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Cambridge Working Papers in Economics

Measuring Energy Security

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CWPE 1305

UNIVERSITY OF CAMBRIDGE
Electricity Policy Research Group

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EPRG Working Paper 1303

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Keywords **Energy Security, Security of Supply, Reliability, Monte-Carlo Simulation, Measurement**

JEL Classification

Contact c.b.winzer@gmail.com
Publication February, 2013
Financial Support EPSRC Grant EP/E04011X/1

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EPRG 1303

Measuring Energy Security

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01.2013

1 Abstract

Continuity of energy supplies is a central aspect of concerns about energy security. Although the continuity of supplies can be influenced by a large number of risks, most models only analyse a small subset of risk sources and often neglect interdependencies between them. In this paper we introduce a probabilistic time-series model that quantifies the impact of inter-dependent natural, technical and human risk sources on energy supply continuity. Based on a case study of Italian gas and electricity markets we conclude that typical simplifications in time-series models and alternative approaches lead to a bias, which justifies the usage of detailed time-series models of interdependent risks such as the framework suggested in this paper, even though more detailed versions of this and other frameworks may quickly become very resource intensive.

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This paper has hugely benefitted from suggestions by and discussions with Johan Lilliestam at the Potsdam Institute for Climate Impact Research (PiK) and Pierre Noël, Benjamin Hobbs as well as my supervisors Danny Ralph and Karsten Neuhoff at the EPRG.

The research on this paper has been funded by the EPSRC Grant EP/E04011X/1 as a part of the Supergen Flexnet Consortium.

2 Introduction

The continuity of energy supplies depends on the performance of a complex supply chain which spans different countries and continents and is subject to a variety of interdependent human, technical and natural risk sources that may cause interruptions at different places within the supply chain. In the electricity sector this is further complicated by the high inelasticity of demand and the non-storability of supplies, which leads to a complicated system behavior.

Nevertheless, the models that are used for quantifying the continuity of commodity supplies are often surprisingly simple. Important reasons for simplicity are a reluctance to quantify uncertain risks such as political disruption probabilities, the desire to avoid intransparent modeling assumptions and the large cost involved with building and maintaining complicated models. Most probabilistic time-series models therefore represent at least some of the intermediate variables in the calculation process by their average values instead of modeling them as stochastic variables, which may lead to errors in the estimation. Most alternative approaches which are used in particular for the quantification of political risk tend to further reduce or completely omit details

heuristics.

In section 7 we summarize our conclusions about the error that is caused by different models that are typically used for quantifying energy security and about the main gaps for the measurement of energy security.

This paper is part of a wider research project to quantify energy security in three steps. The first step of the quantification process is the framing of the analysis. This is treated in (Winzer, 2012). The second step of the quantification process is the description of a fixed infra-structure system within the chosen frame of analysis. This is the focus of this paper. The last step of the analysis is addressing the question how regulatory interventions may influence the investment in the energy supply chain. This step is treated in ##Ref: EPRG WP##.

3 Framing of the case-study

3.1 Definition of energy security

The definition of energy security that we use in our case study is the *"continuity of commodity supplies relative to demand"*. A detailed overview of alternative definitions can be found in (Winzer, 2012).

Discontinuities of the supply – demand balance can lead to a disruption of both the quantity that is delivered and the price at which energy is delivered. Either of these discontinuities can be measured with different metrics.

Technical reliability analyses usually focus on those metrics that describe the continuity of quantities. Two measures that are widely used in this context are the Loss of Load Expectation (LOLE) – which is the cumulative probability of load shedding due to a negative reserve margin – and the Loss of Energy Expectancy (LOEE) – which is integral between amount of energy that is shed at each reserve margin and the probability of having such a reserve margin. An overview of other statistics measuring the continuity of supply quantities, such as the Customer Average Interruption Duration Index (CAIDI) or the Customer Minutes Lost (CML) can be found in (Billinton and Allan, 1996; Council of European Energy Regulators (CEER), 2008). In general, statistics describing the continuity of quantities are easier to calculate because they do not require the estimation of input price volatility or the cost of disruptions. The technical metrics which we use in this paper are illustrated in the left hand side of Figure 1.

Economic reliability analyses on the other hand require the analysis of both discontinuities of the price and the quantity of energy that is available relative to demand. Two metrics which capture both types of discontinuity are the levelized cost to society (LCS) in £/MWh – which is the integral between the sum of fixed and variable production costs at each reserve margin and the probability of having such a reserve margin, divided by the total consumption – and the levelized cost to consumers (LCC) in £/MWh – which is the integral between the total cost to consumers at each reserve margin and the probability of having such a reserve margin, divided by the total consumption. In case of a constant willingness to pay by consumers, the LCS is indirectly also a measure for the continuity of welfare, as the area between the willingness to pay (WTP) of consumers and the supply curve minus the fixed cost equals to the welfare for society. In the same way, the LCC is an indirect measure of consumer welfare, as the area between the WTP and the price level at each reserve margin corresponds to the consumer rent. We assume that in case of load shedding both the cost of production and the price paid by consumers are the same as the WTP. The economic metrics which we use in this paper are illustrated in the right hand side of Figure 1.

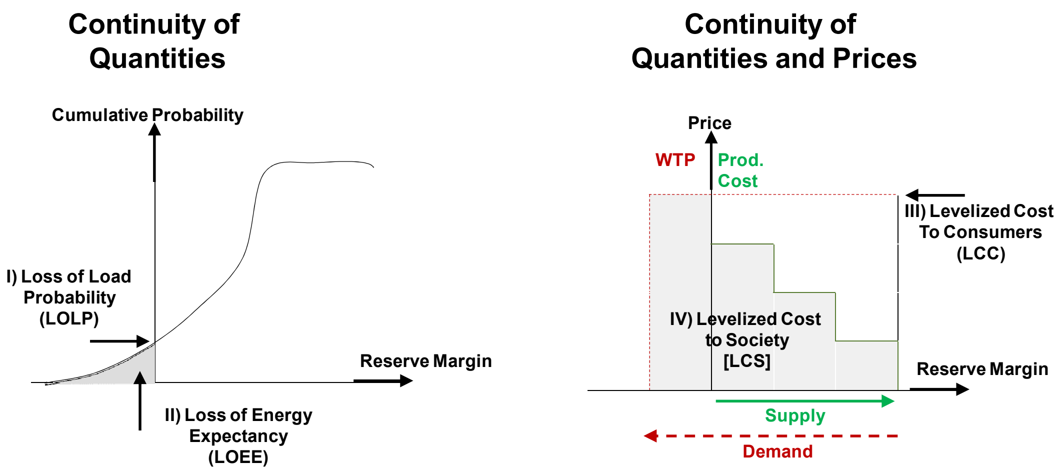


Figure 1: Metrics measuring the continuity of the supply-demand balance.

In our paper we separately report these continuity metrics for each commodity market. If desired, a composite indicator could be calculated by using the weighted sum of discontinuities in individual markets at the expense of losing information about the location of discontinuities.

3.2 Geographical region and infrastructure scenarios

In our case study we investigate the continuity of Italian gas and electricity supplies based on the DGTren Reference Scenario for Italy in 2030 (DG Tren, 2009) but replacing the nuclear capacity with 10GW concentrated solar power imports. The decision which policy makers face is whether it would be warranted to introduce a strategic back-up for these imports. We investigate this by including two infrastructure scenarios with 10GW strategic reserve.

In the first case, in scenario I2, the strategic reserve is provided by back-up gas generators – which are available for unlimited time, but only as long as there are enough gas supplies. In the second case, in scenario I3, the strategic reserve is provided by pumped storage hydro plants – which are also available in case of gas disruptions, but only for a limited time. The relative efficiency of these interventions depends on the frequency, the timing and the duration of gas and electricity disruptions as well as the cost levels. In the rest of this paper, we will compare how well the different modelling approaches can help to answer the question about which – if any - of these interventions would be appropriate.

The question whether these forms of strategic reserve can really provide additional capacity or would simply crowd out investment by private actors is addressed elsewhere.

An overview of the installed capacities for each infrastructure scenario is given in Table 5 in the appendix.

4 Stylised probabilistic energy system model

In this section we will describe a stylised, probabilistic model of the energy system, which quantifies the joint impact of natural, technical and political risk on the continuity of gas and electricity supplies. The model thus combines elements from technical reliability analysis with those that are typical in the analysis of critical infrastructures. Within the model we assume that stochastic variables have a distribution which is from a standard family of probability density functions – such as an exponential distribution for outage probabilities or a lognormal distribution for price inputs, which is a common approach. A previous version of this model, which excludes the analysis of interdependencies between the risk sources, has been applied in a joint publication (Lilliestam et al., n.d.).

4.1 Literature review

Models in technical reliability analysis typically tend to focus on a simulation of stochastic outages within a single fuel network. The two most commonly used approaches for this purpose are the analytical solution of Markov-Chain models and Monte Carlo Simulations (Billinton and Allan, 1996). In case of independent outages, analytical solutions of Markov-Chain models may be calculated using a stepwise, modular procedure as described in (Köppel, 2007). However, in case of interdependency between contingencies, a decomposition of the problem is not possible, and since the multi-variate state space grows exponentially, the analytical approach quickly reaches its limits. In the past this has not been a problem, as reliability analyses used to focus on independent technical failures. However, the push towards smarter grids and introduction of renewable energies lead to an increasing interconnection between networks and correlated local weather conditions.

In the area of critical infrastructure protection, this challenge has been recognized and is addressed in a variety of different models for interconnected infrastructure systems and multiple risk sources (Pederson et al., 2006). Interdependencies that are analyzed can be created by physical flows, geo-spacial co-location, policy or high level decisions and information flows (Dudenhoeffer et al., 2006; Rinaldi, 2004). Due to the complexity and size of a system of systems model, the 'vertical' models which integrate different networks and risk sources tend to use a much less detailed representation of individual networks than the 'horizontal' models for the technical reliability of individual networks that are used in control rooms (Svendsen and Wolthusen, 2007).

