA approach. The North American Journal of Economics and Finance, 38, 1-26.

Corrente, S., Figueira, J. R., & Greco, S. (2014). The Smaa-Promethee method. European Journal of Operational Research, 239(2), 514-522.

Corrente, S., Greco, S., & SłOwińSki, R. (2012). Multiple criteria hierarchy process in robust ordinal regression. Decision Support Systems, 53(3), 660-674.

Dahlgren, R., Liu, C. C., & Lawarree, J. (2003). Risk assessment in energy trading. IEEE Transactions on Power Systems, 18(2), 503-511.

De Condorcet, N. (2014). Essai sur l'application de l'analyse à la probabilité des décisions rendues à la pluralité des voix. Cambridge University Press.

De Matteis, D., Ishizaka, A., & Resce, G. (2019). The 'postcode lottery' of the Italian public health bill analysed with the hierarchy Stochastic Multiobjective Acceptability Analysis. Socio-Economic Planning Sciences, 68, 100603.

De Toni, A., & Tonchia, S. (2001). Performance measurement systems-models, characteristics and measures. International journal of operations & production management.

Denton, M., Palmer, A., Masiello, R., & Skantze, P. (2003). Managing market risk in energy. IEEE Transactions on Power Systems, 18(2), 494-502.

Desa, U. N. (2016). Transforming our world: The 2030 agenda for sustainable development.

Diakoulaki, D., & Karangelis, F. (2007). Multi-criteria decision analysis and cost–benefit analysis of alternative scenarios for the power generation sector in Greece. Renewable and sustainable energy reviews, 11(4), 716-727.

Diakoulaki, D., Antunes, C. H., & Martins, A. G. (2005). MCDA and energy planning. In Multiple criteria decision analysis: state of the art surveys (pp. 859-890). Springer, New York, NY.

Diakoulaki, D., Zopounidis, C., Mavrotas, G., & Doumpos, M. (1999). The use of a preference disaggregation method in energy analysis and policy making. Energy, 24(2), 157-166.

Dias, L. C., Antunes, C. H., Dantas, G., de Castro, N., & Zamboni, L. (2018). A multi-criteria approach to sort and rank policies based on Delphi qualitative assessments and ELECTRE TRI: The case of smart grids in Brazil. Omega, 76, 100-111.

Dinca, C., Badea, A., Rousseaux, P., & Apostol, T. (2007). A multi-criteria approach to evaluate the natural gas energy systems. Energy Policy, 35(11), 5754-5765.

Ding, Y., Fu, Y., Lai, K. K., & Leung, W. J. (2018). Using ranked weights and acceptability analysis to construct composite indicators: A case study of regional sustainable society index. *Social Indicators Research*, *139*(3), 871-885.

Doukas, H. (2013). Modelling of linguistic variables in multicriteria energy policy support. European Journal of Operational Research, 227(2), 227-238.

Doukas, H. C., Andreas, B. M., & Psarras, J. E. (2007). Multi-criteria decision aid for the formulation of sustainable technological energy priorities using linguistic variables. European Journal of Operational Research, 182(2), 844-855.

Doukas, H., & Psarras, J. (2009). A linguistic decision support model towards the promotion of renewable energy. Energy Sources, Part B, 4(2), 166-178.

Doumpos, M. & Zopounidis, C. (2010). A multicriteria decision support system for bank rating. Decision Support Systems 50(1), 55–63.

Doumpos, M. (2012). Learning non-monotonic additive value functions for multicriteria decision making. OR spectrum, 34(1), 89-106.

Doumpos, M., & Figueira, J. R. (2019). A multicriteria outranking approach for modeling corporate credit ratings: An application of the Electre Tri-nC method. Omega, 82, 166-180.

Doumpos, M., & Pasiouras, F. (2005). Developing and testing models for replicating credit ratings: A multicriteria approach. Computational Economics, 25(4), 327-341.

Doumpos, M., & Zopounidis, C. (1999). A multicriteria discrimination method for the prediction of financial distress: The case of Greece. Multinational Finance Journal, 3(2), 71-101.

Doumpos, M., & Zopounidis, C. (2001). Assessing financial risks using a multicriteria sorting procedure: the case of country risk assessment. Omega, 29(1), 97-109.

Doumpos, M., & Zopounidis, C. (2002). Multi–criteria classification methods in financial and banking decisions. International Transactions in Operational Research, 9(5), 567-581.

Doumpos, M., & Zopounidis, C. (2011). A multicriteria outranking modeling approach for credit rating. Decision Sciences, 42(3), 721-742.

Doumpos, M., & Zopounidis, C. (2014). Multicriteria analysis in finance. New York: Springer.

Doumpos, M., Andriosopoulos, K., Galariotis, E., Makridou, G., & Zopounidis, C. (2017). Corporate failure prediction in the European energy sector: A multicriteria approach and the effect of country characteristics. European Journal of Operational Research, 262(1), 347-360.

Doumpos, M., Kosmidou, K., Baourakis, G., & Zopounidis, C. (2002). Credit risk assessment using a multicriteria hierarchical discrimination approach: A comparative analysis. European Journal of Operational Research, 138(2), 392-412.

Doumpos, M., Pentaraki, K., Zopounidis, C., & Agorastos, C. (2000). Assessing country risk using a multi-group discrimination method: A comparative analysis. In Decision Making: Recent Developments and Worldwide Applications (pp. 361-377). Springer, Boston, MA.

Doumpos, M., Zopounidis, C., & Fragiadakis, P. (2016). Assessing the financial performance of European banks under stress testing scenarios: a multicriteria approach. Operational Research, 16(2), 197-209.

