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Probabilistic operational planning using dynamic programming with time-domain simulations☆

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ABSTRACT

A dynamic programming model with time-domain simulations of contingencies is created to find the least-costly operational strategies according to a probabilistic operational criterion with selected preventive and corrective actions. The results show that the operational model can identify strategies which appear to be satisfactory according to a static analysis, but where the system response in the time-domain is violating the systems operational requirements. The model calculates the costs related to many possible operating strategies compared to models which only search parts of the solution space. This can be useful for TSOs that want to use the model for decision support. However, computational times are very limiting due to the time-domain simulations. Consequently, approaches for limiting the number of scenarios or speeding up the time-domain simulations should be investigated.

1. Introduction

It is widely understood that the current practice of deterministic reliability criteria may result in sub-optimal power system operation. In fact, going beyond these criteria to probabilistic reliability criteria was the topic of the recent European research project GARPUR that proposed a roadmap for moving towards probabilistic criteria [1]. In the roadmap they argue that improvements in probabilistic security constrained optimal power flow (SCOPF) is needed before widespread adoption of probabilistic reliability criteria by TSOs. One particular problem they point out is that the AC-SCOPF is non-convex and that solvers may reach a local optima or even diverge for stressed system conditions. A point worth noting is that even if the solver reaches the global optimum, there may be several near-optimal solutions. Since simulation models are rarely perfect, one of the near-optimal solutions may from a practical point of view be the preferred solution. Another aspect they point out is the need to correctly model failure of corrective actions.

Traditionally operational planning was done according to the deterministic N-1 criteria, which states that constraints should not be violated in case of a single contingency. As an alternative to deterministic approaches, it has been proposed to investigate the risk of violating constraints [2,3]. However, decisions should not only be taken based on the risk of violating constraints, instead the aim should be to minimize the expected costs of operation [4].

Approaches where one is minimizing the expected cost incurred in operational planning have been presented [5,6]. In [6] a dc power flow is used for the power flow and in [5] a transport model is used. More recent approaches use machine learning for probabilistic operational planning [7,8]

There has also been research on probabilistic approaches minimizing the cost of operation in real time operation that are relevant for this paper [9–13]. The papers [9,10] use AC-power flow and experience from more detailed dynamic simulations to assess the consequences from contingencies. DC load flow is used in the papers [11,12], whereas the paper [13] uses an AC power flow. Recent works include stability considerations as constraints in the SCOPF. For instance by using a linearized swing equation and ac power flow, thermal line limits and frequency limits are considered [14]. Transient stability constraints are included in an operational planning SCOPF using a deep learning surrogate model for the stability constraints [15].

In the SCOPF literature there are some outstanding challenges that have been pointed out. For instance it has been pointed out that the SCOPF formulations should be more realistic to be useful for operators [16]. In particular an implicit assumption of AC-SCOPF is that the transition from one state to another is stable. However, this may not be the case. A more recent review [17] mentions papers including stability considerations using approximate considerations or coupling the AC-SCOPF with time-domain simulations. However, it also points out that including these constraints may make the problem intractable.

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Nomenclature

Indices

c	Corrective measure
i	Generator
n, m	Bus
p	Preventive measure
u	Uncertainty realization

Parameters

$\Delta_n^{max/min}$	Maximum/minimum voltage angle (rad)
γ_c	Probability of corrective measure success
ρ_u	Probability of realization of uncertainty
B_{nm}	Transmission line susceptance (MW)
C	Generation cost (€/MWh)
D_n	Electricity demand (MW)
F_{nm}	Transmission line capacity (MW)
G_i^{disp}	Generator dispatch (MW)
G_i	Generator capacity (MW)
Q	Load curtailment cost (€/MWh)
R	Redispatch cost (€/MWh)

Sets

$\mathcal{B}$	Buses
$\mathcal{C}$	Corrective measures
$\mathcal{G}$	Generators
$\mathcal{L}_n$	Buses connected to bus n
$\mathcal{P}$	Preventive measures
$\mathcal{U}$	Uncertain parameters

Variables

δ_n	Voltage angle (rad)
Π	Minimum operational cost
$d_i^{+/-}$	Up/down balancing by generator (MW)
f_{nm}	Flow on transmission line (MW)
g_i	Generation (MW)
r_n	Load curtailment (MW)

In this paper we aim at tackling the abovementioned challenges related to exploring near optimal solutions, detailed modeling of preventive and corrective actions, handling of failure of corrective actions, and correctly simulating the transition between states. We want to achieve a benchmark model that can be used for assessing the correctness of other faster and potentially approximate methods. To achieve this, we propose a dynamic programming approach using time-domain simulations. This approach allows us to present several solutions that are realistic in terms of stability constraints. Moreover, the approach can easily integrate commercial software for calculating the power system response to contingencies. This will allow for easier implementation. In summary the novel contributions compared to previous research are:

- A dynamic programming approach that also identifies the near optimal solutions.
- The use of time-domain simulation to ensure that the proposed solutions are stable and that all costs can be captured.