4.2 Model structure and variables

In our case study we follow the typical approach in critical infrastructure protection and model the Italian gas and electricity system as a directional graph (Svendsen and Wolthusen, 2007)[2]. Each node of the graph corresponds to the market of a specific energy form in a particular region. Each of the edges in the graph corresponds to an element of the energy infrastructure. The three main functions of the energy infrastructure are to transport, store and convert different forms of energy or energy services. Energy *transportation infrastructure* such as power-cables, pipelines and ships can be seen as links

[2] Models of combined gas and electricity networks can also be found outside the area of critical infrastructure protection, such as in (Abrell and Weigt, n.d.; Köppel and Andersson, 2009; Munoz et al., 2003).

between the markets for the same fuel in different regions. Energy *storage infrastructure* such as gas storage terminals and hydro reservoirs can be seen as links connecting the market from which they originate with itself across time. Energy *conversion infrastructure*, such as power plants and refineries can be seen as links between the markets for different energy forms in the same region.

The resulting model for our case study is shown in Figure 2.

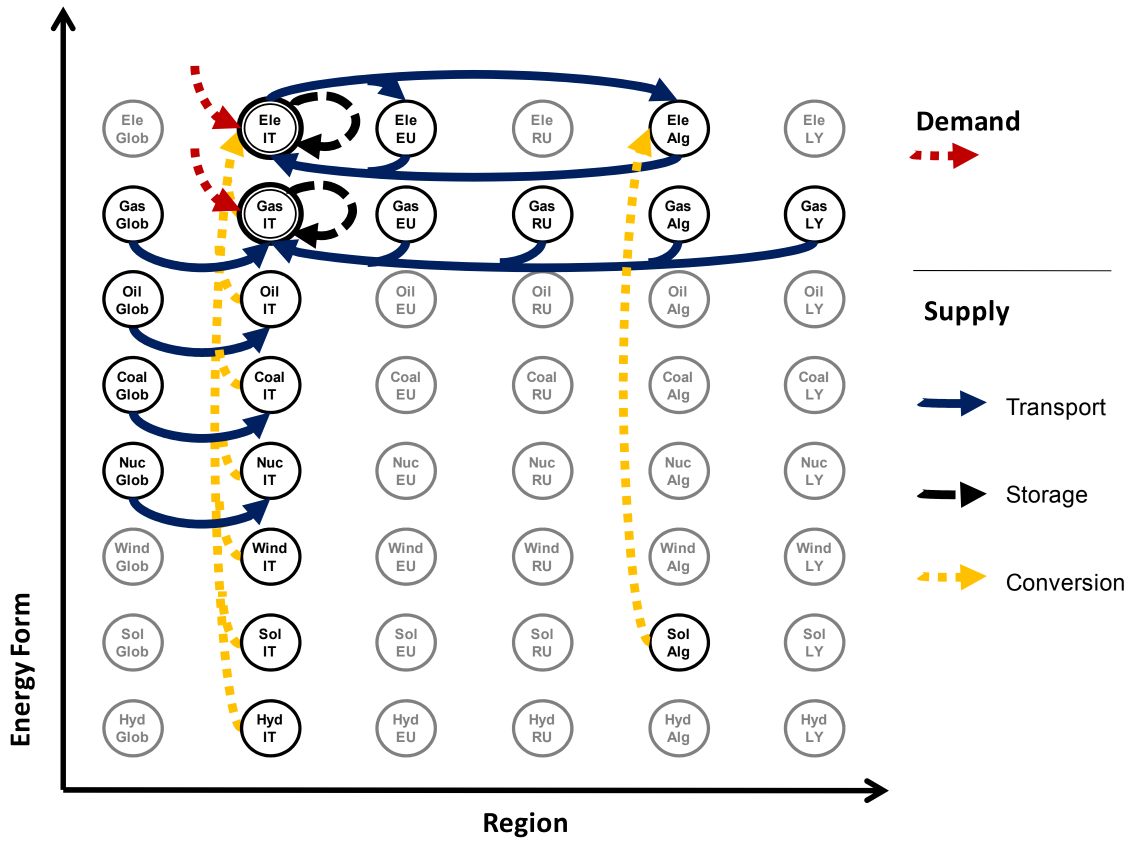


Figure 2: Infrastructure links that are modelled in our case-study.

The graph shows the infrastructure links that are included in the model. The nodes that are not included in the model are greyed. We can see in this graph that the Italian gas storage links the Italian gas market to itself. Electricity transmission lines, which allow bi-directional flows between Algeria and Italy, are represented by two links between these nodes in opposing directions.

Demand for gas and electricity is modelled as an exogenous variable. If the concept was extended to the continuity of services or the continuity of welfare, this could be captured by including the different energy services as separate energy forms, and welfare as the ultimate “energy form” into which all services are transformed.

The regional resolution of our model is on a country level, which excludes the analysis of network constraints within a country. Each time step within our model corresponds to a single day. In order to estimate the impact of diurnal demand variations we use a fixed daily load-duration curve. All other variables are assumed to remain constant throughout the day. As a result of these strong simplifications – which are largely driven by data constraints – the results of our model can only provide qualitative insights at this point.

Each of the infrastructure links is characterised by a set of constant parameters C, and a set of state dependent, variable parameters S. The composition of the parameter sets depends on the detail of the technological resolution. In order to keep data requirements low, we use a relatively simple version in our case study.

The set of constant parameters that we use consists of the nominal output capacity $CapOut_i$, the storage capacity $CapStore_i$, the conversion factor between input and output units $\eta InOut_i$ the fixed cost $CFix_i$ and the additional variable cost $CVar_i$ for each unit of output flowing through the link i. In case of a demand link, the variable cost represents the willingness to pay or the value of lost load for the service. We collect the constant parameter sets of all the links in the matrix C in Figure 3 where the i-th row-vector corresponds to the parameter set for the link number i.

$$C = \begin{bmatrix} NIn_1 & NOut_1 & CapOut_1 & CapStore_1 & \eta InOut_1 & CFix_1 & CVar_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ NIn_n & NOut_n & CapOut_n & CapStore_n & \eta InOut_n & CFix_n & CVar_n \end{bmatrix}$$

Figure 3: Matrix of constant system states C.

The variable parameter set that we choose consists of environmental variables such as wind-speed, temperature, rainfall and insolation to which a link is exposed[3] ($w1_i$ … wK_i), a set of partial availabilities ($aNat_i^t$, $aTec_i^t$, $aPol_i^t$) which – in case of a $aTec^t$ and $aPol^t$are influenced by random component failures with time dependent forced outage rates ($FOR.T^t, FOR.P^t$) and time dependent repair rates ($RR.T^t, FOR.T^t$), the amount of energy (e_i) which is stored in the link at the beginning of a period, and the flows in and out of each link (fIn_i^t, $fOut_i^t$) during time period t. Each partial availability factor corresponds to the percentage of the nominal capacity of link i that is available due to the influence of a particular risk source. The risk sources that we distinguish in our simplified model are natural ($aNat_i^t$), technical ($aTec_i^t$) and human ($aPol_i^t$) risk. The natural (in)availability, in this paper refers to the capacity reduction due to the (in)availability of natural inputs such as wind, cooling water, cool air etc. Technical (in)availability on the other hand describes the capacity reduction due to unintentional damages that require repair, such as deterioration due to ageing, but also mechanical stress, lightning, excavation etc. Political risk finally refers to all intentional capacity reductions, either through sabotage/terrorism or deliberate withholding for non-economic motives.

As we will see in the next section, this distinction is based on the dependency structure within the model: natural availability is a deterministic function of weather variables, technical availability is a random variable conditional on the

[3] Many of the links are exposed to the same weather variables, which are therefore only stored once.

weather state, and intentional political risk is a random variable that depends on the damage that is caused.

We collect the variable parameter sets of all the links at time *t* in the matrix S^t, where the *i* –th row-vector corresponds to the variable parameter set of link *i* at time *t*. The matrices S^t for each time step can further be stacked into the three dimensional matrix of system states *S*. As illustrated in Figure 4, dependencies can occur along all three dimensions of *S*.

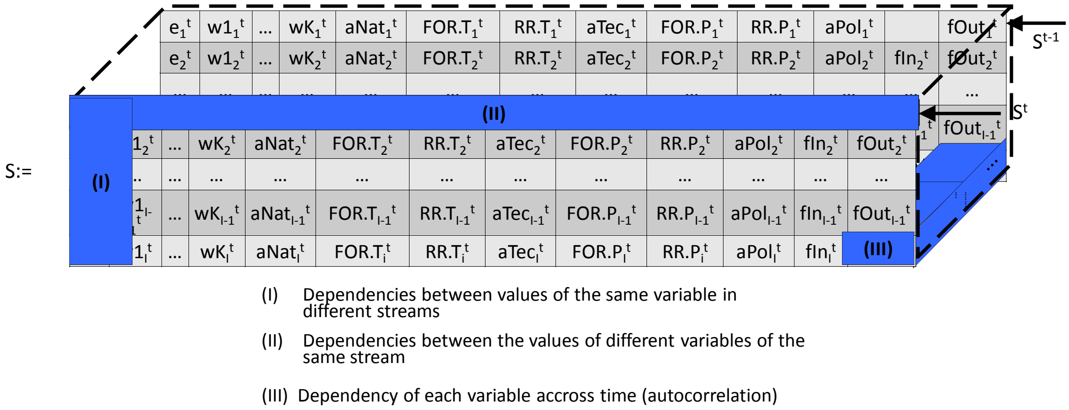


Figure 4: Possible dependencies within the matrix of variable system states S.

4.3 Calculation steps, treatment of uncertainty and dependencies

In this section we will describe the philosophy of treating uncertainty as well as the interdependency structure that is underlying our model by following the sequence of calculation steps that are repeated in each simulation run.

At *step 1* of the calculation process, we draw the value for each of the uncertain parameters that are displayed in Table 1 from their Bayesian distribution.

Table 1: Parameters that are modelled as Bayesian variables.

Parameter	Description	Distrib.Type	Max Std
FOR.T, RR.T	The average technical forced outage rates and repair rates	Lognormal	0.5 * avg
FOR.P, RR.P	The average political forced outage rates and repair rates	Lognormal	5 * avg
$\mathbf{CapIn_{Gas}}$	Maximum level of gas demand	Lognormal	.05 * avg
$\mathbf{CapIn_{Ele}}$,	Maximum level of electricity demand	Lognormal	.1 * avg
$\mathbf{CVar_{i}}$, $\mathbf{CFix_{i}}$	Variable cost and fixed cost of link *i*	Calculated based CapEx, OpEx, and FuelCost	
$\mathbf{CapEx_{i}}$	Capital expenditure for construction of link *i*	Lognormal	Spread reported in data source divided by 4
$\mathbf{OpEx_{i}}$	Operational expenditure for maintenance of link *i*	Lognormal	
$\mathbf{FuelCost_{i}}$	Fuel cost for link *i*	Lognormal	

Using the terminology of (Walker et al., 2003) which is summarized in Box 1 this corresponds to a probabilistic treatment of uncertain parameters and input variables, independent of the nature of uncertainty. Low levels of statistical uncertainty, such as the uncertainty about the average value of *FOR.T* and *RR.T*, are represented by narrow probability distributions, and higher levels of uncertainty, such as the uncertainty about the average *FOR.P* and *RR.P*, are represented by wider probability distributions. Extreme cases of scenario uncertainty, i.e. absence of knowledge about probabilities, could be represented by a uniform distribution over the support of the uncertain variable or parameter.

