UMinho | 2015

Maria João Martins dos Santos Development of a methodology to incorporate risk and uncertainty in electricity power planning

Universidade do Minho
Escola de Engenharia

Maria João Martins dos Santos

Development of a methodology to incorporate risk and uncertainty in electricity power planning

outubro de 2015

Universidade do Minho
Escola de Engenharia

Maria João Martins dos Santos

Development of a methodology to incorporate risk and uncertainty in electricity power planning

Dissertação de Mestrado
Mestrado em Engenharia Industrial

Trabalho efectuado sob a orientação de
Professora Doutor Paula Fernanda Varandas Ferreira
Professora Doutora Maria Madalena Teixeira Araújo

outubro de 2015

DECLARAÇÃO

Nome: Maria João Martins dos Santos

Endereço eletrónico: mariajoaosantos19@hotmail.com   Telefone: +351 916 873 331

Bilhete de Identidade/Cartão do Cidadão: 12812915

Título da dissertação: Development of a methodology to incorporate risk and uncertainty in electricity power planning

Orientadores:

Professora Doutora Paula Fernanda Varandas Ferreira

Professora Doutora Maria Madalena Teixeira Araújo

Ano de conclusão: 2015

Mestrado em Engenharia Industrial

Universidade do Minho, ______/______/__________

Assinatura:

ACKNOWLEDGMENTS

First of all, I would like to thank my supervisors Professora Doutora Paula Fernanda Varandas Ferreira and Professora Doutora Maria Madalena Teixeira Araújo, for their full support, understanding and commitment, and, above all, for believing me to succeed. I would like to thank also to Sérgio Pereira, the developer of the model used in this work, and my colleagues Fátima Lima and Wellington Alves, for their guiding and friendship, allowing me to overcome all challenges and difficulties during the research work.

Finally, a special word for my parents, my brothers and my boyfriend, for their precious patience and encouragement to pursue my goals and my dreams.

To all my friends, I would like to thank the friendship and support through my academic journey, making every day worth looking forward.

Resumo

Planear o sistema elétrico de um país é uma tarefa exigente e complexa que implica o desenvolvimento de decisores na seleção da(s) melhor(es) opção/opções para os planos futuros do sistema, tendo em conta a sua dinâmica com a sociedade, o ambiente e a economia. O sistema elétrico caracteriza-se pela grande escala, sendo também complexo e dinâmico e portanto, tornando-se incomportável incluir todas as relações específicas entre o sistema elétrico e a sua envolvente externa durante o planeamento. Assim, este processo de planeamento requer frequentemente uma representação lógica e simples do sistema elétrico por forma a apoiar a tomada de decisão eficiente.

O planeamento da produção de eletricidade assenta em projeções, restrições e parâmetros que serão incorporados no modelo de planeamento. Desta forma, os modelos determinísticos baseados nestas previsões podem trazer simplicidade ao processo de planeamento mas não incluem explicitamente as incertezas e riscos presentes nos sistemas elétricos. Por outro lado, os modelos estocásticos permitem incluir incertezas consideradas críticas para obter uma solução robusta, mas requerem um maior esforço de modelação e ao nível computacional comparativamente aos modelos determinísticos.

Neste trabalho, é proposta uma metodologia para incluir a incerteza num modelo de planeamento da eletricidade através da análise de cenários, evitando a complexidade da otimização estocástica. Deste modo, o objetivo deste trabalho é apresentar uma metodologia para identificar as principais incertezas presentes no sistema elétrico e demonstrar o seu impacto no mix tecnológico para geração da eletricidade no longo prazo, através da análise de cenários. Um sistema elétrico próximo do caso Português foi usado para demonstrar de que modo as fontes de energias renováveis podem ser incluídas no processo de planeamento de longo prazo, combinando a simulação de Monte Carlo com um modelo de otimização determinístico.

Os resultados deste trabalho indicam que um elevado crescimento na procura de eletricidade combinado com a incerteza sobre as condições climáticas representam importantes fontes de risco para a definição de mixes tecnológicos ótimos e robustos para o futuro. Isto é particularmente relevante para o caso das fontes de energias renováveis terem um contributo elevado para os sistemas elétricos, dado que as alterações climáticas poderão afetar significativamente a geração de eletricidade expectável destas tecnologias renováveis.

Palavras-Chave: Incerteza, Planeamento do Sistema elétrico, Análise de cenários, Fontes de energias renováveis

ABSTRACT

Planning an electricity system of a country is a hard and complex task that involves planners and decision makers in the process of selecting the best option(s) for future energy system plans considering the dynamics of electricity planning process within the society, the environment and the economy. The electricity system is a large-scale, complex and dynamic system and thus, for the purpose of power planning, it is unbearable to consider all specific relations between the electricity system and its external environment. Thus, the planning process frequently requires a logic and simpler representation of the electricity system to support effective decision making.

Electricity power planning relies on future projections, constraints and parameters to be incorporated in the planning model. In line with is, deterministic models based on these most likely forecasts can bring simplicity to the electricity power planning but do not explicitly consider uncertainties and risks which are always present on the electricity systems. On the other hand, stochastic models can account for uncertain parameters that are critical to obtain a robust solution, requiring however, higher modelling and computational effort than deterministic models.

In this work, a methodology is proposed to include uncertainty into electricity planning model using scenario analysis, without adding the complexity of traditional stochastic optimization modelling. Ultimately, the aim of this work was to propose a methodology to identify major uncertainties presented in the electricity system and demonstrate their impact in the long-term electricity production mix, through scenario analysis. An electricity system close to the Portuguese one was used to demonstrate how renewables uncertainty can be included in the long term planning process, combining Monte Carlo Simulation with a deterministic optimization model.

The results of this work indicate that high growth demand rates combined with climate uncertainties represent major sources of risk for the definition of robust optimal technology mixes for the future. This is particularly important for the case of electricity systems with high share of RES as climate change can have a major role on the expected RES power output.

KEYWORDS: Uncertainty, Electricity power planning, Scenario analysis, Renewable energy sources

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS AND NOMENCLATURE

REN	Rede Energéticas Nacionais
DGEG	Direção Geral de Energia e Geologia
APREN	Associação Portuguesa de Energias Renováveis
ERSE	Entidade Reguladora dos Serviços Energéticos
EDP	Energias de Portugal
RES	Renewable Energy Sources
CCGT	Combined Cycle Gas-Turbine
SHP	Small Hydro Power
PV	Photovoltaic
CSP	Concentrated Solar Power
CCS	Carbon Capture and Storage
GEP	Generation Expansion Planning
UC	Unit Commitment
DA	Decision Analysis
CF	Capacity Factor
PDF	Probability Density Function
GAMS	General Algebraic Modelling System
SEPP	Sustainable Electricity Power Planning
MILP	Mixed Integer Linear Programming
CO_2	Carbon dioxide
GHG	Greenhouse Gases
GWh	Gigawatt-hour
MWh	Megawatt-hour
MW	Megawatt

1. INTRODUCTION

1.1 Scope

Electricity power systems are large-scale, complex engineering systems, responsible for the improvement of life quality and economic development of a country. During the last decade, electricity markets were subjected to deregulation and competition (Ventosa et al. 2005), allowing several electricity producers to participate in the supply of electricity, at national, regional or local level. Additionally, planning and managing electricity systems became multifaceted tasks, requiring the acknowledgment of the energy sector relation within society, environment and climate change, technology development and political goals (Möst & Keles 2010). Lately, the world economic crisis has also changed historical patterns of electricity consumption. Nevertheless, the trilemma always prevails: how to provide consistent and affordable electricity, sustain the security of supply and minimize the greenhouse gases (GHG) emissions (Bale et al. 2015).

All these transformations had increased uncertainties in short- and long-term, bringing with it more complexity to the planning process and increasing ambiguity and difficulty in the decision-making process. In this sense, the electricity sector is characterized by a high level of uncertainty and risk, resulting not only from its close relationship with an increasingly dynamic policy and regulatory framework but also from its high sensitivity to parameters such as climate conditions, economic environment or social perception.

One efficient technique recognized and used worldwide for electricity power planning is scenario generation (Santos et al. 2014). Scenarios help to explore what, how and if future pathways are feasible to achieve predefined goals. Traditionally, a set of future scenarios is built on assumptions and constraints, based on deterministic values to all variables and parameters. Even with *a posteriori* sensitivity analysis, that allows determining which variable(s) influences most electricity power planning, uncertainties remain unquantified (Pye et al. 2015). However, not properly considering uncertainties when modelling electricity power systems can turn seemingly cost-effective results into obsolete and inadequate options (Fortes et al. 2008; Vithayasrichareon & MacGill 2012).

Stochastic optimization is the formal approach to deal with uncertainty, allowing the representation of the randomness of uncertain parameters in planning models. Nevertheless, stochastic optimization implies resourcing to extremely specialized theoretical and practical knowledge and, as such, the modelling approach is deemed to be much more complex than deterministic optimization for electricity systems planning.

The particular goals and needs of the electricity system in each country, region or community, opens a vast area for the exploration and development of new tools and methodologies for electricity planning purposes Also, including risk and uncertainty in power planning and decision making is, today, not an option but a requirement to support the sustainable development of an economy.

1.2 Objectives of the research and methodological approach

This work aims to contribute to the theme of power planning under uncertainty, recognizing that a deterministic approach can be too limited, especially in systems characterized by high levels of RES, but also that a stochastic approach is rather complex and time consuming. To overcome this limitation, a methodology combining the historical information of uncertain parameters with Monte Carlo simulation and generation expansion planning model is proposed. The methodology was demonstrated for an electricity system close to the Portuguese one. The specific objectives of this work were:

– Identifying the major uncertain parameters affecting long-term electricity power planning;

– Proposing a methodology to include uncertainties in the power planning process;

– Generating and comparing scenarios for the electricity production system until 2035, considering a 20 years horizon planning period.

In order to gather all relevant information and construct the theoretical basis of the work, an extensive literature review was undertaken. For this, scientific publications, national and international reports and legislation, addressing uncertainty and risk in electricity systems planning, energy planning models and the evolution of the Portuguese electricity system were used as sources of information.

During the literature review, it was realized that there are different forms to classify energy planning models but sometimes the categories for the classification are not comprehensive enough to distinguish models with different characteristics or purposes. It was also noted that different authors may have different perspectives or interpretations for the same category. Given the context of this research work, it was found noteworthy to propose a classification for energy planning models, based on literature review and compilation, aiming to contribute to the achievement of a common language to classify energy models.

The uncertainty analysis was conducted in @Risk software, allowing to explore several useful tools of the program, namely Monte Carlo simulation and Pearson correlation factors. Based on possible combinations of RES uncertainties, six scenarios were constructed, ranging from scenarios where availability of RES is rather limited, to scenarios with increasing availability of RES.

A recently developed optimization model (Pereira et al. 2015a) was adapted to this research work, in order to optimize the different scenarios and returns economic, environmental and technical parameters to compare them.

1.3 Organization of the dissertation

The work is organized as follows.

Chapter 2 presents the state of the art of the relevant themes to be explored, beginning with a brief description of the main technologies presented in electricity systems, followed by a review of several models applied to energy systems planning, and their classification, and finally a review of sources of risk and uncertainty in power systems.

Chapter 3 describes the Portuguese electricity system, including the evolution of power production and consumption, the external dependence on fossil fuels and the main national and international goals related to the electricity system.

Chapter 4 presents the methodology applied to the work and describes the sequential steps to accomplish the specific objectives previously outlined.

Chapter 5 presents the results and a detailed discussion of the uncertainty analysis, the comparison of scenarios and the impacts of uncertainties in the electricity system.

Chapter 6 draws the main conclusions and presents the suggestions for future work.

2. THE STATE OF THE ART

2.1 Energy sources for the electricity generation

Electricity generation is the process of producing electric power from primary energy sources, i.e. energy sources found in nature that have not been converted or transformed in other forms of energy. Such primary energy sources include fossil fuels, wind, sun, water, biomass, waves and geothermal energy. A brief description of the main characteristics of each energy source used for electricity generation is presented next. The description emphasises the main energy sources present in the Portuguese electricity system, and thus oil and nuclear power are not considered.

2.1.1 Wind

The electricity produced by wind is a result of a two-step energy conversion: when wind blows, the turbine blades start rotating, transforming the kinetic energy of the wind movement into mechanical energy, which is subsequently converted into electricity. Wind power plants are provided with a controller that allows triggering the turbine rotor system when wind reaches the minimum cut-in speed, until the maximum speed allowed by the turbine (Santos et al. 2015). At this point, the wind power output remains constant. If the wind speed exceeds the maximum allowed by the turbine (cut-out speed), the rotor system stops and the power output falls to zero (Schaeffer et al. 2012).

Wind speed is the most important factor affecting wind turbine performance because the energy in wind is proportional to the cube of wind speed (Baños et al. 2011). As an example, if the wind speed increases by 67%, from 6 m/s to 10 m/s, the energy produced will increase 134% (SETIS 2010a). Wind speed is highly affected by climate conditions, period of the day, season, location, orography and obstacles, and usually increases with height. Also, at sea, the wind speed is much higher and less turbulent than in land.

Wind power plants can be located in land (onshore) or in the sea (offshore). The onshore technology is in a maturity stage and has become a well-established participant in the electricity supply around all Europe. Therefore, the main innovations to improve technology performance and economic characteristics are directed at increasing the turbine dimension, repowering of older parks in favourable wind locations and the improvement on the capacity factor by technology learning and evolution (INESCPORTO & ATKearney 2012). Usually, wind power turbines are grouped together into a single wind power plant, distanced from each other 5 times their diameter, forming a wind farm (Pereira 2012). This configuration of wind farms brings economy of scale and reduces the risk of variable wind output. Stand-alone turbines are typically used for water pumping or to supply remote windy areas.

The offshore technology, oppositely, is in an early stage of development and research has been conducted with the purpose of finding new ways to implant the tower foundations and new materials adapted to marine environments (SETIS 2010a). The lower degree of maturity characterising offshore technology today, makes it very expensive when compared to onshore wind farms, particularly the high costs of investment in infrastructure and maintenance (Ferreira & Vieira 2010). However, since the wind speed at sea is more favourable to electricity generation and wind farms suffer several constraints regarding their locations, offshore technology is thus presented as a promising alternative to reinforce the pathway of wind as a fundamental contributor to the sustainability of the electricity matrix.

One of the main challenge to wind power plants deployment, for both onshore and offshore, is related with the transmission grid requirements. Until recently, the electricity transmission and distribution grid was designed to attend a conventional electricity system, based mainly on thermal and hydro power plants, i.e. the grid was not prepare to receive the large contribution of electricity produced by the wind source. Therefore, the transmission and distribution grid has been adapting this new green reality, as the main driver to achieve global goals for the sustainability of the planet is the large penetration of renewables sources in the energy supply systems. In this sense, there is a fundamental need to create operational procedures for the transmission and distribution, develop new infrastructures and increase flexibility and robustness of the grid lines.

2.1.2 Sun

The electricity generation from the sun can be performed through two main options, namely photovoltaic panels (PV) or concentrated solar panels (CSP).

Photovoltaic panels receive and absorb solar radiation and convert it into electricity, through the photovoltaic effect. A PV panel or module is composed by several devices made of semiconductor materials with electricity-producing properties – PV cells or solar cells. Presently, three photovoltaic technologies are in the market: crystalline silicon modules (the most mature photovoltaic technology, with efficiencies between 14% and 20%); thin film modules (efficiencies between 7% and 12% but with lower costs than silica and higher flexibility) and concentrating photovoltaics (CPV) (uses optical elements to concentrate solar radiation with efficiencies between 35% and 40%) (INESCPORTO & ATKearney 2012). The main drivers of photovoltaic technology costs are related to the increase of efficiency and life-cycle of the modules, and through the economic scale of the modules production (Schleicher-Tappeser 2012).

Concentrated solar panels are mirrors that reflect and concentrate sun light to warm up a fluid that will generate steam, which in turn will spin a turbine, creating a movement that will produce electricity. CSP can be used in different configurations namely linear concentrator system, dish/engine system and power tower system. Concentrated solar power (CSP) has the advantage of being a renewable technology with storage capacity but, even so, their capital costs keep being very expensive nowadays (Jeon & Shin 2014).

2.1.3 Water

Hydro technology is the most mature renewable technology and is indeed the major support of energy systems in many countries, such as Brazil where 80% of total electricity production is provided by large hydro power plants.

Electricity generated by hydro power plants is the last stage of a series of energy transformations. The water, located at a high level, stores potential energy, which is converted into kinetic energy, when the water is released, due to the downward movement of water flows. The kinetic energy is converted into mechanical energy, when the turbine starts rotating, and finally, into electricity through a generator or alternator attached to the turbine (SETIS 2010b).

Large hydro power plants can have an effective and crucial role in the management of power systems. First, hydro power technology can better deal with fluctuation of variable sources, such as wind, since large hydro power plants have the capacity to store electricity in reservoirs (Cunha & Ferreira 2014) and second, have a fast response time that allows reserves to be fed into the grid (SETIS 2010b).

Large hydro power plants with pumped-storage can provide a backup to the electricity system – when the demand is low, water from a reservoir is pumped to an upper reservoir and, when electricity demand is high, the water is released and electricity is generated (SETIS 2010b).

A second hydropower technology is the run-of river power plant whereas not being able to store energy, since it does not have a large reservoir, part of the water can be diverted from the normal river flow to a canal, feeding a low-head turbine (SETIS 2010b). Run-of-river plants depend on the water flows and thus provide base load electricity.