We want to achieve a benchmark model that can be used for assessing the correctness of other faster and potentially approximate methods. To achieve this we propose a dynamic programming approach using time-domain simulations. This approach allows us to present several solutions that are realistic in terms of stability constraints. Moreover, the approach can easily integrate commercial software for calculating the power system response to contingencies. This will allow for easier implementation.

In Section 2, we present the considered reliability criterion and the different aspects that influence the operational costs of a power system. Our methodology for calculating these costs is presented in Section 3, and the Case Study in Section 4. The results are presented in Section 5, and the conclusions in Section 6.

2. Theory and definitions

2.1. Power system probabilistic operational planning

In our probabilistic operational planning, we aim at finding the preventive action $p \in \mathcal{P}$, contingent on an uncertainty set $\mathcal{U}$ and a set of corrective actions C, that leads to the lowest expected system operational cost Π (1).

$$\Pi = \min_{p \in \mathcal{P}} S(p \mid \mathcal{U}, C) \tag{1}$$

where

$$S(p \mid \mathcal{U}, C) = D(p, \mathcal{U}) + \sum_{u \in \mathcal{U}} \rho_u \min_{c \in C} C(p, u, c) \tag{2}$$

The cost of an operational strategy S is calculated by finding the generator dispatch cost D and the corrective operation cost C as shown in (2). The corrective operation cost is calculated by the probability ρ_u of the uncertainty realizations $u \in \mathcal{U}$, while the optimal corrective action c is activated after observing the realization of the uncertainties. In practice the uncertainty set $\mathcal{U}$ include possible realizations of load, generation price, fault and successful activation of actions uncertainties. Moreover, the uncertainty increases for the actions that are further ahead in the future.

For calculating the expected system operation costs we use the following equations:

$$C(p, u, c) = \gamma_c R(p, u, c) + (1 - \gamma_c) R(p, u, c^0) \tag{3}$$

$$R(p, u, c) = FCR(p, u, c) + SPS(c) + CENS(p, u, c) + BAL(p, u, c) \tag{4}$$

We account for the probability of successful SPS activation, γ_c, by weighting the system response costs R with SPS activation against the case without SPS activation, c^0 (3). The failure of other corrective actions can be included in the same manner. As shown by (4), the system response costs R, for each combination of preventive action, realization of uncertainty (e.g. fault) and corrective action is the sum of the following costs: frequency containment reserves (FCR) activation cost, SPS activation costs, cost of energy not supplied (CENS) and balancing costs (BAL).

2.2. Operational requirements and protection

Power system components are protected against harmful operating conditions. This is done using protection systems that include overcurrent and voltage protection of components, such as generators, transformers and transmission lines. However, the protection systems should allow for short periods of operation outside rated values to increase resilience to faults. This is ensured by requiring that the power system protection do not disconnect important components due to non-critical dynamic phenomena after faults [18]. An example is *fault ride-through curves* which specifies lower and upper bounds on voltage and frequency within which the protection should not trip.

Similar to protection of system components there are also *system protection schemes*. System protection schemes include strategic disconnection of specific generators or loads in order to reduce the consequences of a specific contingency. Contingencies which might

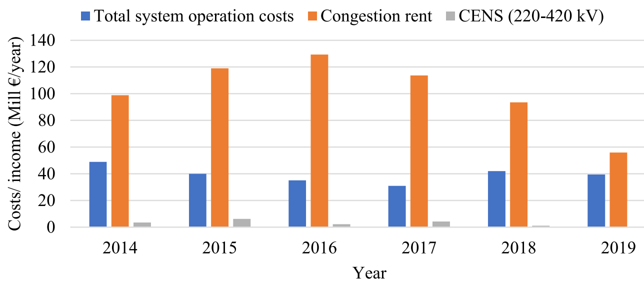

Fig. 1. Comparison between the total system operational costs, bottleneck costs and cont of energy not served (CENS) on the 220–420 kV transmission grid level in the Norwegian power system for the period 2014–2019. CENS is missing for 2019.

