Scenario Selection in Composite Reliability Assessment of Deregulated Power Systems

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Abstract

Power market analysis should be incorporated in reliability assessments of deregulated power systems. For the Nordic power system, this is done by using The Multi-area Power-market Simulator (EMPS) for long-term power market analysis, where EMPS finds the optimal socio-economic dispatch on a weekly basis, with respect to, e.g., hydro reservoir levels. The EMPS analysis results in a set of load and generation scenarios, and these scenarios are interpreted as a sample of future power market behaviour, and is used as basis for a reliability assessment. These load and generation scenarios are referred to as power market scenarios.

The power market analysis produces a large number of power market scenarios, and to include all these scenarios in a reliability assessment results in excessive computation time. The scenario selection method is presented and discussed. Scenario selection is used to pick out a subset of the generated power market scenarios, to only use this subset of scenarios as a basis for the reliability assessment. It is shown that the scenario selection method can reduce the scenario set by about 90%, with little loss of accuracy in the reliability assessment.

Keywords: Power market analysis, Deregulated power systems, Reliability assessment, Unsupervised learning

1. Introduction

In power system reliability analysis, probabilistic analysis is a very popular and useful technique for objective assessment of the power system reliability level, both for long-term adequacy assessment and short-term security analysis [1]. The system reliability is affected by, e.g., forced outages, maintenance schedules, load level, and generation dispatch. With more and more intermittent generation built into power systems, an increasing share of the generation system has a stochastic nature. This causes an increase in the variability in the generation scenarios compared to those of conventional power systems where the generation system mainly consisted of thermal and coal power plants.

In most restructured and deregulated power systems, there is no single central operator who has full control over the system, as the generation and transmission systems are handled by independent companies, and the load and generation schedules are determined by bids in the power market. Thus, the power market behaviour should not be neglected when load and generation scenarios are modelled in reliability assessment of deregulated power systems.

When the reliability assessment is based on Monte Carlo simulation techniques [2], load and generation scenarios are generated by random sampling. The generated scenarios reflect the stochastic nature of intermittent generation, but these scenarios are usually generated without considering how the power market affect the generation and load scenarios. In analytical techniques, the reliability assessment is usually based on one load scenario only, typically the heavy load situation. To make a connection between the power market and the generation and transmission system models used in the reliability assessment, a power market model is used to generate load and generation schedules for the power system under study [3]. The discussions and analyses in this paper focus on the Nordic power system. However, the ideas and methods should be very relevant for analysis of other deregulated power systems, but adjustments might be necessary due to, e.g., different market structure.

The Nordic power system is a hydro-thermal power system, but an increasing share of the generation capacity is wind power. The Multi-area Power-market Simulator (EMPS) [5] is designed for simulation of hydro-thermal power systems, where the market analysis is done by finding the optimal socio-economic dispatch considering, e.g., different hydro inflow scenarios and unit commitment costs. In EMPS, the stochastic nature of hydro inflow is included in the analysis by using historic weather data as expected future hydro inflow scenarios. Wind speeds and temperatures are also coupled with the historic weather data [6]. Typically, 50-75 years of historic data are used in the EMPS analysis, with a planning horizon of 3-5 years.

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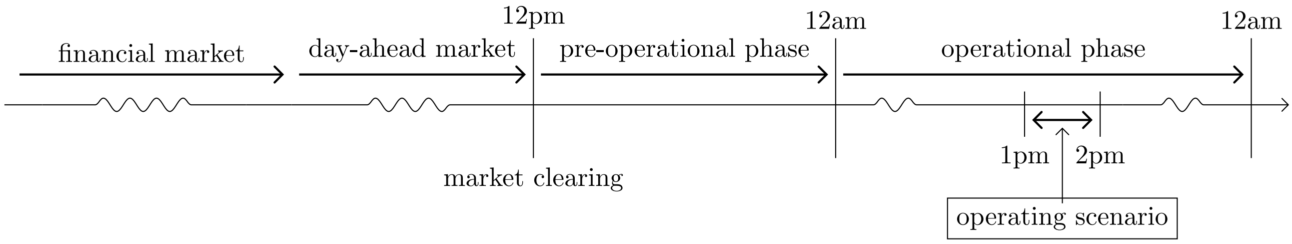


Figure 1: The organisation of the Nordic power market. The trading in the financial and day-ahead markets ends with a market clearing at noon (12pm) for each hour of the following day starting at midnight (12am to 12am) [4]. After the market clearing, the TSOs are responsible for trading balancing services to ensure secure system operation. Balancing services are traded in the pre-operational and operational phase. An operating scenario is the system state for a given hour, after the market clearing, but before balancing services are in effect.

The load model (used in EMPS) is defined to approximate the expected load in this 3-5 years period. The EMPS analysis yields a set of load and generation scenarios, which are referred to as power market scenarios. These power market scenarios are interpreted as possible future power system states, after market clearing, and used as a basis for a reliability assessment. The annual variation in hydro inflow, wind speed, and temperature is represented by the historic data, while the variation in load and generation schedules on a daily, weekly, and seasonal basis, within a given year, is represented by the power market scenarios EMPS generated for that year. Thus, the generated power market scenarios are regarded representative for the load and generation profiles over the whole year. The (up to) 75 years of historic data is a way of representing the stochastic variability in generation due to weather (hydro inflow, wind, and temperature), and is not to be interpreted as 75 years of planning.