Du Jardin, P. (2016). A two-stage classification technique for bankruptcy prediction. European Journal of Operational Research, 254(1), 236-252.

EBRD (2013). Energy sector strategy. Document of the European bank for reconstruction and development (https://www.ebrd.com/downloads/policies/sector/energy-sector-strategy.pdf).

Edwards, D. (2014). The link between company environmental and financial performance (Routledge Revivals). Routledge.

Engelmann, B., Hayden, E., & Tasche, D. (2003). Measuring the discriminative power of rating systems (No. 2003, 01)

Erol, I., Sencer, S., & Sari, R. (2011). A new fuzzy multi-criteria framework for measuring sustainability performance of a supply chain. Ecological Economics, 70(6), 1088-1100.

EU Commission. (2011). Energy roadmap 2050. Brussels, XXX COM (2011), 885(2).

Eyüboglu, K., & Çelik, P. (2016). Financial Performance Evaluation of Turkish Energy Companies with Fuzzy AHP and Fuzzy TOPSIS Methods. Business and economics research Journal, 7(3), 21.

Farsi, M., Filippini, M., & Kuenzle, M. (2007). Cost efficiency in the Swiss gas distribution sector. Energy Economics, 29(1), 64-78.

Fawcett, T. (2006). An introduction to ROC analysis. Pattern recognition letters, 27(8), 861-874.

Figueira, J. J., De Smet, Y., & Brans, J. P. (2005). MCDA methods for sorting and clustering problems: Promethee TRI and Promethee CLUSTER.

Figueira, J., & Roy, B. (2002). Determining the weights of criteria in the ELECTRE type methods with a revised Simos' procedure. European journal of operational research, 139(2), 317-326.

Figueira, J., Greco, S., & Ehrgott, M. (Eds.). (2005). Multiple criteria decision analysis: state of the art surveys (Vol. 78). Springer Science & Business Media.

Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., ... & Suh, S. (2009). Recent developments in life cycle assessment. Journal of environmental management, 91(1), 1-21.

Gaganis, C. (2016). Assessing the overall performance of microfinance institutions. International Journal of Banking, Accounting and Finance 7(1), 52–83.

García, F., Guijarro, F., & Moya, I. (2013). Monitoring credit risk in the social economy sector by means of a binary goal-programming model. Service Business, 7(3), 483-495.

Gasser, P., Cinelli, M., Spada, M., Burgherr, P., & Stojadinović, B. (2019). Indices under the spotlight: An approach to unveil and manage the implicit trade-offs between indicators. In European Safety and Reliability Conference.

Gasser, P., Suter, J., Cinelli, M., Spada, M., Burgherr, P., Hirschberg, S., Kadziński, M. & Stojadinović, B. (2020). Comprehensive resilience assessment of electricity supply security for 140 countries. Ecological Indicators, 110, 105731.

Geldermann, J., Spengler, T., & Rentz, O. (2000). Fuzzy outranking for environmental assessment. Case study: iron and steel making industry. Fuzzy sets and systems, 115(1), 45-65.

Geneletti, D., & Ferretti, V. (2015). Multicriteria analysis for sustainability assessment: concepts and case studies. In Handbook of sustainability assessment. Edward Elgar Publishing.

Georgopoulou, E., Lalas, D., & Papagiannakis, L. (1997). A multicriteria decision aid approach for energy planning problems: The case of renewable energy option. European journal of operational research, 103(1), 38-54.

Ghalayini, A. M., & Noble, J. S. (1996). The changing basis of performance measurement. International journal of operations & production management

Golabi, K., Kirkwood, C. W., & Sicherman, A. (1981). Selecting a portfolio of solar energy projects using multiattribute preference theory. Management Science, 27(2), 174-189.

Gorzałczany, M. B., & Rudziński, F. (2016). A multi-objective genetic optimization for fast, fuzzy rule-based credit classification with balanced accuracy and interpretability. Applied Soft Computing, 40, 206-220.

Goumas, M. G., Lygerou, V. A., & Papayannakis, L. E. (1999). Computational methods for planning and evaluating geothermal energy projects. Energy policy, 27(3), 147-154.

Goumas, M., & Lygerou, V. (2000). An extension of the PROMETHEE method for decision making in fuzzy environment: Ranking of alternative energy exploitation projects. European Journal of Operational Research, 123(3), 606-613.

Greco, S., Figueira, J., & Ehrgott, M. (2016). Multiple criteria decision analysis. New York: Springer.

Greco, S., Matarazzo, B., & Slowinski, R. (2001). Rough sets theory for multicriteria decision analysis. European journal of operational research, 129(1), 1-47.

Greco, S., Słowiński, R., Figueira, J. R., & Mousseau, V. (2010). Robust ordinal regression. In Trends in multiple criteria decision analysis (pp. 241-283). Springer, Boston, MA.

Greening, L. A., & Bernow, S. (2004). Design of coordinated energy and environmental policies: use of multi-criteria decision-making. Energy policy, 32(6), 721-735.

GRI - Global Reporting Initiative (2002). The Global Reporting Initiative – An overview. Global Reporting Initiative, Boston USA. (http://www.globalreporting.org)

Guo, D., Chen, H., & Long, R. (2016). Who reports high company performance? A quantitative study of Chinese listed companies in the energy industry. SpringerPlus, 5(1), 20-41.

Haddad, B., Liazid, A., & Ferreira, P. (2017). A multi-criteria approach to rank renewables for the Algerian electricity system. Renewable energy, 107, 462-472.;

Hämäläinen, R. P., & Karjalainen, R. (1992). Decision support for risk analysis in energy policy. European Journal of Operational Research, 56(2), 172-183.