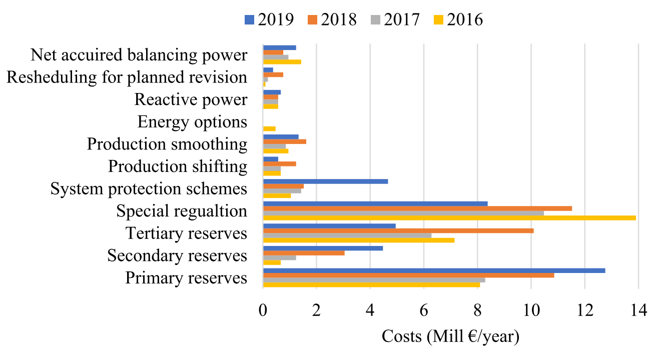

Fig. 2. Breakdown of the system operation costs for the Norwegian TSO Statnett from 2016 to 2019.

result in large-scale disconnection of loads or total system collapse from cascading generator tripping can be avoided by fast and strategic disconnection specific generators or loads. This can improve the system state such that it is within the specified operational limits for the system.

2.3. Cost of power system operational measures

In the Norwegian and most European power systems, structural bottlenecks on transmission corridors are handled by splitting the power markets into bidding zones. This results in a price difference between the zones on each side of the bottleneck. Moreover, transmission congestions limit the most cost efficient generators from serving the loads of the system leading to socio-economic losses. For a congested corridor between two zones the socio-economic loss is proportional to the reduced flow due to the congestion [19]. The Norwegian regulator does not report the congestion cost, however, the *congestion rent* is reported. This is the price difference times the flow from the surplus to the deficit area and is collected by the TSOs. In Fig. 1, the congestion rent is compared with the total system operational costs and the CENS [20]. The congestion rent is mainly a result of insufficient transmission capacity, due to thermal or dynamic line ratings. However, the transmission capacity between two market areas can also be reduced as a preventive measure to increase the system reliability and improve the dynamic stability of the power system. The share of the congestion rent which is a result of lacking transmission capacity or operational measures is unclear. On the other hand, most of the power system operational costs are very transparent.

A breakdown of the costs related to system operational measures in Norway from 2016 to 2019 is shown in Fig. 2 [21]. Procuring sufficient operational reserves represents a major part of the total power system operational costs. There are three types of reserves differentiated based on activation times, from short to long. These are FCR, frequency restoration reserves (FRR) and restoration reserves (RR). The three

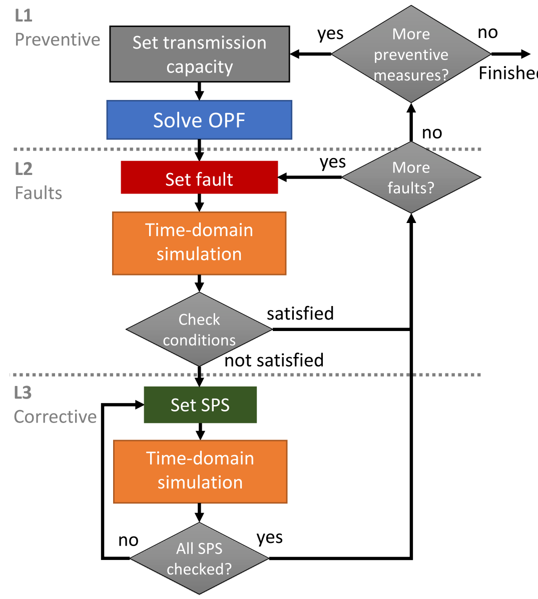

Fig. 3. Flow chart for illustrating the algorithm used to simulate power system operation with preventive and corrective actions.

types of reserves are used for different purposes after a disturbance. FCR are used to contain frequency variations. FRR are used to restore the frequency to the nominal value. RR are used to relieve FRR such that they are available for activation if needed.

Another significant system operation cost is *special regulation*. Special regulation is when a reserve is activated due to a situation which cannot be resolved by the balancing market (the market for activation of RR). In such cases balancing might be needed at a specific point in the system such that a balancing resource is activated, which might not be the least expensive according to the balancing market merit order. Special regulation is for example used to relieve congestion on transmission lines within market areas or local system imbalances after a fault.

The total cost of SPSs is typically lower than for reserves and special regulation as it is less frequently used. However, the cost of SPSs was increased by a factor of 2–3 in 2019. This might be indicative of the future as less risk-averse operating strategies compared to the N-1 criterion might rely more heavily on SPSs in the case of contingencies. Relying on SPSs allow TSOs to increase transmission capacities in the power markets which often results in lower operating costs.

3. Methodology

A dynamic programming model is implemented to simulate the cost of power system operation subject to selected preventive and corrective actions. The model consists of three main levels that discretize and simulate all combinations of preventive actions, faults and corrective actions, as illustrated by the flow chart in Fig. 3.