According to the taxonomy introduced in (Walker et al., 2003) uncertainty can be categorized along three dimensions: its location in the modelling process; the level of uncertainty; and the nature of uncertainty. Similar distinctions can be found in other publications on uncertainty (Morgan, 1990). The categories for the location of uncertainty are the model context, the model structure, model parameters or the valuation of model outcomes. The categories for uncertainty levels are statistical uncertainty – where the probabilities of outcomes are known, scenario uncertainty –where the outcomes are known, but not their probability, recognised ignorance – where one is aware of an effect, but neither the outcomes nor their probability and complete ignorance – where one is not aware of an effect. The nature of uncertainties can either be epistemic, i.e. a lack of knowledge about otherwise well determined outcomes, or variability uncertainty, i.e. an inherent, ontological indeterminacy of the outcomes even in case of perfect information. We can summarize the possible categories in the form of a cube as displayed in Figure 5.

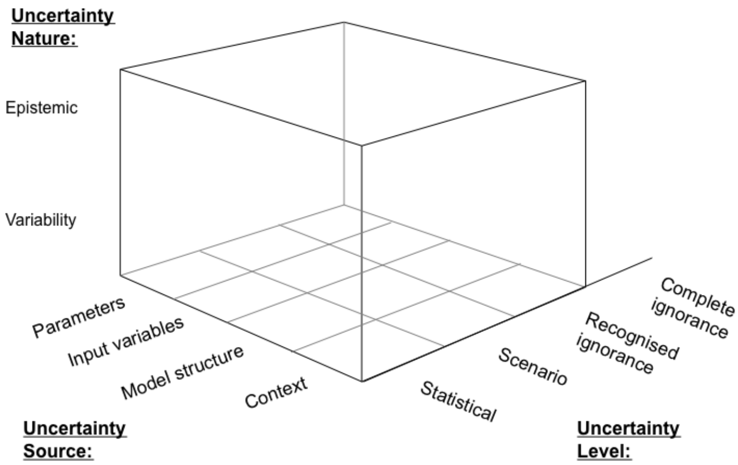


Figure 5: Uncertainty categories, illustration based on (Walker et al., 2003).

The treatment of uncertainty deviates along the dimensions. The nature of different uncertainties is largely discussed in philosophical debates. In theory any source and type of uncertainty until the level of scenario uncertainty can be treated with the tools of Bayesian averaging. In practice an averaging over alternative model structures is associated with much higher effort than averaging over a large number of different parameter sets and is therefore much less common. An overview of aggregation techniques that can be used for averaging can be found in (Clemen and Winkler, 1999) and (Osherson and Vardi, 2006).

Box 1: Types of uncertainty

In *step 2* of the calculation process, we calculate the natural availability $aNat_i^t$ of each link i at each time step t as a function of the exogenously given time series of weather variables ($w1_i$ ... wK_i) to which the link is exposed. The functions for the calculation of *aNat* which we use at this step are described in the appendix in section 0.

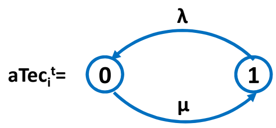
In *step 3* of the calculation process we calculate the weather dependent technical forced outage and repair rate $FOR.T_i^t$ and $RR.T_i^t$ of each link i at each time step t as a function of the exogenously given time series of weather variables ($w1_i$ ... wK_i) to which the link is exposed. The functions for the calculation of *FOR.T and RR.T* which we use at this step are described in the appendix in section 0.

In *step 4* of the calculation process we calculate the technical availability $aTec_i^t$ of each link i at each time step t by simulating a random outage with probability $FOP.T_i^t$ for every link that was technically available at time step t-1 and a random repair with probability $RP.T_i^t$ for every link that was unavailable for technical reasons at time t-1. The formula for calculating outage and repair probabilities on the basis of forced outage rates $FOR.T_i^t$ and repair rates $RR.T_i^t$ and the duration of a time step is explained in Box 2.

In *step 5* of the calculation process we calculate the state dependent political forced outage and repair rate $FOR.P_i^t$ and $RR.P_i^t$ of each link i at each time step t as a function of the reserve margin at the output node of the link ($w1_i$ ... wK_i) at time t. The functions for the calculation of *FOR.P and RR.P* which we use at this step are described in the appendix in section 0.

In *step 6* of the calculation process we calculate the political availability $aPol_i^t$ of each link i at each time step t by simulating a random outage with probability $FOP.P_i^t$ for every link that was politically available at time step t-1 and a random repair with probability $RP.P_i^t$ for every link that was unavailable for political reasons at time t-1. The outage and repair probabilities are calculated on the basis of political forced outage rates $FOR.P_i^t$ and repair rates $RR.P_i^t$ and the duration of the time step in the same way as for technical risk in Box 2.

Within our model, the availability due to technical risk $aTec_i^t$ of a link i at time t is represented by a simple birth-death process with a time-dependent forced outage rate $\lambda = FOR.T_i^t$ and repair rate $\mu = RR.T_i^t$:



The transition probability $FOP.T_i^t$ of the link being in an outage state at time $t+\theta$ if it was available at time t is obtained by solving the following differential equation system:

$$(1) \qquad \frac{d\pi_0(t+\theta)}{d\theta} = \lambda \cdot \pi_1(t+\theta) - \mu \cdot \pi_0(t+\theta)$$

$$(2) \qquad \pi_0(t+\theta) + \pi_1(t+\theta) = 1$$

$$(3) \qquad \pi_1(t) = 1$$

where $\pi_0(t+\theta)$ is the probability of being unavailable at time $t+\theta$ and $\pi_1(t+\theta)$ is the probability of being available at time $t+\theta$.

As a solution we obtain the forced outage probability depending on the duration θ of a time step:

$$(4) \qquad FOP.T_i^t = \pi_0(t+\theta) = \frac{\lambda}{\lambda+\mu} \cdot e^{-\theta\cdot(\lambda+\mu)} \cdot (-1 + e^{\theta\cdot(\lambda+\mu)})$$

If we change the starting condition in equation (3) so that $\pi_1(t) = 0$, we obtain the transition probability $RP.T_i^t$ of link i being available at time $t+\theta$ if it was available at time t:

$$(5) \qquad RP.T_i^t = \pi_1(t+\theta) = \frac{\mu}{\lambda+\mu} \cdot e^{-\theta\cdot(\lambda+\mu)} \cdot (-1 + e^{\theta\cdot(\lambda+\mu)})$$

Box 2: Calculation of transition probabilities based on outage and repair rates.

In *step 7* of the calculation process we finally determine the system dispatch and the flows in and out of each link[4] (fIn_i^t, $fOut_i^t$) during time period t as a function of the natural, technical and human availability ($aNat_i^t$, $aTec_i^t$ and $aPol_i^t$) of each link i at time t. In the current model we assume a simplified deterministic

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[4] In our example, links that connect different markets have zero storage capacity so that

$fOut = fIn * \eta InOut_i$. Storage links connect back to the same market, so that either fIn=0 or fOut=0. We can therefore simplify by using only one flow variable f=fIn + fOut, which is positive – in case of supply – and negative – in case of demand.

generation capacity is available.

An overview of the calculation process and the resulting dependency structure is shown in Figure 6.

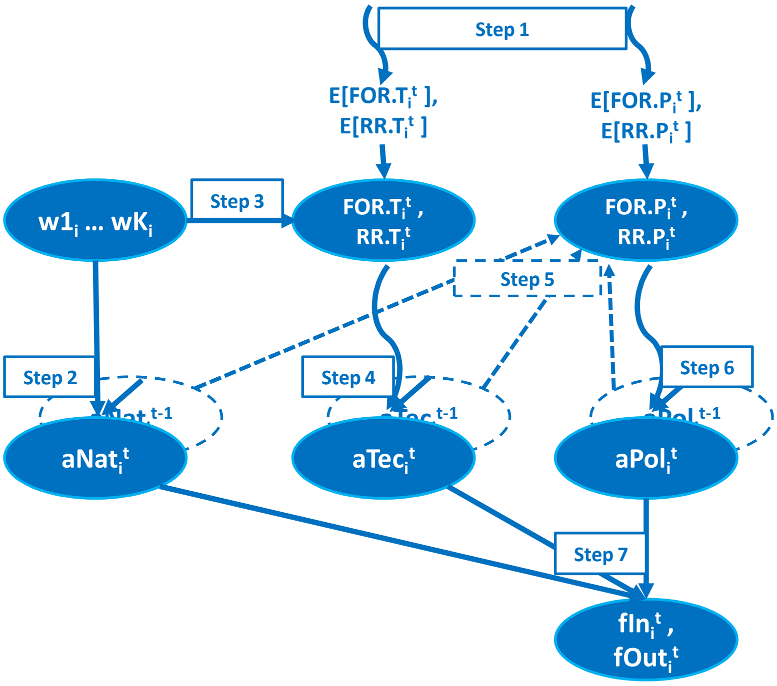


Figure 6: Calculation steps and dependencies between variables.

Our model thus includes interdependencies along all three dimensions of the matrix of system states in Figure 4.

Along dimension I, the interdependency between links is generated by geographical proximity, which exposes different links to the same weather variables, as well as by the network flow equations, which determine the flows in and out of each link depending on the available capacity of all other links.

Along dimension II, dependencies occur because the technical forced outage and repair rates may be influenced by the weather, political forced outage and repair rates may be driven by the reserve margins that result from both natural and technical availability.

Along dimension III, the availability of each link at time is a function of the availabilities ($aNat_i^t$, $aTec_i^t$, $aPol_i^t$) of each link at time t are a function of the availabilities at time $t\text{-}1$ and the corresponding forced outage and repair rates.

The dependencies between variables are important because as a result of the flaw of averages (Savage, 2009) in case of a non-linear dependency the average value of the dependent variable is likely to be different from the value that results from the mean of the independent variable. For example, as illustrated in Figure 7, the failure rate for the average wind speed may be different from the average failure rate due to a distribution of wind speeds. The bias that is caused by neglecting dependencies is further increased if the probability distribution of the independent variable is broadened by modelling it as an uncertain, Bayesian variable.