A third hydropower technology is the small hydro power (SHP), which generally serves a local community or industrial plant and is limited to a maximum installed power of 10 MW. SHP can be further divided into mini-generation (100 to 1000 kW) and micro-generation (5 to 100k W).

2.1.4 Biomass

Biomass is all of the organic material resultant from plants, animals and microorganisms and can be used for electricity and heating/cooling generation, as well as a fuel for vehicles. Among all renewable sources, biomass is the only one not directly affected by weather conditions, time of day or season or geographical locations, even if these parameters are able to influence some economic and operational aspects. Additionally, biomass can be stored and thus contributes to base load capacity.

The biomass can be distinguished into three classes. Primary biomass, which is produced by forests and agriculture (dedicated crops), and secondary biomass, which is the sub-product of primary biomass processing, including residues from agricultural, forestry and waste treatment. Although dedicated crops have been stressed out as the most efficient strategy to produce bioenergy, currently, secondary biomass is the most used raw material for the electricity production in biomass power plants (Carneiro & Ferreira 2012). Finally, third generation biomass is starting to emerge but technologies did not reach a commercial phase yet and include for example algae-based biofuels.

As with other thermal technologies, in order to produce electricity, biomass power plants emit pollutants gases from the fuel combustion and the combustion process will determine the type and amount of pollutants. Nevertheless, CO_2 emissions from biomass power plants are very low compared with fossil fuel power plants, such as coal and natural gas. On the other hand, many experts emphasize that CO_2 emissions from biomass power plants can be compensated since they replace the forest residue carbon in the natural carbon cycle, although this is not a consensual argument (Carneiro & Ferreira 2012).

2.1.5 Wave

Electricity produced by waves is the result of the energy transported by ocean surface wave and is captured by a wave energy converter (WEC).

The wave power is determined by the height, speed and length of the wave, as well as by water density. The wave height is however the major determinant of the power output and is a function of the speed and duration of wind near seawater surface.

Wave farms can be located shoreline, nearshore and offshore, being the latter the most promising wave technology for electricity generation.

2.1.6 Geothermal

Geothermal is the heat energy from the inner of the earth, mainly available on sites with volcanic activity. This energy is used in thermal power plants to produce electricity, through the movement of a turbine, caused by the flow of steam, which is provided by the heat of the Earth.

Geothermal areas can be classified into high- and low-temperature fields. High-temperature fields have temperatures above 180°C and are found near tectonic plates, where volcanic activity is very high. Low-temperature fields retain other resources such as heat rocks or heat water entrapped and released in faults and fractures (World Energy Council 2013).

2.1.7 Fossil fuels

Fossil fuel power plants use coal or natural gas to generate electricity from steam, or combustion gas, creating the movement of a turbine and driving an electric generator.

Coal is the world's most abundant fossil fuel and is relatively cheap, compared with natural gas or petroleum fuel prices. However, coal is also the most pollutant source for electricity production. Coal transportation between consumer and supplier countries is made by road for short distances and by train and barges for longer distances. Additionally, coal can be transported by pipelines.

For electricity production from natural gas, several options are available. Combined Cycle Gas-Turbine (CCGT) is a very well established technology and has a significant role on the Portuguese electricity power system. In CCGT, natural gas is used by a power plant that combines a gas turbine with a heat recovery steam generator. CCGT power plants have higher efficiency, lower CO_2 emissions and lower investment costs than coal power plants. However, presently natural gas prices are also higher than coal.

Several efforts have been made in order to improve efficiency and to reduce the adverse effects of fossil fuel power plants on pollution, ecology and society. Two measures that stand out as means to reduce pollutant gases emissions are the partial or complete replacement of the fossil fuel by biomass and/or residues, or the complementation of power plants with carbon capture and storage (CCS) (IEA 2015).

CCS is a technology that allows the capture up to 90% of CO_2 emissions, and their storage at underground (Carbon Capture & Storage Association 2015).

2.2 Energy planning models

One simple definition of energy planning was proposed by Hiremath et al. (2007), as they state (pg. 730) "... (the energy planning) involves finding a set of sources and conversion devices so as to meet the energy requirements/demand of all the tasks in an optimum manner". Today, it is recognized that energy planning must consider three important fundamentals: (i) the main goal is sustainable development, (ii) the energy supply and demand must be in constant equilibrium, and (iii) decision making is influenced by economic, engineering, environmental, social and political objectives and/or constraints.

The oil crisis in 1973 shook up the energy system planning field, revealing unseen complexities and, consequently, pressing for an urgent intervention. So far, the energy system was perceived as a closed system and the planning approach was based only on least cost objectives (Koltsaklis et al. 2014). In the 70's, the world's major power industries were severely affected by petroleum shortages and a drastic increase in oil prices. The main large effect was the stagnation of the economy in many countries, along with a high rate of unemployment. This situation claimed for a new approach for interpreting the energy system, designing strategic plans and supporting decision-making. Therefore, many models were developed, or existent ones were adapted, in order to include interactions between energy and economy, as well as strategic planning (Bhattacharyya & Timilsina 2010). Thenceforward, new exogenous dimensions of energy systems were put into perspective and new models emerged in order to incorporate interactions between energy, the environment and climate change. Lately, much attention is being directed to the analysis and incorporation of uncertainties and risks.

Several emergent energy models were presented and discussed by Jebaraj & Iniyan (2006), particularly those incorporating high penetration of renewable energy in the energy system and GHG emission reduction, as the main planning goals. Bhattacharyya & Timilsina (2010) presented a systematic comparative overview of well-known energy models and discussed their suitability for energy, environment and climate policies analysis, and simultaneously, their capacity to be extended to developing countries. Gargiulo & Gallachóir (2013) had focused on system's planning integrating the climate change dimension, and thus they had described and discussed 18 long-term energy models that incorporate these issues.

Baños et al. (2011) made an extensive review of optimization models applied to RES integration in electricity systems and stressed out that optimization methods applied to renewable sources, mainly wind and solar, have been very investigated and evolved exponentially. They also highlighted several studies regarding the modelling of uncertainties from intermittent sources. Foley et al. (2010) also discussed several proprietary electricity system models that include uncertainty analysis in short- and long-term planning.

Prasad et al. (2014) made an overview of different facets of energy planning based on literature review focusing risks, errors and uncertainty in energy planning, inquiry method, geographic level and validation methods. They also presented and discussed five computer-assisted energy planning tools with great potential for the long-term planning in small developing island countries (SDIC).

Another review was held by Pang et al. (2014), focusing on models addressing environmental and sustainability issues. The review comprised energy models specifically designed to include interactions among sectors, such as energy-economy, energy-emission, energy-social, energy-technology-economy-emissions and ecological assessment models. Pfenninger et al. (2014) analysed energy models which look at the system and its dynamic relationship with the wider economy, grouping them into four categories: energy system optimization, energy system simulation, power system and electricity market, and qualitative and mixed-methods. The main purpose of this study was to examine how existent models are overcoming the challenges imposed by climate change and sustainability, and analyse new models that are emerging in this new context.

The development of new models in order to include new dimensions beyond the scope of the energy system and the least cost-based decision making approach only, has intensified the rising of new and distinct models, begging for an exercise of classification and distinction between them.

Beeck (1999) undertook an extensive overview of different ways to classify energy models and the problem he found out was that there are many ways to classify a model but only a few, if any, that fit into one distinct category. Later, Connolly et al. (2010) compared 37 computational energy tools for the analysis of the integration of renewable sources in energy-systems. He used interviews with the tools' developers and a feature that stood out immediately was the inexistence of a common language to classify different energy tools.

In this context, several attempts were made in order to define a common classification for energy models. Beeck (1999) introduced an extensive classification for energy models, which was a result of a process of "reflections", questions about the purpose of using a model and the problem being analysed. The classification comprises nine categories: i) general and specific purposes of energy models, ii) the model structure iii) the analytical approach, iv) the underlying methodology, v) the mathematical approach, vi) geographical coverage, vii) sectoral coverage, viii) the time horizon, and ix) data requirements.

Recently, Després et al. (2014) proposed a new methodology to describe energy models, guiding the modeller in order to find a proper tool for the study specifics. In its very interesting structure, the classification comprises three categories: i) the general logic of the model, ii) the representation of the power system and iii) spatiotemporal characteristics. Each category is further divided into two or three subcategories.

Based on the literature review presented, it is proposed, on the following section, a possible classification list for energy models, composed by nine categories. It is intended to cover the characterization of underlying theories for the problem to be analysed in this dissertation and the model to be used.

2.2.1 General and specific purposes of the energy model

Any model will always represent a simplification of the reality, thus including only those aspects regarded to be the most important, in the perspective of the planner, at that time (Hiremath et al. 2007).

The general purposes of the model could be one of the two categories: to *predict/forecast* the future or to *explore* the future (Beeck 1999).

Models intending to *predict or forecast the future* apply econometric or/and simulation models to analyse the impacts of decisions in short-term planning (Beeck 1999).

Models intending to *explore the future* apply scenario analysis, i.e., alternative options are created for future pathways and compared to a reference scenario. Scenarios consider multiple possible futures that would represent alternative plans for the actual business-as-usual plan, allowing the decision-maker(s) to select the best alternative, among the scenarios generated, considering his/their interests (Soontornrangson et al. 2003; Amer et al. 2013).

A new category for the general purpose was introduced by Beeck (1999) – *backcasting* models, which refers to the process of constructing future scenarios by interviewing experts, and then, look backwards in order to find solutions or pathways to accomplish the desired future.

As for specific purposes of the model, the classification comprises four categories: *energy demand*, *energy supply*, *impact* and *appraisal* (Beeck 1999).

Energy demand models regard demand as a function of changes in population, income and energy prices, while *energy supply* models shift their focus to the technical aspects of the energy system.

Impact models are used to analyse the impact of a given decision in the energy system or policies, while *appraisal models* are used to select, from several options, the best one according to several predefined criteria. In both purposes, several criteria are enrolled in the final goal and so, a multi-criteria approach is usually required.

Nevertheless, integrated approaches combining two or more specific purposes, have being progressively applied to energy models (Pang et al. 2014).

2.2.2 Sectoral coverage

The logic of the planning process can be applied to a *single sector* (energy sector) or *multiple sectors*.

Single-sector coverage will enable a deep knowledge of the energy system, not considering however the interactions between other sectors. Furthermore, the energy sector can cover a part of the sector (e.g. electricity), or more (e.g. electricity and heat) or the whole energy system (Després et al. 2014).

Multi-sector coverage has the advantage of handling energy as an integrated system, enable the identification of important options that cannot be understood looking to a single technology or commodity or sector (Gargiulo & Gallachóir 2013).

2.2.3 Perspective of the planner

The perspective of the planner can be that of a *private actor* or following a *systems approach*.

In the *private actor* perspective, a private system compete in the liberalised market and thus, the only interests considered are those relating to the individual actor (e.g. maximization of profitability).

Following a *systems approach*, the interests of the planning concerns the social and environmental dimensions (e.g. minimization of total system cost) (Després et al. 2014). It is considered the traditional government controlled or regulated market perspective.

2.2.4 Geographical coverage

The geographical coverage refers to the extension of the planning model to a community, a city, a region, a country, several countries or worldwide.

Global level intents to describe the world economy (Hiremath et al. 2007) and involves highly aggregated data of all countries or continental regions, in order to handle the modelling process. But this, in fact, becomes the main disadvantage of the planning at global level, because it rises the difficulty to analyse the behaviour at the borders of different countries, and also global targets may not be synchronized with national targets of each country (Gargiulo & Gallachóir 2013).

National level comprises the national economy and a large range of energy technologies, which requires a complete energy and non-energy database for robust planning (Prasad et al. 2014).

Regional level could be referred to a region or a city within a country (Prasad et al. 2014), or, from the perspectives of other authors, *regional level* could be referred to international regions, such as Europe (Beeck 1999; Hiremath et al. 2007). The latter authors use the designation of *local level* when referring to a region within a country.

Hiremath et al. (2007) highlighted the importance of defining the geographical coverage for the model structure, hence extended it to other sublevels, namely *village* (the bottom limit), *block* (cluster of villages) and *district level* (multiple blocks).

2.2.5 Time horizon

The time horizon of the planning model can be classified into *short-term*, *medium-term* and *long-term*.

Short-term planning models are concerned with operational objectives and the time horizon ranges from hours to a year. Short-term planning considers the scheduling of energy demand of existent technologies, which is highly subjected to operational requirements.

Medium-term planning models are concerned with tactical objectives and the time horizon ranges from a year to 10 years. Medium-term planning includes the possibility of integrating new technologies in the energy system for meeting the demand for a longer period.

Long-term planning models are concerned with strategic objectives and the time horizon is beyond 15 years. Long-term planning encompasses the construction of new infrastructures for the energy system and thus, considers economic criteria as a major driving force for the energy planning (Prasad et al. 2014).

Particularly, for the electricity power system, the short- and long-term planning model is designated as Unit Commitment (UC) and Generation Expansion Planning (GEP), respectively. UC model aims to find the optimal start-up and shutdown schedules for all power generators present in the electricity system, under operational constraints (Pereira et al. 2013). GEP is applied to determine how many units of what type of power generators to build at which year and how much electricity should be produced by each type of generator (Pereira et al. 2011; Koltsaklis et al. 2014).

2.2.6 Modelling approach or paradigm

Modelling approach, also called paradigm (Bhattacharyya & Timilsina 2010), classifies the model according to the strategy used to process information and knowledge. Therefore, the information data would be highly aggregated to study the problem at a wider extent – *top-down approach*, or, on the other side, the information would be highly detailed to study the problem at a narrow extent – *bottom-up approach*.

Top-down models are regarded as a macroeconomic approach which departs from a general overview of the system as a whole and decomposes it into subsystems. These models follow an economic approach, using inputs such as capital, labour and energy in order to return useful outputs (Beeck 1999; Prasad et al. 2014).

Oppositely, *bottom-up* models specify the base elements in great detail, which are then linked to form subsystems and, eventually, a whole system. Bottom-up approach is regarded as a built up process, describing current and future options (Gargiulo & Gallachóir 2013). These models follow an engineering approach and, thus, the planning model is independent of the energy market behaviour (Pfenninger et al. 2014).

Hourcade et al. (2006) exposed a new category for the modelling approach of energy systems – *Hybrid* models, which link technology detailed bottom-up models with general economics top-down models, in an effort to characterize the sensitivity of the economy to changes in the energy system. Hybrid models can be obtained by hard-link, if bottom-up and top-down models are totally integrated into a new single model, or soft-link, if these models are solved separately, recurring to an iterative process to exchange the information between them (Gargiulo & Gallachóir 2013).

2.2.7 Modelling tool

Several authors classify the model type in two main categories: simulation and optimization, but they state as well that energy planning can be fluid within these two boundaries, based on the general and specific purposes of the model and data used (Pfenninger et al. 2014; Després et al. 2014). Even though, other categories founded in literature are also presented.

Simulation models are recursive and descriptive models, based on logical representation of a system, and simulate future pathways based on projected trends of energy drivers (Gargiulo & Gallachóir 2013). They are used to provide forecasts of how the system may evolve, to predict the system's most likely evolution (Pfenninger et al. 2014). Simulation models can be built in modules and integrate a large range of methods, including optimization methods.

Optimization models are prescriptive in nature, using a bottom-up approach. They are based on mathematical formulation of one or more parameters to be optimized in order to maximize or minimize one or more objective functions, subjected to constraints (Gargiulo & Gallachóir 2013). They are used to provide scenarios of how the system could evolve. Optimization models can be further divided in *operation optimization* and *investment optimization* (Connolly et al. 2010; Després et al. 2014).

Econometric models apply statistical methods to extrapolate past market behaviour into the future and therefore, allowing to predict the evolution of economic parameters or theories (Prasad et al. 2014). *Macroeconomic* models are applied to an entire economy, including the interactions between different sectors composing such economy. Usually Input-Output tables are employed to describe the interactions among sectors and hence, to support the analysis of the energy-economy interactions (Beeck 1999). Both, econometric and macroeconomic models are based on a top-down approach, where the energy sector is one of the many composing an economy, and applied to short- and medium-term horizon.

Equilibrium models are a subcategory of optimization models in the perspective of Gargiulo & Gallachóir (2013), or an additional classification of the modelling tool category, in the perspective of Ventosa et al. (2005). Equilibrium models are used to explain the behaviour of long-term supply, demand and prices of an economy. Equilibrium models can be further divided in *general equilibrium*, which considers the whole economy and the energy system is described very simplistic, and *partial equilibrium*, also known as energy system (Gargiulo & Gallachóir 2013), which is technology detailed and covers one sector only (Després et al. 2014). In this sense, general equilibrium models follow a top-down approach, while partial equilibrium models follow a bottom-up approach.

Decision analysis (DA) is not exactly a planning model; instead it intends to guide the decision making process, considering uncertain outcomes and difficult trade-offs (Prasad et al. 2014). DA van be divided into three different categories: *Single objective decision making (SODM)*, *Decision support systems (DSS)* and *Multi-criteria decision making (MCDM)*, covering many qualitative and mixed-methods approaches to be used as a complement to quantitative models (Pfenninger et al. 2014).

2.2.8 Mathematical formulation

Linear programming (LP) is used to find the best combination of variables that minimizes or maximizes a given objective function, and where all relationships among variables, as well as the objective function, are expressed in linear equalities or inequalities.

Mixed Integer Programming (MIP) is an extension of LP which allows relationships to be expressed also as integer programming (decisions Yes/No or 0/1) or discrete nonconvex relations.

Non-linear Programming (NLP) is also used to find the best combination of variables that minimizes or maximizes a given objective function, but where relationships among variables, as well as the objective function, can be expressed with non-linear and linear equalities or inequalities.