3.1. Simulation model

On the first level, inter-area transmission capacities are discretized to obtain a finite number of preventive strategies. These preventive strategies represent the available inter market-area capacities which are set by the TSO. For a given preventive strategy, an optimal power flow (OPF) is solved to find the cheapest generation schedule to serve the electricity demand as shown in (5) to (10).

$$\min \sum_{i \in \mathcal{G}} C g_i \tag{5}$$

$$\sum_{i\in\mathcal{G}_n} g_i + \sum_{m\in\mathcal{L}_n} f_{nm} = D_n \qquad \forall n \in \mathcal{B} \tag{6}$$

$$f_{nm} = B_{nm}(\delta_n - \delta_m) \qquad \forall n \in \mathcal{B}, \forall m \in \mathcal{L}_n \tag{7}$$

$$0 \le g_i \le G_i \qquad \forall i \in \mathcal{G} \tag{8}$$

$$F_{nm} \le f_{nm} \le F_{nm} \qquad \forall n \in \mathcal{B}, \forall m \in \mathcal{L}_n \tag{9}$$

$$\Delta_n^{min} \le \delta_n \le \Delta_n^{max} \qquad \forall n \in \mathcal{B} \tag{10}$$

This includes the energy balance (6), dc power flow (7), generator capacity (8), transmission line capacity (9) and voltage angle limits (10). The OPF represents the day-ahead market clearing. The system state after the day-ahead market is cleared is defined by the generation, load, and power flows. The dispatch cost is defined as $D(F_{nm}) = \sum_{i\in\mathcal{P}} Cg_i$, where F_{nm} define the preventive strategy by limiting transfer capacity on inter-area transmission lines.

A contingency analysis is performed on the second level to evaluate the reliability of the system state subject to a list of predefined contingencies. A time-domain simulation is performed for each contingency in the contingency list to check if the system response to these failures is within certain power system operational requirements specified by the TSO. The operational requirements are typically upper and lower limits for bus voltage, system frequency and loading of components such as generators transformers and transmission lines. The time-domain simulation includes detailed models with differential equations that describe the dynamic behavior for all components in the power system, such as transmission lines, transformers, buses, loads and generators, including turbine governors and automatic voltage regulators.

On the third level of the algorithm, SPS are activated in a new time-domain simulation if the combination of a contingency and a system state leads to a system response that violates the operational requirements. The algorithm iterates through a predefined list of SPS in order to find the one that gives the best system response and lowest costs.

3.2. Post-processing and calculation of costs

After the simulation model is finished, the results from the OPF and the time-domain simulations are collected and post-processed. The costs of the operational strategy is calculated according to (2)–(4). The FCR costs are given directly by the system response, while the SPS activation costs are given by the optimal corrective action. The optimal CENS and balancing costs (BAL) are calculated by two optimization models for emergency response and balancing, both models are defined by the equations in (11) to (17).

$$\min \sum_{i\in\mathcal{G}} R(d_i^+ + d_i^-) + \sum_{n\in\mathcal{B}} Qr_n \tag{11}$$

$$\sum_{i\in\mathcal{G}_n} g_i + \sum_{m\in\mathcal{L}_n} f_{nm} + r_n = D_n' \qquad \forall n \in \mathcal{B} \tag{12}$$

$$d_i^- - d_i^+ = G_i^{disp} - g_i \qquad \forall i \in \mathcal{G} \tag{13}$$

$$f_{nm} = B_{nm}(\delta_n - \delta_m) \qquad \forall n \in \mathcal{B}, \forall m \in \mathcal{L}_n \tag{14}$$

$$0 \le g_i \le G_i' \qquad \forall i \in \mathcal{G} \tag{15}$$

$$F_{nm}' \le f_{nm} \le F_{nm}' \qquad \forall n \in \mathcal{B}, \forall m \in \mathcal{L}_n \tag{16}$$

$$\Delta_n^{min} \le \delta_n \le \Delta_n^{max} \qquad \forall n \in \mathcal{B} \tag{17}$$

In the emergency response model, emergency limits are used for the capacity on system components such as generators, transformers and transmission lines and, selects the optimal load that has to be curtailed to satisfy these limits. The capacity of generators or loads that are disconnected due to SPS are set to zero, while generator re-dispatch is restricted $d_i^+ = 0, d_i^- = 0$. In the balancing model, we allow the generators to balance production and consumption, $d_i^+ \ge 0, d_i^- \ge 0$, in addition to load curtailment to reduce the loading of the system components within the nominal capacity limits (G_i, F_{nm}). CENS is calculated by $CENS = \sum_{n\in\mathcal{B}} Qr_n$ from both models, while the balancing costs are calculated by $BAL = R(d_i^+ + d_i^-)$ from the balancing model.