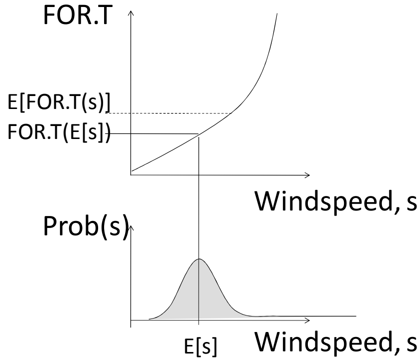


Figure 7: Flaw of averages in case of non-linear dependencies.

5 Impact of simplifications in probabilistic models

Many probabilistic models neglect uncertainty about input variables and parameters as well as dependencies between the model variables. In this section we will introduce a number of simplified model versions to test the impact this has on results. We find that while the usage of averaging can lead to biased results if dependencies work in the same direction, it may not cause a distortion if dependencies work in an opposite direction and cancel each other out.

Energy market simulations typically neglect dependencies by using average values at one or several steps of the calculation process described in Figure 6. In models, such as the pathways 2050 calculator of the Department for Energy and Climate change (Department of Energy and Climate Change (DECC), 2011) or the project discovery by Ofgem (Ofgem, 2010) averages are used at all steps of the calculation process up to step 6 by assuming a constant average de-rating factor for each component. By contrast, technical reliability models used by system operators include variability at step 4 of the calculation process by simulating individual component failures instead of using average de-rating factors (Rei and Schilling, 2008; Schilling et al., 2008). However, averaging may still be used at steps 1 and 3 of the calculation process by assuming constant forced outage rates and repair rates. This has been recognised as a problem in technical reliability literature, and different factors – such as plant age, wind speeds and precipitation - have been identified which lead to a variation of the forced outage rates across time and space (Carer and Briend, 2008; Chan and Shaw, 1993; Foley and Gutowski, 2008; Rothenstein and Halbig, 2010). More advanced technical reliability models may therefore also include variability at the third step of the calculation process by calculating forced outage rates as a function of current environmental conditions. However, they will typically still use averaging at the first step of the calculation process by assuming that the forced outage rate at each point in time is perfectly known. In case of technical reliability model, the bias due to this assumption may already be significant (Dent and Bialek, 2010), even though the outage probabilities can be determined reasonably well. If political risk is included in the probabilistic model, the uncertainty is expected to be much larger and therefore cause a bigger impact.

In order to explore the impact of successively adding variability at the different steps of the calculation process for a number of selected variables from the matrix *S* in Figure 4, we calculate the results for a number of simplified versions of our probabilistic model that are described in Table 2 to Table 4. Each of the model versions M1 to M11 is characterised by the settings in the respective columns.

Table 2: Treatment of variability due to stochastic outages (calculation steps 4 and 6) in different probabilistic model versions.

Variability at Calculation Steps 4 and 6: Simulation of stochastic outages:											
Model Version	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**	**M11**
aNat	no*	no*	no*	no*	no*	no*	no*	no*	no*	no*	no*
aTec	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
aPol	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
*) availability is a deterministic function of the corresponding weather variable, which is calculated at step 2.											

Table 3: Treatment of variability due to interdependencies between variables (calculation steps 2, 3 and 5) in different probabilistic model versions.

Variability at Calculation Steps 2, 3 and 5: Interdependencies between availabilities:											
Model Version	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**	**M11**
aNat	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
FOR.T	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes
RR.T	no	no	no	no	yes	yes	yes	yes	yes	yes	yes
FOR.P	no	no	no	no	no	yes	yes	yes	yes	yes	yes
RR.P	no	no	no	no	no	no	yes	yes	yes	yes	yes

Table 4: Treatment of variability due to uncertainty (calculation step 1) in different probabilistic model versions.

Variability at Calculation Step 1: Bayesian Uncertainty described by Stdev as %Avg:											
Model Version	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**	**M11**
FOR.T	0	0	0	0	0	0	0	2.50%	2.50%	2.50%	2.50%
RR.T	0	0	0	0	0	0	0	2.50%	2.50%	2.50%	2.50%
FOR.P	0	0	0	0	0	0	0	0	25%	25%	25%
RR.P	0	0	0	0	0	0	0	0	25%	25%	25%
CapOutGas	0	0	0	0	0	0	0	0	0	5%	5%
CapOutEle	0	0	0	0	0	0	0	0	0	10%	10%
CVar, CFix	0	0	0	0	0	0	0	0	0	0	100*%
*) % of the spread reported in the data sources divided by 4											

Model version M1 represents a deterministic model which does not include any variability of the supply side and uses constant averages at all steps of the calculation process. Model version M2 uses the same settings as M1, but includes the simulation of stochastic technical and political outages at step 3 of the calculation process. For the variable *aNat*, there is no simulation of stochastic outages at step 3 of the calculation process, because the capacity that is available due to the availability of wind, sunlight, cooling water etc. is calculated as a deterministic function of these variables in step 2 of the calculation process.

Model versions M3 to M7 use the same settings as M2 at calculation step 1 and 3, but successively introduce variability at step 2 of the calculation process for an increasing number of parameters from the natural availability, in M3, until technical forced outage rates, in M4, technical repair rates, in M5, political forced outage rates, in M6, and political repair rates, in M7. The dependencies that are introduced are described in detail in the appendix.

Model versions M8 to M11 use the same settings as M7 at calculation steps 2 and 3, but successively include variability at step 1 within the model calculations for an increasing number of parameters from the technical forced outage and repair rates, in M8, until political forced outage and repair rates, in M9, gas and electricity demand, in M10, and fixed and variable cost of different infrastructure elements, in M11. The values in the table indicate the standard deviation of the respective Bayesian variable at step 1 of the calculation process as a percentage of its mean. We assume that the Bayesian uncertainty for technical parameters (standard deviation of 2.5%) is much smaller than for political risk parameters (standard deviation of 25%). In case of cost parameters, we assume that the difference between minimum and maximum values reported in the data source corresponds to four times the standard deviation. This would mean that in case of a normal distribution the reported range would correspond to the 90% confidence interval.

In order to make sure, that a difference in the results is caused by the introduction of dependencies as such and not by different average input parameter values, we calibrate each of the look-up functions in model versions that include dependencies until the average value of the dependent variable is the same as in absence of dependencies, so that for example the average value of

FOR.P in model M5 and M6 is the same. In practice, neglecting dependencies may also lead to a bias in the input parameter values. For example, the average technical forced outage rates *FOR.T* of CCGT plants in the U.S. may be a biased estimator of the average forced outage rates of CCGT plants in the U.K. if they are not adjusted by differences in age, environmental and operating conditions. We do not estimate this second type of error within this paper.

In Figure 8 and Figure 9 we show the average value, as well as the 5% quantile and the 95% quantile of the continuity metrics that were explained in section 3.1 for each of the probabilistic model versions M1 to M11.

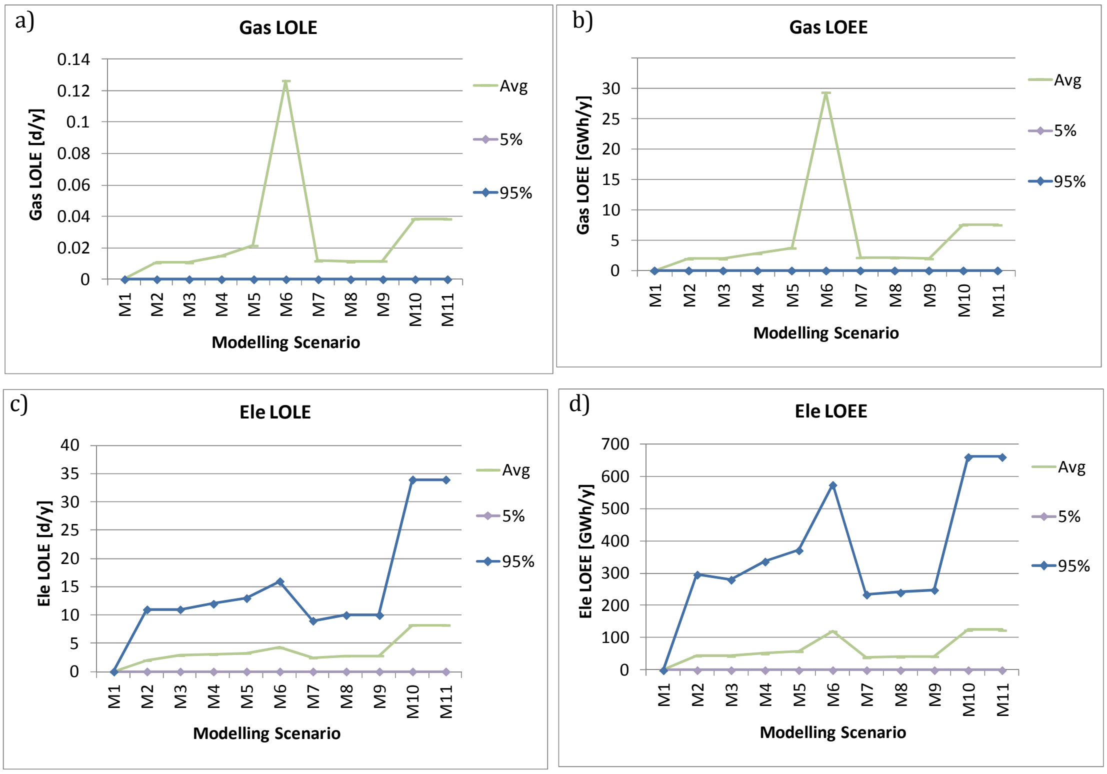
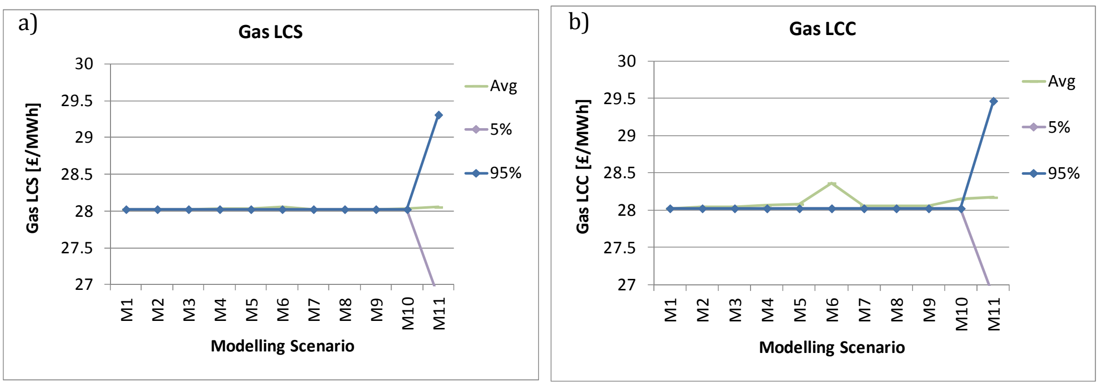


Figure 8: Average value, 5% quantile and 95% quantile of the LOLE a) for gas, c) for electricity and of the LOEE b) for gas and d) for electricity in case of infrastructure scenario I1 model versions M1 to M11.