Haralambopoulos, D. A., & Polatidis, H. (2003). Renewable energy projects: structuring a multi-criteria group decision-making framework. Renewable energy, 28(6), 961-973.

Hatefi, S. M., & Torabi, S. A. (2010). A common weight MCDA–DEA approach to construct composite indicators. Ecological Economics, *70*(1), 114-120.

Hera Group. Consolidated non-financial report (2017) p. 220 (https://www.gruppohera.it/binary/hr_gruppo/download_center/GruppoHera_Bilancio_di_Sostenibilita2017.1522856170.pdf).

Hirschberg, S., Dones, R., Heck, T., Burgherr, P., Schenler, W., & Bauer, C. (2004). Sustainability of electricity supply technologies under German conditions: a comparative evaluation. Paul Scherrer Institut, 04-15.

Hu, Y.-C. & Chen, C.-J. (2011). A PROMETHEE-based classification method using concordance and discordance relations and its application to bankruptcy prediction. Information Sciences 181(22), 4959 – 4968.

Ibáñez-Forés, V., Bovea, M. D., & Pérez-Belis, V. (2014). A holistic review of applied methodologies for assessing and selecting the optimal technological alternative from a sustainability perspective. Journal of Cleaner Production, 70, 259-281.

Iberian Data Flyer 2017- EDP Espana. The living energy book. Market shares in the Iberian Peninsula p.4 (https://espana.edp.com/sites/default/files/portal.es/documents/iberian_data_flyer_2017.pdf) | Accessed 17 June 2019.

IEA, IRENA, UNSD, World Bank and WHO (2020). Tracking SDG 7: The energy progress report 2020. International Renewable Energy Agency, United Nations Statistics Division, World Bank and World Health Organization, Washington, D.C.

IRENA (2018). Global energy transformation: A roadmap to 2050. International Renewable Energy Agency, Abu Dhabi.

IRENA (2020). Global renewables outlooks: energy transformation 2050. International Renewable Energy Agency, Abu Dhabi.

Jaber, J. O., Jaber, Q. M., Sawalha, S. A., & Mohsen, M. S. (2008). Evaluation of conventional and renewable energy sources for space heating in the household sector. Renewable and Sustainable Energy Reviews, 12(1), 278-289.

Jacquet-Lagreze, E., & Siskos, Y. (2001). Preference disaggregation: 20 years of MCDA experience. European

Journal of Operational Research, 130(2), 233-245.

Jakeman, M. (2019). Global Economy Watch: the global economy has become much more energy efficient. But are there further gains to come? (https://www.pwc.com/gx/en/issues/economy/global-economy-watch/assets/pdfs/efficient-global-economy-july-2019.pdf).

Jamasb, T., & Pollitt, M. (2005). Electricity market reform in the European Union: review of progress toward liberalization & integration. The Energy Journal, 11-41.

Jamasb, T., Orea, L., & Pollitt, M. (2012). Estimating the marginal cost of quality improvements: The case of the UK electricity distribution companies. Energy Economics, 34(5), 1498-1506.

Jardini, J. A., Ramos, D. S., Martini, J. S. C., Reis, L. B., & Tahan, C. M. A. (2002). Brazilian energy crisis. IEEE Power Engineering Review, 22(4), 21-24.

Joint Research Centre-European Commission. (2008). Handbook on constructing composite indicators: methodology and user guide. OECD publishing.

Jovanović, M., Afgan, N., Radovanović, P., & Stevanović, V. (2009). Sustainable development of the Belgrade energy system. Energy, 34(5), 532-539.

Jun, D., Tian-tian, F., Yi-sheng, Y., & Yu, M. (2014). Macro-site selection of wind/solar hybrid power station based on ELECTRE-II. Renewable and Sustainable Energy Reviews, 35, 194-204.

Jung, N., Moula, M. E., Fang, T., Hamdy, M., & Lahdelma, R. (2016). Social acceptance of renewable energy technologies for buildings in the Helsinki Metropolitan Area of Finland. Renewable energy, 99, 813-824.

Kabak, M., & Dağdeviren, M. (2014). Prioritization of renewable energy sources for Turkey by using a hybrid MCDM methodology. Energy Conversion and Management, 79, 25-33.

Kablan, M. M. (2004). Decision support for energy conservation promotion: an analytic hierarchy process approach. Energy policy, 32(10), 1151-1158.

Kahraman, C., Kaya, İ., & Cebi, S. (2009). A comparative analysis for multi-attribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process. Energy, 34(10), 1603-1616.

Kambo, N. S., Handa, B. R., & Bose, R. K. (1991). A linear goal programming model for urban energy-economy-environment interaction. Energy and Buildings, 16(1-2), 537-551.

Kaya, T., & Kahraman, C. (2010). Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul. Energy, 35(6), 2517-2527.

Keenan, S., & Sobehart, J. R. (1999). Performance measures for credit risk models. Moody's Risk Management Services, 10.

Keeney, R. & Raiffa, H. (1976). Decision with Multiple Objectives: Preferences and Value Tradeoffs. Wiley and Sons, New York.

Keeney, R. L., & Raiffa, H. (1993). Decisions with multiple objectives: preferences and value trade-offs. Cambridge university press

Khodabakhshi, B., & Jafari, H. R. (2010). Environmental impact assessment of water resources development projects using the electre_TRI model (A case study of Ardebil reservoir, drainage, and irrigation network). Water and Wastewater 2, 13(75), 64-74.

Kirppu, H., Lahdelma, R., & Salminen, P. (2018). Multicriteria evaluation of carbon-neutral heat-only production technologies for district heating. Applied Thermal Engineering, 130, 466-476.