Dynamic Programming (DP) is used to find an optimal growth path, dividing the original problem into simpler sub-problems, and for each sub-problem, an optimal solution is obtained (Beeck 1999).

The mathematical formulation of the problem can also include different mathematical languages, such as Mixed Integer Linear Programming (MILP) and Mixed Integer Non-Linear Programming (MINLP).

2.2.9 Uncertainty analysis in energy planning

Not properly considering uncertainties when modelling electricity power systems can turn seemingly cost-effective results into obsolete and inadequate options (Fortes et al. 2008; Vithayasrichareon & MacGill 2012). Models that include uncertainty in the power planning usually rely on optimization models, that include *deterministic optimization*, if the uncertain parameters assume fixed values, or *stochastic optimization*, if the uncertain parameters assume random values (Pfenninger et al. 2014).

Deterministic models are not primarily intended to deal with uncertainty but, making many runs of the model while varying some inputs, an uncertainty analysis can be accomplished. This may be achieved by a simple sensitivity analysis or by extensive simulation. This last option frequently requires the use of a technique recognized as Monte Carlo Simulation, widely used for the analysis of problems involving many and potentially correlated uncertainties, allowing the assignment of a probability for respective output (Vithayasrichareon & MacGill 2012). Monte Carlo is actually a stochastic method that allows the representation of uncertain parameters as probability density function (PDF). Additionally, scenarios generated by deterministic models may also explore the impact of uncertainties, by varying one or more assumptions of the model, through sensitivity analysis (Prasad et al. 2014; Santos et al. 2014).

Stochastic models are recognized as the formal approach to deal with uncertainty specifically, which had bridged the gap between deterministic models and uncertainty analysis. In stochastic models, randomness of uncertain parameters is incorporated into deterministic problems formulation and retrials are taken in order to better fit the uncertain parameters in space, in the search for the optimal solution. Nevertheless, the mathematical formulation of stochastic models is rather complex, in theory and practice, and thus, specialized knowledge and time efforts are needed to develop a stochastic optimization model for the power system planning.

Since the sustainable development is currently the common goal in energy systems, planning the electricity supply considering the fluctuation of renewables sources is inevitable. In fact, for systems with large penetration of RES, the main challenge relies in collecting accurate data to predict the regime flows of RES with variable output. Therefore, spatiotemporal resolution of renewable sources are key elements to balance energy supply and demand (Pfenninger et al. 2014). According to Haydt et al. (2011), the variability of the electricity supply introduced by wind, solar and hydro power generation can be accounted in planning models when using one of three methods. *Integral method* uses load duration curves or capacity factors, *semi-dynamic method* uses time slices of days and seasons, and *fully dynamic method* uses real times series of source potential.

The representation of uncertainty in the planning model can be in the form of *interval*, *fuzzy set*, *probability distribution* or *multiple uncertainties* (Cai et al. 2009a). Represented as an *interval*, possible values for the uncertainty are within a minimum and a maximum limits, without knowledge of the distribution of the uncertain parameter. *Fuzzy sets* express the uncertainty also within an interval, but with a complement of a possibilistic distribution, such for instance, the most likely value that the uncertain parameter can assume. *Probability distribution* expresses the uncertainty as a probability density function (PDF), based on historical data and/or literature review. *Multiple uncertainties* allow the uncertainty to be represented as a combination of two or three previous forms (interval, fuzzy set and probability distribution).

Cai et al. (2009a) developed a fuzzy-random interval programming (FRIP) model that allows the uncertainties to be express as interval, fuzzy sets, and also as multiple uncertainties (interval-fuzzy sets). The model was applied at regional level for the purposes of resource allocation and capacity expansion plan, for a 15 years' time horizon. The uncertainties analysed were end-user demands for coal, natural gas, diesel, gasoline and electricity, and availabilities of RES. In another work, the same authors (Cai et al. 2009b) developed a community-scale model that allows wind and solar availabilities to be expressed as both probability distributions and intervals.

Kim et al. (2012) applied Monte Carlo simulation to address uncertainties facing the electricity production costs of conventional and renewable technologies. To represent the uncertainties, normal distribution functions were assumed for learning rate of technologies, fuel prices and carbon prices. As what concerns to the work of Pye et al. (2015), the uncertainties tackled were the investment costs of power generation technologies, building rates, biomass availability and resources prices (fossil fuel and biomass), for which PDFs were assumed to follow a triangular distribution. The model was applied with the purpose of exploring the uncertainties affecting policy goals to the transition of the UK energy systems to meet decarbonisation and security goals.

Koltsaklis et al. (2014) proposed a deterministic GEP model, applied to national level and for the long-term horizon, which resulted in several scenarios to explore and analyse. They used a sensitivity analysis to study the effects of uncertain parameters, namely the electricity demand, natural gas prices, CO_2 emission allowances and investment costs on wind power plants.

Stochastic optimization was applied to electricity systems planning in order to analyse the effects of random electricity demand growth, plant operating availability, carbon tax rate and fuel prices (Krukanont & Tezuka 2007; Fortes et al. 2008; Feng & Ryan 2013).

2.2.10 Summary of the models reviewed

The classification for energy planning models proposed and discussed above is presented in Table 1.

Table 1 – Classification categories for energy planning models.

Category		**Subcategory**
Purpose of the model	*General*	Predict / Explore / Backcasting
	Specific	Energy demand / Energy supply / Impact / Appraisal
Sectoral coverage		Single sector / Multiple sectors
Perception of the planner		Private actor / System approach
Geographical level		Global / Regional / National / Local / District / Block / Village
Time horizon		Shot-term / Medium-term / Long-term
Modelling approach		Top-down / Bottom-up / Hybrid
Modelling tool		Simulation / Optimization / Econometric / Macroeconomic / Equilibrium
Mathematical formulation		LP / MIP / NLP / DP / Combinations
Uncertainty analysis	*Modelling*	Deterministic / Stochastic
	Representation	Interval / Fuzzy set / Probability distribution

It is worth mentioning that the aim of the section was not to make an exhaustive revision of all models and approaches used by different authors, but rather present an analysis of the different models used in energy planning, their different characteristics and goals. The complexity of energy decision making, leads frequently to the need to combine different models that can be classified in different categories and subcategories. An example can be the recent model described in the work of Pereira et al. (2015a) combining short-term and long-term models previously developed for Portugal (Pereira et al. 2015b; Pereira et al. 2015c). Another example, also for Portugal, is the model described in Ribeiro et al. (2013) combining the specific purpose of the modelling energy supply with the appraisal of the scenarios. The combination of deterministic approaches with statistical analysis of the model parameters is also frequent, for example when building electricity generation portfolios (see for example (Allan et al. 2011)).

2.3 Risk sources and uncertainty in electricity systems

Electricity is an indispensable good for society development and growth of a nation, stimulating the economic and technological development of a country. Electricity has special characteristics that make it very different from other commodities traded in competitive markets, namely the need for instant and continuous generation and consumption, non-storability, high variability in demand over a day and season and non-traceability (Möst & Keles 2010).

It is thus mostly recommended to plan a reliable electricity production system, for a given period of time, considering explicitly the risk sources related to the electricity system and the possibility of uncertain events occur.

Although risk and uncertainty are terms highly dependent on decision making process, namely on the interpretations of the stakeholders involved, their underlying concepts are quite different. Uncertainty is referred to a state of incomplete knowledge, resulting from lack of information or from disagreement about what is known, while risk is a combination of the probability and potential impact of an uncertain event to occur (Kunreuther et al. 2014).

The uncertainties can be generally distinguished in two categories: technical and economic uncertainties (Soroudi & Amraee 2013). Technical uncertainties can be further divided into topological parameters and operational parameters. Topological parameters encompass failure or forced outage of lines, generators or metering devices, while operational parameters are related with operation decisions, namely demand and generation values in power systems. Economic uncertainties cover microeconomics and macroeconomics. Microeconomic parameters include fuel supply, production costs, business taxes, labour and raw materials. Uncertainties related with regulation or deregulation, environmental policies, economic growth, unemployment rates, gross domestic product (GDP) and interest rates are included in macroeconomic parameters.

Watson et al. (2015) classify uncertainties as epistemic or aleatory, according to their source, if the uncertainty arises from the lack of knowledge or if it results from the stochastic behaviour of a variable, a process or a system, respectively. Catrinu & Nordgård (2011), in turn, aggregated aleatory and systemic uncertainties in a category designated as external uncertainties. The category internal uncertainties belongs to those uncertainties arising from the ambiguity in decision making, reflecting the human judgement (preferences, values and risk attitudes). According to Kunreuther et al. (2014), the uncertainty can be classified as paradigmatic, epistemic and translational. Paradigmatic uncertainties are those resulting from the divergences in the opinions about how to address and frame the problem, which methods and tools must be chosen and what knowledge need to be combined in order to provide reliable and adequate solutions. Translational uncertainty derives from scientific investigation that are not completed or validated, or from scientific findings that bring conflicting results with others similar or related.

It must be emphasised however, that uncertainties in power planning at national level are subjective, because they will be reflected in individual characteristics of the country, such as endogenous energy resources, economic structures and environmental restrictions (Krukanont & Tezuka 2007).

Short-term uncertainties are regularly present such as hydrological, wind and solar conditions and oil price fluctuations (Seljom & Tomasgard 2015). Long-term uncertainties are related with long term events such as population growth and climate change.

2.3.1 Intermittency of renewable sources

Intermittency of renewable sources comprises two elements: limited-controllable variability and partial unpredictability (Pérez-Arriaga 2011). Controllable variability is referred to the possibility of adjusting and directing the flows, and thus technologies that can store energy are highly controllable, such as large hydro with reservoirs. Some run-of-river plants can partially store energy while solar and wind technologies cannot store primary energy. Since wind and solar power technologies cannot store this primary energy, the electricity produced by these units have priority in the electricity grid. The unpredictability is referred to the knowledge of the likelihood (or not) of an event to occur, such as a dry or rainy day, for instance. The solar energy is more predictable than wind because it has a more expectable variation over a day and over a season. Wind, in turn, is the most unpredictable form of energy to generate electricity. Wind is highly affected by a myriad of environmental agents, such as water sea level and precipitation, sun and temperature, and it varies often its velocity and direction.

The integration of large scale electricity production by renewable and variable sources has high impact on the security of supply. On one hand, being the source availability variable, the cover capacity to peak hours periods can be jeopardized; on the other hand, due to possible rough variations in the energy source, such as wind speed, the capacity factor of the generator is reduced, leading to the need of increasing the operational reserve.

Wind is sun dependent because the sun radiation heats the Earth's surface and consequently heats the air. Hotter air expands and rises causing cooler air to take its place and forming a pressure gradient. This difference in the air pressures creates the wind. Due to the Earth's movement wind varies across time, and because solar radiation is absorbed differently by different areas (sea, mountains, deserts, forests) wind also varies across space (Pereira 2012). The electricity generated by a wind turbine is a function of air density, swept area of the turbine and the cube of wind speed (Baños et al. 2011). The variability of wind decreases as the number of turbines and wind power plants increase in an area, as well as with spatial aggregation of power plants (Pérez-Arriaga 2011). In Portugal, wind speed varies between 5 and 6 m/s, reaching the highest values on winter season, while the lowest value occurs in the summer (Pereira 2012). Also, wind varies throughout the day, decreasing in the early afternoon, except in winter. In order to better support the knowledge of variable aspects of wind behaviour, some countries have been creating maps of wind speed and/or power content (Widén et al. 2015).

Solar energy output is also variable and uncertain. The power output of PV power plants changes according to the sun position throughout the day and the season. Also, clouds can create shadows that will impact the power output according to clouds' size and speed and PV system size (Pérez-Arriaga 2011). As happens for wind power plants, also spatial aggregation of PV panels or plants can reduce solar power output variability. Solar output is more predictable than wind due to the low forecast errors on clear days, and also because short-term solar can be forecasted by satellite-based models (Pérez-Arriaga 2011). For the long-term, numerical weather models can be used to predict solar insulation (Widén et al. 2015).

Hydro power output is strongly dependent on water sources and therefore, on the hydrological cycle (Schaeffer et al. 2012). However, different water technologies are impacted differently by water inflows. River flow is variable, especially across seasons. Nevertheless, large hydro with reservoirs play a crucial role in matching electricity demand and supply, through the ability of storing potential energy from water at minimum and maximum levels, compensating the seasonal or annual variations. On the contrary, run-of-river and small hydro power technologies present much smaller operational flexibility than large hydro with reservoirs, setting these technologies more vulnerable to climate change and thus raising the unpredictability of power output (Schaeffer et al. 2012).

2.3.2 Electricity demand

The future long-term demand is driven by population's growth, gross domestic product and employment, among others, as well as the correlations between them (Sun et al. 2006). In the short-term, demand is determined by the load curve since electricity demand and meteorological conditions are strongly dependent. Nevertheless, the historical data usually does not provide accurate data to predict the future demand (Sun et al. 2006).

Since 2008, Portugal has gone through a transition in the national electricity consumption, converging with the global evidence of the economic crisis period. Since then, many organisations closed doors and others went through a restructuring process, leading in both cases to a high rate of unemployment in Portugal.

Nevertheless, several programs related with the promotion of a sustainable future for Portugal may also have been contributing to the actual pattern in the electricity consumption. The increasing awareness to the greenhouse gases effects (GHG) and energy efficiency benefits have led to changes in the use of electricity. Some examples that show an increasing demand trend are solar collectors and thermal efficient windows for the residential sector, or, for industries and services, more efficient equipment, management of energy consumption and certification of the energy system.

Another factor that could be underlying the consumption decrease could be due to the uneven migration balance in Portugal, which is clearly deficit for the resident population. In fact, the Portuguese emigration has always been rated as one of the highest in the European Union. According to the last Portuguese statistics (Pires et al. 2014), since 2007, about 82.500 Portuguese per year leave the country and almost 110.000 had left in 2013. The reports point out that the emigration level is expected to continue the increasing rate in the coming years.

2.3.3 Climate change

On the one hand, climate change will alter rainfall, wind speed, solar radiation and global temperature causing changes in the power output of hydro, wind, solar and biofuels power production. On the other hand, there is a significant relationship between electricity demand and temperature variation (Pilli-Sihvola et al. 2010), which is why changes in global temperature will alter the dynamics of actual energy end-uses.

The main impacts of climate change on wind power production are the transformations in the geographical distribution and the variability of wind speed (Schaeffer et al. 2012). As a consequence of climate change, one possible outcome is an increase in the wind energy density, more pronounced on winter (Chandramowli & Felder 2014).

Extreme weather events such as storms, seal level rise and storm surges can bring greater risk to the management of operations and to the infrastructures of coastal power plants, such as wind offshore turbines (Chandramowli & Felder 2014).

Increasing temperature can change the efficiencies of PV cells which would result in a reduction of electricity generation from solar power (Schaeffer et al. 2012; Chandramowli & Felder 2014). Also the precipitation, which is correlated to the clouds formation, can impact on the size and speed of a cloud, which in turn will reduce the PV cells efficiency.

Global warming can put in risk the water reserves due to the increase in the evaporation and/or the reduction in the precipitation phenomena (Schaeffer et al. 2012). Additionally, rising global temperature will cause melting of freshwater glaciers and changes in rivers flows and sea level. An increase in both phenomena, precipitation and river flow, can address great potential to hydropower production, but if the reservoir's capacity is exceeded, there is high risk of flooding or damage of the dam. It is expected that hydropower production will increase in spring and winter seasons while decreasing considerably in summer (Chandramowli & Felder 2014).

The effects of temperature on the bioenergy sources are ruthless. The increase in temperature will display modifications on soil characteristics, conducting to changes in soil fertility and productivity, as well as increasing the risk of fires. Also, temperature increase impacts on insects' metabolism providing favourable conditions to their reproduction and proliferation, thus increasing the probability of incidence of pests that would damage crops and soils. At last, global warming will also increase the occurrence of extreme climate conditions, such as droughts, frosts and storms. All of the above mentioned situations are risk sources for the biomass availability and power production (Schaeffer et al. 2012).

Gas- and coal-based technologies can also experience a reduction in their power output, since the efficiency of a turbine to generate electricity is conditioned by the ambient temperature and humidity. Therefore, an increase in temperature will lead to a decrease in the turbine performance and a higher fuel consumption (Schaeffer et al. 2012; Chandramowli & Felder 2014). Additionally, thermal power plants require large amounts of water in their operation, being highly affected by water supply variations.

Derived from climate change, the surface temperature is expected to increase in the coming years, causing alterations in the season's profiles. It is thus expected shorter and warmer winters and hotter summers (Chandramowli & Felder 2014). It is also foreseen a reduction in the heating energy demand for colder regions of Europe and North America in winter, along with an increase in cooling needs in summer (Chandramowli & Felder 2014).

2.3.4 Technology costs

The investment on renewable energy technologies is a decision based on extremely careful considerations. Some technologies are not yet available and others are just in the demonstration or developing stages (Watson et al. 2015). Also there is the inherent risk of the delays on the power plant construction.

The learning rate influences investment costs and is also to an extent uncertain. Emerging technologies, such as concentrated solar power and wind offshore, are still very expensive when compared with fossil fuel technologies but their costs are likely to be reduced in a near future, however, they are still uncertain.

SHP is one of the most mature renewable technology, with low potential to induce technological changes to improve efficiency. Wind onshore is a relatively mature technology whereas wind offshore is an emergent technology, being the target of intensive investigation and as such, its costs are likely to decrease soon. According to a study carried by INESCPORTO & ATKearney (2012), the levelized cost of energy (LCoE) of the renewable electricity generation technologies in Portugal are assumed to decrease until 2020 as follows: SHP – 4%, wind onshore – 8%, wind offshore – between 19% and 21%, solar photovoltaic – between 43% and 47%, CSP – 30%, and biomass – between 2% and 17%.

