FREQUENCY CONTROL

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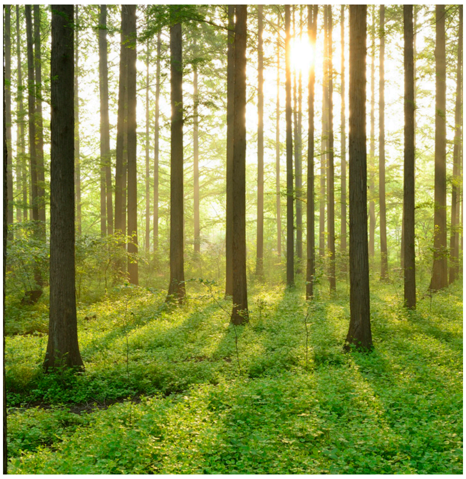

VINDFORSK

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Frequency Control

Operation of Frequency Control Schemes in Power Systems with Large Amounts of Wind Power

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Foreword

Wind power has a great potential to become an important part of the transition to renewable energy resources in Sweden. However, an increasing share of wind power in the power system present some challenges.

The project "Operation of frequency control schemes in power systems with large amounts of wind power" has developed new tools and methods for forecasting wind power, taking into account the certain conditions associated with this energy resource. This can facilitate the security management of a power system with a larger amount of wind power.

The project has been a part of the research program Vindforsk IV. The objective of Vindforsk IV is to contribute to the skills and knowledge needed for designing, constructing and operating and integrating wind farms into power system with highly penetrated wind energy. The program is financed by the Swedish Energy Agency and the wind power industry through Energiforsk AB.

Project participants have been project leader Lennart Söder, PhD student Camille Hamon and post doc Magnus Perninge, at the KTH Royal Institute of Technology. Valuable insights and comments have been provided by the reference group, with the following members: Katherine Elkington (Svenska Kraftnät), Enes Kursumovic (E.on), Fredrik Carlsson (Vattenfall), Elin Broström (Svenska Kraftnät), Oskar Sämfors (Svenska Kraftnät), Mikael Eklund (Statkraft), Anders Nilsberth (Fortum), Erik Thunberg (Svenska Kraftnät), and Lars Abrahamsson (KTH).

Stockholm, May 2016

Åsa Elmqvist

Program manager Vindforsk IV

Sammanfattning

Välfungerande kraftsystem är av avgörande nytta för samhället. Metoder och verktyg används regelbundet för att upprätthålla den begärda säkerhetsnivån genom att säkerställa att produktion och förbrukning är i balans och att alla säkerhetsgränser uppfylls.

Under det senaste årtiondet har viktiga samhällsproblem förknippade med klimatförändringen samt förminskningen av tillgången till fossila bränslen och energisäkerhet uppmärksammats. Detta har lett till betydande investeringar i vindkraft. Den begränsade förmågan att prognostisera vindkraft ger upphov till nya utmaningar i drift och planering av kraftsystem. Vinkraftens prognosfel läggs till den redan befintliga osäkerheten från lastens prognosfel och de slumpmässiga fel som kan inträffa i kraftsystemets komponent. För att beakta denna ökande osäkerhet krävs nya metoder och verktyg.

I detta projekt har sådana metoder och verktyg utvecklats, som bygger på en probabilistisk beskrivning av vindkraftens prognosfel. Genom att ta hänsyn till dessa prognosfel kan de föreslagna metoderna och verktygen ta hänsyn till många olika framtida driftlägen och deras sannolikheter att uppstå. Därmed skiljer sig de föreslagna metoderna mot dagens metoder som bygger på det deterministiska N-1-kriteriet och bara tar hänsyn till ett fåtal framtida driftlägen och som dessutom inte beaktar framtida driftlägens sannolikheter.

Användningen av de föreslagna metoderna möjliggör en mer situationsanpassad drift av systemet. Därmed nyttjas systemets resurser såsom det befintliga transmissionskapacitetet på ett bättre sätt. Detta leder till mer effektiv aktivering av frekvensregleringsresurserna.

Summary

Power systems are critical infrastructures for the society. They are therefore planned and operated to provide a reliable electricity delivery. The set of tools and methods to do so are gathered under security management and are designed to ensure that all operating constraints are fulfilled at all times.

During the past decade, raising awareness about issues such as climate change, depletion of fossil fuels and energy security has triggered large investments in wind power. The limited predictability of wind power, in the form of forecast errors, poses a number of challenges for integrating wind power in power systems. This limited predictability increases the uncertainty already existing in power systems in the form of random occurrences of contingencies and load forecast errors. It is widely acknowledged that this added uncertainty due to wind power and other variable renewable energy sources will require new tools for security management as the penetration levels of these energy sources become significant.

In this project, a set of tools for security management under uncertainty is developed. The key novelty in the proposed tools is that they build upon probabilistic descriptions of the uncertainty induced by wind power forecast errors. By considering these forecast errors, the proposed tools can consider a wide range of possible future operating conditions as well as the likeliness of these operating conditions. By contrast, today's tools are based on the deterministic N-1 criterion that only considers one future operating condition and disregards its likelihood.

The use of the proposed methods entails power system operation practices that are adapted to current and forecasted situations. System resources, such as the available transmission capacity and the frequency control reserves, are therefore utilized more efficiently.

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1 Introduction

Power systems are critical infrastructures providing and enabling essential services to the society. Failure in power systems can have severe consequences in terms of societal cost and national security. Reliable electricity delivery is therefore of utmost importance for the whole society.

Raising awareness about human-induced climate change, depletion of fossil fuel reserves and energy security has initiated a move towards large-scale deployment of wind power in power systems in the past decade. Deploying wind power in power systems allows decreasing CO_2 emissions but also brings about fundamental changes in the way power systems are planned and operated. Wind power is less predictable due to forecast errors than conventional energy sources such as hydro (with reservoirs), nuclear, coal and gas.

Securing a reliable electricity supply requires practices in power system operations and planning that enforce the reliability criterion in place (today, N-1 criterion). This report deals with frequency control schemes for power system operations. Frequency control schemes are used to maintain balance between production and consumption. The optimal activation of frequency control reserves requires knowledge of security limits, which are limits beyond which the system would become unstable. An important topic is therefore that of security management, the process by which system security is monitored and enhanced if necessary.

Today's operational practices are not able to directly handle uncertainty. To protect power systems against this uncertainty, system operators today typically schedule larger amounts of reserves or add security margins. With larger amounts of uncertainty entailed by wind power forecast errors, it becomes all the more important to design new methods for security management. This would allow system operators to better assess the risk and control the system against this risk. This in turn enables them to decrease security margins and the amount of reserves, which would lead to a more cost-efficient use of the frequency control reserves.

In this project, methods are designed to consider the uncertainty, due to wind power and load forecast errors as well as random disturbances, for both security assessment and control.

The rest of the report is structured as follows. First, a review of concepts in power system security and today's methods used for security management is provided. Challenges due to more wind power are discussed. Second, the methods developed during this project are presented. Finally, some results obtained in this project are given.

2 Security management and frequency control in power systems

2.1 ELEMENTS OF POWER SYSTEM SECURITY

In power systems, physical limits exist beyond which stability is lost. These stability limits are difficult to monitor. Therefore, in addition to these stability limits, operational limits are set by system operators on quantities such as voltages and power transfers that can be monitored. A key aspect of power system operations is to ensure that these limits are satisfied.

Following this definition, the operating state of power systems can be one of the following five [Fink, 1978]:

- The normal state is the state in which the power system is stable and within all operating limits and can remain so following a contingency.
- The power system is in the alert state if some operating limits can be violated if a contingency occurs, in which case the power system enters the emergency state, unless system operators take adequate preventive actions to bring back the system to the normal state.
- In the emergency state, some operating limits are violated. The system can be brought back to the alert state if adequate emergency control actions are taken. If not, the system may be driven further into the in extremis state.
- In the in extremis state, some operating limits are violated and stability is compromised, initiating a system collapse and the loss of some parts of the system. Emergency control actions must be taken to keep as many parts of the system as possible in operation and to stop the system collapse. Once the collapse has been stopped, the system enters the restorative state.
- In the restorative state, actions are taken to recover the parts of the system that have been lost during the ongoing collapse in the in extremis state. If these actions are successful, the system is brought back to either the normal or the alert state.