For each of the hydro inflow years, the dispatch optimisation in EMPS is done for each hour within a week, or by splitting the week into different load periods. For instance, considering 5 load periods per week for 75 years of historic data, gives 19500 different power market scenarios. This high number of scenarios results in very high computational requirements for the reliability assessment [3].

The scenario selection method, first presented in [7], is designed to reduce the number of power market scenarios that has to be analysed in the reliability assessment. The scenario selection method finds groups of similar power market scenarios, and then, for each group, chooses one scenario to represent the group characteristics. The set of chosen scenarios is denoted the representative set, and only these scenarios will be analysed in the reliability assessment. This will keep the sample variation of the full sample of power market scenarios more or less intact, but at the same time severely reduce the computational requirements of the reliability assessment. Reference [7], discusses the scenario selection method on a very general basis. In this paper, a set of general guidelines for practical applications of the scenario selection method is presented. In addition, it is shown that the method works for both a small test networks and a large (real size) power system.

A short description of the power market analysis is found in section 2. The incorporation of power market scenarios in the reliability assessment, and the evaluation of reliability indices, is discussed in section 3. The scenario selection method is dealt with in section 4. In section 5 and 6, two case studies are included to illustrate the application of the scenario selection method. The case studies are followed by some final remarks in section 7 and a conclusion.

2. The Nordic Power Market

Deregulation of the Nordic power system took place in the 1990's and early 2000's [4], and a common Nordic power market (Nord Pool) has been established. The Nordic transmission system is operated by four TSOs - Energinet.dk (Denmark), Fingrid (Finland), Statnett (Norway), and Svenska Kraftnät (Sweden).

In addition to being responsible for the real time operation of the transmission system, the Nordic TSOs defines available transfer capacities (ATCs) between market zones [4]. Market zones are defined such that transmission corridors with a high anticipated load connect different zones. In situations where the market clearing for the whole system leads to too high power flow through one or more of these corridors, the market zones are used to split the system into price areas, to reduce the power flow through these corridors.

The organisation of the Nordic power market is illustrated in Figure 1. In the financial market, long term contracts are traded, where the main purpose is hedging against price fluctuations. In the day-ahead market, physical power is traded, and at noon the market clearing is done for each hour of the following day according to the supply and demand curves. The price for each hour is determined by the intersection of these two curves. The market clearing is first done for the whole system, but if this leads to violations of one or more of the ATCs, the market zones are used to split the system into two or more price areas.

After the market clearing in the day-ahead market, TSOs trade power in the balancing market to, e.g., resolve congestion problems within market zones or provide

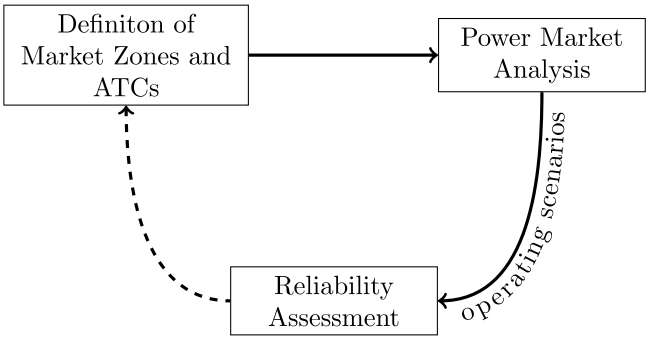


Figure 2: Illustration of how power market scenarios are incorporated in the reliability analysis. Market zones and ATCs are included in the power market analysis, and the operating (power market) scenarios are used as a basis for a reliability assessment. The dotted path indicates that if the results of the reliability assessment do not satisfy the targeted reliability criteria, the results of the reliability assessment should ideally be used to, e.g., indicate how to update the ATCs.

spinning reserve. Balancing power is traded in the pre-operational and operational phase in Figure 1, where both demand response and reserve generation can be bought. For more details about the Nordic power market, see, e.g., [4, 8].

A special characteristic of the Nordic power system is the high share of large reservoir hydro power plants. Hydro power covers about 95% of the installed capacity in Norway, and about 45% of the installed capacity in Sweden. The rest of the installed capacity consists of some nuclear power plants in Sweden and Finland, and thermal generation in Denmark and Finland. In Denmark, 34% of the installed capacity consists of wind power. There are some wind farms in the other countries, with more to be built in the future.

2.1. The Power Market Model

EMPS-NC (Network Constraints) [6, 9], an extension of EMPS, is used for the power market analysis. In EMPS-NC, transmission constraints (the ATCs) are included in the dispatch optimisation, as a linearized power flow is used to check each scenario to ensure that the dispatch does not result in too high power flow through corridors connecting market zones. The TSOs can define ATCs on a daily basis, while market zones are defined for longer time periods. However, in the power market analysis in this paper, the market zones and ATCs are kept constant for the whole analysis period.