2.3.5 Fuel prices

Although fossil fuel prices always played a role on the total investments of power plants, in the pre-liberalised electricity market, the uncertainty associated to the increase in oil prices could be filled by rising electricity prices (Sun et al. 2006). However, in liberalised markets, fuel costs contribute to a large extent to the total operational costs and, being more or less volatile, they are highly uncertain.

Since the liberalization of the electricity market, the obsolete vertically integrated system was transformed into diversified business activities, open to competition in some areas such as electricity production and distribution. This new reality brings conditions prone for the high volatility of fuel prices (Gomes & Saraiva 2009).

For countries like Portugal, whose all fossil fuels have to be imported from foreign countries, fuel prices uncertainty increases the risk of not meeting the required security of supply. Portugal imports natural gas mainly from Algeria (via a pipeline that passes through Spain) but also from Nigeria (imported as Liquid Natural Gas) (DGEG 2013). Both of these countries are politically unstable, thus bringing some issues to the security of supply, particularly in a dry year. Additionally, Portugal does not have a transparent market-based gas price reference (European Comission 2015). In respect to coal, the main supplier is Colombia, although USA and South Africa are potential suppliers too. Diversifying fuel suppliers is thus a measure intended to reduce the risks related to the imports of coal and natural gas.

Another one of the possible ways to reduce these risks is to ensure an electricity power matrix composed by different technologies, by different energy sources.

2.3.6 Social acceptance

Social acceptance has been assumed as a preponderant factor with respect to new infrastructures implantation, as local communities can create barriers to their construction or, on the other hand, encourage their development, according to their perception about renewable technologies (Akgün et al. 2012). It is generally recognised that embedding in the communities and in the society awareness about the benefits and potentialities of generating electricity by RES is not a simple task.

Besides the natural fear of the unknown and the resistance to change, common characteristics of local communities (Bachhiesl 2004), RES technologies deployment are also frequently associated with antithetical landscape and annoying or disturbing noise. Additionally, there is some controversial related to the land space requirements for the technology implantation, especially if the land available is adequate for a most needed purpose, namely agriculture activities (Santos et al. 2014).

As such, social acceptance is a considerable risk source with great impact on the success of electricity systems development and, therefore, a factor to include in the power planning process.

3. THE PORTUGUESE ELECTRICITY SYSTEM

In the 90's, the Portuguese electricity system was operated in a monopoly market sustained only by EDP, a state-owned vertically and horizontally integrated company created in 1976. In 1995, the electricity market was restructured and converted into a dual system operation: the regulated market and the liberalized market (Amorim et al. 2013). It was thus created the National Electricity System (SEN – Sistema Elétrico Nacional) organized in five main activities:

1. The production
2. The transport
3. The distribution
4. The commercialization
5. The organization of the liberalized market

Nevertheless, the dual market structure was abolished in 2006 in favour of the liberalisation of the electricity market and a new electricity generation network emerged (Amorim et al. 2013). Electricity generation in Portugal is today an open market carried by two types of producers:

- Ordinary regime producers: when electricity is produced by thermal power plants based on fossil fuels (coal, natural gas and oil) and large hydro power plants;
- Special regime producers: when electricity is produced by renewable technologies, other than large hydro power plants, and cogeneration.

Once electricity is produced, it is transported at very high voltage from the power plants to the substations. The transport of electricity is handled by Redes Energéticas Nacionais (REN). At the substations, electricity is lowered to high, medium and low voltage so that it can travel over the distribution networks where most of the end consumers are connected. The distribution of electricity is handled by EDP Distribuição and, at minor scale, by some low voltage electricity distribution operators.

The electricity market is entirely open to competition where the suppliers have the free right to buy and sell electricity and to access the networks for the electricity transportation and distribution through the payment of tariffs regulated by Entidade Reguladora dos Serviços Energéticos (ERSE). The electricity can be commercialized on the liberalized market, through free suppliers, or on the regulated market, through the last resort supplier.

The prime fundament to liberalization is to increase the competition in the energy market and also the economic efficiency in the operation of the power system. In consequence, traditional regulated utilities had shifted their focus on cost minimization to profit maximization and thus, all operators in the electricity system are exposed to competitive prices in electricity with high volatility. Electricity price traded in the Iberian Electricity Market is variable along the day, being linked to peak hours, as illustrated in Figure 1.

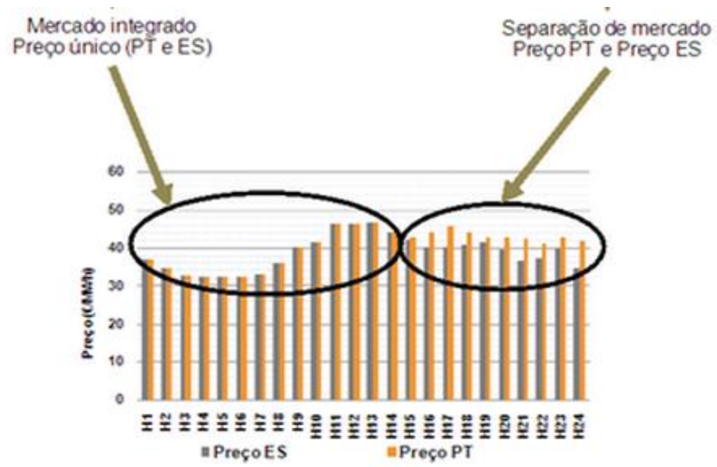

Figure 1 – Hourly electricity prices, in €/MWh, within a day (data obtained from ERSE).

3.1 The electricity demand

The electricity consumption in Portugal keeps a very regular distribution since the beginning of the 21^{st} century, being the services and households sectors responsible for almost two thirds of the electricity consumed, the industry sector representing about one third, and only 1% of the electricity is used for transport activities (European Comission 2013). The electricity consumption has grown considerably since 2000, at a rate of about 2.5% per year until 2010. Afterwards, the electricity consumption has been decreasing at a rate of about 1.6% a year and the projections point out that it is expectable to experience a low demand growth in the coming years (EDP Distribuição 2014). The evolution of the electricity consumption pattern in Portugal can be visualized in Figure 2.

Figure 2 – Evolution of the electricity consumption in Portugal, in TWh, since 2000 (data obtained from REN and DGEG).

Figure 3 shows that the pattern of electricity consumption in Portugal is very similar in each year, particularly for peak months, but the demand has decreased in the last years, particularly since 2008. This shift in the electricity consumption may be caused by several factors, namely global economic crisis, high expression of the emigration phenomenon and/or public awareness of the energy efficiency relevance. It is plausible to assume that a stable level of electricity consumption in Portugal is far from being achieved. Nevertheless, it is expected that the economy and industry development could grow and evolve in the coming years, and thus, the electricity consumption may return to its historical pattern. On the other hand, promoting social awareness and the implementation of measures to increase energy efficiency, could contribute to stabilize, or even reduce, the electricity consumption. In line with this, seems to be reasonable presume that, at this moment, no forecasts can be accurately obtained for the electricity consumption in Portugal.

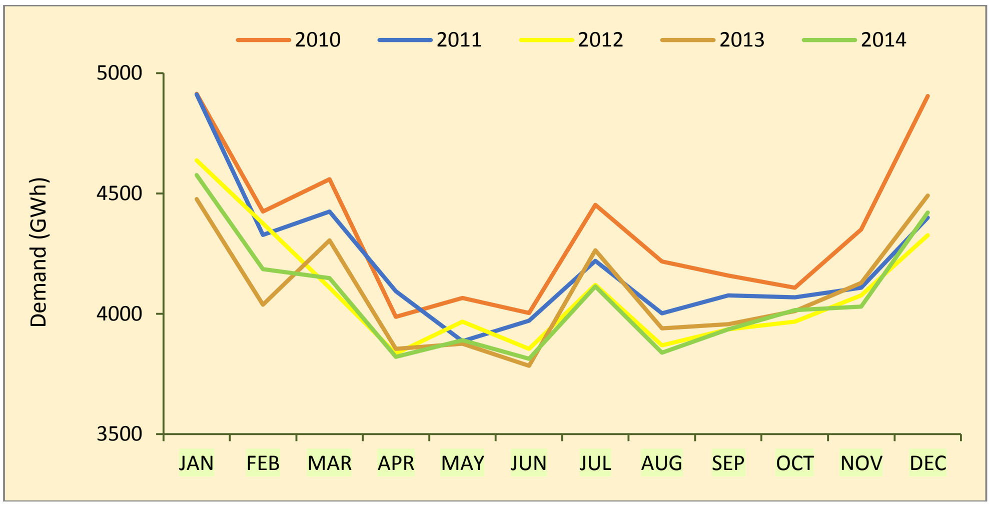

Figure 3 – Monthly electricity consumption since 2010 in Portugal (data obtained from REN).

3.2 The electricity supply

The main changes respecting the supply of electricity in Portugal arise from the diversification of the technology mix to produce electricity and the increasing contribution of RES to the total production. Additionally, fossil fuels to produce electricity are being replaced by RES produced in Special Regime, as illustrated in Figure 4.

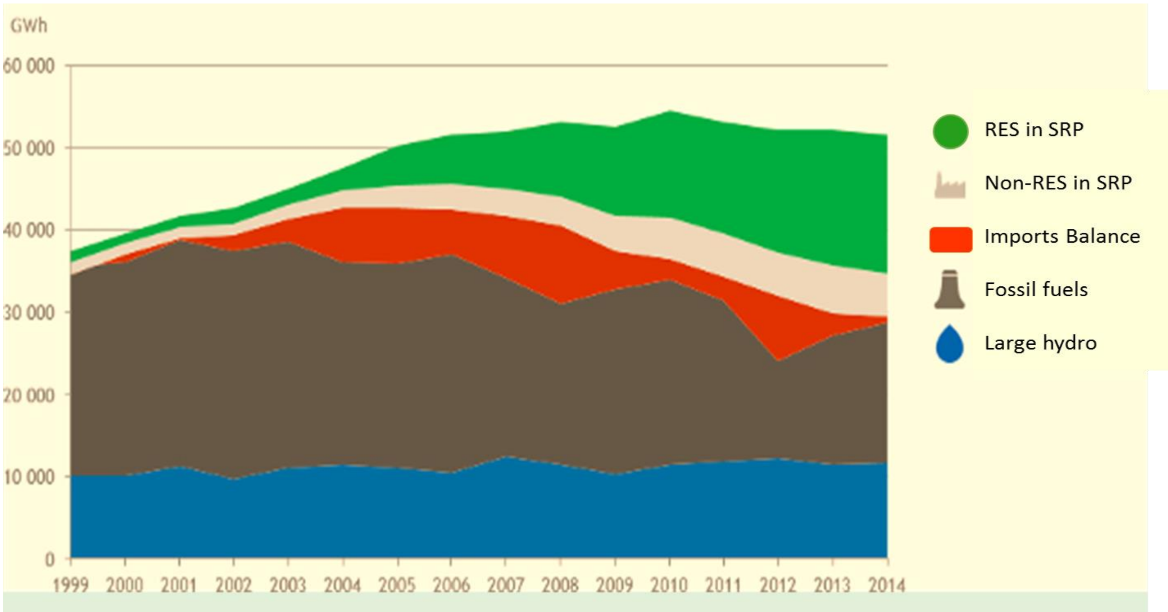

Figure 4 – Evolution of the electricity power production in Portugal, since 1999 (adapted from APREN 2014).

Since the existent coal mines in Portugal were inactivated in 1970, all fossil fuels are imported from foreign countries. Oil is no longer used to produce electricity in Portugal, since the shutdown of the last active oil thermoelectric plants in 2012. The external dependency of the country has been showing a decreasing pattern, achieving a record in 2014, as illustrated in Figure 5. Additionally, Figure 5 also shows the evolution of the electricity imports from Spain. In 2012, the electricity imports were high because it was a year with a low hydraulic index (REN 2015), but in the follow years a decrease in the electricity imports can be observed.

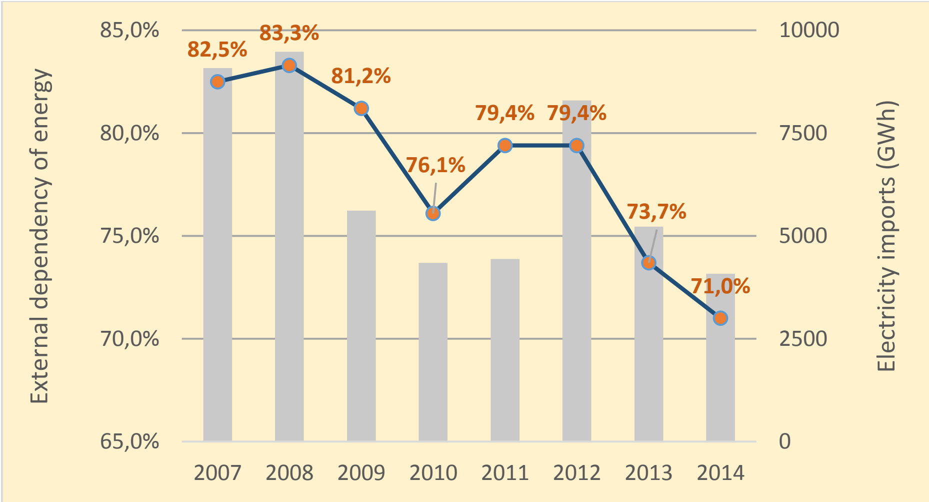

Figure 5 – External dependency of Portugal, since 2007 (data obtained from REN and APREN).

In 2014, RES technologies contributed to more than 62% to the total electricity production (REN 2015). The integration of RES in the power system is the main driving force for Portugal to achieve global goals in respect to the reduction of GHG emissions. Figure 6 presents some RES contribution to electricity production in the last years. Wind onshore is a fairly well-developed technology and, along with large hydro power plants, is the major renewable technology contributing to the electricity production in Portugal. One aspect that deserves particular attention is the substantial integration of solar photovoltaic technology in the technology mix since 2007. In respect to SHP technology, mostly mini-generation, its integration is still very limited when compared with wind onshore or solar photovoltaic.

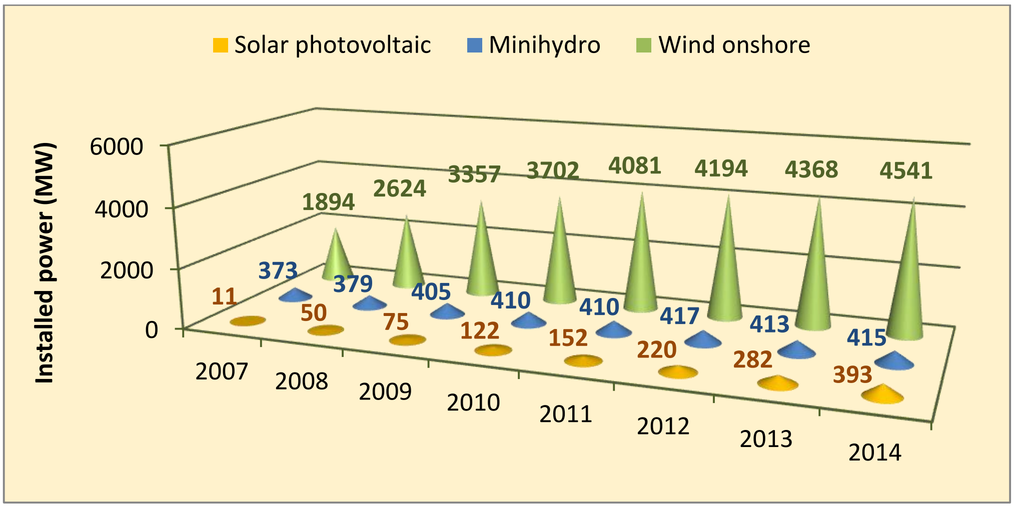

Figure 6 – Installed power of intermittent RES technologies in Portugal, since 2007 (data obtained from REN).

3.2.1 Wind power

The most mature wind technology is onshore and uses three horizontally oriented blades connected to a rotor. Combined with hydropower, wind power is the technology that ensure the higher contribution to the Portuguese electricity matrix.

In Portugal, wind farms have an average capacity factor of 2300 equivalent annually hours (INESCPORTO & ATKearney 2012) and are mainly installed in coastal areas and mountains. Since the Portuguese coast is highly density populated, the mountains in the interior regions of the country are preferred to implant wind farms. Also, better locations for wind farms in Portugal are on the North of the country, but Algarve region has also some areas with high wind power potential (Zane et al. 2011).

Wind offshore brings more advantage than onshore configuration for power production, due to higher wind intensity at less altitude, which enables the use of lower towers and achieve a capacity factor of about 3400-3700 equivalent annually hours (Ferreira & Vieira 2010). Wind offshore is an emergent technology, only at demonstration phase in Portugal and it is expected that this will remain until 2020. The major costs for offshore deployment are related to the distance to the coast and the depth of the tower foundation. Due to the characteristics of the Portuguese coast, the offshore potential has not yet been explored – the continental platform is very deep, which adds several complex technical issues for the fixation of the offshore tower base. So far, only a prototype has been projected – the Wind Float, with an installed power of 2 MW (EDP Renováveis 2015). However, it is expected that Wind Float will provide a total power capacity of 25 MW.

3.2.2 Solar power

Photovoltaic technology has seen high expansion at global scale with a learning curve favourable to costs reduction. Their modular characteristics and the potential of scaling-up has also favoured microgeneration and decentralization of electricity production, reducing losses in transmission and distribution (Winskel et al. 2014). Developing the solar sector and its technologies is thus highlighted as one of the most promising strategies to achieve RES targets worldwide.