Security management refers to the set of all tools and methods used to, first, assess the operating state of the system and, second, control the system by taking on suitable preventive and emergency control actions.

2.1.1 Security assessment

Security assessment consists in three consecutive steps:

- State estimation
    - The state of the system, mainly in terms of voltages and flows on the transmission lines, is estimated from online measurements. These measurements have historically been obtained by the SCADA system through remote terminal units. Recently, the use of phasor measurement units has enabled system operators to have more accurate and up-to-date measurements.

- Contingency selection
    - There is a huge number of possible contingencies. Analyzing the impact of all of them is obviously not tractable. Therefore, a list of relevant contingencies whose impact should be studied is selected. Several methods, based on ranking indices or contingency screening, have been designed and used in practice to obtain this list. Due to integration of power systems and electricity markets, the set of contingencies of interest to study has increased in size.
- Contingency analysis
    - Using the latest state estimation, analyses are performed to assess whether stability and operating limits are satisfied following any of the contingencies in the list.

In the following, the set of all considered stability and operating limits is denoted the operating constraints.

2.1.2 Security control

Security control (or enhancement) is the process in which system operators determine preventive control actions to bring the system from the alert state back to the normal state before any violation of the operating limits occurs, or corrective actions to remove violations and bring back the system to the alert or normal state.

The set of possible actions available to system operators depend on the time available to compute and enforce these actions. Corrective actions in the in extremis state, for example, must be computed and enforced fast to prevent any further development of a collapse. On the other hand, more time is available for computation and enforcement of preventive actions. Examples of control actions are generation re-dispatch, changes in the settings of phase-shifting transformers and load shedding.

In the scope of this dissertation, only preventive actions in the form of generation re-dispatch are considered. Determining optimal preventive actions to ensure system stability is an optimization problem known as security-constrained optimal power flows (SCOPF).

2.1.3 Frequency control

System operators are responsible for maintaining the real-time balance between production and consumption during the operating period. Frequency control schemes are used for this purpose. Production is scheduled ahead of the operating period to meet the expected load on average during the operating period[1]. The latter is estimated with forecasts. Forecasts are also used to estimate how much wind power plants can produce. The offers submitted by the market participants depend on these forecasts. During the actual operating period, deviations between the actual load and the planned production occur resulting in imbalances between production and consumption.

For example, the influence of load forecast errors is illustrated in Figure 1: the actual load (thick line) is larger than the forecasted one (dashed line). Due to the deviations described above, the production plan (horizontal line) is not optimally adapted to the actual load. The striped and dotted areas are the deviation between the production

[1] On average means that the planned production covers the load on an energy basis, but not on a power basis.

plan and forecasted or actual load, respectively. The difference between these two deviations corresponds to the additional use of frequency control schemes due to forecast errors. The effect of wind forecast errors is similar.

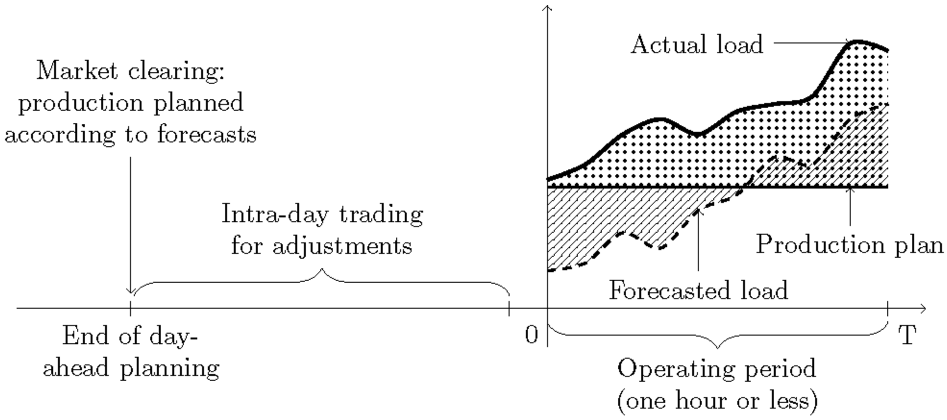

Figure 1: Influence of load forecast errors on frequency control schemes: the production is not planned optimally.

These deviations result in a change in frequency, which is undesirable for a secure and reliable operation because power systems are designed to work at a nominal frequency (e.g. 50 Hz in Europe and 60 Hz in the U.S.). Hence, the frequency should be kept within certain limits, and frequency control reserves are assigned to meet these deviations. Frequency control reserves are power reserves kept in participating power plants. Some frequency control reserves are continuously controlled so as to quickly respond to changes in the system, while some others correspond to discrete actions taken by the system operator who can ask power producers to manually increase or decrease the production levels of some of their power plants. The former are controlled by the so-called primary and secondary frequency control schemes, while the latter are controlled by the so-called tertiary frequency control schemes. Each of these layers has a specific role and acts within a certain time frame.

In response to an event such as a load change or the loss of a generation unit, the frequency will change. The inertial response of the synchronously connected generators (or of the non-synchronously connected generators equipped with a dedicated control loop) will limit the rate of change of frequency. Then, the reserves dedicated to primary control will be automatically activated within a few seconds (and fully activated within less than two to three minutes) in order to stabilize the frequency at a new value, which results in a steady-state frequency deviation from the nominal value. The secondary control reserves will automatically react to this steady-state frequency deviation, and be activated in order to bring back the frequency to zero and refill the primary control reserves. In the Nordic system, secondary control has been introduced in 2013. In some systems, secondary control also controls the generation to restore the tie-line interchanges to their contracted value. Finally, the tertiary control will act in order to relieve the secondary control reserves.

Figure 2 illustrates the different layers of frequency control schemes. The inertial response is strictly speaking not part of the frequency control schemes, but its role is important in the study of frequency stability. ENTSO-E now uses the terms frequency containment reserves, frequency restoration reserve and replacement reserve to denote primary, secondary and tertiary control reserves, respectively.

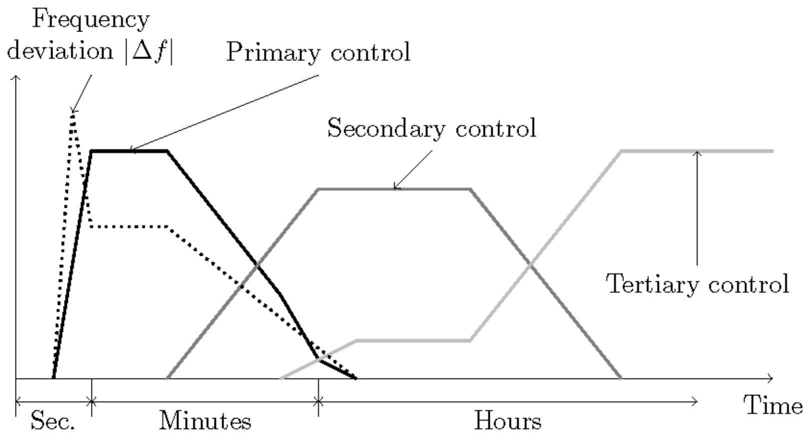

Figure 2: The different layers of frequency control schemes.

In the scope of this project, primary control is considered in the choice of the so-called slack bus. The choice of the slack bus is an important parameter when performing security assessment and control. A single slack bus model has been used throughout this thesis. In practice, synchronous generators are equipped with turbine governors which enable them to participate in primary control. Therefore, a more appropriate model for primary control would be a distributed slack bus model. The use of a distributed slack bus model is left as future work. Secondary control has not been considered in the power system models used in this dissertation. Its implementation in the methods used in this thesis is left at future work. Tertiary control is the manual activation of dedicated reserves and is therefore a re-dispatch of the participating generators. This re-dispatch can be performed by using the methods developed in this thesis. The next section presents how tertiary control reserves are used in Sweden for security management.