EMPS-NC models loads per bus, and production per generator, in the analysed power system. Thus, the generated power market scenarios are suitable as a basis of both generation and transmission system reliability assessment.

3. Incorporating Power Market Scenarios in the Reliability Assessment

Depending on the time resolution of the dispatch optimisation (hourly or by load periods), EMPS-NC predicts the system state for that hour or period after the market clearing, which so far has been referred to as a power market scenario. In the reliability assessment in this paper, the reliability indices are calculated based on the OPAL methodology [10]. In the OPAL methodology, an operating scenario is defined as "... a system state valid for a period of time, characterized by load and generation composition including the electrical topological state (breaker positions etc.) and import/export to neighbouring areas".

In this paper, the EMPS-NC analysis is done considering a constant network topology, thus the electrical topological state of all the power market scenarios is the same. In the composite reliability assessment of the Nordic power system, the power flow problem is solved for the whole synchronous area of Eastern Denmark, Finland, Norway, and Sweden. The import/export to Central and Eastern Europe, through HVDC connections, are modelled as negative/positive loads in the power flow problem. Thus, with respect to the reliability assessment discussed in this paper, power market scenarios and operating scenarios are used synonymously.

The incorporation of power market (operating) scenarios in the reliability assessment is illustrated in Figure 2. For each operating scenario, reliability indices are evaluated by using analytical contingency enumeration techniques, based on minimal cuts and approximate techniques. The per operating scenario indices are combined to give annual indices for each of the hydro inflow years included in the EMPS-NC analysis. Only evaluation of indices used in the case studies, described in section 5 and 6, are presented here. A complete description of the reliability analysis is found in [3, 10].

3.1. The Operating Scenarios

The ATCs are defined by the TSOs using the N-1 criterion, and thus the probabilistic reliability level is unknown. The objective of the reliability assessment is to determine the long-term reliability level (adequacy analysis) of the power system. As the operating scenarios are interpreted as a sample of possible future day-ahead market scenarios, the reliability assessment is concerned with the long-term adequacy assessment of the operational phase in Figure 1. In long-term adequacy analysis, the main question is if there are enough available resources in the system, after market clearing, to take care of potential system problems due to forced outages of generators, transmission system failures, or within market zone congestion. The problem of within market zone congestion is discussed in [4].

3.2. Consequence Analysis

For each operating scenario, a set of contingencies is analysed with respect to violations of the operating criteria. The consequence analysis aims at minimising the consequences, as seen by end users at delivery points, of these violations. This includes an analysis of the operating scenario itself, to check for overload on transmission system components.

If a forced outage of a component results in violation of the operating criteria, optimal power flow is used to minimise the cost of the generation rescheduling needed to bring the system back within its operating limits. For linearised power flow, this optimisation problem, denoted the minimal rescheduling model (MRM), is:

$$\min_{\vec{P},\boldsymbol{\theta}_{\text{shift}}} \quad \vec{c}_P \cdot \Delta\vec{P}, \quad \text{where } \Delta P_k = |P_k - P_k^{\text{sched}}| \tag{1}$$

$$\begin{aligned} \text{subject to } & \vec{Y}^{\text{DC}}\boldsymbol{\theta} = \vec{P} \\ & \vec{h}_{\min} \leq \vec{h}(\boldsymbol{\theta}, \vec{P}) \leq \vec{h}_{\max} \\ & \boldsymbol{\theta}_{\text{shift,min}} \leq \boldsymbol{\theta}_{\text{shift}} \leq \boldsymbol{\theta}_{\text{shift,max}} \\ & \vec{P}_{\min} \leq \vec{P} \leq \vec{P}_{\max} \end{aligned}$$

Here, $\vec{c}_P$ is a vector of marginal costs of rescheduling per generator included in the optimisation problem, P_k the power output of generator k after rescheduling, P_k^{sched} the scheduled power output of generator k (after market clearing), and $\vec{Y}^{\text{DC}}$ is the admittance matrix. The branch flow constraints are defined in $\vec{h}(\boldsymbol{\theta}, \vec{P})$, and $\vec{P}$, $\boldsymbol{\theta}$, and $\boldsymbol{\theta}_{\text{shift}}$ are the generator outputs, bus voltage angles, and phase shifting transformer settings.

There is a cost related to both up and downward regulation of the generators, since from the TSOs perspective, this balancing power has to be bought in the balancing market. In (1), the marginal cost of upward and downward regulation is the same, which in general is not true. The actual cost of rescheduling is determined by the bids in the balancing market, submitted daily by the generators, and thus it is difficult to estimate this cost in long-term analysis. However, from an adequacy analysis point of view, the actual cost is not too important, as the analysis mainly look into the problem of sufficient reserves. Therefore, the cost can, e.g., be set equal to (or a little higher than) the area price.