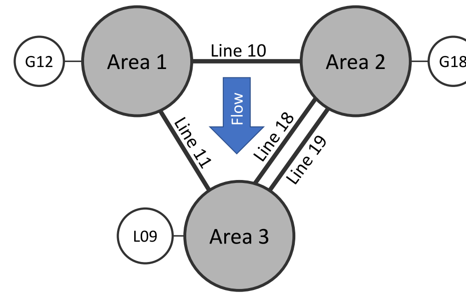

Fig. 4. A simplified illustration of the three area case system. Only inter-area transmission lines and generators/loads which are part of the SPS are included. For a fully detailed description of the system see [22].

3.3. Model limitations

The model focuses on reducing transmission capacities between market areas as preventive actions. No reserve requirements are directly enforced in each market area. However, limiting the transmission capacities between the market areas results in both available generation capacity in surplus areas and minimum generation in deficit areas. Thus, reserves are indirectly allocated as a part of the preventive strategies. In this work, we focus on the effect of using SPS compared to preventive strategies in general, as opposed to a very detailed and realistic model where the results might be complex to interpret and computational times would be excessive. A more detailed representation of reserves should be included in future studies or if the model is used for supporting real-world decision making.

Furthermore, we do not consider how SPSs are implemented or activated in practice for a specific contingency. The model simply finds the SPSs which lead to a satisfactory system response in the most cost-efficient manner. In practice, this can provide indication of which SPSs that are most cost-effective and serves as a foundation for further studies on how the SPSs can be implemented.

4. Case study

The algorithm is tested on the three area system which is illustrated in Fig. 4 that represent parts of the Nordic power system [22]. The relatively limited size (25 buses and 29 lines) makes it well suited for computationally intensive market and reliability analysis.

We assume marginal generation costs of 30, 40 and 50 €/MWh in area 1, 2 and 3 respectively. Solving the OPF for this system results in a surplus of generation in area 1 and 2, while there is a energy deficit in area 3. This leads to high power flows on the inter-area transmission lines from the north to south. The capacity of Line 11 is fully utilized while Lines 18 and 19 are loaded at 53.6 and 47.7% of maximum capacity.

In the contingency list, we consider a short-circuit on all the inter-area transmission lines (line 10, 11, 18 and 19). The short-circuit occurs after 5 s of the 50 s dynamic simulation and is cleared with a delay of 0.2 s. After the fault is cleared the line that was short-circuited is set out-of-service.

The system response after a contingency is evaluated by the system operational requirements which are formulated in Table 1. The system requirements are defined by inequalities related to the minimum and maximum values of the variable of interest. The inequalities can be breached for a limited duration.

We consider the response to be unsatisfactory if a fault results in a system response that violates any of the operational requirements. This results in losing the relevant system components. Violation of the operational requirements can for example trip generator protection relays which takes the generators offline. At this point, we have to resort to SPS to improve the system response such that it does not violate the

Table 1
Power system operational requirements.

Variable	Unit	From time (s)	min	max	dur (s)
frequency (Hz)	–	0	42.5	57.5	1
	–	10	45.0	55.0	1
	–	25	47.5	52.5	1
voltage (p.u)	load	10	0.82	1.18	0
	load	35	0.85	1.15	1
	generator	0.15	0.25	–	0
	generator	1.0	0.9	–	1
loading (%)	generator,	10	–	220	1
	generator,	30	–	150	1
	generator,	40	–	115	1
	branch	0	–	175	1
	branch	30	–	120	1

Table 2
Parameters used when calculating system operational costs.

Parameter	Symbol	Value	Unit
SPS	–	13000	€/trip
CENS	Q	6000	€/MWh
Redispatch cost	R	60	€/MWh
Discretization step size	–	5	% of line cap

operational requirements (or violates fewer operation requirements). The SPSs considered in this case study are tripping of generator 12 and 18 in the surplus areas (area 1 and 2) and disconnection of load 9 in the deficit area (area 3).

The model parameters in Table 2 are used to calculate the cost of the corrective measures. These parameters are input for the post-processing optimization models which determine optimal load curtailment and balancing. The OPF and time-domain simulations are executed in PowerFactory,[1] while the algorithm in Fig. 3 is implemented in Python.

5. Results

5.1. Operational costs

Contingency related system operational costs are calculated according to (2), assuming a fault probability of 1% and a SPS reliability of 100%. The system operational costs without preventive actions[2] are used as a reference value for all costs. The reliability related operational costs are shown in Fig. 5 as a function of the power flow on Line 11, which is the critical line with fully utilized capacity without preventive actions.

The stacked areas in Fig. 5 represent the lowest expected costs for flows on Line 11. The lowest cost strategy is selected using a rolling window of 5 MW for all power flows on Line 11. The cost components in Fig. 5 are defined in (2)–(4).