Klassen, R. D., & McLaughlin, C. P. (1996). The impact of environmental management on firm performance. Management science, 42(8), 1199-1214.

Kočenda, E., & Čábelka, Š. (1998). Liberalization in the energy sector: transition and growth. Journal of Economics, 70(1), 65-94.

Köne, A. Ç., & Büke, T. (2007). An Analytical Network Process (ANP) evaluation of alternative fuels for electricity generation in Turkey. Energy policy, 35(10), 5220-5228.

Kontu, K., Rinne, S., Olkkonen, V., Lahdelma, R., & Salminen, P. (2015). Multicriteria evaluation of heating choices for a new sustainable residential area. Energy and Buildings, 93, 169-179.

Kosmidou, K., Doumpos, M., & Zopounidis, C (2004). Multicriteria methodology for the evaluation of country's financial risk. Springer

Kosmidou, K., Doumpos, M., & Zopounidis, C. D. (2002). A multicriteria hierarchical discrimination approach for credit risk problems.

La Rovere, E. L., Soares, J. B., Oliveira, L. B., & Lauria, T. (2010). Sustainable expansion of electricity sector: Sustainability indicators as an instrument to support decision-making. Renewable and Sustainable Energy Reviews, 14(1), 422-429.

Lahdelma, R., & Salminen, P. (2001). SMAA-2: Stochastic multicriteria acceptability analysis for group decision making. Operations research, 49(3), 444-454.

Lahdelma, R., & Salminen, P. (2006). Stochastic multicriteria acceptability analysis using the data envelopment model. European Journal of Operational Research, 170(1), 241-252.

Lahdelma, R., Hokkanen, J., & Salminen, P. (1998). SMAA-stochastic multiobjective acceptability analysis. European Journal of Operational Research, 106(1), 137-143.

Lahdelma, R., Makkonen, S., & Salminen, P. (2006). Multivariate Gaussian criteria in SMAA. European Journal of Operational Research, 170(3), 957-970.

Lahdelma, R., Makkonen, S., & Salminen, P. (2009). Two ways to handle dependent uncertainties in multi-criteria decision problems. Omega, 37(1), 79-92.

Lahdelma, R., Miettinen, K., & Salminen, P. (2003). Ordinal criteria in stochastic multicriteria acceptability analysis (SMAA). European Journal of Operational Research, 147(1), 117-127.

Langhans, S. D., Reichert, P., & Schuwirth, N. (2014). The method matters: a guide for indicator aggregation in ecological assessments. Ecological indicators, 45, 494-507.

Larsen, E. R., van Ackere, A., & Osorio, S. (2018). Can electricity companies be too big to fail? Energy Policy, 119, 696-703.

Laurent, A., & Hauschild, M. Z. (2015). Normalisation. In Life cycle impact assessment (pp. 271-300). Springer, Dordrecht.

Léautier, T., & Crampes, C. (2016). Liberalisation of the European electricity markets: a glass half full. Florebce School of Regulation.

Lee, S. K., Mogi, G., & Kim, J. W. (2008). The competitiveness of Korea as a developer of hydrogen energy technology: the AHP approach. Energy policy, 36(4), 1284-1291.

Lee, S. K., Yoon, Y. J., & Kim, J. W. (2007). A study on making a long-term improvement in the national energy efficiency and GHG control plans by the AHP approach. Energy policy, 35(5), 2862-2868.

Liang, D., Lu, C. C., Tsai, C. F., & Shih, G. A. (2016). Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study. European Journal of Operational Research, 252(2), 561-572.

Liko G. (2019). Impacts of Energy Sector on Economy, Social and Political Landscape, and Sustainable Development. DOI: 10.13140/RG.2.2.12626.91847.

Liu, C. H., Lin, S. J., & Lewis, C. (2010). Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. Energy policy, 38(2), 1049-1058.

Liu, K. F., & Lai, J. H. (2009). Decision-support for environmental impact assessment: A hybrid approach using fuzzy logic and fuzzy analytic network process. Expert Systems with Applications, 36(3), 5119-5136.

Lotfi, F. H., & Fallahnejad, R. (2010). Imprecise Shannon’s entropy and multi attribute decision making. Entropy, 12(1), 53-62.

Loikkanen, O., Lahdelma, R., & Salminen, P. (2017). Multicriteria evaluation of sustainable energy solutions for Colosseum. Sustainable cities and society, 35, 289-297.

Lozano-Minguez, E., Kolios, A. J., & Brennan, F. P. (2011). Multi-criteria assessment of offshore wind turbine support structures. Renewable Energy, 36(11), 2831-2837.

Luthra, S., Mangla, S. K., & Kharb, R. K. (2015). Sustainable assessment in energy planning and management in Indian perspective. Renewable and Sustainable Energy Reviews, 47, 58-73.

Madlener, R., Kowalski, K., & Stagl, S. (2007). New ways for the integrated appraisal of national energy scenarios: the case of renewable energy use in Austria. Energy Policy, 35(12), 6060-6074.

Mardani, A., Jusoh, A., Zavadskas, E., Cavallaro, F., & Khalifah, Z. (2015). Sustainable and renewable energy: An overview of the application of multiple criteria decision making techniques and approaches. Sustainability, 7(10), 13947-13984.

Mareschal, B. & Brans, J. (1991). Bank adviser: An industrial evaluation system. European Journal of Operational Research 54(3), 318 – 324.

Mareschal, B., Brans, J. P., & Vincke, P. (1984). PROMETHEE: A new family of outranking methods in multicriteria analysis (No. 2013/9305). ULB: Universite Libre de Bruxelles.