If rescheduling is not sufficient to solve the system problems, or if sufficient amounts of demand response cannot be bought in the balancing market, load shedding is included in the objective functions given by (2).

$$\min_{\vec{P},\boldsymbol{\theta}_{\text{shift}}} \quad \vec{c}_P \cdot \Delta\vec{P} + \vec{c}_L \cdot \vec{P}^{\text{lshed}} \tag{2}$$

Here, $\vec{c}_L$ is a vector of marginal cost of load shedding per delivery point with an interruptible load, $\vec{P}^{\text{lshed}}$ is the vector of the amount of load shedding done at each of those delivery points. $\Delta\vec{P}$, $\vec{c}_P$, and the constraints are as above.

The marginal cost of load shedding per delivery point $\vec{c}_L$ depends on, e.g., customer type, interruption duration, and time of interruption, see [11–13].

There are two main reasons for using the minimal rescheduling model. First, it minimises the long-term cost of balancing services, and second, it will (approximately) minimise the difference between the actual generation scheduling and the (hydro power) scheduling given by EMPS-NC. If a forced outage causes a large deviation from the schedule given by the power market model, this might affect the power market, and will require an update of the power market analysis. However, the effect of forced outages on the power market can only be analysed if a sequential simulation approach is used, as the time and duration of the outages matter, and is not covered by the analysis described here.

3.3. Reliability Indices

For operating scenario i, and component outage j, the interrupted power at delivery point d is:

$$P_{i,j,d}^{\text{inter}} = P_{i,d} - SAC_{i,j,d} \quad [\text{MW}], \tag{3}$$

where $P_{i,d}$ is the demand at delivery point d given by EMPS-NC, and $SAC_{i,j,d}$ is the system available capacity at the delivery point, after MRM is used to resolve all system problems (if any).

Minimal cut sets are found per delivery point, where each cut in the set causes an (partial) interruption at the given delivery point ($P_{i,j,d}^{\text{inter}} > 0$).

3.3.1. Delivery point indices per operating scenario

Reliability indices are calculated for all delivery points. The expected annualised interruption duration, at delivery point d, is:

$$U_{i,d}^a = \sum_{j=1}^{n_{\text{mc},i,d}} r_j \cdot \lambda_j \quad [\text{h/year}],$$

where λ_j and r_j are the equivalent yearly failure frequency and mean time to repair for minimal cut set j, and $n_{\text{mc},i,d}$ is the number of minimal cuts for delivery point d for operating scenario i. The annualised expected energy not supplied (EENS) for delivery point d is:

$$EENS_{i,d}^a = \sum_{j=1}^{n_{\text{mc},i,d}} P_{i,j,d}^{\text{inter}} \cdot r_j \cdot \lambda_j \quad [\text{MWh/year}], \tag{4}$$

where λ_j, r_j, and $n_{\text{mc},i,d}$ are as described above.

3.3.2. System indices per operating scenario

System indices are also found per operating scenario i. The system annualised EENS is:

$$EENS_i^a = \sum_d EENS_{i,d}^a \quad [\text{MWh/year}], \tag{5}$$

where the sum is over all delivery points, and $EENS_{i,d}^a$ is given by (4).

The average interruption duration per delivery point in the system (U_i^a) is defined as the mean of the expected annualised interruption durations of all the delivery points.

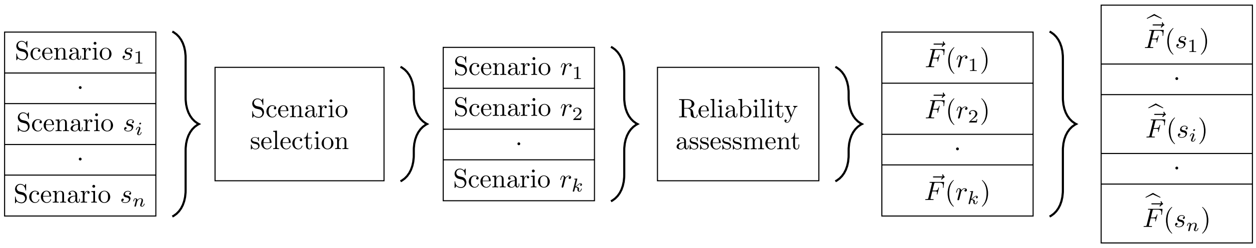


Figure 3: Illustration of the scenario selection process. The n scenarios, generated by EMPS-NC, are represented by k scenarios, which forms the representative set. For each scenario in the representative set, at set of reliability indices $\vec{F}(r_i)$ are calculated. As it is assumed that all scenarios within a cluster/group have the same value of the reliability indices, this is used to estimate the value of reliability indices $\hat{\vec{F}}(s_i)$ for each of the n original scenarios.

3.3.3. Annual indices

EMPS-NC analyse different (hydrological inflow) years, and annual indices are found for each of those years. For delivery point d, the annual indices for year y is:

$$U^a_{y,d} = \sum_{i=1}^{n_{os}} U^a_{i,d} \cdot \frac{h_i}{h_{year}} \quad \text{[h/year]}, \tag{6}$$

$$EENS^a_{y,d} = \sum_{i=1}^{n_{os}} EENS^a_{i,d} \cdot \frac{h_i}{h_{year}} \quad \text{[MWh/year]}, \tag{7}$$

where n_{os} is the number of operating scenarios in year y, h_i the duration (in hours) of operating scenario i, and $h_{year} = 8736$, the number of hours in an EMPS-year. The same approach is used to get the annual system indices.

