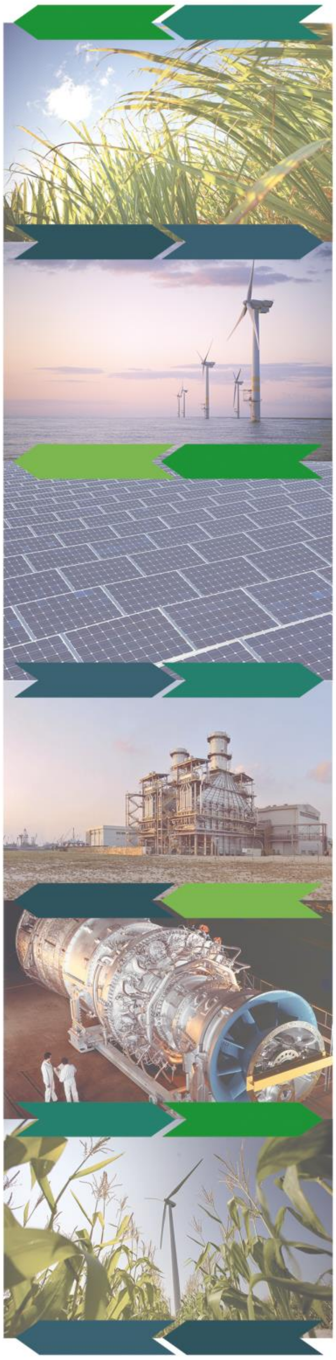
Navigating the Roadmap for Clean, Secure and Efficient Energy Innovation



Issue Paper on

Risk and Uncertainty Modelling in Energy Systems

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1 Introduction

The energy consumption is growing worldwide as a result of population growth and economic development (IEA, 2014). The vulnerability of the energy carriers can have high impact on society with significant economic consequences. Therefore, the risk assessment of energy systems is extensively been performed by the research community and industry. Various approaches for modelling risk in energy systems are developed.

The reliability of the electrical energy supply is challenged by the recent deployment of intermittent energy sources in remote areas and by the market liberalization, which resulted in large long-distance power transfer that frequently exceeds transmission capacity and increasingly outpace the expansion of transmission network facilities. The increased interconnectivity among neighbouring control areas and the integration of volatile renewable energy sources (RES) enhance the risk of cascading failures in power systems (Sansavini et al., 2014).

The challenge of creating an efficient, sustainable energy system requires solving design and control problems in the presence of different sources of uncertainty (Powell, 2013). The stochastic nature of the RES requires the consideration of the uncertainty of wind speed and solar radiation in the risk modelling as well.

1.1 Risk and uncertainty definitions

A large amount of literature on the subject of the risk is available. In this literature the term ''risk'' is used in many different senses (Kaplan and Garrick, 1981). The common definition of risk relevant for a single scenario is probability times consequence. In such case (single scenario) the probability times consequence viewpoint would equate a low-probability high-damage scenario with a high-probability low-damage scenario, clearly not the same thing at all. Therefore a more robust definition of risk is derived in (Kaplan and Garrick, 1981). In analysing risk one attempts to envision future events if a certain course of action (or inaction) is undertaken. Fundamentally, a risk analysis consists of an answer to the following three questions (Kaplan and Garrick, 1981):

I. What can happen? i.e., what can go wrong?
II. How likely is it that will happen?
III. If it does happen, what are the consequences?

The answer of these questions for a given outcome or “scenario” can be formulated as a triplet:

(1)

$$\langle S_i, p_i, x_i \rangle$$

where S_i is a scenario identification or description; p_i is the probability of that scenario; and x_i is the consequence or evaluation measure of that scenario, i.e., the measure of damage.