Mateo, J. R. S. C. (2012). Multi-criteria analysis. In Multi criteria analysis in the renewable energy industry (pp. 7-10). Springer, London.

Mavrotas, G., Diakoulaki, D., & Capros, P. (2003). Combined MCDA–IP approach for project selection in the electricity market. Annals of Operations Research, 120(1-4), 159-170.

Maxim, A. (2014). Sustainability assessment of electricity generation technologies using weighted multi-criteria decision analysis. Energy Policy, 65, 284-297.

Mays, F. E., & Lynas, N. (2004). Credit scoring for risk managers: The handbook for lenders. Ohio: Thomson/South-Western

McDaniels, T. L. (1996). A multiattribute index for evaluating environmental impacts of electric utilities. Journal of environmental management, 46(1), 57-66.

McNamara, W. (2002). California Energy Crisis: Lessons for a Deregulating Industry. PennWell Books.

Mendecka, B., Lombardi, L., & Kozioł, J. (2020). Probabilistic multi-criteria analysis for evaluation of biodiesel production technologies from used cooking oil. Renewable Energy, 147, 2542-2553.

Meyer, N. I. (2003). Distributed generation and the problematic deregulation of energy markets in Europe. International Journal of Sustainable Energy, 23(4), 217-221.

Michalik, G., Khan, M. E., Bonwick, W. J., & Mielczarski, W. (1997). Structural modelling of energy demand in the residential sector: 2. The use of linguistic variables to include uncertainty of customers' behaviour. Energy, 22(10), 949-958.

Mohsen, M. S., & Akash, B. A. (1997). Evaluation of domestic solar water heating system in Jordan using analytic hierarchy process. Energy Conversion and Management, 38(18), 1815-1822.

Mousavi, M. M., & Lin, J. (2020). The application of PROMETHEE Multi-criteria Decision Aid in Financial Decision Making: Case of Distress Prediction Models Evaluation. Expert Systems with Applications, 113438.

Mundial, F. E. (2017). Global Energy Architecture Performance Index. Report 2017. Cologny/Geneva (Switzerland), World Economic Forum.

Neely, A. D., Adams, C., & Kennerley, M. (2002). The performance prism: The Business performance measurement and management: implementation of principles in smes and enterprise networks scorecard for measuring and managing business success. London: Prentice Hall Financial Times.

Neves, L. P., Martins, A. G., Antunes, C. H., & Dias, L. C. (2008). A multi-criteria decision approach to sorting actions for promoting energy efficiency. Energy Policy, 36(7), 2351-2363.

Nikolic, N., Zarkic-Joksimovic, N., Stojanovski, D., & Joksimovic, I. (2013). The application of brute force logistic regression to corporate credit scoring models: Evidence from Serbian financial statements. Expert Systems with Applications, 40(15), 5932-5944.

Ofgem Data Portal, Retail energy market and indicators. State of the energy market 2017 (https://www.ofgem.gov.uk/data-portal/retail-market-indicators) | Accessed 17 June 2019.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Journal of accounting research, 109-131.

Osorio, S., Larsen, E. R., & van Ackere, A. (2017). Too Big to Fail in the Electricity Sector. In Meeting the Energy Demands of Emerging Economies, 40th IAEE International Conference. International Association for Energy Economics.

Ozturk, I. (2010). A literature survey on energy–growth nexus. Energy policy, 38(1), 340-349.

Pan, J., Teklu, Y., Rahman, S., & de Castro, A. (2000). An interval-based MADM approach to the identification of candidate alternatives in strategic resource planning. IEEE Transactions on Power Systems, 15(4), 1441-1446.

Papadopoulos, A., & Karagiannidis, A. (2008). Application of the multi-criteria analysis method Electre III for the optimisation of decentralised energy systems. Omega, 36(5), 766-776.

Pasiouras, F., Gaganis, C., & Zopounidis, C. (2010). Multicriteria classification models for the identification of targets and acquirers in the Asian banking sector. European Journal of Operational Research, 204(2), 328-335.

Payne, J. E. (2010). Survey of the international evidence on the causal relationship between energy consumption and growth. Journal of Economic Studies.

Pelissari, R., Oliveira, M. C., Amor, S. B., Kandakoglu, A., & Helleno, A. L. (2019). SMAA methods and their applications: a literature review and future research directions. Annals of Operations Research, 1-61.

Peng, C., Wu, X., Fu, Y., & Lai, K. K. (2017). Alternative approaches to constructing composite indicators: an application to construct a Sustainable Energy Index for APEC economies. Operational Research, 17(3), 747-759.

Pilavachi, P. A., Stephanidis, S. D., Pappas, V. A., & Afgan, N. H. (2009). Multi-criteria evaluation of hydrogen and natural gas fuelled power plant technologies. Applied Thermal Engineering, 29(11-12), 2228-2234.

Poh, K. L., & Ang, B. W. (1999). Transportation fuels and policy for Singapore: an AHP planning approach. Computers & industrial engineering, 37(3), 507-525;

Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. Renewable and sustainable energy reviews, 8(4), 365-381.

Powers, D. M. (2015). What the F-measure doesn't measure: Features, Flaws, Fallacies and Fixes. arXiv preprint arXiv:1503.06410.

Prescott, J. E., Kohli, A. K., & Venkatraman, N. (1986). The market share-profitability relationship: An empirical assessment of major assertions and contradictions. Strategic Management Journal, 7(4), 377-394.

Psillaki, M., Tsolas, I. E., & Margaritis, D. (2010). Evaluation of credit risk based on firm performance. European Journal of Operational Research, 201(3), 873-881.