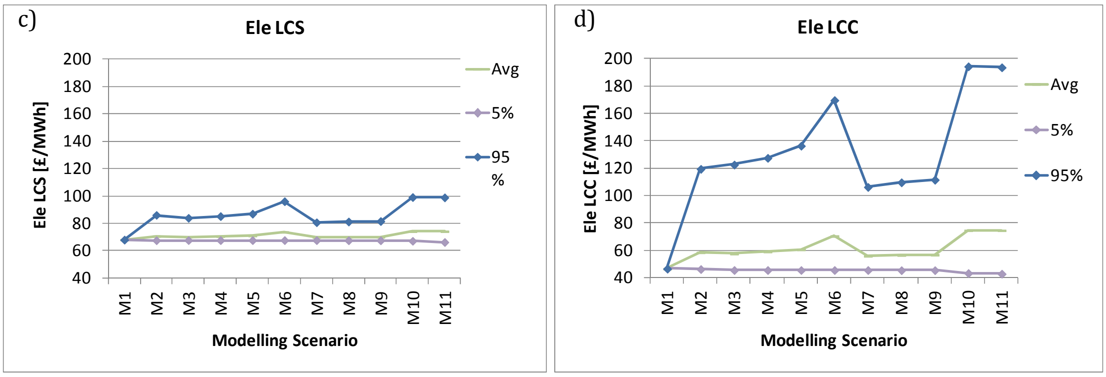


Figure 9: Average value, 5% quantile and 95% quantile of the LCS a) for gas, c) for electricity and of the LCC b) for gas and d) for electricity in case of infrastructure scenario I1 and model versions M1 to M11.

In Figure 8 d) we can see that in case of the deterministic model, in M1, there are no outages, i.e. the LOLE and the LOEE in both the gas and the electricity markets are zero. As we allow for more variability in each of the following model versions M2 to M11, the probability of disruptions, measured by the LOLE and the LOEE in both markets tends to increase. However, the increase is not monotonic. The introduction of a variable RR.P in model version M7 leads to a drastic reduction of the LOLE and the LOEE, because we assume that the variable repair rate is smaller than average during high reserve margins – when there is no risk of disruptions - but larger than average during low reserve margins – when there is a high risk of disruptions. In case of the gas market, even in case of model version M11, which allows for variability at all steps of the calculation process, the disruptions are so in-frequent that the 95 percentile of the LOLE and the LOEE is still zero, i.e. more than 95% of the simulation runs do not result in an outage.

In Figure 9 we can see that the economic continuity measures, LCS and LCC in both markets follow a similar shape as the technical continuity measures in Figure 8. The costs are lowest in case of the deterministic model M1 and increase as we allow for more variability in the model versions M2 to M11. The magnitude of changes of the LCC for electricity in Figure 9 d) that is caused by different model versions is roughly similar to the changes of the corresponding technical continuity measures in Figure 8 c) and d). However, we can see that the LCS in Figure 9 c) reacts less strongly to the increasing variability than the LCC in Figure 9 d). The reason for this goes back to the difference between LCS and LCC that is described in Figure 1. In case of a disruption, the LCC weighs all consumption by the VOLL, while the LCC only weighs the unserved load by VOLL. The economic continuity measures for the gas market also show a higher impact of variability on the LCC, in Figure 9 b) than on the LCS in Figure 9 a). However, the overall impact on both the LCS and the LCC of increasing the variability by moving from model version M1 to M10 is much smaller than for the electricity market, and is almost negligible compared to the impact that is caused by allowing uncertainty about future prices in M11.

Overall, the largest impacts in our example are caused by the introduction of stochastic outages instead of fixed de-rating (in M2ff) and uncertainty about future demand levels (in M10ff). The impact of using situation specific forced outage rates for technical risk (in M4ff) or political risk (in M6ff) depends on the direction and the extent of the dependency for the respective repair rates.

In case of technical risk, repair rates during high wind periods are expected to be lower than on average. The introduction of variable repair rates (in M5ff) thus re-inforces the impact on output metrics of introducing situation specific outage rates in model version M4.

In case of political risk, on the other hand, variable repair rates (in M7ff) are expected to increase as a result of larger urgency in case of low reserve margins. The introduction of variable repair rates thus reduces the impact on output metrics of introducing situation specific outage rates in model version M6. The dependency of political risk on reserve margins may thus be very relevant, if the repair rate remains constant as in model version M6, or negligible, if the higher risk during times of scarcity can be compensated by higher repair rates as in model version M7.

After the above observations, which were all based on an analysis of the infrastructure scenario I1, we will now address the question, whether the impact of increasing variability in the model versions M1 to M11 depends on the infrastructure scenario. If an increasing variability affects the continuity measures of some infrastructure scenarios more than others, the amount of variability that is included in the model could determine the choice between the infrastructure scenarios.

We illustrate this in Figure 10 and Figure 11 by showing the impact of an increasing variability in model versions M1 to M11 on the average value of the continuity metrics for each of the infrastructure scenarios I1 to I3.

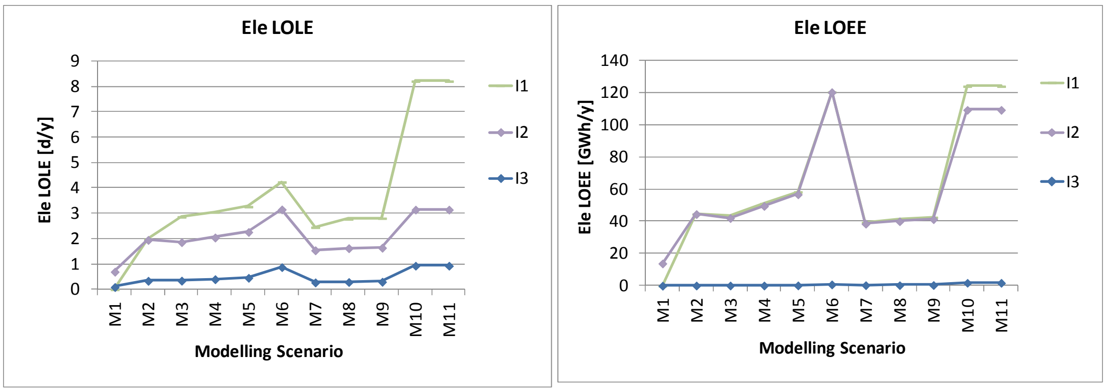


Figure 10: Average value of a) LOLE and b) LOEE for infrastructure scenarios I1 to I3 and model versions M1 to M11.

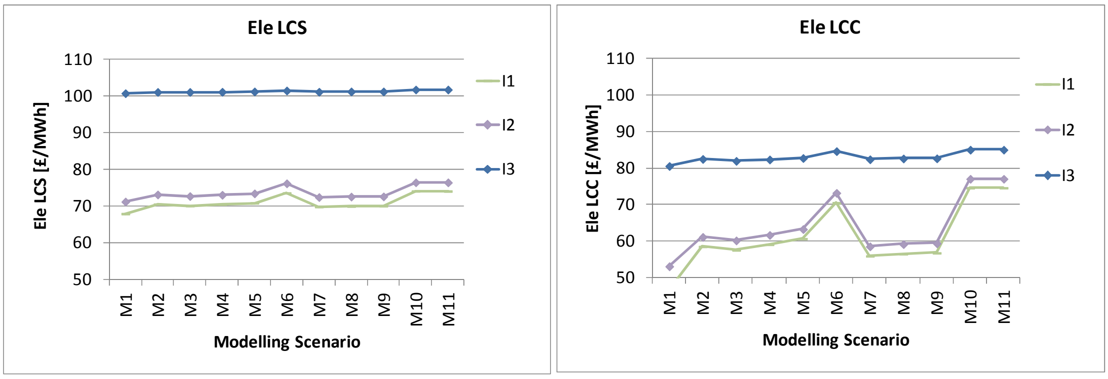


Figure 11: Average value of a) LCS and b) LCC for infrastructure scenarios I1 to I3 and model versions M1 to M11.

As we can see in Figure 11 the impact of an increasing variability in model versions M1 to M11 on the LCS and the LCC is much smaller in case of infrastructure scenario I3 than in case of the infrastructure scenarios I1 and I2. The reason for this can be seen by looking at the technical continuity metrics.

We can see in Figure 10 a) that for all of the model versions M1 to M11, both the additional gas plants in infrastructure scenario I2 and the additional strategic hydro storage in infrastructure scenario I3 lead to a reduction of the LOLE. However, the hydro storage seems to be much more effective as infrastructure scenario I3 reduces the LOLE much more than infrastructure I2. The difference is even bigger if we look at the LOEE in Figure 10 b). Here we can see that the additional gas plants in I2 have almost no impact on the amount of energy that is lost, while the hydro storage is almost completely eliminating all losses.

In summary, we can see that the additional gas plants can avoid a number of outages that are due to disruptions in the electricity market which would not have led to significant losses, while they cannot protect against the remaining outages which are due to disruptions in the gas market and lead to significant losses. The strategic hydro storage can protect against both types of outages and the storage capacity is enough to almost completely eliminate losses in all model versions. As we can see in Figure 11 b), the cost of hydro storage is still too high for I3 to be cheaper than I1 in any of the model versions. However, m

6 Impact of simplifications made by alternative approaches

In an attempt to avoid the probabilistic simulation of highly uncertain events such as political supply disruptions, many authors have suggested the usage of alternative, simplified modelling approaches. However, we find that with the exception of scenario approaches, the alternative models are likely to increase the modelling errors. Scenario approaches on the other hand offer limited help if decisions depend on a complex set of probabilities. A fully probabilistic approach may be an uncomfortable necessity in these cases.