Investing in CSP could have been an interesting option to the Portuguese technology mix since it has the capacity to store energy. However, its viability is strongly dependent on production scale up, due to CSP plants being only economically viable at power capacity higher than 50 MW (INESCPORTO & ATKearney 2012).

The deployment of mini-generation systems to supply small areas or communities, such as industrial parks, can also contribute to improve local economies and stimulate the interest in new investments. In Portugal, this is particularly relevant since the regions with high solar radiation are also the poorer ones in terms of industry and economy development (Carvalho et al. 2011). It is expected that, by 2020, solar mini- and micro-generation could provide 500 MW of electricity to supply services and industrial sectors (Zane et al. 2011).

3.2.3 Hydro power

Hydro power plants are the most known and mature renewable technologies in Portugal, beginning its contribution to the electricity system in the 1940's (Zane et al. 2011). As a mature technology, investment and operations costs of hydropower plants are becoming relatively stable. Also, there is a low potential in Portugal for additional locations for SHP (INESCPORTO & ATKearney 2012).

In order to explore the hydro potential in Portugal, the National Programme for High-Capacity Hydroelectric Dams (PNBEPH) was launched in 2007 (Coba SA & Procesl Lda. 2007). The strategic actions proposed by the programme includes increasing the total hydro power capacity to 7000 MW, increasing pump storage capacity and reinforcing the complementarity between hydro and wind power production.

3.2.4 Biomass power

Biomass-based electricity production has a very similar operation principle to that of a conventional thermal unit, making the technology very well established (INESCPORTO & ATKearney 2012).

Electricity production by biomass is mainly operated in dedicated plants, for which there exists two main technologies: biomass combustion and biomass gasification. Biomass combustion is a simple, mature technology with efficiencies rounding 20-28% and nominal potential of 2-20 MW. Biomass gasification is much more complex and higher capital intensive, but achieves efficiencies of 28-32% (INESCPORTO & ATKearney 2012).

The type of biomass mostly used in dedicated facilities in Portugal is based on forest residues. This is one of the major strengths of biomass technology deployment since it brings income to local communities or regions in Portugal, promoting the development of rural areas, reducing the rural exodus and engaging in industry development (Carneiro & Ferreira 2012). In addition, biomass from industrial residues (e.g. wood or cork) is also frequently used in cogeneration units feeding also the national electricity grid.

3.2.5 Other RES

The world's first wave farm was officially operational in 2008, in Póvoa de Varzim, in Portugal. The wave farm has the designation of Aguçadoura Wave Park and is made up by three Pelamis generators with a total installed capacity of 2.25 MW. However, two months later the wave farm was shut down, due to particular structural flaws, and today there is no perspectives of the reopening. Nevertheless, once overcome these problems, it is expected that the wave farm will produce 24 MW of electricity. Additionally, a pilot zone in the Portuguese coast, in Leiria, is being prepared to receive demonstration projects for the wave energy utilization to produce electricity (APREN 2015).

The geothermal technology to produce electricity in Portugal is only operational in São Miguel Island, in Azores. There are five geothermal power units with a total installed capacity of 28 MW.

3.3 The national goals

The goals stated in the last governmental program for energy policies in Portugal (Resolução do Conselho de Ministros nº 2/2011) include:

- Assuring competitive prices for end-use energy sources;
- Improving the energy efficiency by reducing 25% of the energy consumption until 2020;
- Diversifying primary energy sources;
- Maintain the commitment in reducing GHG emissions;
- Reducing the external fuel dependency;
- Promoting the liberalization of all energy markets;
- Reducing the energy intensity, in medium-term, to the lowest value in European Union.

Henceforward, several actions plans were launched in order to achieve such goals. The National Action Plan for Energy Efficiency[1] started in 2008 and had established a target of 10% reduction in the end-use energy consumption until 2015. The National Strategy for Energy[2] extended the previous target to a 20% reduction until 2020 and later, the Portuguese Government reinforced the target to 25%. The 2020 National Action Plan for Renewable Energies[3] predefines minimum RES shares in several sectors, namely 31% in primary energy consumption, 55.3% in electricity production, 10% in transport sector and 30.6% in heating/cooling sector. It also establishes targets concerning external energy supply, namely reducing the external fuel dependency to 74% (which was already consecutively achieved in 2013 and 2014) and reducing imports in 25%.

[1] PNAEE - Plano National de Ação para a Eficiencia Energética
[2] ENE – Estratégia Nacional para a Energia
[3] PNAER 2020 – Plano Nacional de Ação para as Energias Renováveis

4. Research Methodology

The main purpose of this study is to propose a methodology to identify major uncertainties present in the electricity system and demonstrate their impact in the long-term electricity production mix, through scenario analysis. The research methodology to be adopted in order to successfully achieve the propose research objectives, follow a multi-method approach, combining two quantitative methods – a stochastic method to analyse and represent the uncertain parameters, and a deterministic model to optimise the electricity system over a 20 year' horizon. The data gathering for the stochastic method follow a qualitative approach, thus, overall, the study presents a mixed method research strategy. The final outcome, the proposed methodology, was demonstrated for an electricity system close to the Portuguese one.

The proposed methodology is summarized in Figure 7 including the: (1) Selection of risk and uncertain parameters, supported on a qualitative approach; (2) Definition of probability functions and correlation values for the selected parameters, according to historical data series and statistical analysis; (3) Generation of combined RES scenarios through Monte Carlo simulation and (4) Adoption of a deterministic generation expansion planning model for the final outcome of presenting optimal electricity power scenarios.

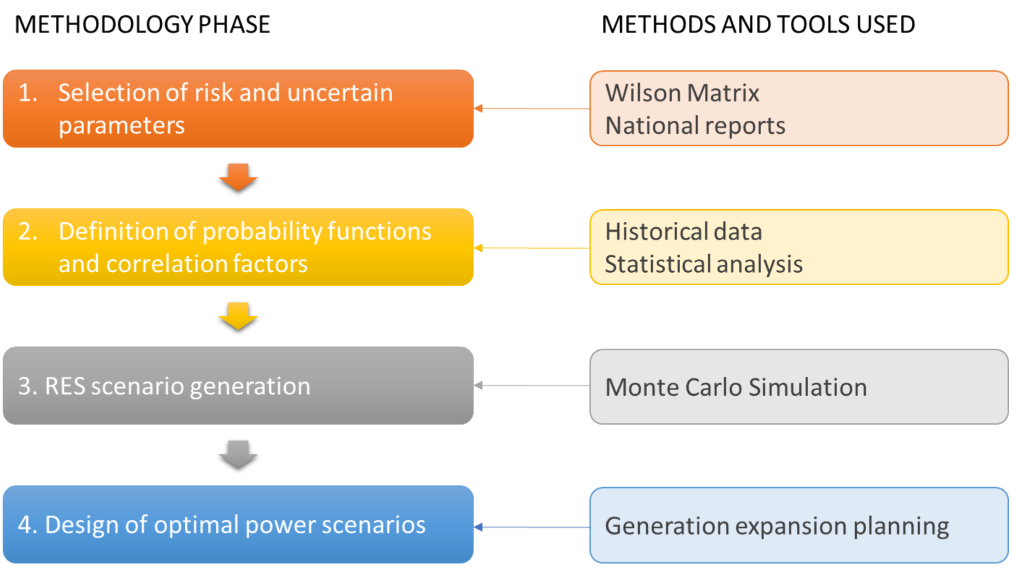

Figure 7 – Research methodology applied to the study.

The work departed from the identification of parameters usually considered in most planning models, based on a review of scientific papers. Simultaneously, the identification process was being tapered in order to enhance those uncertain parameters that directly affect the electricity production. As a result, a set of parameters were identified with a few of the most important ones being selected for demonstrating the proposed modelling approach. Therefore, a Wilson Matrix was used to select, from this set of identified parameters, those with greater potential to affect the long-term electricity power planning for the Portuguese case. The Wilson Matrix is a simple impact/uncertain matrix with a high-medium-low scoring system, which can help positioning the variables based on their potential risk (Ian Wilson 1998). The potential risk is a combination of the degree of uncertainty of the variable future course and the level of impact that it causes in the key decision factors to the system to be analysed. Thus, the matrix does not provide an exact measure of the risk but, instead, is a useful tool to prioritize those variables that mostly affect the system.

The data to perform the analysis of time variability of renewable sources (wind, solar and hydro) were obtained from the electricity production data series, within frames of 15 minutes, since 2007, provided from REN. For each RES technology, the capacity factor (CF) was calculated. The capacity factor expresses the ratio between the actual electricity produced by a given power plant and the theoretical maximum achieved if the power plant would operate full time. Capacity factor was used due to its dependence on the regime flow (Casadei et al. 2014).

The data to perform the analysis of the future electricity demand was collected from the results of recent national reports. In the Monitoring Report of the Security of Supply of the National Electricity System for the period 2013-2030, the electricity demand evolution was considered to grow within an interval of 0.8% - 1.4%, per year (DGEG 2013). The Development and Investment Plan of the Electricity Transmission Grid 2014-2023 introduces some changes to the previous report, namely the forecasted evolution of future electricity demand, which was lowered to an interval of 0.8% and 1.1% annually growth rate (REN 2013). On the other hand, the Development and Investment Plan of the Electricity Distribution Grid 2015-2019 assumes a bolder prediction of 1.6% annually demand growth until 2019 (EDP Distribuição 2014).

Uncertainty analysis was conducted with @Risk software, from Palisade, which is a suitable tool intended to measure the risk related to a given decision and provides very useful tools that were explored in this work. @Risk is one of the most used software programs for uncertainty and risk analysis. It is able to convert complex problems into simple Excel worksheets (Sugiyama 2008). @Risk is a quantitative simulation tool that resources to the Monte Carlo simulation method to produce the results in the form of a PDF. With @Risk, a PDF can characterize a variable or a combination of several variables, and can also seek for correlations between them.

@Risk was first used to adjust the behaviour of each variable studied, in each month, into a PDF that better fits its pattern. Then, correlations between variables were determined, according to the Pearson correlation coefficient, and integrated in the respective PDF of each variable. Thereafter, Monte Carlo Simulation was used to simulate combinations of variables in each month, resulting in a PDF for the capacity factor of each RES technology for each month. Each PDF represents then a wider range of possible combinations of correlated variables and the probability of occurrence of such combinations.

According to Amer et al. (2013), when more than two uncertain parameters are involved, the standard approach for scenario generation must be no less than three and no more than eight scenarios. Hereupon, five RES scenarios were created selecting five possible combinations obtained from @Risk and also a reference scenario, based on the average RES power production in the Portuguese electricity system for the 2008-2014 period.

For scenario optimization, a model developed under the SEPP Project[4] was adapted to this work. Originally, the SEPP model was developed for a 10 years' time period, with the purpose of analysing the impact of incremental wind power penetration in the Portuguese electricity system, as described in Pereira et al. (2015a). The characteristics of the adapted version of SEPP model are presented in

Table *2*, according to the classification proposed in this work and detailed in Table 1. For this study, the model was adapted to a 20 years' time horizon, other RES technologies were included (SHP, sun photovoltaic and biomass) and additional constraints were defined, namely predefined shares of RES contribution to the electricity production system. Also, the model was modified to operate in loop, i.e., the

[4] Sustainable Electricity Power Planning (SEPP) was a research project developed in the University of Minho during 2010-2013, intending to create new models to support decision making on future electricity generation technologies (available at http://sepp.dps.uminho.pt/),

scenarios are sequentially optimized and the results of each one of them are properly identified at the end of the run.

Table 2 – Classification of the model used in the work.

Category		Subcategory
Purpose of the model	*General*	Explore the future (apply scenario analysis)
	Specific	Focus on the energy supply side of the system
Sectoral coverage		Single sector; electricity system only
Perception of the planner		System approach
Geographical level		National level
Time horizon		Long-term (20 years' time horizon) – generation expansion planning
Modelling approach		Bottom-up – RES and non-RES technologies detailed in the model
Modelling tool		Multi-objective optimization model – minimization of total costs and total CO_2 emissions
Mathematical formulation		MILP, equations written in GAMS code
Uncertainty analysis		Deterministic optimization, probabilistic analysis of RES scenarios and optimal power scenarios

Scenario generation and optimization involves the information gathered about some technical and economic aspects of the power system and their evolution perspectives. Hence, several assumptions were required to introduce into the model in order to simplify the representation of the electricity system.

– Information about economic and technical aspects of each power unit is presented in Table 3. All costs related issues were collected from Schröder et al. (2013) which provides a relatively recent survey of current and future cost estimates in the electricity sector, covering renewable and non-renewable generation. All costs are assumed to remain constant for the next 20 years and so, the technology learning effect and the variations in fuel prices are not considered.

– CO_2 emission factors were calculated from the ratio between annual emissions release by each thermal power plant and its respective annual electricity production. CO_2 emissions from biomass were considered to be negligible.

– The assumed potential for RES until 2030 were obtained from a project designated New Energy Technologies – Roadmap Portugal 2050 (E. VALUE & CENSE 2011).

– CO_2 emissions allowances are assumed to remain unchanged at 25€/ton CO_2, as well as the discount rate, which was set at 8%.

– The reserve margin used in this study was defined to be 1%. This value was obtained from the work developed and described in Pereira et al. (2015a).

Table 3 – Economic and technical characteristics of power plants.

Power plant	Investment cost (€)	FO&M costs (€/MW)	VO&M costs (€/MWh)	Pumping costs (€/MWh)	Fuel costs (€/MWh)	CO2 emission factor (t/MWh)	Lifetime (years)	Potential until 2030 (MW)
Coal	1800000	60000	6	-	8.4	0.844	40	-
CCGT	800000	20000	4	-	21.6	0.369	30	-
Large hydro	3000000	20000	-	-	-	-	50	
Large hydro w/ pumping	2000000	20000	-	1.5	-	-	50	4595
Run-of-river	3000000	60000	-	-	-	-	50	
Wind onshore	1300000	35000	-	-	-	-	25	2650
Wind offshore	3000000	80000	-	-	-	-	20	4000
Solar photovoltaic	1560000	25000	-	-	-	-	25	9035
SHP	3000000	60000	-	-	-	-	40	400
Biomass	2500000	100000	-	-	7	-	30	1042

The main outputs of the model are total costs and emissions released by the electricity production system for the entire period analysed, as well as a combination of different electricity generation options and their contribution to the electricity production. The scenarios were then fully characterized and are expected to represent relevant information for supporting future electricity planning decisions.

5. Analysis and Discussion of Results

5.1 Selection of uncertain parameters

The classification of each variable analysed in the Wilson Matrix is presented in Figure 8. Wind availability was classified as a "critical scenario driver" due to its high unpredictability both in time and space. Also wind power is a significant player in the Portuguese electricity system, with growing perspectives at a global scale. Solar availability is also unpredictable in the long term but today, solar power contributes with a low percentage to the national electricity production system, and as such it is assumed that it does not impact the system as much as wind availability. Solar availability was thus classified as an "important scenario driver".

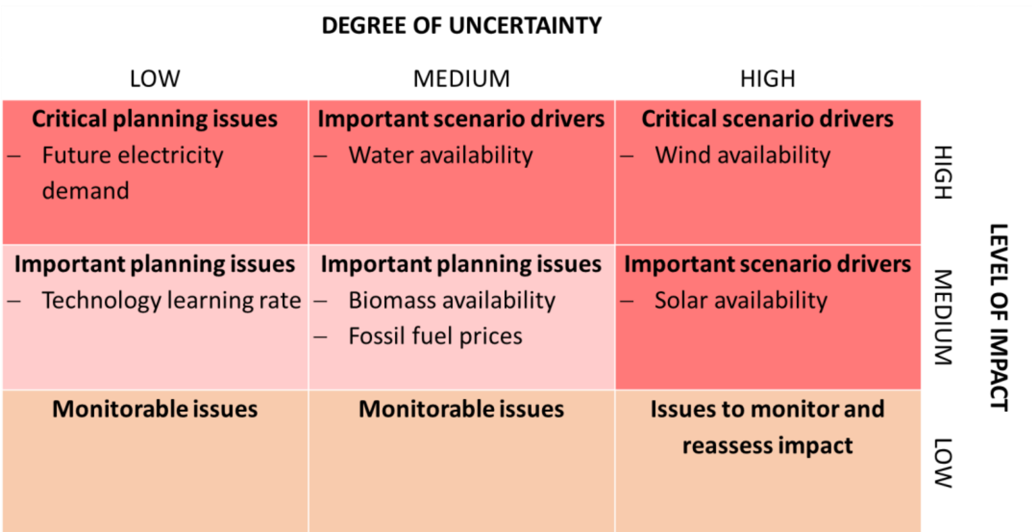

Figure 8 – Uncertain parameters classification using the Wilson Matrix.

Water availability was also classified as "important scenario driver". Water availability has huge impact on the Portuguese electricity power system and contributes to a large extent to the backup system and security of supply. Nevertheless, its degree of uncertainty is lesser than wind or solar availability, because even being the water availability highly affected by climate conditions, large hydropower technologies have reservoirs that can store energy, unlike wind and solar photovoltaic technologies.

Electricity demand was classified as a "critical planning issue" since it plays an obvious role in the electricity system, driving the electricity power production and the backup activation. However, and even being the historical data not representative of the evolution of the electricity demand in the last five years, there are several methods and tools designed to provide reliable demand projections.