Rahman, M. M., Paatero, J. V., & Lahdelma, R. (2013). Evaluation of choices for sustainable rural electrification in developing countries: A multicriteria approach. Energy Policy, 59, 589-599.

Rahman, M. M., Paatero, J. V., Lahdelma, R., & Wahid, M. A. (2016). Multicriteria-based decision aiding technique for assessing energy policy elements-demonstration to a case in Bangladesh. Applied energy, 164, 237-244.

Ramanathan, R., & Ganesh, L. S. (1993). A multi-objective programming approach to energy resource allocation problems. International journal of energy research, 17(2), 105-119.

Ramanathan, R., & Ganesh, L. S. (1995). Energy resource allocation incorporating qualitative and quantitative criteria: An integrated model using goal programming and AHP. Socio-Economic Planning Sciences, 29(3), 197-218.

Ramaswami, S. N., Srivastava, R. K., & Bhargava, M. (2009). Market-based capabilities and financial performance of firms: insights into marketing’s contribution to firm value. Journal of the Academy of Marketing Science, 37(2), 97.

Razeghi, G., Shaffer, B., & Samuelsen, S. (2017). Impact of electricity deregulation in the state of California. Energy Policy, 103, 105-115.

Ren, F. (2010). Optimal site selection for thermal power plant based on rough sets and multi-objective programming. In 2010 International Conference on E-Product E-Service and E-Entertainment (pp. 1-5). IEEE.

Rogers, M., & Bruen, M. (1998). A new system for weighting environmental criteria for use within ELECTRE III. European Journal of Operational Research, 107(3), 552-563.

Roulet, C. A., Flourentzou, F., Labben, H. H., Santamouris, M., Koronaki, I., Dascalaki, E., & Richalet, V. (2002). ORME: A multicriteria rating methodology for buildings. Building and Environment, 37(6), 579-586.

Roy, B. (1990). Decision-aid and decision-making. European Journal of Operational Research, 45(2-3), 324-331.

Roy, B. (1996). Multicriteria Methodology for Decision Aiding (Vol. 12). Springer Science & Business Media.

Roy, B. (2013). Multicriteria methodology for decision aiding (Vol. 12). Springer Science & Business Media.

Rusinko, C. (2007). Green manufacturing: an evaluation of environmentally sustainable manufacturing practices and their impact on competitive outcomes. IEEE Transactions on Engineering Management, 54(3), 445-454.

Saaty, T. L. (2016). The analytic hierarchy and analytic network processes for the measurement of intangible criteria and for decision-making. In Multiple criteria decision analysis (pp. 363-419). Springer, New York, NY.

Sadeghi, M., & Ameli, A. (2012). An AHP decision-making model for optimal allocation of energy subsidy among socio-economic subsectors in Iran. Energy Policy, 45, 24-32.;

Safai, M. (2011). California Electricity Crisis 2001.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Computer physics communications, 181(2), 259-270.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). Methods based on Decomposing the Variance of the Output. Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models, 216.

San Cristóbal, J. R. (2011). Multi-criteria decision-making in the selection of a renewable energy project in spain: The Vikor method. Renewable energy, 36(2), 498-502.

Sánchez-Lozano, J. M., Antunes, C. H., García-Cascales, M. S., & Dias, L. C. (2014). GIS-based photovoltaic solar farms site selection using ELECTRE-TRI: Evaluating the case for Torre Pacheco, Murcia, Southeast of Spain. Renewable Energy, 66, 478-494.

Sarkar, M. B., Echambadi, R. A. J., & Harrison, J. S. (2001). Alliance entrepreneurship and firm market performance. Strategic management journal, 22(6-7), 701-711.

Sayers, T. M., Jessop, A. T., & Hills, P. J. (2003). Multi-criteria evaluation of transport options—flexible, transparent and user-friendly? *Transport policy*, *10*(2), 95-105.

Sen, P., & Yang, J. B. (2012). Multiple criteria decision support in engineering design. Springer Science & Business Media.

Şengül, Ü., Eren, M., Shiraz, S. E., Gezder, V., & Şengül, A. B. (2015). Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. Renewable energy, 75, 617-625.

Shakouri, H., Nabaee, M., & Aliakbarisani, S. (2014). A quantitative discussion on the assessment of power supply technologies: DEA (data envelopment analysis) and SAW (simple additive weighting) as complementary methods for the “Grammar”. Energy, 64, 640-647.

Sheikh, N. A., Wang, Z., & Khan, S. (2013). The impact of internal attributes of corporate governance on firm performance. International Journal of Commerce and Management.

Shiue, Y. C., & Lin, C. Y. (2012). Applying analytic network process to evaluate the optimal recycling strategy in upstream of solar energy industry. Energy and Buildings, 54, 266-277.

Shrivastava, P. (1995). Environmental technologies and competitive advantage. Strategic management journal, 16(S1), 183-200.

Siddipi, N. (2012). Credit risk scorecards: developing and implementing intelligent credit scoring (Vol. 3). John Wiley & Sons.

Silva, E. S., & Pereira, A. (2014). Credit risk measures: a case of renewable energy companies. In II International Conference Economy-Ethics-Environment. Nicolaus Copernicus University in Torun.

Siskos, J., & Hubert, P. (1983). Multi-criteria analysis of the impacts of energy alternatives: a survey and a new comparative approach. European Journal of Operational Research, 13(3), 278-299.

Slowinski, R., & Zopounidis, C. (1995). Application of the rough set approach to evaluation of bankruptcy risk. Intelligent Systems in Accounting, Finance and Management, 4(1), 27-41.

Smith, R. L. (1984). Efficient Monte Carlo procedures for generating points uniformly distributed over bounded regions. Operations Research, 32(6), 1296-1308.