2.1.4 Security management in Sweden

In Sweden, one of the tools used in security management by Svenska Kraftnät is called SPICA. It is run every fifteen minutes to determine the transmission limits across identified bottlenecks. Transmission limits are computed across each bottleneck in the current state of the power systems as well as in all post-contingency systems reflecting the topology of the system should any disturbance in a predefined list occur. This list of studied contingencies is selected by Svenska Kraftnät.

To compute the transmission limits across a bottleneck, the power transfer is increased until a stability limit is reached. The corresponding power transfer is called the Total Transfer Capacity (TTC). The TTC is formerly defined as follows [ENTSO-E, 2015].

TTC is the maximum exchange program between two areas compatible with operational security standards applicable at each system if future network conditions, generation and load patterns were perfectly known in advance.

Once the TTC is found, an operational margin called Transmission Reliability Margin (TRM) is subtracted from it to get the Net Transfer Capacity (NTC). The TRM is formerly defined as follows [ENTSO-E, 2015].

TRM is a security margin that copes with uncertainties on the computed TTC values arising from:

a) *Unintended deviations of physical flows during operations due to physical functioning of load-frequency regulation,*

b) *Emergency exchanges between TSOs to cope with unexpected unbalanced situations in real time,*

c) *Inaccuracies, e.g. in data collection and measurements.*

The resulting NTC is defined as follows [ENTSO-E, 2015].

NTC is the maximum exchange program between two areas compatible with security standards applicable in both areas and taking into account the technical uncertainties on future network conditions.

The NTC across each bottleneck is computed every 15 minutes by Svenska Kraftnät. During real-time operations, the system operator monitors the actual power transfers against the latest computations of the NTC.

Figure 3 illustrates the monitoring of one bottleneck. The bottommost curve in the figure is the actual power transfer across that bottleneck, while all the other curves higher up are the transmission limits in the present system and in the system if some contingencies occur. It can be seen how, at around 8 a.m., all transmission limits decrease, probably due to a contingency. At 10 a.m., all limits are restored to their values before occurrence of the contingency, indicating that some actions have been taken by the system operator.

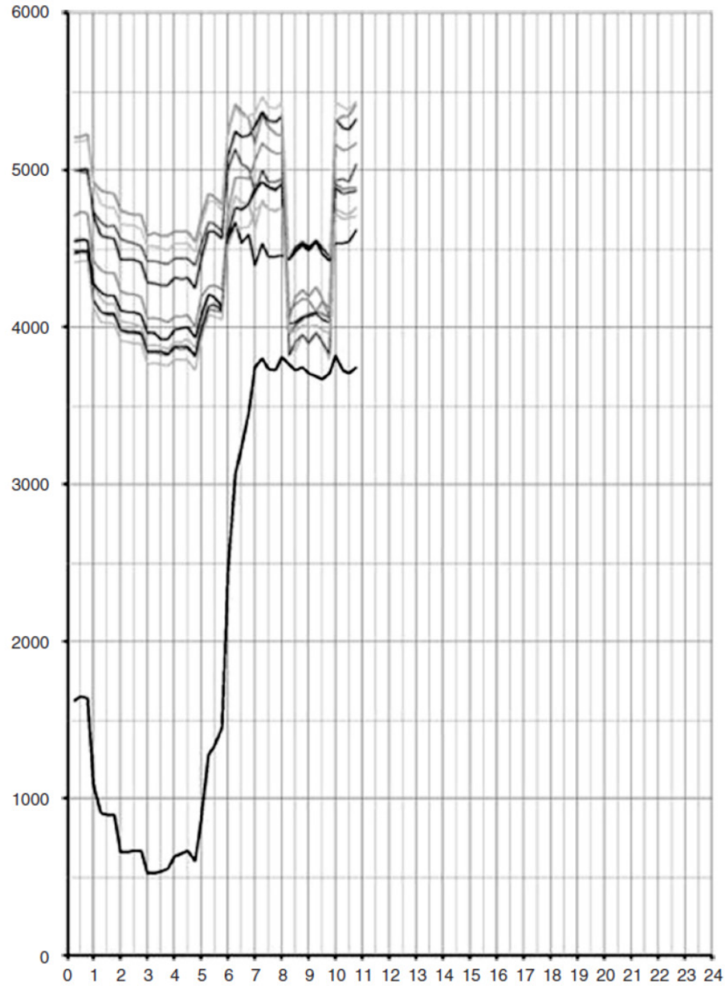

Figure 3: Monitoring the power transfer across one bottleneck. The x-axis is for the hours of the current day, and the y-axis for the power transfer and the transmission limits in MW. y-axis: power transfers and transmission limits in MW

2.1.5 N-1 criterion

The N-1 criterion states that the system must remain stable for an operating situation of interest even after a contingency occurs. In practice, what is meant by "contingency" is system specific and can include several coincidental events, such as the tripping of two parallel lines. The considered contingencies for which the N-1 criterion applies are selected by system operators. The N-1 criterion is at the center of today's tools for security management. Given an operating situation in the form of consumption and generation patterns across the system, ensuring the N-1 criterion means ensuring that there are no violations of the operating constraints before and after any of the contingency of interest occurs.

In the context of the operation of the Swedish system, it corresponds to ensuring that all power transfers are below all computed transmission limits.

2.1.6 Stability boundary

Power system security depends on the occurrence of contingencies and on the operating condition as is apparent from definition given in Section 2.1. The operating conditions are the current load consumptions and generators' productions, including the wind power plants' productions. These quantities are hereon referred to as the system parameters.

The stable domain is defined as the set of all operating conditions for which the system is stable and within the operating limits. It is bounded by the stability boundary. If the current operating condition goes beyond this stability boundary, the system would become unstable or violate some of the operational constraints. If a contingency occurs, the stable domain changes.

Figure 4 illustrates a system with two system parameters denoted ζ_1 and ζ_2. The red cross marks the current operating condition. The blue line (Σ_0) is the stability boundary in the current system. The red line (Σ_1) is the stability boundary for the system after a given contingency occurs. The black lines from the current operating points are possible future changes in the current operating point that could lead to instability in the current system. The distance to the stability boundaries are the stability margins. It can be seen how the contingency reduces the stability margin, since the current operating point is closer to the red stability boundary than to the blue one.

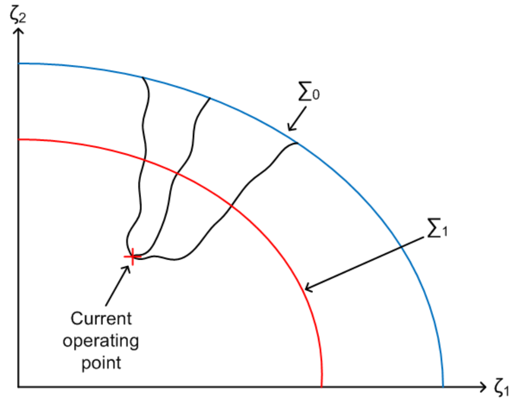

Figure 4: Illustration of stability boundaries before (Σ_1) and after (Σ_2) a contingency happens, in the space of two system parameters ζ_1 and ζ_2.

The N-1 criterion can be reformulated as ensuring that the system remains inside the pre- and post-contingency stable domains.

2.2 SHORTCOMINGS OF USING THE N-1 CRITERION FOR HANDLING UNCERTAINTIES

Two shortcomings of the N-1 criterion have been identified

- The N-1 criterion is deterministic in the sense that it does not consider uncertainties due to

  - the probability of occurrence of contingencies. The security level is therefore the same if operating limits are satisfied following a very unlikely contingency or a much more likely contingency[2].
  - the forecast errors in load and generation. The security level is determined from expected values or worst-case scenarios of the future load and wind power production without considering the likelihood of these situations and disregarding all possible other outcomes due to forecast errors. With large-scale integration of wind power, uncertainty due to forecast errors is increasing and the adequacy of the N-1 criterion is more and more questionable.
- The N-1 criterion is binary in that it only classifies an operating state as secure or insecure. In particular, the extent or severity of the violations is not considered.