At last, technology learning rate, biomass availability and fossil fuel prices were assigned in “important planning issues”. Technology learning rate has a lower uncertainty degree compared with biomass availability, because it is a process with an evolution pattern and relevant only for long term power planning. But they both have a medium impact on the electricity power planning: biomass availability has a relatively significant role in the electricity production and technology learning rate directly affects the investment and fixed costs of the electricity generation options. Fossil fuel (coal and natural gas) prices are subjected to economic and geopolitical conditions of the external supplier, since Portugal is dependent of fossil fuels imports. Nevertheless, in the last decades, Portugal has diversified their suppliers in order to reduce the risk related to the external supply of fuels. Fossil thermal power production contributes to a large share of the total electricity production. Notwithstanding, the tendency of the Portuguese electricity system is to rely less and less in fossil fuels for electricity production, in opposition to the promotion of renewable sources, in order to reduce the external dependency of Portugal.

According to Maack (2001), the key elements for a good scenario plot are the variables positioned in the categories “critical planning issues” and “critical scenario drivers”. Nevertheless, the variables positioned in the category “important scenario drivers” are also deemed to be important for the Portuguese electricity power planning. Therefore, the uncertain parameters selected for this study were renewable sources availability (wind, solar and water) and future electricity demand.

5.2 Uncertainty representation and scenario generation

Each energy source displays a particular behaviour that is different between them and different at each month. This behaviour, related to the capacity factor (CF) of the respective electricity generation technology, could be translated into a PDF. The data collected for the period 2007-2014, hourly, for each of the considered RES technologies at each month, was adjusted to a PDF that better fits the time series. After the adjustment, a Monte Carlo simulation with 100 iterations was run in @Risk. As an example, the results for January for wind (green line), solar (yellow line), SHP (light blue line) and run-of-river (purple line) are presented overlaid in

Figure 9.

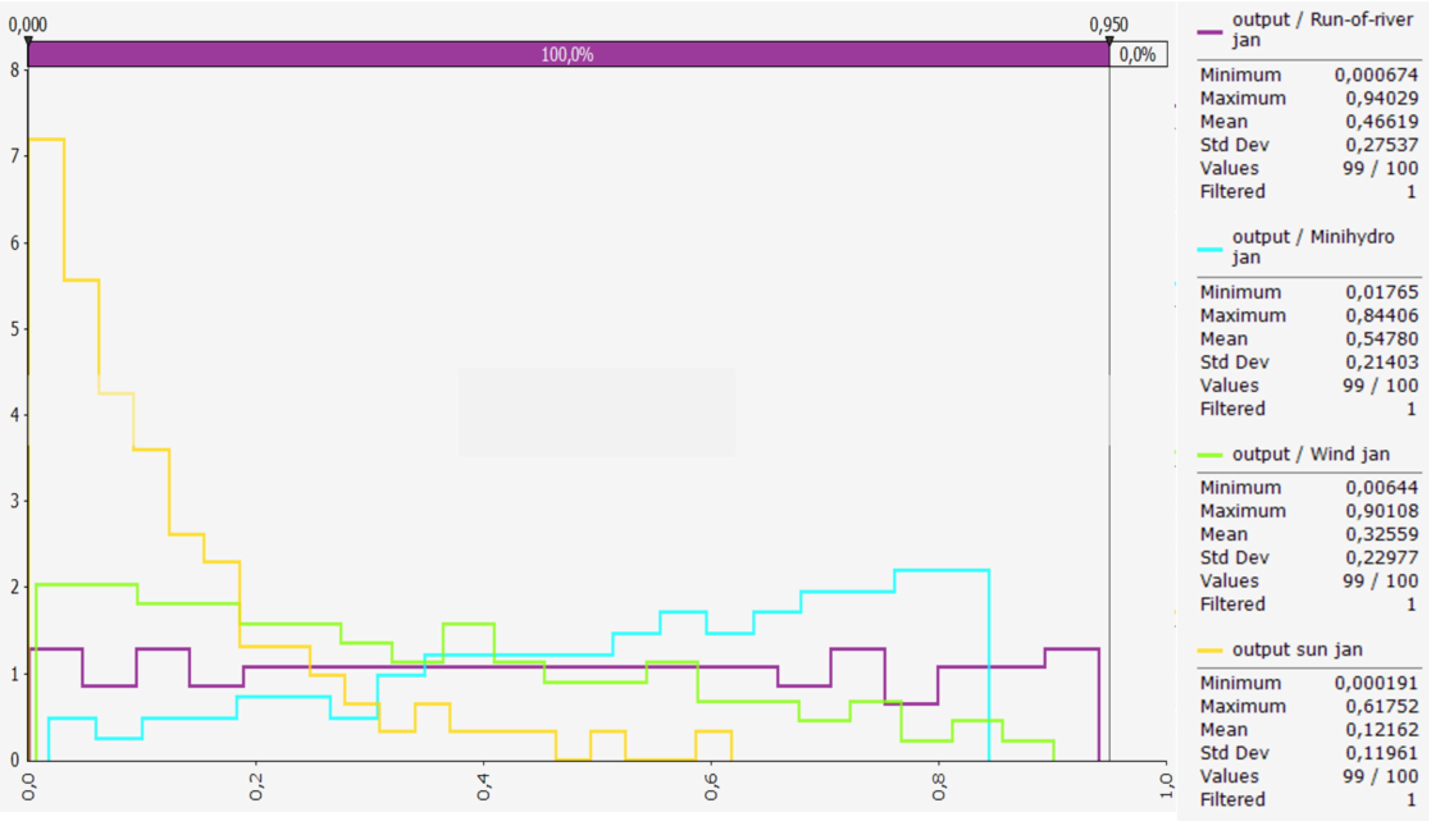

Figure 9 – Probability distribution of the CF of each technology, in January, for the 2007-2014 period.

The information in

Figure 9 can be interpreted as follows. In January:

– CF of run-of-river power plants follows a uniform distribution, within a large interval between almost zero and little more than 0.94, which means that the probability is equal for all possible values within the interval.

– CF of SHP plants follows a triangular distribution within an interval between 0.176 and 0.844, being the most likely values closer to the upper limit of the interval.

– CF of wind power plants also follows a triangular distribution within an interval between 0.006 and 0.901. The average CF is 0.325 and the most likely values are within this average and the lower limit of the interval.

– CF of solar power plants follows an exponential distribution, which indicates that is possible to achieve a value of 0.617 but the most likely value is 0.121.

Table 4 shows the PDF that better fits each technology at each month. Wind onshore technology reveals a behaviour along the year that can be expressed as a triangular distribution from January to April and a beta distribution the rest of the year, except during the months September and October for which a gamma distribution is the best fit. As for solar technology, its capacity factor exhibits an exponential distribution during the entire year. Water-based technologies, namely SHP and run-of-river, present miscellaneous distributions, varying from triangular, exponential, uniform, beta, gamma, Weibull and Pearson.

Table 4 – Probability distribution for each technology, at each month.

Month	Wind onshore	Solar photovoltaic	SHP	Run-of-river
Jan	RiskTriang	RiskExpon	RiskTriang	RiskUniform
Feb	RiskTriang	RiskExpon	RiskTriang	RiskUniform
Mar	RiskTriang	RiskExpon	RiskUniform	RiskUniform
Apr	RiskTriang	RiskExpon	RiskBetaGeneral	RiskUniform
May	RiskBetaGeneral	RiskExpon	RiskBetaGeneral	RiskBetaGeneral
Jun	RiskBetaGeneral	RiskExpon	RiskGamma	RiskTriang
Jul	RiskBetaGeneral	RiskExpon	RiskWeibull	RiskWeibull
Aug	RiskBetaGeneral	RiskExpon	RiskWeibull	RiskExpon
Sep	RiskGamma	RiskExpon	RiskPearson5	RiskTriang
Oct	RiskGamma	RiskExpon	RiskInvgauss	RiskTriang
Nov	RiskBetaGeneral	RiskExpon	RiskTriang	RiskTriang
Dec	RiskBetaGeneral	RiskExpon	RiskUniform	RiskTriang

The different PDFs obtained for each RES technology, in each month, gives valuable information about the limits and most likely values for the capacity factors. Additionally, each PDF is expressed by its own parameters.

Triangular distribution function (RiskTriang) is expressed in terms of minimum, maximum and most likely value. In this sense, triangular distribution could be seen as a fuzzy set, considering the previously definition given in Chapter 2.

Beta distribution function is expressed in terms of two shape parameters, denoted α_1 and α_2, that control the shape of the distribution. Beta general distribution (RiskBetaGeneral) adds to beta function two more parameters: minimum and maximum possible values.

Gamma distribution (RiskGamma) is expressed by a shape parameter α and a scale parameter β, which is the reciprocal of the shape parameter. Gamma distribution is the maximum entropy of probability distributions.

Exponential distribution (RiskExpon) is a special case of gamma distribution, where the function is expressed in terms of a scale parameter β. This parameter coincides with the mean value.

Uniform distribution (RiskUniform), or rectangular distribution, is symmetric and thus, assumes that all values within minimum and maximum limits are equally likely to occur.

Inverse Gaussian distribution (RiskInvgauss) is expressed by a parameter μ, which is the mean value, and a shape parameter λ.

Pearson type V distribution (RiskPearson5), as well as Weibull distribution (RiskWeibull), is expressed by a shape parameter α and a scale parameter β. The scale parameter refers to the scale of the horizontal axis, inducing the stretching or squeezing of the distribution graph.

Thus, from these results, it is shown that assuming average values for RES uncertainty can be a flawed option if the point is to get reliable solutions. Additionally, disregarding potential correlations between the CFs of RES technologies may conduct to low reasonable scenarios. Figure 10 presents the correlation factors between the CF of RES technologies, in each month, according to Pearson correlation. It can be observed that run-of-river and SHP have the stronger correlation factors between CFs, especially in the first months of the year, achieving a positive factor of about 0.8. Between the CFs of hydro and wind technologies, the correlation is very week along the year. The same happens with the correlation between solar and wind technologies, but this correlation is always negative. Finally, for the CFs between solar and hydro technologies, the correlation is positive.

JAN	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,83	1		
Wind	0,17	0,32	1	
Sun	0,02	0,03	-0,17	1

MAY	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,42	1		
Wind	-0,14	0,00	1	
Sun	0,29	0,30	-0,18	1

SEP	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,40	1		
Wind	-0,23	-0,04	1	
Sun	0,40	0,15	-0,21	1

FEB	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,82	1		
Wind	0,05	0,19	1	
Sun	0,05	0,02	-0,20	1

JUN	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,55	1		
Wind	-0,22	0,04	1	
Sun	0,38	0,37	-0,23	1

OCT	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,43	1		
Wind	-0,15	0,17	1	
Sun	0,23	0,03	-0,20	1

MAR	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,84	1		
Wind	-0,04	0,16	1	
Sun	0,06	0,03	-0,16	1

JUL	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,51	1		
Wind	-0,22	-0,07	1	
Sun	0,46	0,32	-0,28	1

NOV	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,48	1		
Wind	-0,14	0,01	1	
Sun	0,07	0,03	-0,13	1

APR	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,77	1		
Wind	-0,17	0,07	1	
Sun	0,17	0,19	-0,14	1

AUG	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,44	1		
Wind	-0,19	-0,13	1	
Sun	0,41	0,30	-0,29	1

DEC	Run-of-river	SHP	Wind	Sun
Run-of-river	1			
SHP	0,59	1		
Wind	-0,01	0,18	1	
Sun	0,07	0,10	-0,21	1

Figure 10 – Correlation factors between the CF of RES technologies, for each month.

The main purpose of using Monte Carlo Simulation in this analysis was to assign a probability to the occurrence of a possible combination of different RES technologies with particular regime flow. In order to find possible combinations, however, it was necessary to represent properly and somehow the inputs relations. For this, a simplistic equation was elaborated representing the sum of the CFs of RES. It must be noted that even very simplistic, it fills the required objective of providing simulations representing different combinations of RES outputs. Also the correlation factors are well integrated in the inputs leading the equation to seek possible combinations based on the correlations between RES technologies. This sum equation was designated as the output of the problem and for each month, a simulation was run in the @Risk, with 100 iterations.

From each simulation, five possible combinations of RES were selected and used to construct five scenarios. These scenarios will be latter compared with a reference scenario and are designated as follows:

– Business-as-usual scenario (BUS), reference scenario considering the average capacity factor of each power generator from 2008-2014;

– Lower central (LC), Central (C) and Upper central (UC), intermediate scenarios presenting combinations of CFs for RES technologies with moderate resource availability;

– Pessimist (Pess) and Optimist (Opt), extreme scenarios presenting respectively, very low and very high availability of all renewable resources.

Each RES scenario was then limited to its probability of occurrence and is expected to obtain a full range of possible outcomes. It must be noted that, for continuous distribution functions, the probability of the occurrence of a single value is zero and thus the probability is expressed in terms of an interval.

According to Figure 11 the scenario analysis will cover five possible combinations of RES availabilities ranging from percentile 10% (lower limit of Pessimist scenario) to percentile 85% (upper limit of Optimist scenario). Also, between Pessimist and Lower Central scenarios, a gap is presented and will be discussed next, when comparing BUS with these five RES scenarios. Besides Pessimist scenario, all others demonstrate a connection between the upper limit of a scenario and the lower limit of the next scenario.

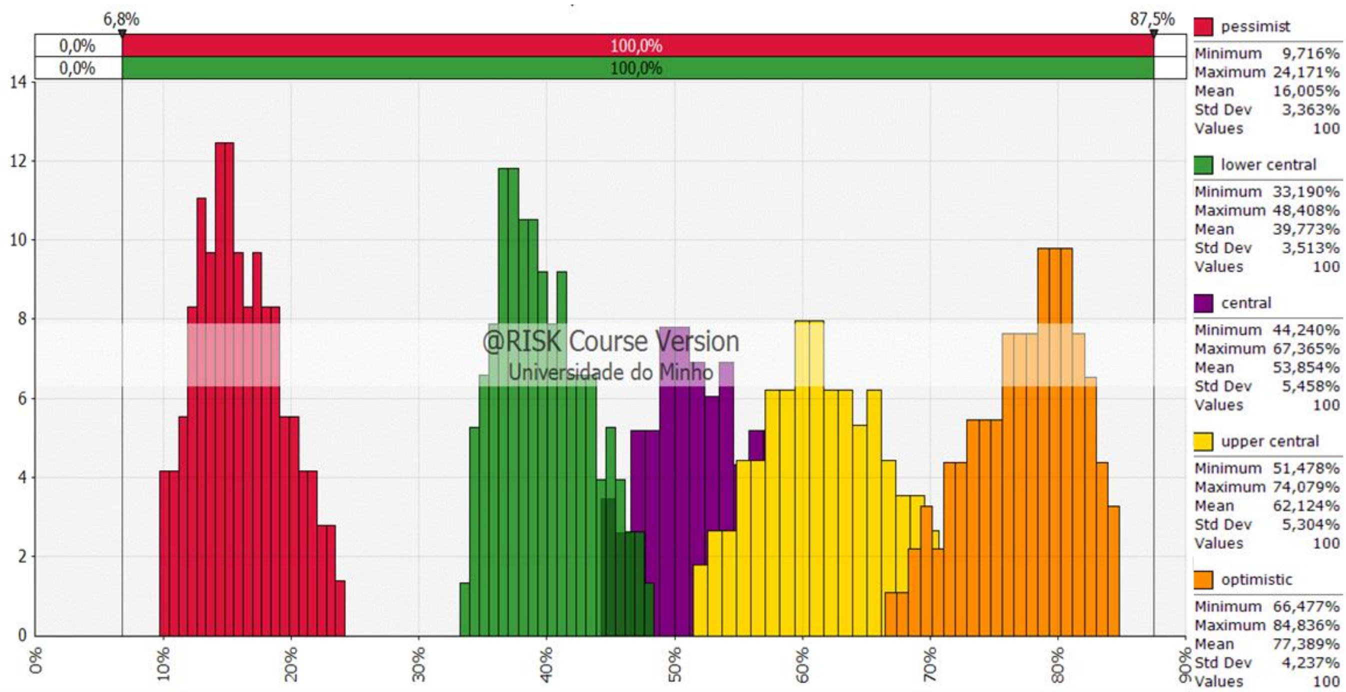

Figure 11 – Probabilistic characterization of each RES scenario, with the respective lower and upper boundaries.

The capacity factor range of each technology characterizing each scenario, along a year, is illustrated in Figure 12. It is demonstrated that increasing the ambitiousness of scenarios, i.e., following the order Pessimist to Optimist, the range of the values for each CF expands along with an increasing in the upper limit of the range. According to Figure 12, the BUS scenario is positioned between Lower central and

Central scenarios for solar technology and between Pessimist and Lower central scenario for wind and run-of-river technology. Nevertheless, SHP technology presents an unique behaviour, since the BUS scenario is more similar to Optimist scenario than all the others. The reason behind this is related to the high capacity factor of SHP technology since 2008, because the period considered in the BUS scenario was characterized by a high Hydraulic Productivity Index (HPI), resultant from the high level of precipitation during some years of this period.