The state of the system response is highlighted by colored points. This state is grouped into three categories, N-1 safe, saved by SPS and not N-1 safe. If the system is N-1 safe, the system response satisfies all the operational criteria for each fault in the contingency list separately. If the system is not N-1 safe, but are within the operational criteria after activating any one of the corrective actions in the SPS list the state is considered "saved by SPS". Finally, if the corrective actions are not able to keep the system response within the system limits the system state is considered not to be N-1 safe. It should be noted that the states that are saved by SPS are not strictly N-1 secure, however, some TSO operate with SPS.

The preventive strategies with lowest expected costs restrict the power flow on Line 11 to 60–90 MW. In this range there is low

[1] https://www.digsilent.de/en/powerfactory.html
[2] All lines have a capacity equal to the thermal capacity.

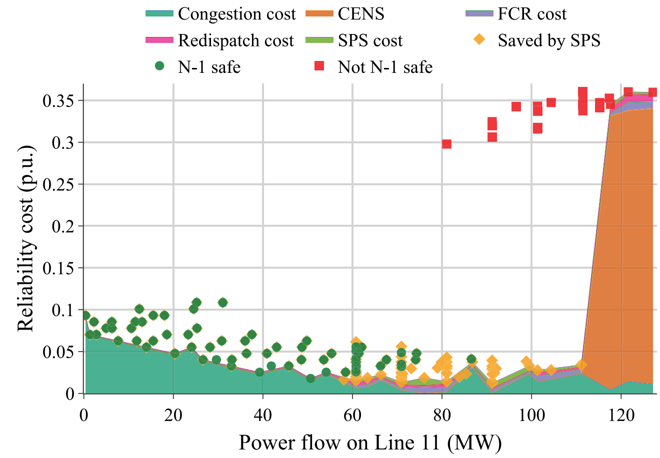

Fig. 5. Reliability related power system operational costs as a function of the total power flow between the market-areas. The points represent the contingency state of the system, i.e. if the system state fulfill the N-1 criterion, are saved by SPS or neither.

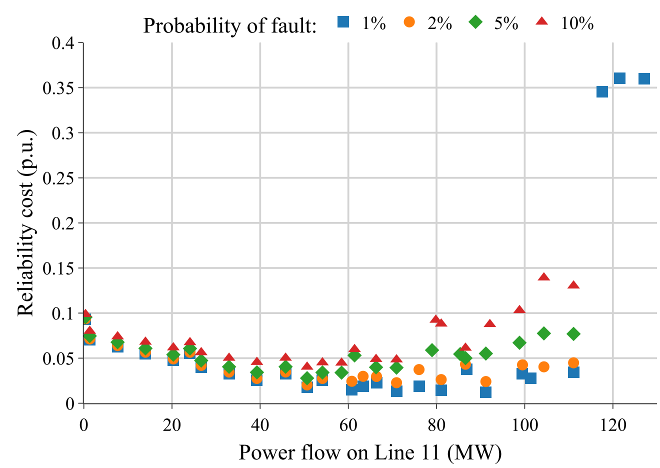

Fig. 6. Sensitivity of costs to different fault probabilities.

difference in cost between the strategies, but the TSO must rely on SPS in case of one or more faults. Restricting the flow below 60 MW results in a system that satisfies the N-1 criterion but also higher congestion costs in the electricity markets due to the preventive actions. Increasing the flow beyond 90 MW also increases the congestion costs as flow on other lines have to be decreased. No SPS is sufficient to enable higher flows than 110 MW on Line 11. In this case, the optimal power flow in Line 11 is 91 MW if the TSO is operating the system according to the expected value. However, there are strategies where the power flow on Line 11 is 50–60 MW which practically have the same cost but are more robust in case of some faults. This highlights the advantage of using dynamic programming where many solutions are explored, while more advanced algorithms might only find the least-cost solution.

5.2. Sensitivity to fault probability and SPS reliability

The impact of fault probability on the operational costs are plotted in Fig. 6, which show the lowest cost strategies for a rolling window of 5 MW for power flow on Line 11. Increasing the probability of fault has little impact on the operational costs when the system state is N-1 safe at power flows less than 60 MW. However, the impact of increasing fault probability on operational costs is much higher when SPSs are needed. As a result, the optimal flow on line 11 is reduced to 50 MW by marginally increasing the fault probability to 2%. The range

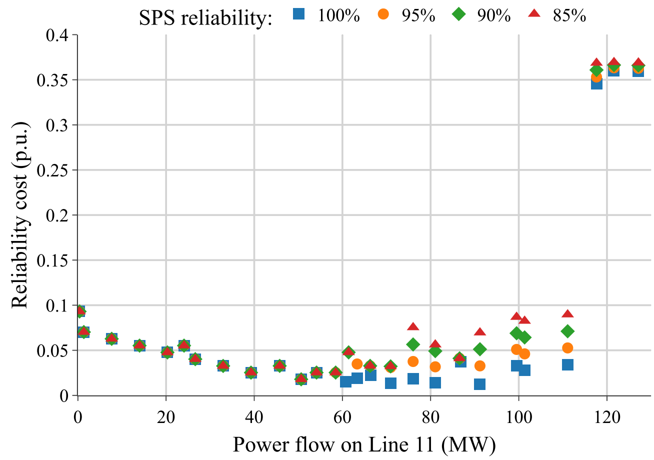

Fig. 7. Sensitivity of costs to different SPS reliability.