Today, system operators usually hedge against risks associated with uncertainty by having some operational margins and larger reserve capacity. Considering uncertainties directly in security management would allow a more flexible and efficient use of the system resources.

In the context of the operation of the Swedish power system, the system operator hedges against risk associated with deviations from forecasts through a fixed transmission reliability margin described in Section 2.1.4.

2.3 PROPOSED CHANGES

The methods proposed within the scope of this report address the first shortcoming above. The methods would allow having a more flexible use of the system resources by avoiding having a fixed TRM. Instead, monitoring an operating risk that measures the probability of exceeding the limits due to the uncertainty is proposed. The proposed tools are detailed in more detail in next section.

[2] The probabilities of occurrence of contingencies are used to a certain extent today by some system operators for selecting the contingencies to be studied.

3 Proposed tools for security management under uncertainty

3.1 NECESSARY INPUTS

As mentioned in Section 2.2, tools have been developed to consider both the probability of occurrence of contingencies and the load and wind power forecast errors. To do so, it is assumed that the following is available:

- A list of contingencies with associated probabilities of occurrence.
- Probabilistic forecasts for load and wind power. As opposed to point forecasts which only provide one specific possible value (for example the expected value) for the future load and wind power, probabilistic forecasts provide both the marginal probability distributions of all load consumptions and wind power injections for the time of interest and information about the correlation between these quantities. Probabilistic forecasts therefore provide a set of possible future scenarios, the probabilities of occurrence of these scenarios and information about the correlation between these scenarios.

Different methods have been proposed in the literature for obtaining both inputs. Given that they provide the information listed above, any of them can be used as inputs to the tools developed in this project.

Whereas methods exist in the literature, the transmission system operators may not have or collect the necessary data today. The probabilities of occurrence of contingencies can be computed from the failure rates of the components. Some transmission system operators collect this data already today. To have good situation awareness, however, the failure rates must be adapted to the predicted conditions. For example, the probability of tripping of overhead lines depends significantly on the weather. Probabilistic forecasts are, to the knowledge of the authors, not used by system operators today. Different methods to produce such probabilistic forecasts have been developed by the research community.

The results in this thesis show that implementing methods and collecting data that provide these inputs allows for a more efficient use of system resources, see Chapter 4. Applied in an actual power system, the methods could therefore be used to value the availability of the necessary inputs. This valuation can then be compared against the costs associated with the investments in infrastructure and personnel necessary to collect this data.

3.2 OPERATING RISK

3.2.1 Definition

The developed tools all build upon an operating risk that considers the probabilistic information given in the previous section. In this project, the operating risk was defined as a probabilistic counterpart of the deterministic N-1 criterion. More specifically, the operating risk is the sum of the pre- and post-contingency probabilities of violations of the operating constraints. The probabilities of violations appearing in the sum are weighted with the probabilities of occurrence of the corresponding contingency. Mathematically, the operating risk R can be written as

$$R = \sum_{i \in C} q_i Prob\{violations\ of\ operating\ constraints\ in\ system\ i\}, \tag{1}$$

where the set C is made up of the pre- and post-contingency systems of interest, and q denotes the probabilities of occurrence of contingencies.

Recall the definition of the stable domain from Section 2.1.6. In the operating risk, the probabilities of violations of the operating constraints are the probabilities of being outside the stable domain.

If no corrective actions are taken when violations of the operating constraints occur, the system may become unstable and the electricity delivery may be interrupted. To give a sense of the magnitude that the operating risk can take, Figure 5 shows the value of the operating risk for the next fifteen minutes against the number of interruptions in ten years, assuming no corrective actions are taken. For example, if system operators deem that no more than five interruptions every ten years is acceptable, the system must be operated within the next fifteen minutes to keep the operating risk below 1.5×10^{-5}.

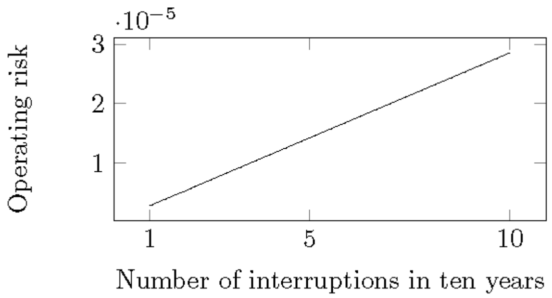

Figure 5: Allowed operating risk in the coming fifteen minutes as a function of number of allowed interruptions over 10 years.

3.2.2 Illustration

Figure 6 and Figure 7 illustrate the definition of the operating risk in a fictitious power system with two uncertain parameters. In both figures, the blue line (respectively the red line) is the stability boundary in the pre-contingency system (respectively in the post-contingency system). The probability of violations of the pre-contingency (respectively post-contingency) operating constraints is the probability of the system to be in the gray area in Figure 6 (respectively in Figure 7).

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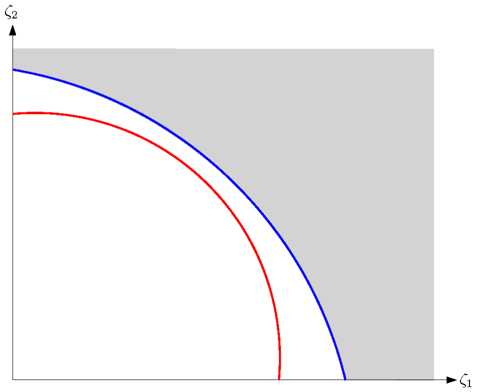

Figure 6: Probability of violating the operating constraints in the pre-contingency system with two uncertain system parameters ζ_1 and ζ_2.

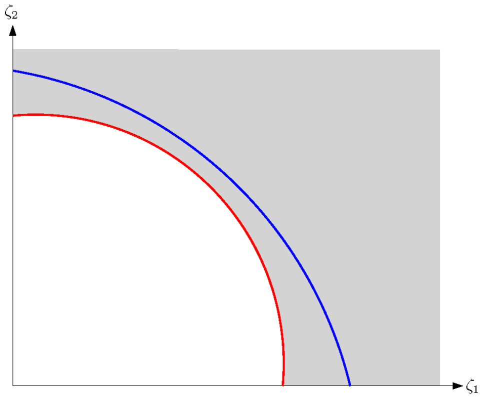

Figure 7: Probability of violating the operating constraints in the post-contingency system with two uncertain system parameters ζ_1 and ζ_2.

3.3 SECURITY ASSESSMENT UNDER UNCERTAINTY

The tools developed in this project for security assessment under uncertainty aim at computing the operating risk, which requires computing the probabilities of violations of the operating constraints in the pre- and post-contingency systems. These probabilities of violations can be computed using usual Monte-Carlo methods. The probabilities of violations are very low during normal operation due to the secure operation of power systems. For this reason, naive Monte-Carlo methods will be computationally demanding for estimating the probabilities of violations.

In this project, two types of methods have been developed to reduce the computational time when computing the probabilities of violation:

- Analytical approximation: A closed-form approximation of the probabilities of violations were developed in this project.
- Speed-up methods for Monte-Carlo simulations. Two speed-up methods were developed in this project.

Analytical approximations are faster than Monte-Carlo simulations using the speed-up methods, but the accuracy of the latter can be made arbitrarily high, at the cost of higher simulation time.

3.3.1 Analytical approximation

The probabilistic forecasts for the loads and wind power injections provide the joint probability density of all operating conditions. For a given system configuration (pre- or post-contingency), the probability of violations of operating constraints is the integral of this probability density beyond the stability boundary for this system configuration.

Consider Figure 6 and Figure 7. Integrating the probability density of loads and wind power injections over the gray area in Figure 6 gives the probability of violating the operating constraints in the pre-contingency system. Doing the same in Figure 7 gives the probability of violating the operating constraints in the post-contingency system.