This method neglects that outages of higher order than those of the minimal cuts might have an additional impact on the EENS, i.e., only outages of order equal to that of the minimal cuts are accounted for in the analysis. This is in general not precise, but is a reasonable approximation as long as the higher order outage combinations have low probabilities.

4. The Scenario Selection Method

The main objective of this section is to provide some general guidelines for application of the scenario selection method [7], where the guidelines are based on practical experiences with the method, see, e.g., [14–16]. Similar ideas for data reduction, in the context of power system analysis, is found in [17–19].

The overall outline of the method is illustrated in Figure 3, following the main steps:

1. Find k groups of similar operating scenarios.
2. For each group: Represent the group characteristics by one of the operating scenarios within that group.
3. Evaluate the reliability indices for the operating scenarios picked to represent the groups.
4. Assume that all operating scenarios within a group have the same value of the reliability indices as the the group representative (found in the previous step).

4.1. Feature Selection and Data Preparation

For clustering algorithms to be able to find groups of similar operating scenarios, a set of features (data points) must be assigned to represent each operating scenario, such that similarity measures can be used to quantify similarity. This feature selection process is discussed in detail in [7].

In the consequence analysis, the objective function (1) (and (2)) is defined such that for forced outages which require rescheduling (and load shedding), the cost of the corrective actions are minimised. In practice, this means that the power injections (sum of load and generation) after rescheduling (and load shedding) are as close as possible to the power injections given by the initial operating scenario. Thus, the power injections (sum of load and generation) at each bus in the analysed system are a natural choice of features when the goal is to find similar operating scenarios, the MRM is used for the consequence analysis, and the initial network topology is the same of all analysed operating scenarios.

The power injections have been used as features, with good results, when the scenario selection method has been used in combination with other consequence models as well [7]. The power injections provide information regarding where in the system large loads are, where the generation is located, and thus indicate how power is transferred around in the system. The geographical placements of large loads are especially important in terms of transmission system reliability. This feature set has also been used, with success, when classification and clustering algorithms have been used in other power system reliability studies [18, 20].

Thus, for each operating scenario s_i, the data given as input to the clustering algorithm is:

$$s_i = \vec{s}_i = [P_{i,1}, P_{i,2}, \ldots, P_{i,j}, \ldots, P_{i,d}],$$

where d is the number of buses in the system.

Feature selection is a case dependent process [21], and ideally the feature selection should be customised to suit the analysis to get optimal results. However, the power injections give good results when used as features for scenario selection, and is the best general recommendation.

To use the power injections as features can lead to an extensive number of features for large systems. Correlation analysis and projection methods, e.g., principal component analysis or multidimensional scaling [21], can in these situations be used to reduce the dimensionality of the problem.

4.2. Clustering Algorithm and The Number of Clusters

There is a great variety of unsupervised learning algorithms that can be used to cluster the operating scenarios [7, 14]. Some techniques exist for determining the number of clusters k in a dataset [7, 14, 22], but these methods are usually only suitable (and successful) when applied to datasets with a few number of clusters.

In the context of scenario selection, different clustering algorithms and methods for determining the number of clusters have been tested [7, 14], but there is no evidence in favour of a clear clustering structure among the operating scenarios (generated by EMPS-NC). This is not too surprising, as the power market behaves in a continuous way. The problem of finding groups of similar operating scenarios can therefore be interpreted as a segmentation problem [21].

In a segmentation problem, the goal of the clustering algorithm is to group together scenarios which are very similar. An agglomerative clustering algorithm with complete linkage will in general produce small and compact clusters [21, 23], and should therefore be an appropriate algorithm for this problem. Results from applications of the scenario selection method indicates that this is true, as agglomerative clustering with complete linkage has been, overall, the algorithm with the best results when applied for scenario selection.

As the clustering problem in the scenario selection process is interpreted as a segmentation problem, it is hard to define an objective criteria that can be used to determine k. Thus, choosing the number of groups k by setting k at a value of about 10% of the total number of scenarios has been a good compromise between reducing the number of scenarios, while maintaining the variation in the sample of operating scenarios. This reduce the computational requirements of the reliability assessment by about 90%.

4.3. Group Characteristics and Estimating Reliability Indices

For each group of operating scenarios, the medoid will be chosen to represent the whole group. The medoid is the operating scenario closest to the centre of the group. The reliability indices of the medoid operating scenario are evaluated as explained in section 3, and it is assumed that all operating scenarios within each group have the same value of the reliability indices as the medoid.

Within each group, the reliability indices of each operating scenario is set equal to the group representative, which for, e.g., the annual expected interruption duration will be marked with a hat, $\widehat{U}^a_{y,d}$, as it now is only an approximation of the reliability index of the operating scenario. To get the annual indices per year y:

$$\widetilde{U}^a_{y,d} = \sum_{i=1}^{n_{os}} \widehat{U_{i,d}} \cdot \frac{h_i}{h_{year}} \quad \text{[h/year]}, \tag{8}$$

$$\widetilde{EENS}^a_{y,d} = \sum_{i=1}^{n_{os}} \widehat{EENS}_{i,d} \cdot \frac{h_i}{h_{year}} \quad \text{[MWh/year]} \tag{9}$$

This is equivalent to what was done in (6) and (7). These indices will be the scenario selection indices. Indices per operating scenario are marked with a hat (as seen in the last block in Figure 4), while tilde marks annual indices per modelled hydro inflow year.