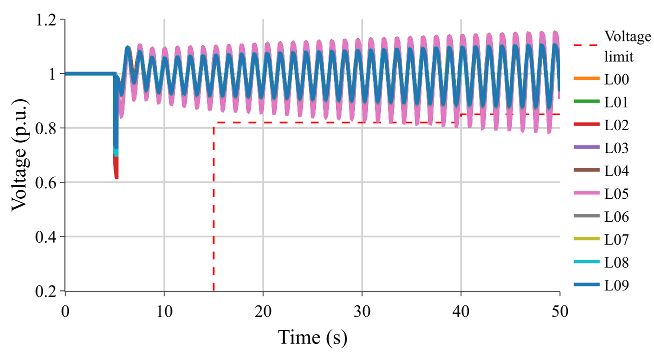

Fig. 8. Voltage at loads after fault on Line 11 for the optimal preventive strategy in the base case.

of strategies with similar costs are also much smaller such that more risk averse operation by deviating from the optimal solution given by the expected value is less desirable.

The operational costs are also calculated for a line outage probability of 1% and SPS reliability from 85%–100% as shown in Fig. 7. The cost of strategies which rely on SPS increase quickly if the reliability is less than 100%. Relying on SPS is not optimal for SPS reliability less than 95%. This shows that SPS must have a high level of reliability to be actively used by the TSO.

5.3. Violation of operational requirements by the dynamic system response

The optimal strategy from Fig. 5 is not purely preventive such as strategies based on the traditional N-1 criterion, but it is a "hybrid" strategy which also rely on corrective actions in the form of SPS. The dynamic system response subject to Line 11 fault results in under-dampened oscillating load voltages as shown in Fig. 8. The lower load voltage limit set by the TSO requirements is violated for load 3, 4 and 5, such that they are assumed to be disconnected. This results in significant operational costs as energy not served to loads are very costly for the TSO. This represents a very important consequence of strategic decisions which would be ignored in most contingency analyses which do not include time-domain simulations.

In case of a fault on Line 11, SPS can disconnect Load 9 to improve the system response. This results in a system response where the load voltages are still oscillating, but within the operating requirements as shown in Fig. 9. A SPS which disconnects Load 9 ensures that all other loads remain connected to the power system in the case of a fault on Line 11. This shows that the value of including SPSs would not be

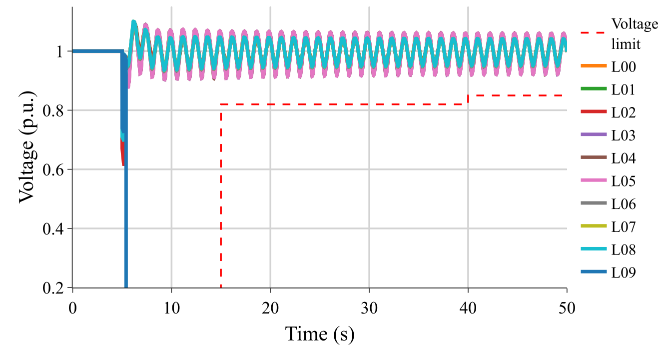

Fig. 9. Voltage at loads after fault on Line 11 and tripping of Load 9 for the optimal preventive strategy in the base case.

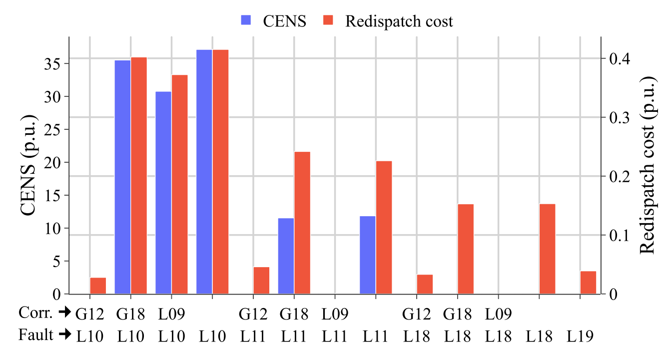

Fig. 10. CENS and re-dispatch cost from the combination of line faults and corrective actions for the optimal preventive strategy in the base case.

correctly calculated by a static load-flow based contingency analysis.