Sobehart, J., & Keenan, S. (2001). Measuring default accurately. *Risk*, *14*(3), 31-33.

Song, L., Fu, Y., Zhou, P., & Lai, K. K. (2017). Measuring national energy performance via energy trilemma index: A stochastic multicriteria acceptability analysis. Energy Economics, 66, 313-319.

Spathis, C., Doumpos, M., & Zopounidis, C. (2004). A multicriteria discrimination approach to model qualified audit reports. Operational Research, 4(3), 347-355.

Spronk, J., Steuer, R. E., & Zopounidis, C. (2005). Multicriteria decision aid/analysis in finance. In Multiple criteria decision analysis: State of the art surveys (pp. 799-848). Springer, New York, NY.

Stanghellini, E. (2009). Introduzione ai metodi statistici per il credit scoring. Springer Science & Business Media.

Stein, E. W. (2013). A comprehensive multi-criteria model to rank electric energy production technologies. Renewable and Sustainable Energy Reviews, 22, 640-654.

Stenhouse K., Hanania J., Afework B., Donev J. (2020a). Electrical transmission. Energy education. (https://energyeducation.ca/encyclopedia/Electrical_transmission)

Stenhouse K., Hanania J., Donev J. (2020b). Distribution grid. *Energy education*. (https://energyeducation.ca/encyclopedia/Distribution_grid)

Stern, D. I. (2010). The role of energy in economic growth. USAEE-IAEE Working Paper, (10-055).

Strantzali, E., & Aravossis, K. (2016). Decision making in renewable energy investments: A review. Renewable and Sustainable Energy Reviews, 55, 885-898.

Štreimikienė, D., Šliogerienė, J., & Turskis, Z. (2016). Multi-criteria analysis of electricity generation technologies in Lithuania. Renewable Energy, 85, 148-156.

Stuebi, R. (2001). California Energy Crisis: Causes and Consequences. Next wave Energy.

Szymanski, D. M., Bharadwaj, S. G., & Varadarajan, P. R. (1993). An analysis of the market share-profitability relationship. Journal of marketing, 57(3), 1-18

Tasri, A., & Susilawati, A. (2014). Selection among renewable energy alternatives based on a fuzzy analytic hierarchy process in Indonesia. Sustainable energy technologies and assessments, 7, 34-44.

Taticchi P. (2008). Business performance measurement and management: implementation of principles in SMEs and enterprise networks, PhD Thesis, University of Perugia, Italy.

Taylor, J. & Van Doren, P. (2001). California's Energy Crisis: What's Going On, Who's to Blame, and What to Do. Cato Institute Policy Analysis Report Number 406. Accessed June 23 2020, (https://www.cato.org/publications/policy-analysis/californias-electricity-crisis-whats-going-whos-blame-what-do)

Taylor, S. (2010). Nuclear power and deregulated electricity markets: lessons from British energy. Security of Energy Supply in Europe: Natural Gas, Nuclear and Hydrogen, 155.

Tervonen, T., & Lahdelma, R. (2007). Implementing stochastic multicriteria acceptability analysis. European Journal of Operational Research, 178(2), 500-513.

Tervonen, T., van Valkenhoef, G., Baştürk, N., & Postmus, D. (2013). Hit-and-run enables efficient weight generation for simulation-based multiple criteria decision analysis. European Journal of Operational Research, 224(3), 552-559.

Tiba, S., & Omri, A. (2017). Literature survey on the relationships between energy, environment and economic growth. Renewable and Sustainable Energy Reviews, 69, 1129-1146.

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. International Review of Financial Analysis, 30, 394-419.

Toossi, A., Camci, F., & Varga, L. (2013). Developing an AHP based decision model for energy systems policy making. In 2013 IEEE International Conference on Industrial Technology (ICIT) (pp. 1456-1460). IEEE.

Troldborg, M., Heslop, S., & Hough, R. L. (2014). Assessing the sustainability of renewable energy technologies using multi-criteria analysis: Suitability of approach for national-scale assessments and associated uncertainties. Renewable and Sustainable Energy Reviews, 39, 1173-1184.

Tsoutsos, T., Drandaki, M., Frantzeskaki, N., Iosifidis, E., & Kiosses, I. (2009). Sustainable energy planning by using multi-criteria analysis application in the island of Crete. Energy policy, 37(5), 1587-1600.

Tylock, S. M., Seager, T. P., Snell, J., Bennett, E. R., & Sweet, D. (2012). Energy management under policy and technology uncertainty. Energy Policy, 47, 156-163.

U.S. Energy Information Administration (EIA). Glossary of U.S. Energy Information Administration (2012). (https://www.eia.gov/tools/glossary/index.php?id=C)

U.S. Energy Information Administration (EIA). State Electricity Profiles, Total retail sales (2017) (https://www.eia.gov/electricity/state/) | Accessed 17 June 2019.

Ulutaş, B. H. (2005). Determination of the appropriate energy policy for Turkey. Energy, 30(7), 1146-1161.

Union, E. (2009). Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. Official Journal of the European Union, 5, 2009.

Union, E. (2018). Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources. Official Journal of the European Union, 5, 82-209.

US-Canada Power System Outage Task Force. (2004). Final report on the August 14, 2003 blackout in the United States and Canada: Causes and recommendations. US-Canada Power System Outage Task Force.

Van Dijk, B. M. (2010). AMADEUS: A database of comparable financial information for public and private companies across Europe. Bureau Van Dijk. (https://amadeus.bvdinfo.com/home.serv?product=amadeusneo&loginfromcontext=ipaddress)

Vetschera, R. & de Almeida, A. (2012). A PROMETHEE-based approach to portfolio selection problems. Computers & Operations Research 39(5), 1010 – 1020.