If one considers all the scenarios that one can think of, than this set of scenarios is the answer to the question above and therefore is the risk. More formally, the risk, R, “is” is defined a set of triplets:

(2)

$$R = [\langle S_i, p_i, x_i \rangle], \qquad i = 1,2, \dots, N$$

The risk formulation from Eq. 2 can be extend by considering uncertainty. In general the notion of risk, involves both uncertainty and some kind of loss or damage that may occur. Symbolically, it could be written as: risk = uncertainty + damage. The degree of uncertainty depends upon the total state of knowledge; upon all the evidence, data, and experience with similar courses of action in the past. Naturally, the uncertainty is expressed using probability, thus the Eq. (2) is given as follows:

(3)

$$R = [\langle S_i, p_i(f_i), x_i \rangle], \qquad i = 1,2, \ldots, N$$

where the $p_i(f_i)$ is the probability density function for the frequency f_i of the occurrence of scenario i.

2 Electrical power system risk assessment

The primary objectives of the modern power systems are to provide a reliable and economic supply of electric energy to their customers. The basic concept of reliability-cost/reliability-worth evaluation is relatively simple and can be presented by the cost/reliability curves of Figure 1 (Billinton and Allan, 1996). These curves show that the investment cost generally increases with higher reliability. On the other hand, the customer costs associated with failures decrease as the reliability increases. The total costs therefore are the sum of these two individual costs. This total cost exhibits a minimum, and so an "optimum" or target level of reliability is achieved. This concept is quite valid. Two difficulties arise in its assessment. First, the calculated indices are usually derived only from approximate models. Second, there are significant problems in assessing customer perceptions of system failure costs.

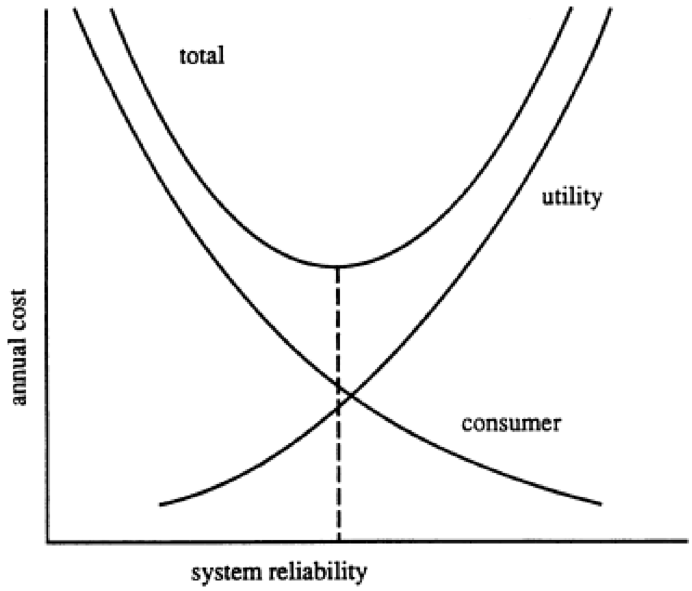

Figure 1: Total reliability costs (Billinton and Allan, 1996)

Power system reliability indices can be calculated using a variety of methods. The two main approaches are the analytical and the simulation approach (Billinton and Allan, 1996). Analytical techniques represent the system by a mathematical model and evaluate the reliability indices from this model using direct numerical solutions. They generally provide expectation indices in a relatively short computing time. Unfortunately, assumptions are frequently required in order to simplify the problem and produce an analytical model of the system. Simulation methods estimate the reliability indices by simulating the actual process and random behaviour of the system. The method therefore treats the problem as a series of real experiments. The techniques can theoretically take into account virtually all aspects and contingencies inherent in the planning, design, and operation of a power system.

In general, the electrical power system operation consists of two phases: the planning and the operating phase. The main issue in the planning and in the operating phases is providing the adequate capacity of generating reserves. Consequently, the level of redundancy and the associated cost are directed as the prime question (Billinton and Allan, 1996).

Various design, planning and operating criteria and techniques are developed over many decades in an attempt to resolve and satisfy the dilemma between the economic and reliability constraints. Most of these criteria and techniques are mainly used in practical applications, are inherently deterministic. However, lately many probabilistic methods for assessment of power systems reliability are developed.