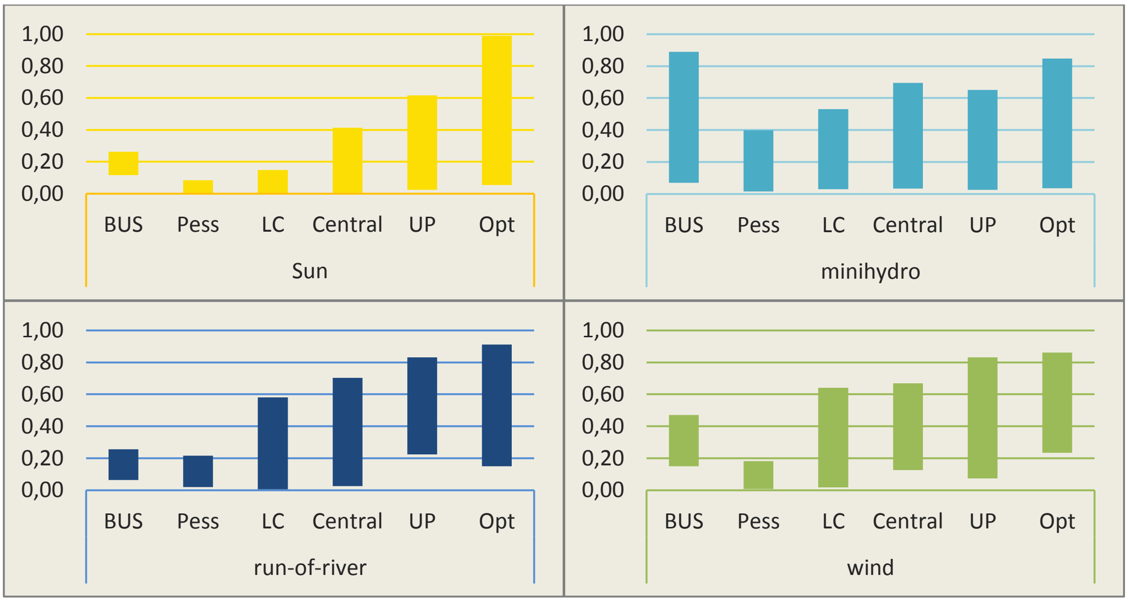

Figure 12 – Capacity factors range of each RES technology, in each scenario.

The analysis of the uncertainty of future electricity demand was not handled by Monte Carlo Simulation, due to the lack of extensive data on demand projections. Instead, three growth rates were analysed: i) 0.95%, the report's medium value obtained with the most recent data; ii) 2%, a value near the electricity demand growth before 2011; and 5%, a very aggressive growth rate that is unlikely to occur until 2035, but that can be seen as an extreme case, useful to analyse the robustness of the obtained scenarios. Using three different growth rates in scenario generation it is expected to have a wider view of possible outcomes in different electricity needs situations, as illustrated in Figure 13.

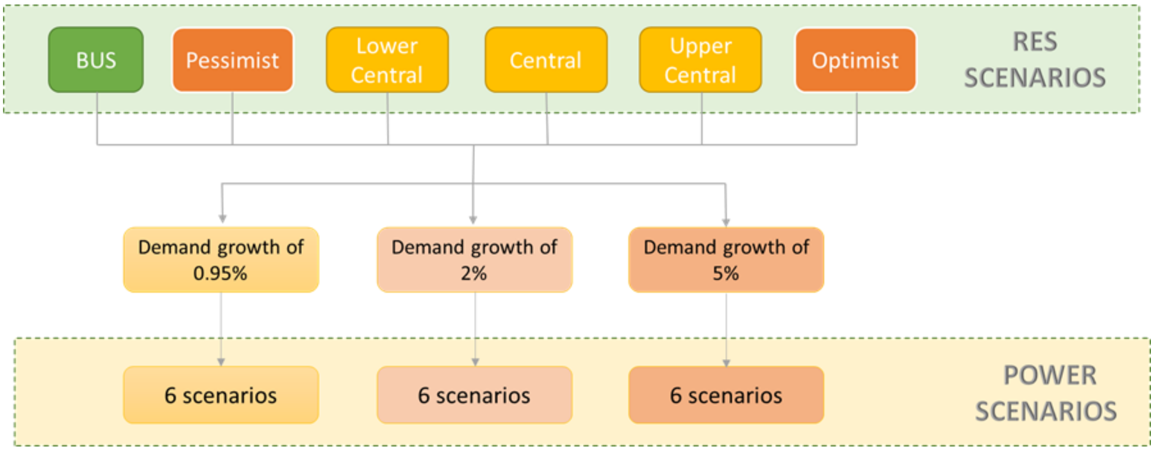

Figure 13 – Scenario construction for the electricity power system.

5.3 Scenario optimization

The main indicators for each scenario in 2035 are presented in Table 5, including the average cost of electricity production, the average CO_2 emissions, the total RES share to the electricity system and the electricity production exceeding the demand needs, also known as critical excess or overproduction.

Table 5 – Main indicators for scenario comparison.

INDICATORS	Cost of electricity production (€/MWh)			CO_2 emissions (ton/MWh)			Total RES share (%)			Excess Production (%)		
Demand growth	*0,95%*	*2%*	*5%*	*0,95%*	*2%*	*5%*	*0,95%*	*2%*	*5%*	*0,95%*	*2%*	*5%*
RES SCENARIOS BUS	*11,2*	*12,3*	*18,5*	*0,236*	*0,257*	*0,248*	*65,9*	*72,7*	*70,8*	*4*	*11*	*9*
Pessimist	17,7	20,8	18,5	0,269	0,264	0,248	75,1	67,9	70,4	13	6	8
Lower central	10,1	11,4	17,7	0,204	0,235	0,238	62,2	72,3	71,3	0	10	9
Central	8,5	10,1	16,0	0,158	0,218	0,238	66,0	69,0	70,8	0	7	9
Upper central	5,8	7,9	13,9	0,098	0,170	0,227	74,0	65,0	70,6	0	3	9
Optimistic	2,8	4,3	9,9	0,027	0,084	0,167	88,5	71,4	62,4	2	0	0

Through a first analysis to results, one remark generalized in all indicators is that the BUS scenario can be positioned between Pessimist and Lower central scenarios. For example, the cost of electricity and excess production of the system for BUS scenario is close to the equivalent in the Lower central scenario, while the value of CO_2 emissions and total RES share in electricity system is close to the equivalent in the Pessimist scenario.

Following the scenario order from Pessimist to Optimist a consistent decrease in the cost of electricity production as well as in CO_2 emissions can be seen. Total RES contribution to the electricity system in

2035, as well as the excess production, have not such an evident relation between scenarios. With the exception of the extremes scenarios (Pessimist and Optimist), total RES share increases in the electricity system along with crescent capacity factors and there is no excess production in all of those scenarios. In fact, a higher RES share does not mean more productivity, if there is electricity overproduction. Table 5 shows that an increase in electricity demand will lead to an increase in RES share but, simultaneously, to a higher excess production of the system. One cause of overproduction may be due to wind and solar photovoltaic power that are generating electricity whenever the source is available and have no energy storage capacity. As such, very favourable wind and sun conditions may lead to an overproduction of the system in some months, if not properly balanced with power units with rigid output.

Costs decreasing is due to higher values in the capacity factors of RES, increasing the power generated by these sources. In this way, lesser fossil fuels to generate electricity are required, and thus, significant savings in fuel costs can be obtained. Additionally, increasing capacity factors of RES technologies will lead to an increase in the electricity produced, with variable costs near zero. The main reason behind cost decreasing is also the same for the CO_2 emissions decreasing – since electricity production by fossil fuels is gradually substituted by RES power output, significant savings in CO_2 emissions could be achieved, as well as saving with CO_2 emissions allowances.

Considering now the increase in the electricity demand from 0.95% to 5% annual growth, it can be observed a natural increase in the electricity costs, resulting from the need of installing more power plants to match the respective demand, as illustrated in Figures Figure 14 to Figure 16. Taking BUS scenario as an example, with a most likely growth demand of 0.95% the additional installed power until 2035 would be near 450 MW; with a growth demand of 2% the additional power would be about 2500 MW; and in an extreme scenario with a 5% demand growth the additional installed power would be 23600 MW.

Figure 14 up to Figure 16 present the proposed new installed capacity for each technology in the system in the last year of the planning period, aiming to analyse the robustness of the BUS scenarios traditionally used on the optimization approach.

In Figure 14, it is shown that total installed power in BUS, apart from the Pessimist scenario, is very similar to all the others, both for in the total installed power and for the selected technologies. This may indicate that, with a moderate electricity demand growth of 0.095% in the next 20 years, the Portuguese electricity system could be prepared to meet the demand at all time, but with a slight excess production.

Still, besides the Pessimist scenario, BUS presents the highest case compared with scenarios with moderate and high availability of RES, demonstrating that favourable conditions of wind, sun and/or hydro will lead undoubtedly to a more efficient electricity system, with lower production costs and no excess production.

Comparing Figure 14 and Figure 15, it is demonstrated that an increase from 0.95% to 2% in the electricity demand would lead to additional investments mostly on CCGT power plants. Although CCGT power plants require higher fuel costs from imported natural gas, these plants have the smallest investment costs of all the technologies analysed and were assumed to have longer lifetime than wind or solar power plants. Therefore, the electricity production costs are not very distant from one scenario to another considering the increasing demand to 2%. Optimist scenario does not share the same pathway; instead of investing in CCGT power plants, the alternative future electricity system would consist only on renewable technologies investments. Also, Optimistic scenario is the only which presents additional installed capacity in solar photovoltaics, taking the advantage of high CF values for this technology.

Comparing Figure 14 and Figure 16, a very different combination of technologies is shown when electricity demand increases to 5%. Among particular remarks of each scenario, one that provides an interesting information is the similarity of BUS and Pessimist scenarios, indicating that, at this demand growth rate, the Portuguese electricity system would require a large increase on the total installed capacity. Lower central scenario is the only with investments on wind offshore power plants, assuring about 30% of the total installed power in wind technologies, almost the same as in hydro power. Solar power is installed in almost all the scenarios and, particularly for the Optimist scenario, the additional solar photovoltaic installed power represents half of the total installed power.

Another interesting point that deserves some consideration is that when installed wind power increases with the offshore power plants implementation, no solar power is required (Lower central scenario). On the other hand, installing all solar power potential until 2035 will lead to zero installation of additional wind power. One interpretation of such results may be attributed to the existence of a negative correlation of some characteristic of wind and solar power. In fact, correlations determined in @Risk suggest that wind and solar capacity factors, although having a very week correlation factor in all months, always presents a negative value, which indicates a negative relation. In this sense, the combination of wind and solar power technologies must be carefully chosen in order to optimise power production and avoid excess production.

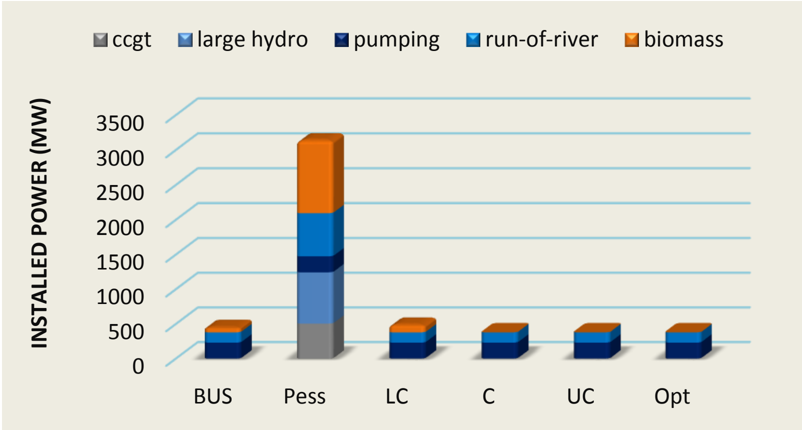

Figure 14 – New installed power from each technology until 2035, for 0.95% annual demand growth.

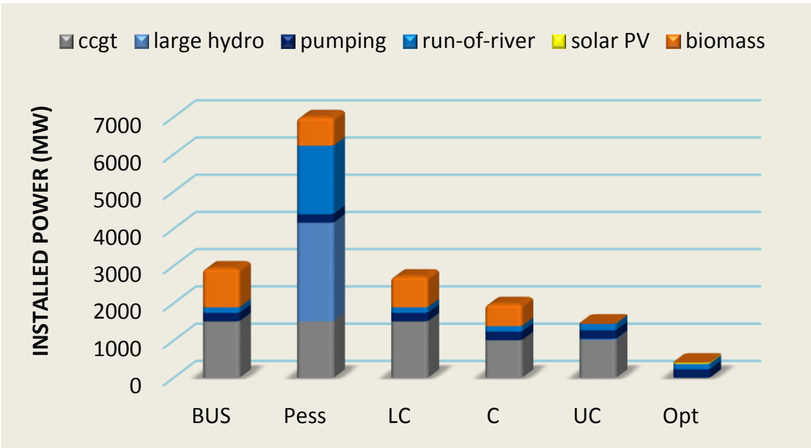

Figure 15 – New installed power from each technology until 2035, for 2% annual demand growth.

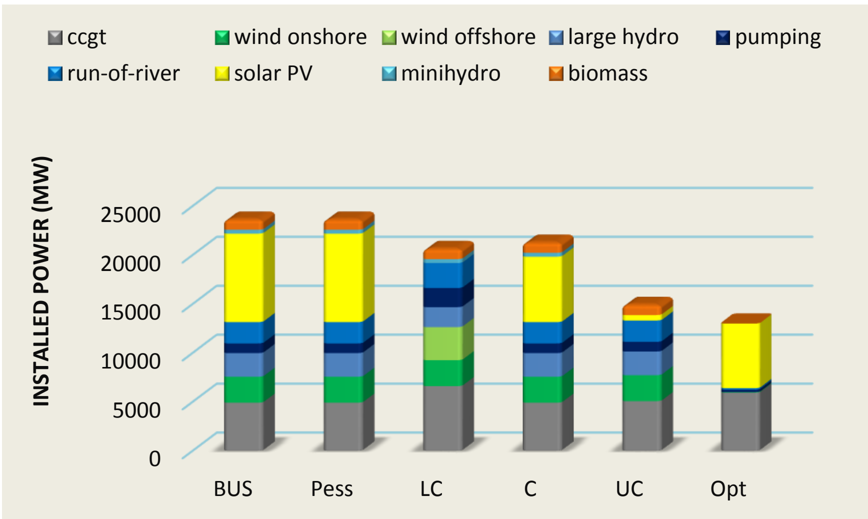

Figure 16 – New installed power from each technology until 2035, for 5% annual demand growth.

According to the results, the BUS scenario seems to be less robust for high demand growth perspectives, meaning that the optimal mix of new technologies to add to the system strongly depends on the RES availability assumptions which in turn are largely affected by the climate conditions.

For low demand growth perspectives, the BUS scenario is close to most of the other scenarios in what concerns the new installed power mix, apart from the pessimistic scenario. This can be explained by the low needs for new installed power, as the already existing power plants would be able to cover most of the demand requirements. This would mean that under the perspective of low demand growth rate, the cost and CO_2 emissions would still be largely influenced by climate conditions but the optimal technology mix is less sensitive to these assumptions.

For most of the considered RES scenarios a high demand growth rate would be compensated by not only RES power plants but also new installed power including CCGT. This means that high demand growth rate will tend to result in higher costs, higher CO_2 emissions and lower RES share and consequently higher fossil fuel imports. High demand growth rate has a significant impact on technology mix obtained for each RES scenario demonstrating that climate assumptions will have a major role on the definition of optimal power scenarios. Also, a high demand growth rate does not necessarily lead to a reduction of excess electricity production but in some cases can even increase it.

It is also interesting to notice that scenarios with high RES share are frequently associated to higher excess electricity production, demonstrating that the efficient management of RES in the electricity system requires the inclusion of other options incorporating for example electricity storage or interconnection capacity. Although Portugal is already interconnected with Spain in the Iberian electricity market, for the sake of simplicity, the possibility of market trading was not considered in these simulations.

6. CONCLUSIONS

Deterministic models are well-recognized in the electricity power planning field and are presented as a good strategy to develop long-term scenarios. However, these models frequently rely on assumptions of the future behaviour based on fixed parameters and historical data, as if the future is well known in advance. To deal with uncertain parameters, deterministic models can use sensitivity analysis, and so, they are viewed as a useful simple approximation of reality, that is easier to build and interpret than stochastic models. On the other hand, stochastic models, instead of using deterministic values, identify uncertain parameters and assign to them probability distributions mapping their possible occurrences, increasing reliability of the scenario generation process but requiring additional resources and higher computational efforts.

This work intended to analyse several uncertain parameters that could affect electricity systems and that should be included in electricity power planning. For this, a methodology combining risk evaluation of the model parameters, Monte Carlo simulation and generation expansion planning with a cost optimization model was proposed and demonstrated for an electricity system close to the Portuguese one. The parameters i) availability of renewable energy sources and ii) future electricity demand were selected as critical uncertain factors, using a Wilson matrix, and then, a quantitative analysis was carried with a suitable software for selecting best fit PDF functions for each parameters, perform correlation analysis and scenarios generation. Quantitative analysis had enabled the creation of several possible combinations of uncertain parameters that were used to differentiate scenarios. Six RES scenarios were analysed: a business-as-usual scenario (BUS), two extreme scenarios and three intermediate scenarios. These were then modelled in SEPP Model and fully characterized.

The results of this work indicate that the Portuguese electricity production system is largely influenced by RES availability assumptions, in particular under high growth electricity demand scenarios. Ensuring a low growth of electricity demand seems to be not only an important strategy to reach economic and environmental objectives but also to mitigate risk associated with the variability of RES resources.

The results also demonstrate that costs, CO_2 emissions and imports ratios can be clearly improved by ensuring a high capacity factor for RES technologies, particularly wind and solar-based, as the Portuguese electricity system will be able to operate more efficiently, with no excess production and at lower costs. This is particularly important for the case of the electricity systems with high share of RES as climate change can have a major role on the expected RES power output. Capacity factors of these technologies are highly correlated to the regime flows of wind and sun and so, the choice of the location to implant the power unit is crucial for the power production potential. Also, increasing the efficiency of power units by, for example, increasing the rotor diameters of wind turbines or introducing PV cells with higher power conversion capacity, will increase consequently the capacity factor.