Vishnupriyan, J., & Manoharan, P. S. (2018). Multi-criteria decision analysis for renewable energy integration: A southern India focus. Renewable energy, 121, 474-488.

Voropai, N. I., & Ivanova, E. Y. (2002). Multi-criteria decision analysis techniques in electric power system expansion planning. International journal of electrical power & energy systems, 24(1), 71-78.

Voulgaris, F., Doumpos, M., & Zopounidis, C. (2000). On the evaluation of Greek industrial SME's performance via multicriteria analysis of financial ratios. Small business economics, 15(2), 127-136.

Vučijak, B., Kupusović, T., Midžić-Kurtagić, S., & Ćerić, A. (2013). Applicability of multicriteria decision aid to sustainable hydropower. Applied Energy, 101, 261-267.

Waheed, R., Sarwar, S., & Wei, C. (2019). The survey of economic growth, energy consumption and carbon emission. Energy Reports, 5, 1103-1115.

Walker, A., Cox, E., Loughhead, J., & Roberts, J. (2014). Counting the cost: the economic and social costs of electricity shortfalls in the UK-A report for the Council for Science and Technology.

Wang, H., Duanmu, L., Lahdelma, R., & Li, X. (2017). Developing a multicriteria decision support framework for CHP based combined district heating systems. Applied Energy, 205, 345-368.

Wang, H., Jiao, W., Lahdelma, R., Zhu, C., & Zou, P. (2015). Stochastic multicriteria acceptability analysis for evaluation of combined heat and power units. Energies, 8(1), 59-78.

Wang, H., Lahdelma, R., & Salminen, P. (2018). Stochastic multicriteria evaluation of district heating systems considering the uncertainties. Science and Technology for the Built Environment, 24(8), 830-838.

Wang, J. J., Jing, Y. Y., Zhang, C. F., & Zhao, J. H. (2009). Review on multicriteria decision analysis aid in sustainable energy decision-making. Renewable and sustainable energy reviews, 13(9), 2263-2278.

Wang, J. J., Jing, Y. Y., Zhang, C. F., Shi, G. H., & Zhang, X. T. (2008). A fuzzy multicriteria decision-making model for trigeneration system. Energy Policy, 36(10), 3823-3832.

Weber, O., Koellner, T., Habegger, D., Steffensen, H., & Ohnemus, P. (2008). The relation between the GRI indicators and the financial performance of firms. Progress in Industrial Ecology, an International Journal, 5(3), 236-254.

World Energy Council (2017). "World Energy Trilemma Index 2017". (https://trilemma.worldenergy.org/)

World Energy Issues Monitor (2020). World Energy Council. (https://www.worldenergy.org/assets/downloads/World_Energy_Issues_Monitor_2020__Full_Report.pdf)

Wu, Y., Geng, S., Zhang, H., & Gao, M. (2014). Decision framework of solar thermal power plant site selection based on linguistic Choquet operator. Applied energy, 136, 303-311.

Xiao, F. (2019). EFMCDM: Evidential fuzzy multicriteria decision making based on belief entropy. IEEE Transactions on Fuzzy Systems.

Xu, W., Pan, Y., Chen, W., & Fu, H. (2019). Forecasting Corporate Failure in the Chinese Energy Sector: A Novel Integrated Model of Deep Learning and Support Vector Machine. Energies, 12(12), 2251.

Yap, B. W., Ong, S. H., & Husain, N. H. M. (2011). Using data mining to improve assessment of credit worthiness via credit scoring models. Expert Systems with Applications, 38(10), 13274-13283.

Yedla, S., & Shrestha, R. M. (2003). Multicriteria approach for the selection of alternative options for environmentally sustainable transport system in Delhi. Transportation Research Part A: Policy and Practice, 37(8), 717-729.

Yin, L., Deng, X., & Deng, Y. (2018). The negation of a basic probability assignment. IEEE Transactions on Fuzzy Systems, 27(1), 135-143.

Yu, L., Wang, S., & Lai, K. K. (2009). An intelligent-agent-based fuzzy group decision making model for financial multicriteria decision support: The case of credit scoring. European journal of operational research, 195(3), 942-959.

Yu, X., Nongaillard, A., Sekhari, A., & Bouras, A. (2015, October). An environmental burden shifting approach to re-evaluate the environmental impacts of products. In IFIP International Conference on Product Lifecycle Management (pp. 56-65). Springer, Cham.

Yunna, W., & Geng, S. (2014). Multicriteria decision making on selection of solar–wind hybrid power station location: A case of China. Energy Conversion and Management, 81, 527-533.

Zadeh, L. A. (1965). Fuzzy sets. Information and control, 8(3), 338-353.

Zhou, P., Ang, B. W., & Poh, K. L. (2007). A mathematical programming approach to constructing composite indicators. *Ecological economics*, *62*(2), 291-297.

Zionts, S. (1979). MCDM—if not a roman numeral, then what? Interfaces, 9(4), 94-101.

Zopounidis, C., & Doumpos, M. (1999). Business failure prediction using the UTADIS multicriteria analysis method. Journal of the Operational research Society, 50(11), 1138-1148.

Zopounidis, C., & Doumpos, M. (2000). Building additive utilities for multi-group hierarchical discrimination: The MH DIS method. Optimization Methods and Software, 14(3), 219-240.

Zopounidis, C., & Doumpos, M. (2002a). Multicriteria classification and sorting methods: A literature review. European Journal of Operational Research, 138(2), 229-246.