When one discuses power system reliability, one must consider the adequacy and the security aspects. This division implicates that two aspects are different in both concept and evaluation. However, in reality it is not intended to indicate of two distinct processes involved in power system reliability, but is intended to ensure that reliability can be calculated in a simply structured and logical fashion (Billinton and Allan, 1996).

2.1 Adequacy assessment

The power system adequacy is defined as the ability of the system to provided sufficient generation and transmission capacity to cover the load demand (Billinton and Allan, 1996). One of the major tasks in providing a certain level of adequacy to power system operations is the planning of the generating reserves considering the flexibility provided by the interconnection lines (Gjorgiev et al., 2015). One of the most commonly used indexes of power system adequacy are the loss of load expectation (LOLE) and expected energy not served (EENS) (Billinton and Allan, 1988). The LOLE is defined as:

(4)

$$LOLE = \sum_{i=1}^{n} cp_i\,(C_i < L_i) \quad \text{(days/period)}$$

where C_i is the available capacity on day i, L_i is the forecast peak load demand on day i, $cp_i(C_i < L_i)$ is the cumulative probability calculated for loss of load on day i (system state i), and n is the number of days. The LOLE index can also be calculated using the load duration curve or the individual hourly values, e.g. expressed in hours/day. The EENS is defined as:

(5)

$$EENS = \sum_{i=1}^{n} cp_i\,(C_i < L_i) * L_i^C * t \quad \text{(MWh/period)}$$

where L_i^C is the amount of load not supplied $(L_i - C_i)$ in MW at interval i and t is the duration of interval i. The capacity outage probability tables is the most common technique to determine the cumulative probability, cp_i, used by the LOLE and EENS adequacy indices. The capacity outage probability tables are two-dimensional matrices comprising the capacity levels, or the corresponding capacities being out of service as well as the associated probabilities of their occurrence (Billinton and Allan, 1992, 1996). These probabilities are defined as the probability that the indicated capacity will be out of service. Usually, the cumulative probability of occurrence is applied for the capacity modelling, defined as the sum of the probabilities corresponding to outage capacities equal to or larger than the indicated amount. Capacity outage probability tables can be created using a convolution algorithm (Billinton and Allan, 1996).

2.2 Security of supply

Power system security is defined as the ability of the system to respond to disturbances arising within the system (Billinton and Allan, 1996). Security is therefore associated with the response of the system to whatever disturbances they are subjected. These are considered to include conditions causing local and widespread effects and the loss of major generation and transmission facilities. These conditions, e.g. faults, loss of components can cause cascading events with local or even total system blackouts.

Two types of approaches for evaluation of the cascading failures in power systems exists: deterministic and probabilistic approaches (Henneaux et al., 2016). The deterministic approaches consider that the evolution of the power system follows a precise trajectory: overloaded branches are tripped, generators and loads suffering extreme voltages are disconnected, and so on. These methods reveal the mainstream potential cascades. These approaches implicitly assume that the power system acts as expected during the cascade, thus they neglect potential scenarios due to the unexpected failures of the system components during the unfold of the cascade. On the other hand, the probabilistic approaches consider that the evolution of the power system after an initial set of contingencies can follow multiple pats with different probability of occurrence, according to failures that can be encountered during the cascade.

Over the time various probabilistic models are developed, such as the OPA model, the Manchester model and the Two-Level PRA model.

2.2.1 OPA model

The OPA model (Carreras et al., 2004) begins with initial sampling of the load and generation pattern. The electrical post-contingency steady state is computed using a DC optimal power flow (DC-OPF) minimizing the amount of load shedding. Once the steady state has been computed, stochastic failures of overloaded lines are simulated by using the failure probabilities of the bulk overloaded lines. The process of steady-state computation and sampling of overloaded line failures is repeated until if one or more new failures occur. The consequences are estimated in terms of load shed after it is determined that no more failures occur. Thus, the model is able to estimate accurately the loss of load due to the loss of connectivity entailed by overloaded line outages. Alternatively, instead of the DC-OPF one can apply the AC-OPF to improve the simulation accuracy (Mei et al., 2008).