Instead of choosing one operating scenario to represent each group, an alternative is to choose a set of operating scenarios from each group, evaluate the reliability indices for each of these operating scenarios, find a weighted average of these reliability indices, and use this weighted average to represent the reliability level of each group. However, this would require a method for picking out the group characteristics, and would increase the computational requirements. Practical experiences, such as the case studies included in section 5 and 6, have shown that to only use the medoid as a group representative gives good results.

5. Case Study I - Test Network

In this case study, a reliability assessment incorporating power market scenarios is done on a small test network, which is designed for test purposes for EMPS, see, e.g., [6]. The network consists of three meshed areas, with fairly weak connections between them, and export to a fourth area through an HVDC cable.

For the given network, EMPS-NC use four load periods per week, for 50 years of historic time series, which gives a total of 10400 operating scenarios.

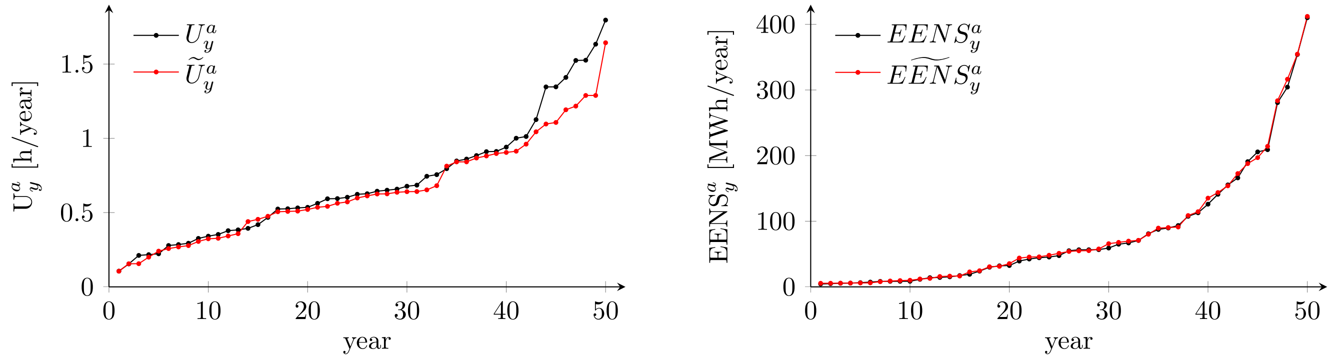
The reliability assessment includes all third order outages of lines, transformers, and generators. All generators and loads are included in the optimisation problems in (1) and (2).

5.1. Reliability Indices

In Figure 4, the average interruption duration and the system EENS are shown for all 50 years, where the indices are calculated based on both a full analysis of all 10400 operating scenarios, and based a reduced set found by scenario selection method.

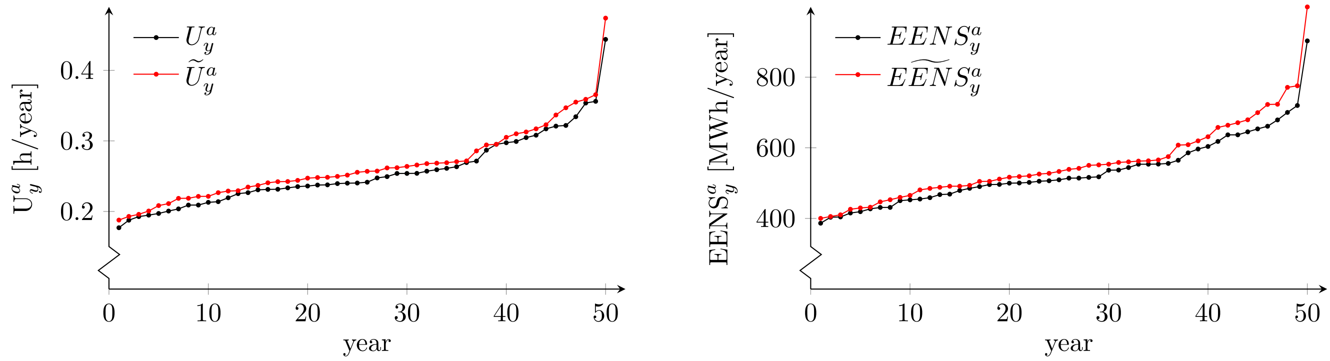
For the average interruption duration in Figure 4a, the difference between U^a_y and $\widetilde{U}^a_y$ is in the range of $[0, 0.2]$ (h/year), which means that the scenario selection index ($\widetilde{U}^a_y$) is within a 10% margin of the value of target index (U^a_y) for all the 50 years.