The issue when computing these probabilities is that the stability boundary is not known parametrically. Running security analyses, on for example multiple load flows or continuation power flows, allows finding points on the stability boundary. The analytical approximations developed in this project address this issue by doing the following for all considered pre- and post-contingency systems:

1) So-called important points are found on the stability boundaries. These important points correspond to operating conditions (loads and wind power injections) that are locally most likely and located on the stability boundaries. "Most likely" refers to the fact that these operating conditions are local maximum of the joint probability density given by the probabilistic forecasts. A continuation method adapted from the continuation power flow method has been developed in this project to carry out this step.

2) At each of these important points, the stability boundary is approximated by its second-order Taylor expansion. This results in a local quadratic approximation of the stability boundary at each important point. Formulae for the quadratic approximations have been developed in this project.

3) Given the finite set of all quadratic approximations, the probability of violating the operating constraints can be approximated by an inclusion/exclusion method that sums up the probabilities of operating conditions being beyond the quadratic approximations and subtracts the probabilities of being beyond some pairs of quadratic approximations. The subtraction is necessary to avoid counting twice the probability of the parts of the space that are beyond more than one quadratic approximation. This step requires

    a) an analytical formula to compute the probability of operating conditions being beyond one quadratic approximation,

    b) an analytical formula to compute the probability of operating conditions being beyond two quadratic approximations, and

    c) a method to select which pairs of quadratic approximations must be considered in the subtraction.

These three ingredients have been developed in this project. The result of these three steps is an analytical formula to approximate the probability of violating the operating constraints for a given system configuration (pre- or post-contingency). The formulae for all considered system configurations are then used in Equation (1) to obtain an analytical approximation of the operating risk.

The accuracy of the analytical approximation is investigated in Section 4.1.

3.3.2 Speed-up methods for Monte-Carlo simulations

Naïve Monte-Carlo simulations can be performed as follows to estimate the probability of violating the operating constraints of a given system configuration:

1) Initialize a violation counter to zero.

2) Draw a number of samples of the loads and wind power injections by sampling the joint probability density given by probabilistic forecasts.

3) For each sample of loads and wind power injection

a) Set the loads and wind power injections to their values in the sample.

b) Perform load flow calculations

c) If the load flow does not converge, increase the violation counter by one.

4) After all samples have been analyzed, check if a convergence criterion is fulfilled. If it is, stop. Otherwise, go back to step 2).

5) Compute the Monte-Carlo estimate by taking the ratio between the violation counter and the total number of samples.

This procedure requires defining a convergence criterion. For estimating low probability of violations, the convergence criterion of choice is a threshold on the coefficient of variation, which is defined as the ratio between the standard deviation of the estimate and the estimate itself [Bucklew, 2004]. The convergence criterion is fulfilled when the coefficient of variation becomes lower than the threshold.

The issue with the naïve Monte-Carlo simulations is that the probability of violations being very small, the required number of samples to fulfil the convergence criterion is very high. Several speed up techniques can be used to decrease the computational time of estimation of low probabilities by Monte-Carlo simulations. In this project, two importance sampling technique were used.

The principles of importance sampling are to sample the regions in which the operating conditions contributed the most to the probability of violation of operating constraints and to adjust the Monte-Carlo estimate by a likelihood ratio that ensures that the final estimate is not biased. It is expected that the probability of operating conditions decrease away from the average value of the forecasts. Furthermore, all operating conditions beyond the stability boundary contribute to the estimate, while those inside the stability boundary do not. Since the probabilities of the operating conditions are decreasing away from the stability boundary, it is expected that the operating points beyond but close to the stability boundary will contribute the most to the probability of violations. This intuition can be used to design efficient importance sampling techniques that draw samples close to the stability boundary. It was theoretically proven in [Bucklew, 2004] that the resulting importance sampling distributions are efficient. To use this intuition, two importance sampling distributions that draw samples close to the stability boundary have been developed in this project.

The first one starts with the first step in the analytical approximation, see Section 3.3.1. After this step, a finite set of points on the stability boundary is obtained. Following the guidelines in [Bucklew, 2004], the first importance sampling distribution is obtained by shifting the original joint probability distribution of loads and wind power injections to the most likely operating condition (according to the probabilistic forecast) among these points. The speed-up gains achieved by using this method are investigated in Section 4.2.1.

The second one starts with the first two steps in the analytical approximation, after which a finite set of quadratic approximations of the stability boundary has been obtained at important points. The second importance sampling method is an adaptation of a method developed originally in the context of mathematical finance [Glasserman, 1999], [Glasserman, 2000]. This method allows us to design an efficient importance sampling distribution that considers the second-order information captured by a quadratic approximation of the stability boundary. While the speed-up method only shifted the distribution to the most likely operating conditions on the stability boundary, the second method tunes the mean and covariance of the sampling distribution to follow the curvatures of the stability boundary. The speed-up gains achieved by using this method are investigated in Section 4.2.2.

Both methods use the most likely point on the stability boundary. This most likely point corresponds to the most likely operating conditions as defined by probabilistic forecasts the load and wind power injections. When searching for the most likely point, it is assumed that the production at all other generators (so-called conventional generators) remains unchanged. Therefore, both methods design importance sampling distributions for a specific value of the productions at these generators. The speed-up gains when using these importance sampling distributions for other values of the productions at the conventional generators are investigated in Section 4.2.2.

3.4 SECURITY CONTROL UNDER UNCERTAINTY

As discussed in Section 2.1.2, performing security control requires solving an optimization problem in which the cheapest control actions that ensure satisfaction of the operating constraints are determined. In the scope of the project, re-dispatch of controllable generators is considered as a control action. When using the operating risk defined in Equation (1), the optimization problem contains a single constraint that puts an upper bound, or threshold, on the operating risk. This threshold represents the maximal allowable operating risk in the system. It is assumed that it would be set by system operators.

The resulting optimization problem is a so-called chance-constrained optimization problem with one chance constraint:

$$\begin{aligned} \min \quad & \text{Redispatch cost} \\ \text{subject to} \quad & \text{Operating risk} \leq \text{threshold} \end{aligned} \tag{2}$$

Different methods have been proposed in the literature to solve such problems. In this project, it is proposed to use either the analytical approximation developed for security assessment. Using the analytical approximation makes the probabilistic constraint in the optimization problem more tractable, and allows for using commercial solvers. An example is given in Section 4.3.

3.5 MODELLING OF THE UNCERTAIN LOAD AND WIND POWER INJECTIONS

The methods presented above have originally been developed assuming that both the loads and wind power injections could be modelled by Gaussian distributions. Gaussian distributions are attractive because they make the methods tractable. A probabilistic model of wind power injections must appropriately represent two characteristics:

1) The marginal distributions of the wind power injections: these are the probability distribution functions of the individual wind power injections.
2) The dependence structure of the wind power injections: it captures how the wind power forecast errors of the individual wind power injections relate to each other.

When wind power injections are assumed to be appropriately modelled by Gaussian distributions, the underlying assumptions are that

1) the forecast error of each individual wind power injection are Gaussian distributed;
2) the correlation matrix of the Gaussian distribution appropriately captures the dependence between the individual wind power forecast errors.

However, several works have shown that the marginal distributions of forecast errors on wind power are not Gaussian distributed, see [Bludszuweit, 2008] and [Hodge, 2012]. Assumption 1) above is therefore not valid.

A widely use stochastic representation to separate the marginal distributions from the dependence structure is the use of copulas. There is a wide variety of possible copula models. In the case of wind power forecast errors, however, some works have shown that the so-called Gaussian copula is adequate to model the wind power forecast errors, see [Pinson, 2009]. The Gaussian copula is not a Gaussian probability distribution. The main difference is that it allows considering arbitrary marginal distribution functions, whereas the Gaussian probability distribution implies marginal Gaussian distributions.

In this project, Gaussian copulas have therefore been used to model the uncertainty on wind power injections due to forecast errors. Since the methods presented above were originally designed for Gaussian distributed forecast errors, they needed to be adapted to the use of Gaussian copulas. This was done in this project by transforming the wind power injections to other random variables that have a Gaussian distribution. This transformation is common when using Gaussian copulas and details can be found in [Papaefthymiou, 2009]. The methods are then applied on these transformed random variables. This transformation is performed before the methods are used and allows keeping the method unchanged.