2.2.2 Manchester model

The Manchester model (Rios et al., 2002) begins randomly generating initiating outages from an initial load and generation pattern. The electrical post-contingency steady state is then computed using an AC load flow. If the iteration does not converge, load is shed by blocks in the area of the largest power mismatch until convergence is achieved. Once the steady state has been computed, stochastic failures of overloaded lines are simulated by using bulk overloaded lines' failure probabilities. If one or more new failures occur, the process of steady-state computation and sampling of overloaded line failures is repeated. When no more failure occurs, the consequences are estimated in terms of load or energy not served. This model is thus able to estimate accurately the loss of load due to the loss of connectivity entailed by overloaded line outages, and tries to estimate approximately the loss of load due to voltage instability.

2.2.3 Two-Level PRA model

The Two-Level PRA model is based on the decomposition of the analysis in two levels, level-I and level-II, corresponding to the two typical phases of a cascading failure. Two different dynamic PRA methods are developed for the level-I and for the level-II, respectively, as general frameworks in order to consider the mechanisms of cascades occurring in each phase. The coupling between these two levels can lead to an estimation of the frequency and the loss of load for the scenarios leading to a power disruption. The model estimates the loss of supplied power for each scenario.

In addition, an evaluation of the restoration is made in order to estimate the energy not supplied. The model uses a clustering technique to group the scenarios at the end of level I in order to make the dynamic analysis manageable from a computational viewpoint.

3 Gas networks risk assessment

Gas networks in Europe are exceedingly utilized by the households and industry. Besides for manufacturing purposes the industry, i.e. the electrical power sector uses natural gas for generation of electrical energy, mainly supplied directly by the gas network. Thus, the gas network reliability directly affects both society and the electrical power system reliability. In general, the approaches that assess gas networks reliability can be divided on probabilistic and deterministic (based on physical models).

3.1 Probabilistic assessment

In general, the probabilistic assessment of the gas networks can be based on Monte Carlo Simulation (MCS) or Fault Trees (FT) methods. In (Praks et al., 2015) a MCS for stochastic network model with a priority supply pattern represents a general approach, which can be used for security of supply modelling of various transportation networks (gas networks, crude oil, water). The approach is based on the distance from the source node: In order to concurrently model both reliability and capacity constraints of the gas transmission network, a stochastic network representation is used, where each node and edge of the flow network can randomly fail, according to a given probabilistic model of the network component. These component failures in the network are modelled using the MCS technique.

A FT method for gas networks reliability assessment is present in (Praks et al., 2014). FT's are used to ass the probability of gas not supplied to a selected node, i.e. a new FT has to be created for each node. The application of such method for large gas networks will require a software for automatic creation of FT's based on the connectivity of network components and the path from the selected node to the source node(s).

3.2 Physical models

A framework for dynamic scheduling and simulation of coupled electric power and natural gas infrastructures where intra-day interdependence effects are closely approximated is presented in (Zlotnik et al., 2017). The framework formulates optimization problems for different coordination scenarios, from none to fully integrated optimization, and for different operational methods for gas compressors. In each case, numerical solutions to optimization problems with gas dynamics are validated using continuous-time simulations. This methodology enables performance assessment at various levels of coordination and operational sophistication, and quantifies the benefits of coordination between the sectors.