For the EENS in Figure 4b, the difference between $EENS^a_y$ and $\widetilde{EENS}^a_y$ is in the range of $[0, 12]$



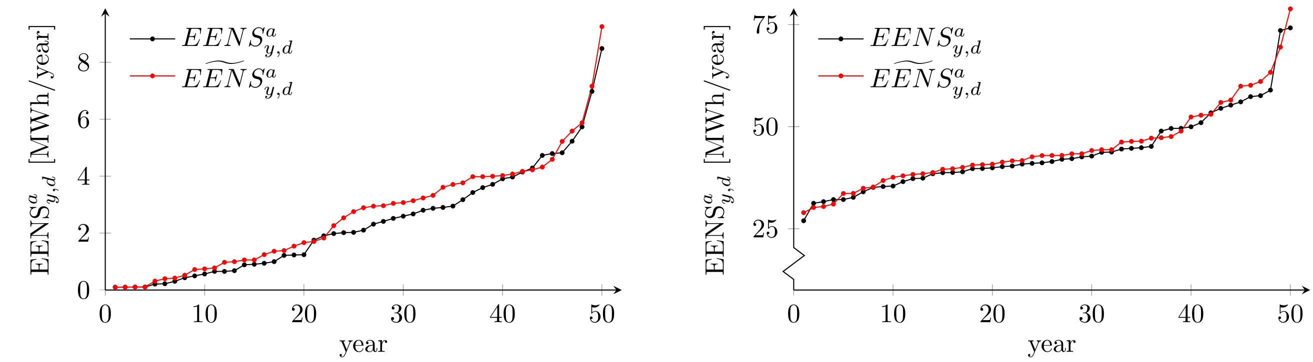
(a) Average interruption duration (b) Annualised expected energy not supplied

Figure 4: Left: Average interruption duration for the test network. For the scenario selection index, the maximum point wise error is 0.2 h/year. Right: Expected energy not supplied. For the scenario selection index, the maximum point wise error is 12 MWh/year.



(a) Average interruption duration (b) System expected energy not supplied

Figure 5: Left: Average system interruption duration for the subsystem in the Nordic system. For the scenario selection indices, the maximum point wise error is 0.03 h/year. Right: Expected energy not supplied. For the scenario selection indices, the maximum point wise error is 75 MWh/year.



(a) Delivery point one (b) Delivery point two

Figure 6: Annual expected energy not supplied for two delivery points in the Western part of Norway. The value of the scenario selection indices are close to the value of the indices based on a full analysis.

(MWh/year), which means that the scenario selection index ($\widetilde{EENS}_y^a$) is within a 10% margin of the value of target index ($EENS_y^a$) for all 50 years.

For delivery point indices, very similar results apply as for the system indices when comparing indices based on a full analysis and the scenario selection method.

6. Case Study II - Nordic System

This second case study analyses the Nordic transmission system - Eastern Denmark, Finland, Norway, and Sweden. In the model, Sweden is replaced with a 30 bus network equivalent, giving a total of about 1700 buses in the system.

For the Nordic system, EMPS-NC uses five load periods per week, for 50 years of historic time series, which gives a total of 13000 generated operating scenarios.

The reliability analysis includes all second order transmission outages - lines and transformers, in a 60 bus subsystem in the Western part of Norway. Only generators, and loads, within the subsystem can participate in the optimisation in (1) and (2).

6.1. System Indices

In Figure 5, the subsystem average interruption duration and expected energy not supplied are shown for all 50 years, where the indices are calculated based on both a full analysis of all operating scenarios, and based on the scenario selection method.

For the average interruption duration in Figure 5a, the difference between U_y^a and $\widetilde{U}_y^a$ is in the range of $[0, 0.03]$ (h/year), which means that the scenario selection index ($\widetilde{U}_y^a$) is within a 5% margin of the value of target index (U_y^a) for all the 50 years.

For the EENS in Figure 5b, the difference between $EENS_y^a$ and $\widetilde{EENS}_y^a$ is in the range of $[0, 75]$ (MWh/year), which means that the scenario selection index ($\widetilde{EENS}_y^a$) is within a 10% margin of the value of target index ($EENS_y^a$) for all 50 years.

6.2. Delivery Point Indices

In Figure 6 the EENS is shown for two delivery points in the subsystem, where the error is within a 15% margin in the left plot and an 8% margin in the right plot, i.e., the scenario selection method works with reasonable accuracy for delivery point indices as well.

6.3. Comments

Only transmission outages are included in the analysis, since this part of the network have some bottlenecks in the transmission system which dominates the reliability indices. Including generator outages in the analysis will only have a marginal effect on the value of the reliability indices.

Comparing the scenario selection indices in Figure 6a and Figure 6b, the scenario selection method seems to give better results for delivery point two than delivery point one. Delivery point two has a higher load, and a higher load variability, compared to delivery point one. Thus, delivery point two has a more dominant feature value than delivery point one when quantifying similarity of operating scenarios, which is why the scenario selection method performs better at delivery point two. If all features should have equal weight (importance), this can be achieved by scaling all features onto $[0, 1]$ before the clustering process is started. However, this will result in worse overall performance of the scenario selection method, as it is in fact the larger loads that are the most important in order to get overall good estimates for the reliability indices.