4 Results

4.1 SECURITY ASSESSMENT BY THE ANALYTICAL APPROXIMATIONS

4.1.1 Small power system

The power system in Figure 8 is studied to evaluate the accuracy of the analytical approximation. The power plant at bus 2 is assumed to be a wind power plant with installed capacity 250 MW. The active power injection of this wind power plant and the load at bus 4 are assumed uncertain due to forecast errors. The uncertain load is modelled by a Gaussian distribution $N(\mu,\sigma^2)$ and the uncertain wind power injection by a Beta distribution $B(a,b)$. Seven scenarios corresponding to different values of the parameters μ,σ,a and b for these distributions are studied, as defined in Table 1

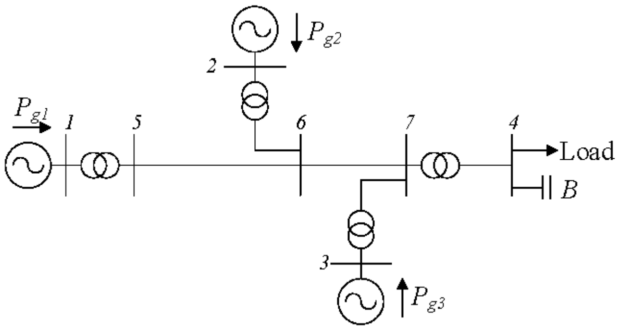

Figure 8: Power system with two conventional generators at buses 1 and 3, one wind power plant at bus 2.

Table 1: Definition of the seven scenarios. The parameters are given in per unit, with a base power of 100 MW. A dash indicates that the value is the same as that in the above row.

Scenario number	μ [p.u.]	σ [p.u.]	a	b
0	4.3	0.5	2	5
1	3	_	_	_
2	3.5	_	_	_
3	_	_	7	7
4	_	_	20	20
5	_	_	50	50
6	_	_	20	50

Figure 9 shows, for the different scenarios and different values of the production in generator 3, the exact operating risk (dotted line) and its approximations by the analytical approximation presented in Section 3.3.1 (solid line). The two lines are almost indistinguishable, which shows the good accuracy of the proposed approximation.

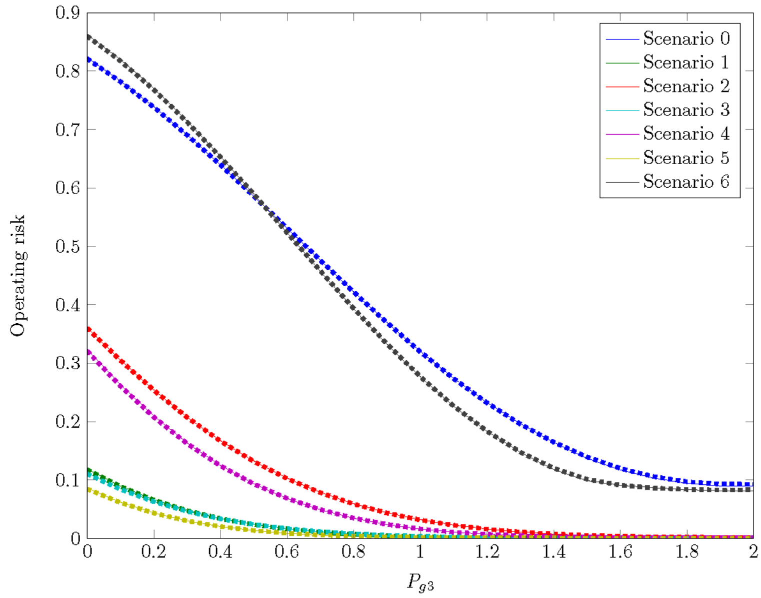

Figure 9: Operating risk as a function of the production in generator 3. Solid lines give the estimations using the proposed analytical approximation. Dotted lines give the exact operating risk. The two lines are almost indistinguishable.

4.1.2 IEEE 39 bus system

The IEEE 39 bus system in Figure 10 is studied to evaluate the accuracy of the analytical approximation. Generator 7 is assumed to be a wind power plant. The wind power injection at bus 7 and the loads at buses 1 to 5 are assumed uncertain due to forecast errors. The loads are modelled by a Gaussian distribution with mean values equal to the loads in the base case and their standard deviations equal to 2% of the mean values. The base case of the IEEE 39 bus system can be found in MATPOWER [Zimmerman, 2009].

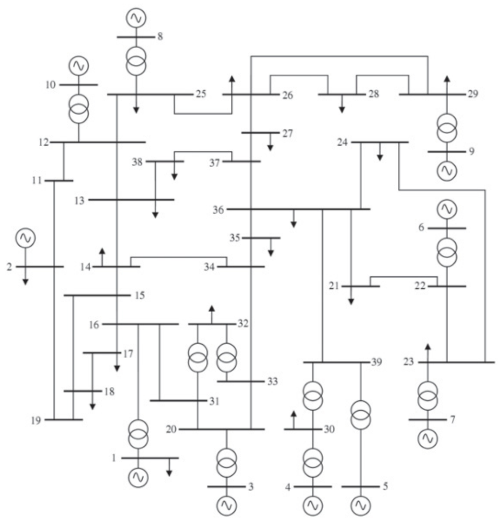

Figure 10: IEEE 39 bus system.

Table 2 shows the exact operating risk as obtained by Monte-Carlo simulation and its approximation by the analytical approximation, for different values of the production at generators 2 and 9. The accuracy is good in all cases. Furthermore, computing the

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exact operating risk requires 13000 seconds whereas computing its approximation requires 40 seconds.

Table 2: Comparison of the exact operating risk as obtained by Monte-Carlo simulation and its approximation by the first analytical approximation

Gen. 2 (MW)	Gen. 9 (MW)	Exact Op. Risk	Approximation
1 570	190	7.7e-3	7.4e-3
1 610	230	8.2e-5	9e-5
1 660	190	1.1e-4	1.3e-4
1 570	260	1.7e-4	2.6e-4
1 480	300	2e-3	1.8e-3

4.2 SECURITY ASSESSMENT BY THE SPEED-UP METHODS FOR MONTE-CARLO SIMULATIONS

4.2.1 Speed-up method 1

In this section, the decrease of the computational demand by using the first speed-up method for Monte-Carlo simulations is assessed. The first speed-up method was described in Section 3.3.2. The IEEE 39 bus system from Figure 10 is modified by installing wind power plants some buses as shown in Figure 11. The power injections of the five wind power plants and all 19 loads are assumed uncertain due to forecast errors. The uncertain loads are assumed to follow a Gaussian distribution. The wind power injections are modelled by a Gaussian copula with beta distributed marginal distributions. Copula allows modelling correlated wind power injections with arbitrary marginal distributions. More information about this modelling option for wind power can be found in [Hamon, 2016].

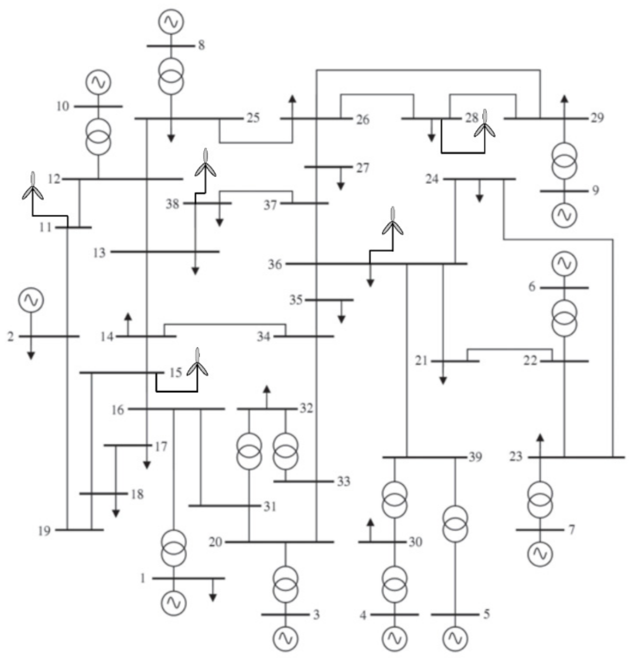

Figure 11: Modified IEEE 39 bus system.