The methodology proposed was presented and tested in order to provide an alternative to the high complex and time consuming stochastic optimization modelling and operation. The analysis of the Portuguese electricity system produced a set of six scenarios obtained in short running times (just over 2 minutes), supported on previous Monte Carlo simulation of relevant parameters of the model. The SEPP optimization model demonstrated to be strategically useful for scenario design, combined with uncertainty analysis, but put in evidence also the importance of the data quality and assumptions for the design of a robust plan for the future.

The proposed methodology for electricity power planning provide a low time consuming, relatively simple and multi-method methodology to cope with the complexity of incorporating uncertainty and risk analysis in power planning and decision making processes. This methodology exhibits flexibility to be adapted to the analysis of diverse uncertain parameters and risk sources, guided by other objectives than the ones studied in this research. It is also worth mentioning that the proposed methodology enables the planner or decision maker to explore and assign probability distributions for future scenarios, as well as to determine the possible range of the inputs or outputs of the problem to be analysed.

6.1 Future research

The proposed methodology should be validated by comparing the presented results of the model used in this work with other models or methodologies used for the electricity power planning considering uncertainty and risk. One validation approach can be achieved through the comparison with the results obtained by a stochastic optimization model. Also, as Foley et al. (2010) reported, one validation approach for long-term optimization models can be done through the testing of outputs with a similar model, in this case a deterministic model, in order to determine the sensitivity analysis of choices given by both models.

Moreover, other uncertainties and scenarios should be investigated in order to increase knowledge of overall risks presented in the electricity system and study possible measures to manage them. In particular, climate change projections and their impact on the operating performance of RES technologies is an important aspect to be taken into account in future planning models. Extreme conditions could also be modelled in order to analyse catastrophic failure situations and risks in power supply systems.

Additional development of the optimization model would be of great interest, including not only other technologies for electricity generation but considering also the inclusion of storage or/and interconnection capacity that can have a critical role on the management of high RES systems.

REFERENCES

Akgün, A.A., van Leeuwen, E. & Nijkamp, P., 2012. A multi-actor multi-criteria scenario analysis of regional sustainable resource policy. *Ecological Economics*, 78, pp.19–28.

Allan, G. et al., 2011. The regional electricity generation mix in Scotland: A portfolio selection approach incorporating marine technologies. *Energy Policy*, 39(1), pp.6–22.

Amer, M., Daim, T.U. & Jetter, A., 2013. A review of scenario planning. *Futures*, 46, pp.23–40.

Amorim, F. et al., 2013. How much room for a competitive electricity generation market in Portugal? *Renewable and Sustainable Energy Reviews*, 18, pp.103–118.

Anon, Resolução do Conselho de Ministros 2/2011. *Diário da República, 1.ª série — N.º 8 — 12 de Janeiro de 2011*, pp.270–271.

APREN - Associação De Energias Renováveis, 2014. A Produção de Eletricidade em Portugal. *Dados técnicos nacionais*. Available at: http://www.apren.pt/pt/dados-tecnicos-3/dados-nacionais-2/producao-2/a-producao-de-electricidade-em-portugal-2/1-1/evolucao-da-producao-de-electricidade-em-portugal-entre-1999-e-2013-c/correccao-de-hidraulicidade-2/ [Accessed October 10, 2015].

APREN - Associação De Energias Renováveis, 2015. Ondas e Marés. *Energias Renováveis*. Available at: http://www.apren.pt/pt/energias-renovaveis/ondas-e-mares/ [Accessed October 9, 2015].

Bachhiesl, U., 2004. Measures and Barriers towards a Sustainable Energy System. In *19th World Energy Congress, Sydney, Australia 5-10 september*.

Bale, C.S.E., Varga, L. & Foxon, T.J., 2015. Energy and complexity: New ways forward. *Applied Energy*, 138, pp.150–159.

Baños, R. et al., 2011. Optimization methods applied to renewable and sustainable energy: A review. *Renewable and Sustainable Energy Reviews*, 15(4), pp.1753–1766.

Beeck, N. van, 1999. *Classification of Energy Models*, Tilburg: Operations research.

Bhattacharyya, S.C. & Timilsina, G.R., 2010. A review of energy system models. *International Journal of Energy Sector Management*, 4(4), pp.494–518.

Cai, Y.P., Huang, G.H., Yang, Z.F., Lin, Q.G., et al., 2009b. Community-scale renewable energy systems planning under uncertainty—An interval chance-constrained programming approach. *Renewable and Sustainable Energy Reviews*, 13(4), pp.721–735.

Cai, Y.P., Huang, G.H., Yang, Z.F. & Tan, Q., 2009a. Identification of optimal strategies for energy management systems planning under multiple uncertainties. *Applied Energy*, 86(4), pp.480–495. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0306261908002328 [Accessed November 17, 2014].

Carbon Capture & Storage Association, 2015. What is CCS? Available at: http://www.ccsassociation.org/what-is-ccs/ [Accessed October 23, 2015].

Carneiro, P. & Ferreira, P., 2012. The economic, environmental and strategic value of biomass. *Renewable Energy*, 44, pp.17–22.

Carvalho, D. et al., 2011. Photovoltaic energy mini-generation: Future perspectives for Portugal. *Energy Policy*, 39(9), pp.5465–5473.

Casadei, S., Liucci, L. & Valigi, D., 2014. Hydrological Uncertainty and Hydro-power : New Methods to Optimize the Performance of the Plant. *Energy Procedia*, 59, pp.263 – 269.

Catrinu, M.D. & Nordgård, D.E., 2011. Integrating risk analysis and multi-criteria decision support under uncertainty in electricity distribution system asset management. *Reliability Engineering & System Safety*, 96(6), pp.663–670.

Chandramowli, S.N. & Felder, F. a., 2014. Impact of climate change on electricity systems and markets – A review of models and forecasts. *Sustainable Energy Technologies and Assessments*, 5, pp.62–74.

Coba SA & Procesl Lda., 2007. *Programa Nacional de Barragens com Elevado Potencial Hidroeléctrico (PNBEPH)*.

Connolly, D. et al., 2010. A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied Energy*, 87(4), pp.1059–1082.

Cunha, J. & Ferreira, P., 2014. A Risk Analysis of Small-Hydro Power (SHP) Plant Investment. *International Journal of Sustainable Energy Planning and Management*, 2, pp.47–62.

Després, J. et al., 2014. Modelling the impacts of variable renewable sources on the power sector: Reconsidering the typology of energy modelling tools. *Energy*, pp.1–10.

DGEG - Direção Geral de Energia e Geologia, 2013. *Relatório de Monitorização da Segurança de Abastecimento do Sistema Elétrico Nacional 2013-2030*.

E. VALUE - Estudos e Projectos em Ambiente em Economia & CENSE - Center for Environmental and Sustainability Research, 2011. *Novas tecnologias energéticas Roadmap Portugal2050: Análise das novas tecnologias energéticas nacionais e cenarização do seu impacto no sistema energético nacional*,

EDP Distribuição, 2014. *Plano de desenvolvimento e investimento da rede de distribuição (PDIRD) 2015-2019*.

EDP Renováveis, 2015. Wind Float. *Inovação*. Available at: http://www.edpr.com/pt-pt/negocio/inovacao/wind-float/ [Accessed October 10, 2015].

European Comission, 2013. Electricity consumption by industry, transport activities and households/services. *Eurostat: Products Datasets*. Available at: http://ec.europa.eu/eurostat/web/products-datasets/-/ten00094 [Accessed October 10, 2015].

European Comission, 2015. *Portugal Report*, pp.172–180.

Feng, Y. & Ryan, S.M., 2013. Scenario construction and reduction applied to stochastic power generation expansion planning. *Computers & Operations Research*, 40(1), pp.9–23.

Ferreira, P. & Vieira, F., 2010. Evaluation of an offshore wind power project: Economic, strategic and environmental value. *World Academy of Science, Engineering and Technology*, 47, pp.161–166.

Foley, A.M. et al., 2010. A strategic review of electricity systems models. *Energy*, 35(12), pp.4522–4530.

Fortes, P. et al., 2008. Long Term Energy Scenarios under Uncertainty. In *5th International Conference on European (EEM 2008), Lisboa, Portugal 28-30 may*.

Gargiulo, M. & Gallachóir, B.Ó., 2013. Long-term energy models: Principles, characteristics, focus, and limitations. *Wiley Interdisciplinary Reviews: Energy and Environment*, 2(2), pp.158–177.

Gomes, B.A. & Saraiva, J.T., 2009. Demand and generation cost uncertainty modelling in power system optimization studies. *Electric Power Systems Research*, 79(6), pp.1000–1009.

Haydt, G. et al., 2011. The relevance of the energy resource dynamics in the mid/long-term energy planning models. *Renewable Energy*, 36(11), pp.3068–3074.

Hiremath, R.B., Shikha, S. & Ravindranath, N.H., 2007. Decentralized energy planning; modeling and application-a review. *Renewable and Sustainable Energy Reviews*, 11(5), pp.729–752.

Hourcade, J.C. et al., 2006. Hybrid Modeling: New Answers to Old Challenges. *The Energy Journal, International Association for Energy Economics*, 2(Special issue), pp.1–12.

Ian Wilson, 1998. Mental maps of the future: an intuitive logics approach to scenarios. In L. Fahey & R. M. Randall, eds. *Learning from the Future: Competitive Foresight Scenarios*. John Wiley & Sons, Inc., pp. 81–108.

IEA - International Energy Agency, 2015. Industrial application of CCS. *Carbon capture and storage*. Available at: http://www.iea.org/topics/ccs/subtopics/industrialapplicationsofccs/ [Accessed October 10, 2015].

INESCPORTO - Instituto de Engenharia de Sistemas e Computadores do Porto & ATKearney, 2012. *Recomendações para uma estratégia sustentável de eficiência energética e exploração de energias renováveis para Portugal*.

Jebaraj, S. & Iniyan, S., 2006. A review of energy models. *Renewable and Sustainable Energy Reviews*, 10(4), pp.281–311.

Jeon, C. & Shin, J., 2014. Long-term renewable energy technology valuation using system dynamics and Monte Carlo simulation: Photovoltaic technology case. *Energy*, 66, pp.447–457.

Kim, S. et al., 2012. Optimization of Korean energy planning for sustainability considering uncertainties in learning rates and external factors. *Energy*, 44(1), pp.126–134.

Koltsaklis, N.E. et al., 2014. A spatial multi-period long-term energy planning model: A case study of the Greek power system. *Applied Energy*, 115, pp.456–482.

Krukanont, P. & Tezuka, T., 2007. Implications of capacity expansion under uncertainty and value of information: The near-term energy planning of Japan. *Energy*, 32(10), pp.1809–1824.

Kunreuther, H. et al., 2014. Integrated Risk and Uncertainty Assessment of Climate Change Response Policies. *Climate Change 2014: Mitigation of Climate Change, contribution of Working Group III to the IPCC Fifth Assessment Report*, pp.151–206.

Maack, J.N., 2001. *Chapter 5. Scenario Analysis: A Tool for Task Managers*, Washington, D.C.

Möst, D. & Keles, D., 2010. A survey of stochastic modelling approaches for liberalised electricity markets. *European Journal of Operational Research*, 207(2), pp.543–556.

Pang, X., Mörtberg, U. & Brown, N., 2014. Energy models from a strategic environmental assessment perspective in an EU context—What is missing concerning renewables? *Renewable and Sustainable Energy Reviews*, 33, pp.353–362.

Pereira, J.P., 2012. *Wind Energy potential in Portugal*, pp.1-18.

Pereira, S., Ferreira, P. & Vaz, A.I.F., 2015a. Optimization modelling to support renewables integration in power systems. *Renewable and Sustainable Energy Reviews (accepted for publication)*.

Pereira, S., Ferreira, P. & Vaz, A.I.F., 2015b. A simplified optimization model to short-term electricity planning. *Energy (accepted for publication, in press)*.

Pereira, S., Ferreira, P. & Vaz, A.I.F., 2015c. Generation expansion planning with high share of renewables of variable output. *submitted*.

Pereira, S., Ferreira, P. & Vaz, A.I.F., 2013. Electricity cost optimization in a renewable energy system. In *International Conference on Energy & Environment: bringing together Economics and Engineering, Porto, Portugal, 9-10 may*.

Pereira, S., Ferreira, P. & Vaz, A.I.F., 2011. Strategic Electricity Planning Decisions. In *Conference on Sustainable Development of Energy, Water and Environment Systems, Dubrovnik, Croatia, 25-29 september*.

Pérez-Arriaga, I.J., 2011. *Managing large scale penetration of intermittent renewables*, In *2011 MIT Associate Member Symposium*. MIT Energy Initiative, pp. 1-43.

Pfenninger, S., Hawkes, A. & Keirstead, J., 2014. Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, 33, pp.74–86.

Pilli-Sihvola, K. et al., 2010. Climate change and electricity consumption—Witnessing increasing or decreasing use and costs? *Energy Policy*, 38(5), pp.2409–2419.

Pires et al., 2014. *Emigração Portuguesa. Relatório Estatístico 2014*, Lisboa.

Prasad, R.D., Bansal, R.C. & Raturi, A., 2014. Multi-faceted energy planning: A review. *Renewable and Sustainable Energy Reviews*, 38, pp.686–699.

Pye, S., Sabio, N. & Strachan, N., 2015. An integrated systematic analysis of uncertainties in UK energy transition pathways. *Energy Policy*, pp.1–12.

REN - Redes Energéticas Nacionais, 2015. Estatísticas do setor elétrico. *Electricidade Centro de Informação*. Available at: http://www.centrodeinformacao.ren.pt/PT/Paginas/CIHomePage.aspx.

REN - Redes Energéticas Nacionais, 2013. *PDIRT Plano de Desenvolvimento e investimento da Rede de Transporte de Eletricidade 2014-2023*.

Ribeiro, F., Ferreira, P. & Araújo, M., 2013. Evaluating future scenarios for the power generation sector using a Multi-Criteria Decision Analysis (MCDA) tool: The Portuguese case. *Energy*, 52, pp.126–136.

Santos, J.A. et al., 2015. Projected changes in wind energy potentials over Iberia. *Renewable Energy*, 75, pp.68–80.

Santos, M.J., Ferreira, P. & Araújo, M., 2014. A Multi-Criteria Analysis of Low Carbon Scenarios in Portuguese Electricity Systems. In *ICOPEV - 2nd International Conference on Project Evaluation, Guimarães, Portugal, 26-27 june*.

Schaeffer, R. et al., 2012. Energy sector vulnerability to climate change: A review. *Energy*, 38, pp.1–12.

Schleicher-Tappeser, R., 2012. How renewables will change electricity markets in the next five years. *Energy Policy*, 48, pp.64–75.

Schröder, A. et al., 2013. *Current and Prospective Costs of Electricity Generation until 2050*, pp.73-79.

Seljom, P. & Tomasgard, A., 2015. Short-term uncertainty in long-term energy system models — A case study of wind power in Denmark. *Energy Economics*, 49, pp.157–167.

SETIS - Strategic Energy Technologies Information System, 2010b. Hydropower. *Technology Information Sheets*. Available at: https://setis.ec.europa.eu/publications/technology-information-sheets/hydropower-technology-information-sheet [Accessed January 25, 2014].

SETIS - Strategic Energy Technologies Information System, 2010a. Wind Energy. *Technology Information Sheets*. Available at: https://setis.ec.europa.eu/publications/technology-information-sheets/wind-energy-technology-information-sheet [Accessed January 25, 2014].

Soontornrangson, W. et al., 2003. Scenario planning for electricity supply. *Energy Policy*, 31(15), pp.1647–1659.

Soroudi, A. & Amraee, T., 2013. Decision making under uncertainty in energy systems: State of the art. *Renewable and Sustainable Energy Reviews*, 28, pp.376–384.

Sugiyama, S., 2008. Monte carlo simulation/risk analysis on a spreadsheet: review of three software packages. *Foresight*, 9(Spring), pp.36–42.

Sun, N., Swider, D.J. & Voss, A., 2006. A Comparison of Methodologies Incorporating Uncertainties into Power Plant Investment Evaluations. In *29th IAEE International Conference. Potsdam, Germany, 7-10 june*.

Ventosa, M. et al., 2005. Electricity market modeling trends. *Energy Policy*, 33(7), pp.897–913.

Vithayasrichareon, P. & MacGill, I.F., 2012. A Monte Carlo based decision-support tool for assessing generation portfolios in future carbon constrained electricity industries. *Energy Policy*, 41, pp.374–392.

Watson, J. et al., 2015. The impact of uncertainties on the UK ' s medium-term climate change targets. *Energy Policy*, pp.1–11.

Widén, J. et al., 2015. Variability assessment and forecasting of renewables: A review for solar, wind, wave and tidal resources. *Renewable and Sustainable Energy Reviews*, 44, pp.356–375.

Winskel, M. et al., 2014. Learning pathways for energy supply technologies: Bridging between innovation studies and learning rates. *Technological Forecasting and Social Change*, 81(1), pp.96–114.

World Energy Council, 2013. Energy resources: Geothermal. *World Energy Resources: 2013 Survey*. Available at: https://www.worldenergy.org/publications/2013/world-energy-resources-2013-survey/ [Accessed October 10, 2015].

Zane, A.B. et al., 2011. Integration of electricity from renewables to the electricity grid and to the electricity market. *RES-Integration - Country Report Portugal*, pp.1–48.