In the following paragraphs we will describe the different groups of approaches with examples from the literature. By comparing the output of these metrics for different infrastructure scenarios with the output from the probabilistic model M11 in the last section, we illustrate the information that is lost if these metrics are used.

6.1 Indicators

Indicators are the least detailed method and at the same time – partly because of their simplicity - one of the most popular approaches for analysing the broader picture of energy security. They range from single indicators, such as import shares or depletion rates of certain fuels to more complex, composite indicators that cover aspects of environmental sustainability in addition to the continuity of energy supplies (Kruyt et al., 2009). Composite indicators are either based on subjectively weighted expert ratings (Institute for 21st Century Energy, 2009; McCarthy et al., 2007; Scheepers et al., 2007) of different categories, on a concentration measure such as the Herfindahl-Hirschmann Index(Frondel et al., 2009; Grubb et al., 2006; Jansen et al., 2004; Lefèvre, 2009) or the Shannon-Wiener Index (Grubb et al., 2006) or on principal component analysis of simple indicators (Gupta, 2008). An index based on the extension of concentration measures by the disparity between components is proposed by for the measurement of diversity.

This corresponds to a partial analyses of the aspects covered in our stylised probabilistic energy system model. Indicators are usually calculated on the basis of nominal capacities stored in the constant matrix *C*. They sometimes adjust for the average value of time-varying reductions of available capacity that are stored in the matrix *S* but usually discard the information about the interdependencies between them. The diversity index by (Stirling, 2007) is the only one that includes information about the interdependency between time-varying availabilities of components in the form of a single number that describes the disparity between each pair of links.

An advantage of using indicators is the easy data availability of simple calculation. On the other hand, they provide limited information and generally speaking tend to deal with uncertainty by ignoring the probability and correlation of time-varying reductions of the available capacity due to different risk sources. Indicators therefore make sense in the case of recognised ignorance where the matrix *S* for risk events is unknown. In case of scenario and statistical uncertainty the information about interdependencies between the availability reduction of different components should not be discarded.

Figure 12 illustrates the disconnection between the two most widely used simple indicators and the levelized cost of electricity to society that was obtained for different infrastructure scenarios using the modelling approach M11.

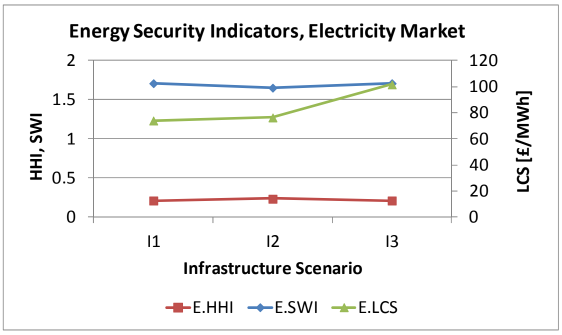


Figure 12: Herfindahl-Hirschmann Index (E.HHI), Shannon-Weiner Index (E.SWI) and Levelized Cost to Society (E.LCS) for the electricity market in case of different infrastructure scenarios.

Both concentration measures take into account neither the impact of storage on the likelihood of disruptions, nor the impact of additional cost on the levelized costs to consumers and society. As a result, the indicator value for scenario I1 and I3 is the same, even though simulation results show that the strategic storage in I3 significantly reduces the disruption risk and adds high fixed cost. While the loss of information is very clear, the hope that a more crude heuristic may include 'hidden' information which was neglected in the probabilistic model may be a reason for the continuing popularity of ratings. However, given the mechanistic construction of the HHI and the SWI, this seems to be highly unlikely. These simple indicators are thus very inadequate measures for the continuity of energy quantities or prices. Nevertheless deterministic indicators of this type continue to be used in policy advice and are also used in regulations (Noël and Findlater, 2009).

6.2 Portfolio theory models

Portfolio theory has recently gained some popularity in the area of energy security, because it builds a link between the concentration measures in the previous section and the continuity of supply quantities or prices. The continuity of supply quantities has been analysed on the basis of correlations between historical fuel production (Neff, 1997) or wind-power output (Roques et al., 2009) without regard to the cost of production. The continuity of prices on the other hand has been analysed on the basis of correlations between generation costs (Lesbirel, 2004) in case of constant load factors. One of the main shortcomings of portfolio theory is the difficulty to analyse the joint impact of variations in price and availability within the same model, as either the load factors or the cost are assumed to be constant.

Portfolio theory corresponds to a significant simplification of the matrix S in our framework along all three dimensions. Firstly, the dependency structure is simplified along dimension I: bottlenecks of transmission capacity are neglected and what counts is only the sum of available capacities or cost. Secondly, the dependency structure is simplified along dimension II: weather states *wK* are not modelled and each component is only characterised by its total availability or cost instead of interdependent partial availabilities *aNat*, *aTec* and *aPol*. And thirdly, the dependency structure is simplified along dimension III: autocorrelation is neglected, and it is only considered how often a component is inavailable on average and how that is correlated with the inavailability of other components. Whether the inavailability occurs during few, very long periods or during many, very short periods cannot be distinguished.

The great advantage of portfolio theory is the easy calculation of optimal portfolios and the intuitive explanation of the rationale of diversification. However, if realistic networks, extreme events and storage shall be assessed, the assumptions of unconstrained transmission, homogenous correlation (Kat, 2003) and the neglection of the time-dimension will lead to wrong results.

It is possible to mitigate some of these shortcomings, by calculating the average, standard devation and correlation between costs on the basis of a probabilistic simulation that takes into account the variations in both the cost and the availability of infrastructure elements and the interdependencies between them. Portfolio theory would then only be used to derive the optimal generation mix. However, this would not reduce the modelling effort, as the calculation of portfolios needs to happen on top of the probabilistic simulation. In addition, the optimality of the resulting generation mix is still doubtful, as a different capacity mix will result in different load factors which lead to different averages, standard deviations and correlations of levelized cost. We have illustrated this in Figure 11, where we calculate the levelized cost in the electricity market on the basis of the probabilistic model M11, and use the average, standard devation and correlations between the levelized cost of individual power plants that were calculated by this model during simulations for infrastructure scenario I1 in order to estimate the total levelized cost of the portfolio in all the infrastructure scenarios.

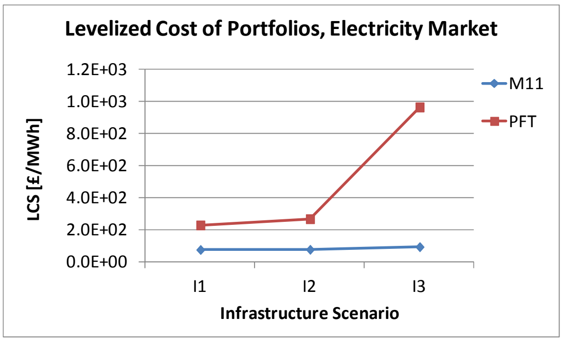


Figure 13: Levelized Cost of Society (LCS) in the electricity market, calculated using a probabilistic model (M11) and portfolio theory (PFT).

We can see that in our example PFT leads to a strong over-estimation of cost, as it does not take into account the reduction of levelized cost due to higher load factors of reserve plant (in I2) or the strategic storage (in I3). Portfolio theory thus provides a very incomplete picture of what would happen if new infrastructure was built, or the existing links were interrupted.

the dependencies described in section 4.

Scenario analyses thus correspond to a simulation of the energy system where some or all of the time-dependent variables in the matrix S will be fixed at a specific value in order to give a feeling for potential upper or lower bounds of the availability. The probability of the scenarios is usually not specified. However, it is possible to calculate break even frequencies that describe how often each individual threat would have to occur in order for a certain policy measure to be profitable (Joode et al., 2004).

An advantage of using scenarios is that they allow a very detailed analysis of the system behaviour in a particular situation. The scenarios can well be described in the form of a story, which makes them very useful for the communication of the selected risks. However, if the number of highly uncertain parameters grows, more scenarios are needed and the comparison between them can quickly become in-tractable. If none of the policy measures dominates the others, the decision in favour of one of them is only efficient for a range of implicit probabilities.

In Figure 14 we illustrate this for the example of the different disruption scenarios of Algerian gas and electricity supplies described in Figure 15.

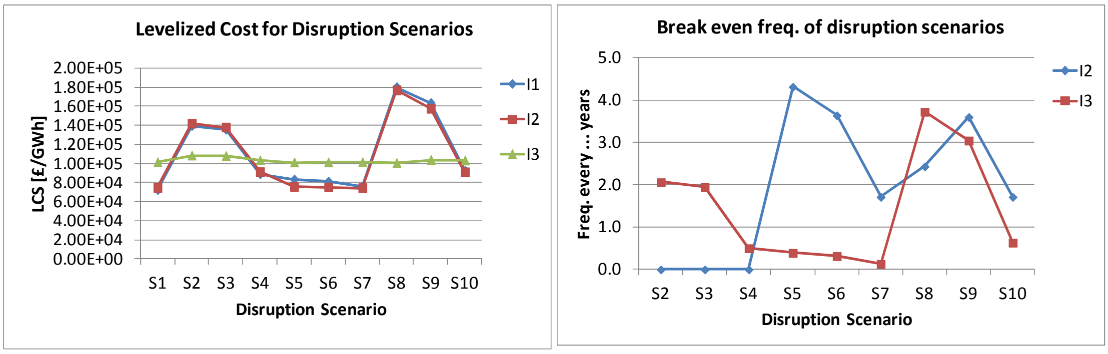


Figure 14: Levelized Cost to Society and break even frequencies in case of I1 to I3 under different disruption scenarios.