Three case studies have been performed, where the accuracy of the load forecasts and the productions at generators 2 and 9 are varied:

1) Case study 1: Standard deviation of all loads equal to 1 % of the base case loading. The production at generator 2 is set to 690 MW and that of generator 9 to 490 MW.

2) Case study 2: Standard deviation of all loads equal to 2 % of the base case loading. The production at generator 2 is set to 780 MW and that of generator 9 to 580 MW.

3) Case study 3: Standard deviation of all loads equal to 4 % of the base case loading. The production at generator 2 is set to 700 MW and that of generator 9 to 750 MW.

Table 3 shows the speed-up factor obtained by using the speed-up method in the Monte-Carlo simulations in the three case studies. The speed-up factor is the ratio between the number of samples needed without and with the proposed speed-up method. The speed-up method is based on local information about the stability boundary. In case study 3, the local information was not accurate enough to allow for a substantial decrease of the computational demand. This shortcoming is addressed in the second speed-up method as shown in the next section.

Table 3: Comparison between Monte-Carlo simulations with and without speed-up method 1.

Case study	Op. Risk	Speed-up factor
1	4.35e-6	333
2	3.3e-5	1111
3	4.7e-4	1.92

4.2.2 Speed-up method 2

In this section, the decrease of the computational demand by using the second speed-up method for Monte-Carlo simulations is assessed. The second speed-up method was described in Section 3.3.2. It differs from the first one in that more information about the stability boundary is considered to better tune the method. The method is tested in the modified IEEE 39 bus system in Figure 11 and in the larger IEEE 118 bus system.

The uncertain parameters in the IEEE 39 bus system are modelled as in case study 2 in Section 4.2.1. In the IEEE 118 bus system, fourteen wind power plants are added. The uncertain wind power injections and loads are modelled as in [Usaola, 2010].

In both systems, the speed-up method is designed assuming specific values of the controllable generators as discussed in Section 3.3.2. In the IEEE 39 bus system, the controllable generators are located at buses 2 and 9, producing 900 MW and 750 MW, respectively. In the IEEE 118 bus system, the controllable generators are located at buses 10, 40 and 89, producing 450 MW, 204 MW and 607 MW, respectively.

Five case studies have been performed in each system in which the method is tested for estimating the operating risk when the conventional generators' production is different from that which was used to design the speed-up method. Case studies 1 and 2 correspond to a 10% and 20% decrease of the production, respectively. Case study 3 corresponds to the production that was used to design the speed-up method. Case studies 4 and 5 correspond to a 10% and 20% increase of the production, respectively.

Table 4 shows the results in the IEEE 39 bus system. Note that, in case study 5, Monte-Carlo simulations are slower when using the proposed method. The only difference between case studies 4 and 5 is that the generation at the controllable generators is higher in case study 5. The fact that the operating risk increases when increasing the generation increasing the generation is detrimental to system security. The impact of increased generation is opposite in this range to what it was for lower levels of generation (case studies 2 to 5). It therefore indicates a change in the structure of the stability boundary, which is not captured by the quadratic approximations, due to controllable active power outputs. Since the speed-up method builds upon the quadratic approximations, this explains the decrease in performance of the method in case study 5. However, the operating risk in this case study is not small any more. In reality, such a value of the operating risk is not relevant for power system operation where values of two to three orders of magnitudes lower are of interest, see the discussion in Section 3.2.

For all cases in which the operating risk was very low (less than 10^{-3}), the proposed method achieves significant speed-up gains compared to the crude Monte-Carlo simulations, up to 2 000 times faster.

Table 4: Comparison between Monte-Carlo simulations with and without the speed-up method, in the IEEE 39 bus system.

Case study	Op. Risk	Speed-up factor
1	0.029	6
2	5.1e-3	28
3	5.6e-4	213
4	3.3e-5	2252
5	0.033	0.017

Table 5 shows the results in the IEEE 118 bus system. Note that, in case study 1, Monte-Carlo simulations are slower when using the speed-up method. As discussed above, such a value of the operating risk is not relevant for power system operations. As for the IEEE 39 bus system, for all cases in which the operating risk was very low (less than 10^{-3}), the proposed method achieves significant speed-up gains compared to the crude Monte-Carlo simulations, up to almost 18 000 times faster.

Table 5: Comparison between Monte-Carlo simulations with and without speed-up method 2, in the IEEE 118 bus system.

Case study	Op. Risk	Speed-up factor
1	0.11	0.6
2	0.012	12
3	7.3e-4	176
4	3.4e-5	1750
5	1e-6	17990

4.3 SECURITY CONTROL BY THE SECOND ANALYTICAL APPROXIMATION

In this section, security control is performed by using the analytical approximation of Section 3.3.1 to solve the optimization problem in Equation (2). The analytical approximation gives an analytical formula of the operating risk. This analytical formula is a function of the production at the controllable generators. It can therefore be used to approximate the constraint in the optimization problem.

This optimization problem gives the cheapest re-dispatch of the generators that ensures that the operating risk stays under a pre-defined threshold. The optimization problem is solved using the approximation of the operating risk given by the analytical approximation to get an approximation of the optimal solution. Then, Monte-Carlo simulations are performed to compute the exact operating risk when the system is run with the approximation of the optimal solution. The exact operating risk is then compared with the pre-defined threshold. The first speed-up method from Section 3.3.2 is used to estimate the operating risk in reasonable amount of time. Note that the objective of this case study is to evaluate the accuracy of using the analytical approximation to approximate the constraint of the optimization problem. The objective is not to evaluate the speed-up gains in the Monte-Carlo simulations.

The IEEE 39 bus system in Figure 10 is considered. All loads are considered uncertain due to forecast errors. The uncertain loads are modelled by Gaussian distributions with mean value equal to the base case loading and standard deviation equal to 2% of the base case loading.

The optimization problem (2) is solved with thresholds ranging from 0.01 to 10^{-6}. The results are given in Table 6. The error is the ratio between the pre-defined threshold and the operating risk given by the approximation of the optimal solution. In all cases, the error induced by using the analytical approximation is very small

Table 6: Comparison between the operating risk of the approximation and the pre-defined threshold

Threshold	0.01	10^{-3}	10^{-4}	10^{-5}	10^{-6}
Error	1.009	1.01	0.98	1.02	1.02

4.4 COMPARISON WITH TODAY'S METHOD

Today, variations of the security-constrained optimal power flows (SCOPF) are used to perform security control, as discussed in Section 2.1.2. Given a specific operating condition (i.e. given values of the loads and of the productions at all conventional generators and wind power plants), security-constrained optimal power flows solve the following problem:

$$\begin{aligned} \min \quad & \text{Redispatch cost} \\ \text{subject to} \quad & \text{Operating constraints hold in system c for given} \\ & \quad \text{operating conditions, } c \in C, \end{aligned}$$

where the set *C* contains all pre- and post-contingency systems of interest to the system operator. Comparing the formulation of the security-constrained optimal power flow (SCOPF) with the chance-constrained optimal power flow (CCOPF) presented in Section 3.4, the main difference is that the operating constraints in SCOPF must hold for a given operating condition while they must hold with a given probability in CCOPF for a set of possible operating conditions given by probabilistic forecasts.

In this section, the SCOPF and CCOPF will be compared in the IEEE 39 bus system in Figure 10 as follows:

1. Load and wind power forecast errors are described by probabilistic forecasts.

2. A few possible future scenarios are chosen. The chosen scenarios include the expected values of load and wind as well as other less likely scenarios corresponding to deviations around the expected values.