4 Uncertainty analyses in power system with high penetration of RES

Various stochastics methods are developed to capture the effects that RES have on the power system reliability. In (Sansavini et al., 2014) an event based stochastic framework which simulates the operations of the electric network under variable conditions is developed. The framework considers the effects of the uncertainties (related to the load and the renewable generation forecasts on one side, and to weather parameters on the other side) that introduce disturbances in the grid and may cause line outages due to overloads. The approach combines: 1) a DC load flow algorithm that computes the distribution of power flow using a linear load flow approximation, 2) the contribution of wind generation power in a transmission power grid, 3) a strategy for generation dispatch in order to balance the power production and consumption throughout the network, 4) the dynamics of line temperatures as function of the power flow and environmental conditions (wind speed and ambient temperature), 5) the event of automatic line disconnection when the rated line temperature is reached, and 6) the event of line reconnection.

The evolution of cascading events in their slow initiating stages is represented by transmission lines failures, caused by overheating due to excessive power flows. To this aim, the evolution of the line temperature and its dependence on electric flow redistributions is modelled using the model of heat conduction in rods of small cross section in which an electric current of constant intensity flows. Further contributing to the evolution of cascades is a line restoration model which prevents a damaged line to be put back in service before a fixed restoration time has passed. The model of transmission line failure due to loading over their transmission capacity and following restoration, is part of the developed event-based stochastic framework which has also the ability to represent daily hourly changes in power requests at customer side of the system, ambient temperature and wind speed variations.

The stochastic framework is based on sequential MCS in which the combination of load requests, ambient temperature, wind power generation; wind speed and network topology is a system realization. Due to the yearly periodicity of the load request and the room temperature average values, each year is considered statistically equivalent to one another and the results are provided on the basis of yearly averages. The simulation begins by establishing the load demand, the room temperature and wind speed values. If no line disconnection due to excessive heating occurs, the next event corresponds to the occurrence of the next hourly time step (“next hour” event) with updated load demand, ambient temperature and wind speed conditions. If the temperature of a line exceeds the critical temperature set for that line, a “line disconnection” event may occur before the scheduled “next hour” event. A DC load flow is performed following the occurrence of each event. The “line reconnection” event occurs after a time chosen a priori for each line that is disconnected. The change time to the next event is computed as the minimum between the time to the next hour change, the minimum failure time among all lines and the minimum time to reconnection of all lines.

5 Stochastic modelling in energy systems

Representing uncertainty in energy systems not only implies employing some kind of “sensitivity analyses” through a deterministic model (Wallace, 2000). Modelling uncertainty also involves defining scenarios for particular parameters deem stochastic in nature that might be important on pursuing a specific analysis. Some examples of modelling parameters stochastically include: representation of water inflows for reservoirs used in hydro power production; characterization of different demand profiles; scenarios on electricity prices either for short-term operations or long-term investment decisions; and stochastic realizations of renewable resources such as wind and solar. To implement the parameter’s stochastic scenarios, various assumptions can be made on its statistical distribution, the number of representative scenarios and the scenario probability (Higle and Wallace, 2003). For example, deterministic models typically use the expected value of the distribution while stochastic models takes into consideration the full distribution or a representation (sampling) of the distribution. In this sense, deterministic models are better position to look for decisions *here-and-now*, i.e. based on present or expected information. For that reason, stochastic and deterministic optimization models are structurally different, especial on crucial decisions that need *wait-and-see,* e.g. decisions for investments in power generation and transmission capacities. In a deterministic world there is no reason to hedge future uncertainty as it does not consider later possible outcomes of random variables (Higle and Wallace, 2003).

A challenge on modelling the parameter's stochastically (i.e. scenario based) is that the model computational complexity increases significantly. In this regard, various solution methods have been developed to decompose the problem, this includes the L-shaped method and Benders decomposition. For example, (Nowak and Römisch, 2000) proposes a solution method by lagrarian relaxation applied to power scheduling of a hydro-thermal system under uncertainty. Similarly, (Gröwe-Kuska et al., 2002) extends the approach to the same model by a stochastic Lagrangian relaxation of coupling constraints. In solving stochastic problems, a major development was the success of stochastic dual dynamic programming (SDDP) (Pereira and Pinto, 1991). In (Shiina and Birge, 2004) further solution approaches based on column generation applied to an energy dispatch model uses SDDP on the scenario tree. In short, optimization approaches for problems under uncertainty are according to (Barroso and Conejo, 2006) and (Sen and Higle, 1999) are mainly categorized by, stochastic dynamic programming, stochastic programming, robust programming and fuzzy programming.