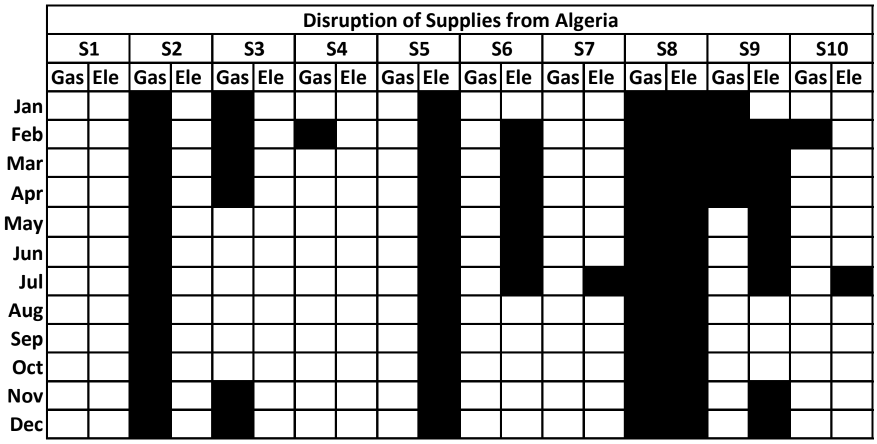


Figure 15: Description of disruption scenarios

We can see that as expected, the additional gas plants in scenario I2 reduce the cost compared to I1 in disruption scenarios S5 to S7 and S9 to S10 where electricity supplies are interrupted during times when gas is available, but is unable to reduce cost in case of gas supply disruptions. The additional strategic storage in I3 leads to a very high cost mark-up in absence of disruptions in S1, but almost completely avoids further cost increases in the disruption scenarios.

Judging from the left hand part of Figure 14 alone it may seem tempting to introduce a strategic storage facility. However, the break even frequencies for the scenarios in the right hand part of Figure 14 put the decision in a different perspective.

In most cases the disruption scenarios would have to occur with a frequency between every two to five years in order for a policy measure to become profitable, which seems unlikely. This is one of the main strengths of the break even approach in (Joode et al., 2004). The calculation of break even frequencies puts the savings into perspective and provides a more balanced way of presenting the outcomes than the description of the mere cost increases – which may be politically unacceptable – in case of different disruption scenarios. It can be argued in how far this is desirable, as the political unacceptability of high cost scenarios may have reasons that are not covered in the analysis. For example the causation of existential threats to vulnerable parts of the population if they lose access to heating during winters which is not captured by the cost function because people's 'willingness' to pay is restricted by their income. On the other hand the reasons for political aversion to high cost scenarios could be the personal consequences for politicians if disruptions happened during their governing period. In any case these reasons need to be explored, and if appropriate, included in the analysis in the form of adjustments to the demand/ cost function to reflect the fact that the loss of a person's life due to price hikes is valued higher than his willingness to pay which may be constrained by his income.

As we can see in Figure 14 and Figure 15, and also in (Joode et al., 2004), break-even frequencies are a helpful tool as long as one of the policy alternatives –in our example the absence of political intervention, which is represented by infrastructure scenario I1 – is clearly dominating the others. However, as soon as there is no clear winner, and the choice between the policy alternatives depends on assumptions about a number of different uncertain parameters, the approaches of scenario analysis and break-even frequencies can quickly reach their limits. We illustrate this in Figure 16 by calculating the break-even frequencies that would result if the additional gas plants in I2 or the strategic storage in I3 could be obtained at 75% lower cost.

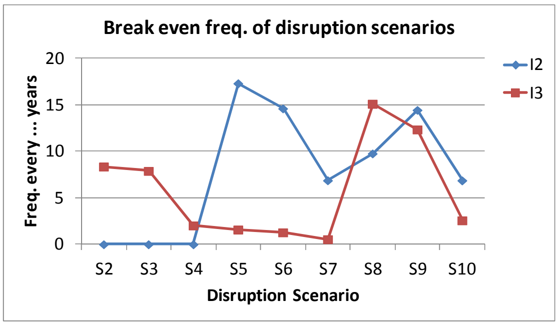


Figure 16: Break even frequencies in case of 75% cost reduction of reserve plants in I2 and I3.

In this case the break even frequency for the best option is in most cases between 8 and 18 years which may be seen as more realistic. However, the decision between the alternatives of no intervention (I1), strategic gas plants (I2) and strategic hydro storage (I3) depends on the likelihood and duration of gas outages – in disruption scenarios S2 to S4, and electricity outages – in disruption scenarios S5 to S7. As the break-even frequencies in both cases are within what could be seen as a realistic range, it is not clear which of the infrastructure alternatives I2 or I3 should be preferred. In case of the joint disruption, the infrastructure scenario I3 has a higher break even frequency in case of a year-long simultaneous disruption of gas and electricity imports from Algeria in S8, which means that it is more economical than I2 in those cases. However, in case of the shorter joint outages with little or no overlap that are described by S9 and S10, the infrastructure scenario I2 has a higher break even frequency and is thus more economical than I3. In case of the joint outage scenarios S8 to S10, the choice between I2 and I3 thus also depends on the length of the disruptions and the overlap between electricity and gas outages. If more policy options - such as different reserve plant technologies, or more uncertain variables – such as the likelihood of interrupting imports from other countries are included in the analysis the picture becomes even more complicated and the approach of break even frequencies reaches its limit.

In order to support decision maker in such a situation, it hence seems desirable to at least complement the approach of scenarios and break-even frequencies, with a fully probabilistic simulation using a model such as the one described in section 4 that includes policy maker's beliefs about the likelihood of different uncertain outages. The disruption scenarios S7 to S10 in Figure 16 confirm what we have also seen in the probabilistic model versions M5 to M7, that in this context it does not only matter how likely individual disruptions are going to happen, but also how likely they are going to coincide which means that political risk needs to be represented in a way that is conditional on the state of the system and the damage that is caused by disruptions. The modelling framework which we have suggested explicitly takes this dependency into account.

7 Conclusions

In spite of the confusion in large parts of literature, the narrow concept of energy security, which is the continuity of the supply demand balance, can be described by a list of well defined metrics from the field of reliability analysis, such as the loss of load expectation (LOLE), the loss of energy expectancy (LOEE) and the levelized cost to consumers (LCC) or society (LCS).

These metrics can be quantified by using probabilistic time-series models to propagate decision makers' beliefs about the uncertain likelihood of different disruptions in a consistent manner and enrich it with detailed information about the technical operation of the system. However, the non-linearity of both the dependencies and the cost function may lead to substantial biases if the variability within the model is reduced by using averages at different steps of the calculation process. Although this has long been recognized as a problem, averages continue to be used for pragmatic reasons. The extent of the bias which is caused by these simplifications depends on the degree to which the variations of different variables re-enforce or compensate each other. In case of technical risk, the variations of forced outage rates and repair rates caused by weather dependencies will tend to re-enforce each other, which increases the importance of modeling weather dependencies. In the case of intentional human risk, the variations of the outage and repair rates caused by higher impact of disruptions may compensate each other to the extent that it is possible to repair or replace the disrupted supply source at a faster rate in case of more damaging disruptions, which could reduce the importance of modeling dependencies for human risk.

Due to the high uncertainty about in particular political risks and the time and resources required to build a probabilistic model that includes all risk sources, a variety of alternative modeling approaches have been suggested, which often use different metrics than the reliability metrics described above. The approaches can be grouped into indicators based on concentration measures, applications of portfolio theory and scenario based analyses. With the exception of scenario analyses these approaches tend to reduce the accuracy of the measurement even further than a fully deterministic time-series based approach. They should therefore only be considered if the budget does not allow for a more refined measurement. Scenario analyses avoid the quantification of unknown probabilities while allowing a probabilistic treatment of better known risks including the interdependencies between them. As a first step break even frequencies can be used to assess whether a policy intervention could be justified. However, in those cases where an intervention could in principle be justified and none of the alternatives is dominating the others in all scenarios, the scenario approach and break-even frequencies quickly reach their limit. As the number of uncertain variables and hence the number of scenarios that need to be evaluated increases, it can quickly become very difficult to decide without a more formalized approach for weighting the probabilities of the different scenarios. In those cases, it may hence be necessary to complement the scenario and break-even analyses with a probabilistic model that includes the uncertain risks as Bayesian variables. Within this paper we have suggested a framework which may be used for this purpose.

In principle this framework could be extended to include a detailed representation of all natural, technical and human risks that are known to have an impact on the continuity of supplies. However, caution is warranted as a detailed simulation, based on half-hourly demand values and a higher geographical resolution can quickly become very resource intensive, both in terms of the data requirements and the calculation speed. What seems to be the largest problem in the analyses of energy security is thus neither the lack of knowledge about individual interdependencies, nor the absence of modeling techniques for stochastic failures but the resources required to gather the data, build and run a model that includes all the known interdependencies and infrastructures at reasonable level of detail and precision.

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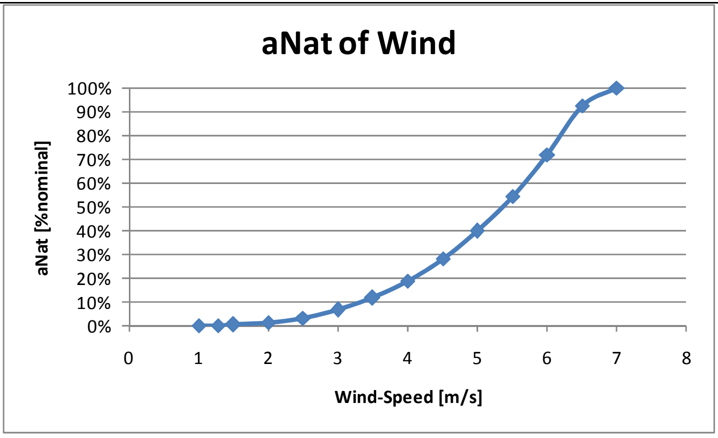
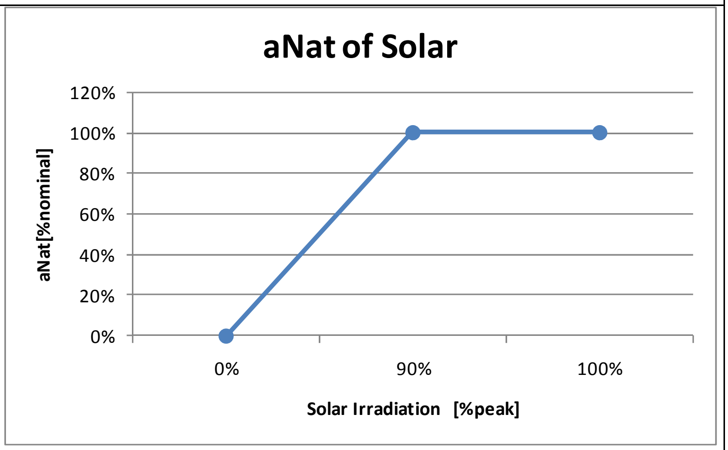
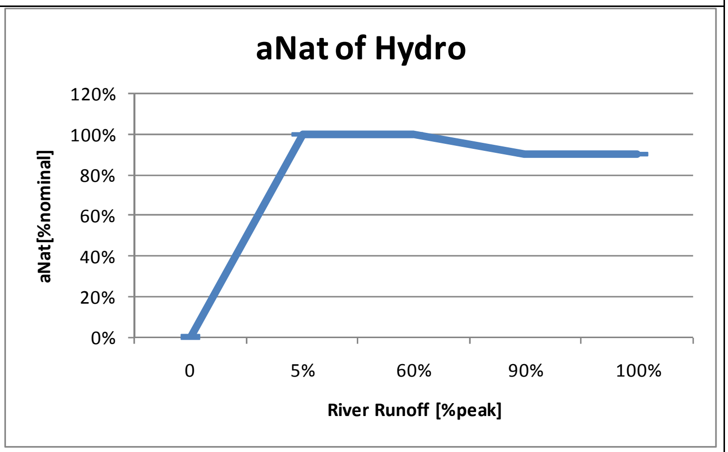
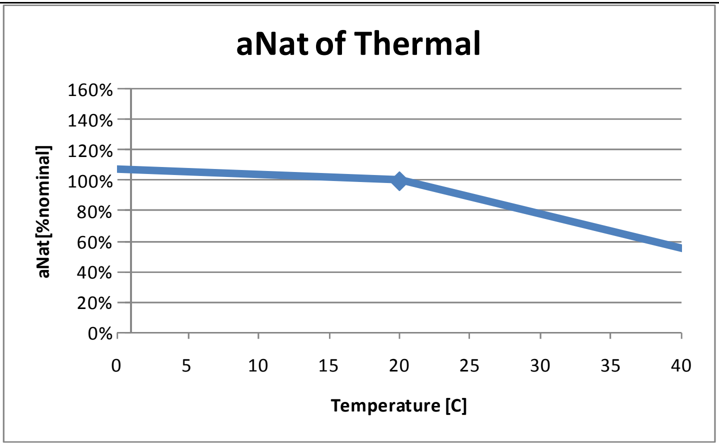
Appendix A: Capacity scenarios