7. Discussion

The scenario selection method can be implemented as a black box algorithm based on the guidelines given in section 4, with good results as shown in the case studies. However, as for all applications of learning algorithms, (small) adjustments to fit the algorithm to the problem at hand, are necessary for optimal results. For instance, the choice of features and the choice of k (the number of groups) might be changed according to the objective of the analysis.

As seen in the case studies, setting $k \approx 0.1 \cdot n$ tends to produce scenario selection indices within a 5-10% range of the target values. The annualised system EENS per operating scenario, as defined by (5), is in the range of 0 [MWh/year] to about 2500 [MWh/year] for the four-area test network. For Western Norway, the annualised system EENS per operating scenario is in the range of 50 [MWh/year] to about 5000 [MWh/year]. Considering the large range of this index, and the fact that there is no clear clustering structure in the data, some error in the scenario selection indices is to be expected. Thus, a 90% data reduction, with scenario selection indices within a 5-10% range of the target values, has been set as a reasonable and acceptable error.

In addition to determine the current probabilistic reliability/risk level, the analysis illustrated in Figure 2, can be used as an objective method of comparing alternative ATCs (and market zone) definitions, or to suggest maintenance schedules. If this is the objective, the analysis in Figure 2 must be done several times, as EMPS-NC is used to generate operating scenarios for, e.g., different values of ATCs, and a reliability assessment is done based on each EMPS-NC analysis. In this situation, the scenario selection method is especially useful as it can be used as an objective method for reducing the computation time of each analysis.

In the power market analysis in this paper, the ATCs were set according to the N-1 criterion, which gives quite high congestion costs [4], and it puts quite heavy restrictions on the market clearing process in EMPS-NC. Thus, the variability in the sample of operating scenarios is limited. If the ATCs are defined according to other criteria, e.g., a probabilistic security criterion [24], this can possibly lead to a larger variability in the sample of operating scenarios. As long as MRM is used for the consequence analysis, the power injections should still be a good feature set, with respect to application of the scenario selection method, as the arguments in section 4.1 are still valid. However, the number of groups k might have to be increased to keep the error in the reliability indices within a reasonable level.

In reliability assessment, the “high impact low probability” (HILP) events are of special interest, as these events have extreme consequences. In the context of scenario selection, the question is if there exist “extreme” operating (power market) scenarios, or if there are cases where an operating scenario in combination with a given contingency constitutes a HILP event. As long as EMPS-NC, in combination with the N-1 criterion, is used for the power market analysis, the operating scenarios themselves are not HILP events, and it is doubtful that an operating scenario can be a contributing factor in the constitution of a HILP event. However, if other security criteria are used for the power market analysis, there might be cases where an operating scenario itself is a contributing factor in the constitution of a HILP event. If so, the operating scenario itself should be considered an outlier, and not be a part of any cluster/group in the representative set. There exist different techniques for outlier detection, but outlier detection is outside the scope of the analysis done in this paper. Outlier detection, in the context of scenario selection, is briefly discussed in [7].

One limitation of the reliability analysis of the Western part of Norway is that only generators within this area can participate in the generation rescheduling (in (1) and (2)). If generators from surrounding areas are to be included in the optimisation problem, a suitable model for this needs to be defined. In addition, information about the amount of available support from other areas should be included in the feature set.

In the reliability assessment, the chronological structure of the operating scenarios is disregarded, as each scenario is analysed independently. This again, makes it possible to use the scenario selection method to reduce the number of scenarios to be included in the reliability assessment. However, when combining the results into yearly indices, the chronological structure of the operating scenarios is used. This type of analysis will thus distribute the consequences of the forced outages over the whole analysis period. Reference [10] contains more details on how to capture the time dependencies.

The load model in EMPS-NC consists of a firm demand and a price sensitive demand. Load uncertainty should ideally be included in the reliability assessment, but this is not considered in this paper.

As a large portion of the generation in the Nordic system is based on hydro power, there could be situations where there is energy shortage due to very low hydro inflow, or there could be capacity shortage due to, e.g., very low temperature [25]. These problems should ideally be solved by the market itself (by increased prices), but the market might not respond fast enough to sufficiently prevent these problems [25]. The reliability analysis method discussed in this paper cannot be used for this type of analysis. An analysis based on sequential simulations, or the approach taken in [25], could be used instead.

8. Conclusion

The incorporation of power market scenarios in a reliability assessment is discussed in the context of the Nordic power system. It is shown how EMPS-NC is used for the power market analysis, and how the reliability assessment is done based on the results of the EMPS-NC analysis.

To include all operating scenarios, generated by EMPS-NC, in the reliability assessment, will in general result in excessive computation time for the reliability assessment. The scenario selection method is presented, and used to reduce the computational requirements. The method picks out a subset of the results of the EMPS-NC analysis, and only use this subset as input in a reliability assessment.

The results of the case studies show that the scenario selection method can reduce the computational requirements by about 90%, with only minor information loss in the final reliability indices.

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