5.1 Characterization of energy models and planning horizons

Energy system models under uncertainty can be distinguished according to the planning horizon, there are operational decisions (short term) and strategic investment decisions (long term).

Long term problems involve technology investments and capacity expansion. In (Albornoz et al., 2004) an investment plan over a 10-year horizon by considering the uncertain availability of the thermal plants (gas turbines and diesel engines) is developed. (Sakalauskas and Žilinskas, 2010) estimates power plants capacity in a region considering investment by taking into account environmental impacts. (Gröwe-Kuska et al., 2002) survey different SDDP solution approaches and create an algorithm that combines medium and long-term hydro scheduling for a local utility. In the gas literature, long-term aspects can be categorized by modelling uncertainty of gas volumes in undeveloped fields, consider discoveries of new fields and long term trends on gas prices and demand (Fodstad M., 2016). These long term models typically calculate the expected net present value under uncertainty on reserves in gas fields.

Short term models are characterized by modelling physical operations. Traditional applications of stochastic programming includes the unit commitment problem and other similar dispatch (operational) models. A unit commitment model represents the energy units' physical constraints and determines when and which units to turn on/off to satisfy demand. The objective is to minimize the operational cost. For instance (Takriti et al., 2000) address the uncertainties of electricity prices by introducing power trading into the model. (Anderson and Philpott, 2002) study strategies to bid into electricity markets by assigning probability distributions to demand. Also, as already addressed on the previous section, modelling intermittent renewable sources has been an area of active research for short-term events. (Crespo Del Granado et al., 2016) proposes a multistage-stochastic model (planning horizon: 1 day discretized in 48 time steps) to valuate local batteries under wind uncertainty. The main result highlights that the deterministic case underestimates the value of batteries around 30% compared to the stochastic solution.

Combining long-term and short-term perspectives is an area of active research. Two-stage stochastic programs are well suited to take into consideration long-term investments on the first stage and then represent the short term operations on the second stage under uncertainty of demand, prices or variable generation (e.g. wind). As long term horizons could feature a 20 to 50 years' time span, (Skar et al., 2016) proposes a multi-horizon stochastic model in which yearly investments are connected to short-term operational uncertainty.

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Strategic Energy Roadmap

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About the project

SET-Nav aims for supporting strategic decision making in Europe's energy sector, enhancing innovation towards a clean, secure and efficient energy system. Our research will enable the European Commission, national governments and regulators to facilitate the development of optimal technology portfolios by market actors. We will comprehensively address critical uncertainties facing technology developers and investors, and derive appropriate policy and market responses. Our findings will support the further development of the SET-Plan and its implementation by continuous stakeholder engagement.

These contributions of the SET-Nav project rest on three pillars: modelling, policy and pathway analysis, and dissemination. The call for proposals sets out a wide range of objectives and analytical challenges that can only be met by developing a broad and technically-advanced modelling portfolio. Advancing this portfolio is our first pillar. The EU's energy, innovation and climate challenges define the direction of a future EU energy system, but the specific technology pathways are policy sensitive and need careful comparative evaluation. This is our second pillar. Ensuring our research is policy-relevant while meeting the needs of diverse actors with their particular perspectives requires continuous engagement with stakeholder community. This is our third pillar.

Who we are?

The project is coordinated by Technische Universität Wien (TU Wien) and being implemented by a multinational consortium of European organisations, with partners from Austria, Germany, Norway, Greece, France, Switzerland, the United Kingdom, France, Hungary, Spain and Belgium.

The project partners come from both the research and the industrial sectors. They represent the wide range of expertise necessary for the implementation of the project: policy research, energy technology, systems modelling, and simulation.

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