Table 5: Nominal output capacities of infrastructure scenarios.

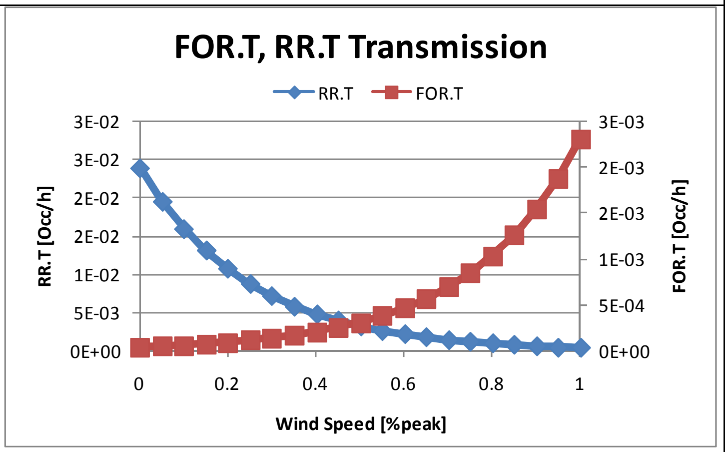
Infrastructure Scenario	I1	I2	I3	Unit	Source
Italy Strategic Pumped Storage	0	0.00	12.41	[GW]	Assumption
Italy Strategic Gas Plants	0	12.41	0.00	[GW]	
Algeria Solar Plant		12.41		[GW]	
Algeria HVDC Cable		12.41		[GW]	
Italy Nuclear Plants		0		[GW]	DGTren 2030 Reference Scenario
Italy Coal& Bio Plant		18.99		[GW]	
Italy Gas Plants		46.17		[GW]	
Italy Oil Plants		4.05		[GW]	
Italy Hydro Plants		17.44		[GW]	
Italy Wind Plants		19.01		[GW]	
Italy PV Plants		7.12		[GW]	
Italy Electricity Demand		-54.16		[GW]	ENTSO-E, maximum daily average demand 2006-2009 scaled by yearly average demand 2009 vs. 2030
Algeria Gas Pipe		3.62		[MMcm/h]	Gas Infrastructure Europe, www.gie.eu
Russia Gas Pipe		4.26		[MMcm/h]	
Neth.& Norw. Gas Pipe		2.58		[MMcm/h]	
Lybia Gas Pipe		1.14		[MMcm/h]	
Italy Gas Prod		3.84		[MMcm/h]	
Italy Gas Storage Withd.		7.75		[MMcm/h]	
Italy Gas Demand		-13.95		[MMcm/h]	SNAM RETE, maximum daily average demand 2006-2009

Appendix B: Dependencies

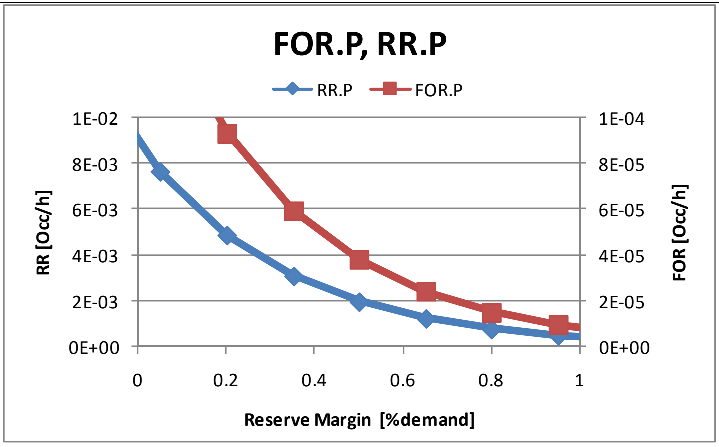
<table>
<tr><th>Dependent Variable</th><th>Indep. Variable</th><th>Graph</th></tr>
<tr><td>aNat of Wind</td><td>Windspeed</td><td rowspan="2">
</td></tr>
<tr><td colspan="2">Source:
Based on Power Curve in (Kiss and Jánosi, 2008), assuming the interval between min and max wind-speeds in Italy is mapped to the interval between s_ci and s_x.</td></tr>
<tr><th>Dependent Variable</th><th>Indep. Variable</th><th>Graph</th></tr>
<tr><td>aNat of Solar</td><td>Solar Irradiation</td><td rowspan="2">
</td></tr>
<tr><td colspan="2">Source:
Assumption that solar output is a linear function of the irradiation and that the collector size is chosen such that plants reach their nominal capacity during days with more than 90% of the yearly maximum irradiation.</td></tr>
<tr><th>Dependent Variable</th><th>Indep. Variable</th><th>Graph</th></tr>
<tr><td>aNat of Hydro</td><td>River Run</td><td rowspan="2">
</td></tr>
<tr><td colspan="2">Source:
Based on (Rothenstein and Halbig, 2010) we assume that availability of turbines declines during dry periods and is also reduced by up to 10% during times with maximum water flow due to damages or blockage by high stress and drift wood.</td></tr>
</table>

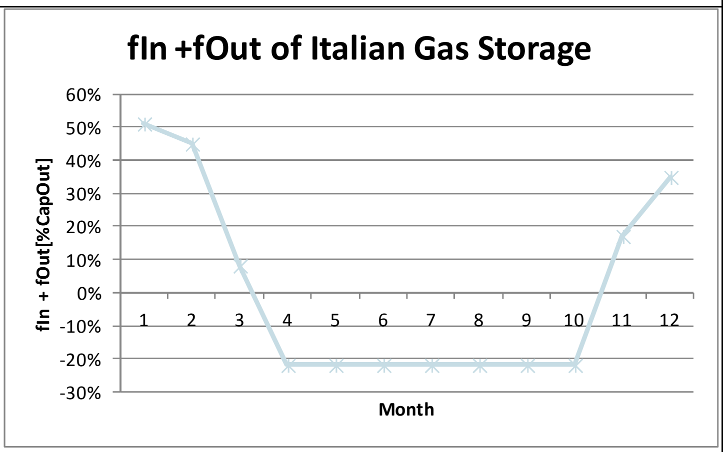
<table>
<tr><th>Dependent Variable</th><th>Indep. Variable</th><th>Graph</th></tr>
<tr><td>aNat of Thermal</td><td>Temperature</td><td rowspan="2">
</td></tr>
<tr><td colspan="2">Source:

Based on (Linnerud et al., 2011) we assume that nominal output is reached at 20C, output increases at 0.35% per degree below 20C, and output decreases at 2.25% per degree above 20C.</td></tr>
</table>

<table>
<tr><th>Dependent Variable</th><th>Indep. Variable</th><th>Graph</th></tr>
<tr><td>FOR.T of Gas pipelines and HVDC cables</td><td rowspan="2">Windspeed</td><td rowspan="3">
</td></tr>
<tr><td>RR.T of Gas pipelines and HVDC cables</td></tr>
<tr><td colspan="2">Source:

Based on (Carer and Briend, 2008) we assume exponential increase of FOR.T of HVDC cables during high wind periods. We further assume that repair rate declines due to bad weather conditions. As (Vlasova and Rakitina, 2010) hints that bad weather may also affect gas transmission we assume the same relationship holds for pipelines. Exponential curves are scaled to yield the average FOR and RR reported elsewhere for HVDC cables (Vancers et al., 2003) and gas Pipelines (EGIG, 2008).</td></tr>
</table>

<table>
<tr><th>Dependent Variable</th><th>Indep. Variable</th><th>Graph</th></tr>
<tr><td>FOR.P of gas and electricity imports</td><td rowspan="2">Reserve margin in the respective gas or electricity market</td><td rowspan="3">
</td></tr>
<tr><td>RR.P of Gas pipelines and HVDC cables</td></tr>
<tr><td colspan="2">Source:
As discussed in (Lilliestam and Ellenbeck, 2011; Salmerón and Baldick, 2004) political risk is likely to be higher if the damage that is caused by disruption is large. We approximate this by assuming an exponential relationship between forced outage rates and reserve margins. In addition to that we assume – as a sensitivity- that repair rates could also be higher in case of increased urgency of repair.</td></tr>
</table>

<table>
<tr><th>Dependent Variable</th><th>Indep. Variable</th><th>Graph</th></tr>
<tr><td>f=fIn + fOut of Italian gas storage</td><td>Month of the year</td><td rowspan="2">
</td></tr>
<tr><td colspan="2">Source:
We assume the historical storage withdrawal and injection rates published in (Fondazione Eni Enrico Mattei (FEEM), 2008, Deliverable 5.6.2).</td></tr>
</table>