The CENS and re-dispatch costs due to faults on the inter-area transmission lines are shown in Fig. 10. CENS and re-dispatch is plotted on two different y-axes, where CENS is significantly larger than the re-dispatch costs. In addition to using the SPS at Load 9 for faults on Line 11, disconnecting Generator 12 is an effective corrective action to avoid CENS in case of faults on Line 10. Line 11 would be overloaded in the case of fault on Line 18, but disconnecting Line 11 would not result in CENS such that no SPS is used. A static contingency analysis would be able to capture the costs related to faults on Line 10 and Line 18 as these are related to line over-loading, but not the costs related to faults on Line 11.

5.4. Computation

The time for executing the model from Fig. 3 for the case study was 1 h 49 min on a Intel Core i7-8650U CPU with 1.90 GHz and 4 cores (8 logical processors). This illustrates the relatively high computation times and limited scalability which is inherent to dynamic programming approaches as it is based on discretization of the state space.

A histogram of the number of simulations and time used for time-domain simulations and OPFs are shown in Fig. 11. The time-domain simulations use between 0.6–1.6 s which is significantly longer compared to the OPFs which typically solves in less than 0.2 s. This further increases the computation time compared to static approaches. Of the total simulation time, around 43 min are used for solving the OPFs and time-domain simulations, this constitutes 39% of the total simulation time. The remaining time is used for reconfiguration of the case system (adding/removing faults and corrective actions), checking operational requirements and saving results.

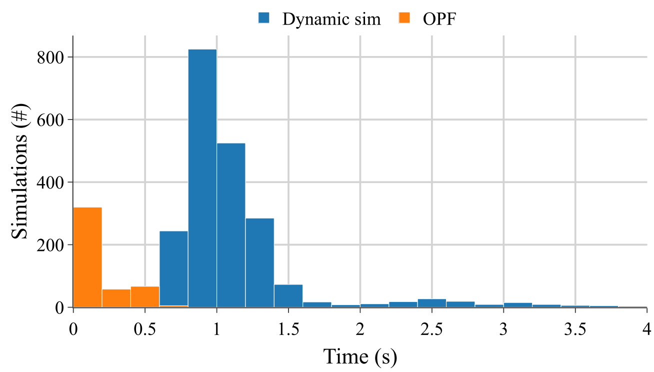

Fig. 11. Histogram showing the number of simulation at different computational times for time-domain simulations and OPF.

The time-domain simulations are also significantly more numerous than the OPFs. For each OPF there is at least one time-domain per fault. If corrective actions have to be taken, the number of time-domain simulations will grow further by the number of corrective actions considered. Load and generation situations that lead to high export between regions typically result in more cases where the operational requirements are not satisfied after a line outage. This implies that the simulation time for the model is very dependent on the level of inter-area flows relative to the transmission capacities as it leads to a higher number of the computationally demanding time-domain simulations.

6. Conclusions

We developed an algorithm for simulating power system operation with preventive and corrective actions. The algorithm includes time-domain simulations for the system response after a contingency. Dynamic simulations enable the contingency analysis to detect situations which are ignored in traditional contingency analysis models based on load flow or OPF.

The model is applied to a case study with a simplified grid representation of parts of the Nordic power system. Results from the case study shows that the model is able to quantify the costs related to preventive and corrective operational measures, such as the costs of congestion, frequency containment reserve activation, system protection schemes, re-dispatch and energy-not-served. The model gives insight into the costs for a wide range of solutions and not only the optimal value. This enables the system operator to use their experience and knowledge about the system when evaluating the best operational strategy. In practice, this is important as it enables the system operator to choose more conservative strategies with higher safety margins when it has little impact on the costs (flat optimal region). The model also shows that the most important costs for the investigated test system are congestion costs and CENS.

The model captures the consequences of the dynamic response on the power system reliability, for example in the case of oscillating load and generator voltages or system frequency. SPSs can mitigate these issues for some of the combinations of preventive strategies and contingencies thus reducing the operational costs. This is shown to be dependent on high reliability of system protection schemes.

The time-domain simulations are numerous and time consuming, especially when simulating constrained load flow situations. In addition, dynamic programming has inherent challenges with computational tractability. In further research, we will investigate options for tackling these challenges. Running the algorithm in parallel on multi-core computers or clusters is expected to be useful for decreasing the simulation times such that more load situations and larger systems can be simulated.

CRediT authorship contribution statement

Espen Flo Bødal: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Writing – review & editing. **Sigurd Hofsmo Jakobsen:** Conceptualization, Methodology, Software, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Oddbjørn Gjerde:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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