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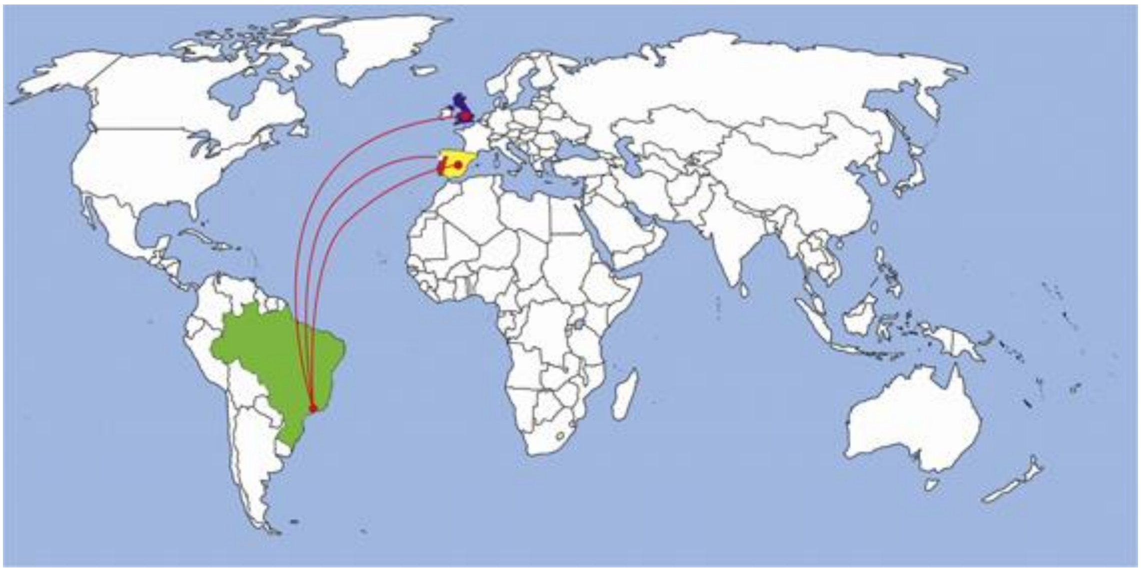

Report

Risk and uncertainty in energy decision making

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Index

1. SUMMARY.....2
2. RISK SOURCES AND UNCERTAINTY IN ELECTRICITY SYSTEMS.....2
Intermittency of Renewable Energy Sources.....5
Electricity Demand.....6
Climate Change.....7
Technology Costs.....8
Fuel Prices.....9
Social Acceptance.....10
3. UNCERTAINTY INCLUSION IN OPTIMIZATON MODELLING.....11
References.....14

1. SUMMARY

This report aims to feed the design of energy planning models and evaluation tools for energy projects, scenarios and technology analysis. Energy decision making requires the establishment of assumptions supported on the best available forecasts. The quality of the results obtained for energy planning problems and consequently the merit of the decisions taken are then highly dependent on the accuracy of these forecasts. Recognizing the uncertainty surrounding the energy sector, it becomes essential both to identify relevant uncertainty sources for energy planning according to the energy systems and markets characteristics (section 2) and to define approaches to deal with this uncertainty (section 3).

2. RISK SOURCES AND UNCERTAINTY

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 (Santos 2015).

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.

1.1 Intermittency of Renewable Energy 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).

1.2 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.

1.3 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).

1.4 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%.

1.5 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.

1.6 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.

Table 1. Uncertainties and risk sources in electricity systems.

Categories	Description	Risks and uncertainties
Economic	Risks arising from the financial aspects of the project, the market conditions and the economic growth of a country.	Project capital costs Commodities prices Operational costs Interest rates External costs
Geopolitical	Risks arising from political decisions of one country's foreign affecting another country or region.	National policies International agreements Environmental regulation
Sociocultural	Risks arising from divergences on social and cultural characteristics of different communities.	Behavioural change Future electricity demand Social acceptance
Environmental	Risks related to the influence of the environmental conditions on the performance of the electricity system.	Extreme climatic events Climate change Natural accidents and catastrophes
Technical	Risks related to topological and operational conditions of the electricity system.	System's infrastructure Reliability of resources Learning rate Failures and forced outages

3. UNCERTAINTY INCLUSION IN OPTIMIZATON MODELLING

Deterministic models are not primarily intended to deal with uncertainty but, 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) that may be used as inputs for the deterministic models.

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 problems formulation and retrials calculated 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 (Loulou et al. 2012).

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. 2009). Represented as an interval, possible values for the uncertainty are comprised within minimum and 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 as the most likely value that the uncertain parameter can assume. Probability distribution expresses the uncertainty as a PDF, based on historical data and/or literature review or even experience from the stakeholders or decision makers. Multiple uncertainties allow the uncertainty to be represented as a combination of two or three previous forms (interval, fuzzy set and probability distribution).

(Kim et al. 2012) focused their work on the uncertainties facing the electricity production costs of conventional and renewable technologies. They applied Monte Carlo simulation to handle uncertainties, such as learning rate of technologies, fuel prices and carbon prices and assuming a normal distribution for all the uncertain parameters. (Pye et al. 2015) explored the uncertainties affecting policy goals to the transition of the UK energy systems to meet decarbonisation and security goals. The uncertainties tackled were investment costs of power generation technologies, building rates, biomass availability and resources prices (fossil fuel and biomass), for which the PDF were assumed to be triangular distribution, in view of lack of data.

Several studies were carried out in order to compare the pros and cons of both deterministic and stochastic approaches. (Fortes et al. 2008) analysed the fragilities of the Portuguese power system associated with the development of deterministic long term energy scenarios. A stochastic approach was adopted, using fossil energy prices and energy demand as uncertain parameters, and the main conclusion of the work was that different drivers result in divergent energy scenarios. (Loulou et al. 2012) analysed alternative climate targets under different cooperation regimes by groups of countries, by both deterministic and stochastic optimization models. The deterministic approach was found not suitable to produce results with mixes of choices, which could only be found by stochastic modelling, although this could be computationally cumbersome. (Cedeño & Arora 2011) made a comparison between deterministic and stochastic optimization for the problem of transmission network expansion planning. They emphasized that deterministic models can produce higher cost impact in the plan when the demand deviate from the assumed fixed scenario, notwithstanding the computational complexity of the stochastic approach.

Another technique designed specifically to analyse complex and uncertain systems is the Exploratory Modelling and Analysis (EMA), an iterative and question-driven research methodology that resources to computational experiments (Bankes 1992). With this technique, many scenarios are designed, allowing the planners to explore the consequences or implications of the uncertain assumptions in the overall system being analysed (Kwakkel & Pruyt 2013). The final goal is to define a set of uncertain scenarios and provide to decision-makers insights of each scenario and trade-offs between them.

NETEP project aims to contribute to the theme of uncertainty on power planning, recognizing that a deterministic approach can be too limited specially in systems characterized by high levels of renewable energy sources (RES) and as such strongly dependent on the availability of the underlying renewable resources. After the identification of the major sources of risk and uncertainty, a methodology will be developed and tested in at least one of NETEP countries to provide a contribution to tackle these challenges via a simplified stochastic approach able to face major uncertain parameters. To the best of the authors' knowledge, no such simplified approach has been proposed and demonstrated in the literature for a case study based on real operating conditions.

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