3. For each of the chosen scenarios, a SCOPF problem is solved to determine the optimal generation re-dispatch.

4. For each of the chosen scenarios, the controllable generators are set to produce their optimal re-dispatch and the resulting operating risk is computed. This operating risk is therefore the operating risk associated with the optimal solution of the SCOPF problem.

5. For each of the chosen scenarios, a CCOPF problem is solved with the threshold on the operating risk set equal to the operating risk given by the optimal SCOPF solution.

Table 7 presents the scenarios that are chosen. Scenario 1 corresponds to solving SCOPF for the expected values of the load and wind power. In scenarios 2 to 4, the loads used to solve SCOPF are assumed larger, equal to their expected values plus one, two and three times their standard deviations, respectively. In scenarios 5 to 7, the produced wind power is decreased, equal to its expected value minus one, two and three times its standard deviation, respectively. Scenarios 8, 9 and 10 are combinations of deviations from the expected values in both wind power and load

Table 7: Operating conditions for which SCOPF is solved.

	Wind Power [MW]	Loads [MW]		
SCOPF scenario	Bus 7	Bus 2	Bus 14	Bus 30
1	2.80	11.04	5	6.28
2	2.80	11.40	5.16	6.49
3	2.80	11.76	5.33	6.69
4	2.80	12.12	5.49	6.90
5	2.41	11.04	5	6.28
6	2.02	11.04	5	6.28
7	1.62	11.04	5	6.28
8	2.41	11.76	5	6.28
9	2.80	10.68	4.84	6.07
10	2.41	10.68	4.84	6.07

The optimal solutions from the SCOPF and from the CCOPF entail the same operating risk in the system. The operating risks for the different scenarios are shown in Figure 12.

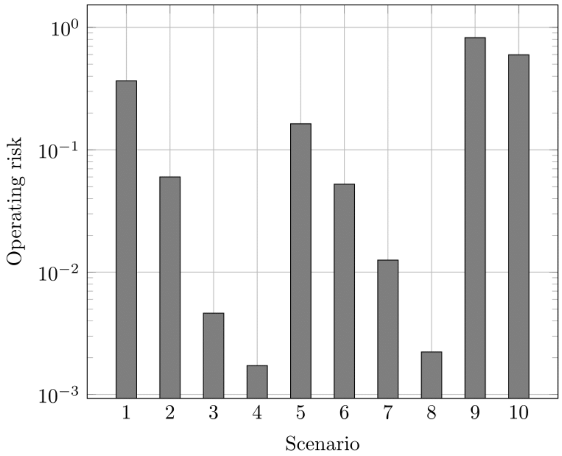

Figure 12: Operating risks in the different scenarios.

The results show that the more stressed the system when solving SCOPF, the lower the operating risk associated with the optimal re-dispatch from SCOPF. This can be seen by comparing the first four scenarios in which the loads used in SCOPF are gradually increased. Since the optimal re-dispatch volumes then increase (because more generation is needed to guarantee system stability when loads are higher), the system will remain stable for a larger range of operating conditions. Therefore, operating risk decreases. The same conclusions can be drawn from scenarios 5 to 7 in which the production in the wind farm in node 7 is gradually decreased from its expected value, thus forcing the controllable generators 2 and 9 to produce more in the optimal solution to keep the system secure. Scenarios 8 to 10 correspond to combined decreases or increases in the loads and wind power production used when solving the SCOPF.

Figure 13 shows the comparison between the costs of the optimal solutions of the SCOPF and CCOPF for the different scenarios.

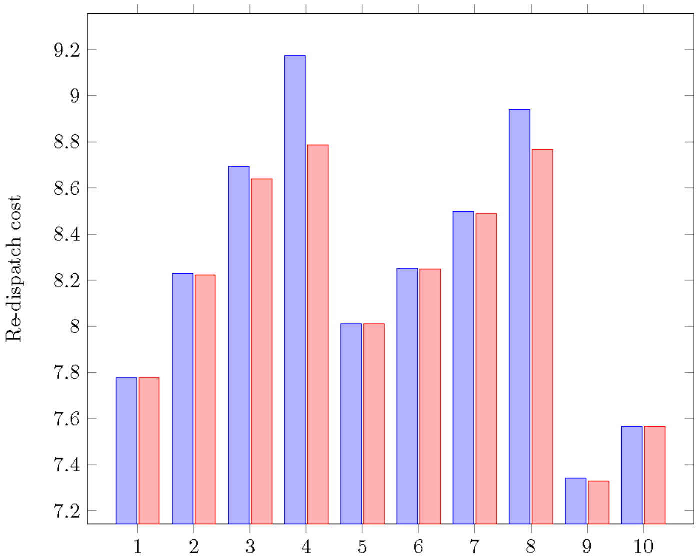

Figure 13: Comparison between the costs of the SCOPF (in blue) and that of the CCOPF (in red).

It can be observed that the costs of the CCOPF solutions are smaller than that of the SCOPF solutions. This is expected since CCOPF finds the cheapest re-dispatch that

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ensures that the operating risk is below the risk of the SCOPF solution. The gains in dispatch cost vary between the different scenarios. The gains are high for scenarios 4 and 8 and small for the others. In larger systems with more controllable generators, the gains can be expected to be larger, since the space of feasible solutions for the CCOPF will be augmented. Conversely, with only one controllable generator, the optimal solutions from SCOPF and CCOPF would be the same since there is a one-to-one correspondence between the level of generation in the controllable generator and the operating risk. Another advantage of using CCOPF is that the operating risk is made visible to the system operator.

5 Conclusion

In this project, a comprehensive framework for security management under uncertainty has been presented. Uncertainty is here understood as the occurrence of contingencies and load and wind power forecast errors. The need for such a framework is motivated by the gap between the deterministic tools used in power system operations today and the probabilistic nature of the uncertainty. This gap is addressed today by having transmission margins or larger amounts of standby reserves to protect the system against situations not considered in deterministic security management. These two measures are costly and do not allow system operators to trade off the risk of an event and the actions to remedy the consequences of these events.

The methods developed in this project build on a proposed definition of an operating risk. This operating risk is defined as the sum of the pre- and post-contingency probabilities of violation of the system's operating constraints, given the load and wind power forecast errors, weighted by the probabilities of occurrence of the considered contingencies. To include the proposed operating risk in security management, tools have been developed for security assessment, on the one hand, and for security enhancement, on the other hand.

Using the proposed methods would allow for using frequency control reserves in a more adequate way by better monitoring of the risk of exceeding the operating limits. The advantages are two-fold. First, this risk is made visible, while it is hidden when using today’s methods. Second, the system’s resources, including frequency control reserves and transmission capacities, are used in a more flexible way than today since power system operation would be adapted to the risk entailed by the current situation as captured in the forecast errors. In comparison, today’s tools usually ensure that the system is operated away from the limit by using a fixed margin that is not situation-dependent.

The proposed methods assume the availability of probabilistic models for the occurrence of contingencies and the forecast errors of loads and wind power injections. These models require data that is typically not available to the transmission system operators today. The results in this project show that cost reduction could be achieved by using the proposed methods while maintaining the same level of risk as today. Starting collecting the data required to build the probabilistic models therefore has a value. The application of the method on real-life power systems may serve as a basis to evaluate this value. This could then be compared with the investment costs associated with the changes necessary to collect this data.

One of the contributions of this project is the development of a method to determine the cheapest amount of generator re-dispatch that maintains the operating risk below a specified threshold. The method could therefore be used to determine the best frequency control bids to activate.

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FREQUENCY CONTROL

Wind power, along with other renewable power sources, are less predictable than the conventional energy resources. The transition to a power system with a larger share of renewable energy has thus created a need for new forecasting methods and tools.

The project "Operation of frequency control schemes in power systems with large amounts of wind power" has developed new tools and methods for forecasting wind power, taking into account the forecast errors associated with this power resource. Thus, these tools consider a wide range of future operating conditions. Also, unlike the N-1 criterion commonly used today, the methods takes into account the likelihood of certain scenarios to occur.

This lessens the need for setting margins to ensure secure management of the power system, and in the long run, facilitates the integration of a larger share of wind power.

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