Robustness analysis for reinforcement actions in distribution grids

Ilmari Saarinen

School of Science

Bachelor's thesis
Espoo January 10, 2024

Supervisor

Prof. Ahti Salo

Advisor

M.Sc. (Tech.) Joaquín de la Barra

Aalto University
School of Science

Aalto University
School of Science

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of the bachelor's thesis

Author Ilmari Saarinen	
Title Robustness analysis for reinforcement actions in distribution grids	
Degree programme Bachelor's Programme in Science and Technology	
Major Mathematics and Systems Sciences	**Code of major** SCI3029
Teacher in charge Prof. Ahti Salo	
Advisor M.Sc. (Tech.) Joaquín de la Barra	
Date January 10, 2024 **Number of pages** 22	**Language** English

Abstract

Electricity distribution networks are a crucial part of critical infrastructure. Thus, making them as reliable as possible is a priority for the distribution system operator (DSO). External hazards, such as weather conditions and cyber-attacks, threaten the reliability of distribution grids. The DSO can protect the distribution system against these hazards by selecting combinations of reinforcement actions.

The portfolio of reinforcement actions, which maximizes system reliability on a certain budget level, can be constructed by portfolio decision analysis (PDA) techniques. Finding optimal portfolios of reinforcement actions requires precise estimation of reinforcement actions' effectiveness and hazards' severity. Accurate estimation is not always possible, e.g. due to a lack of information about certain hazards. Performing robustness and sensitivity analysis helps understand how the reinforcement actions' and hazards' uncertain parameters affect the reliability of distribution grids.

In this thesis, the stability of the optimal portfolio of reinforcement actions is examined by changing how much reinforcement actions improve the distribution system's reliability and how much hazards decrease it. By the stability of the portfolio, we mean how the optimal actions change due to these modifications in the effectiveness of actions or severity of hazards. Robust actions, which are used in most reinforcement strategies, are identified. Studying the robustness of the selection process helps the DSO to exclude redundant actions from the set of possible actions, which makes the problem of choosing an optimal portfolio more efficient.

The sensitivity of the reliability is studied by making a first-stage decision to apply reinforcement actions following changes in the effectiveness of actions or hazards. The reliability of the system with original actions and hazards is then compared to its reliability with the changed actions or hazards. Hazard and action parameters, which affect the reliability most, can be identified. This can help the DSO to determine which parameter accuracy improvements to prioritize.

Keywords Decision analysis, Distribution grids, Sensitivity analysis, Robustness analysis, System reliability

Aalto University
School of Science

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi
Tekniikan kandidaatintyön tiivistelmä

Tekijä Ilmari Saarinen					
Työn nimi Robustness analysis for reinforcement actions in distribution grids					
Koulutusohjelma Bachelor's Programme in Science and Technology					
Pääaine Mathematics and Systems Sciences				**Pääaineen koodi** SCI3029	
Vastuuopettaja Prof. Ahti Salo					
Työn ohjaaja MSc. (Tech) Joaquín de la Barra					
Päivämäärä January 10, 2024		**Sivumäärä** 22		**Kieli** Englanti	

Tiivistelmä

Sähkönsiirtoverkot ovat tärkeä osa kriittistä infrastruktuuria. Sähköjärjestelmien operaattorien tavoitteena on maksimoida sähköverkkojen luotettavuus. Ulkopuoliset uhat, kuten sääilmiöt ja kyberhyökkäykset, voivat vaarantaa sähköverkkojen toimintavarmuuden. Sähköjärjestelmän operaattori voi suojata sähköverkkoja näiltä ulkoisilta uhilta valitsemalla erilaisia suojauskeinojen yhdistelmiä. Suojauskeinoja ovat esimerkiksi kunnossapitoryhmä ja maakaapelointi.

Optimaalinen yhdistelmä suojauskeinoja, joka maksimoi sähköjärjestelmän luotettavuuden tietyllä kustannustasolla, voidaan muodostaa käyttämällä portfoliopäätösanalyysiä (engl. Portfolio Decision Analysis, PDA). Suojauskeinojen yhdistelmän muodostaminen vaatii tarkkaa sekä suojauskeinojen tehokkuuden että uhkien haitallisuuden arviointia. Tarkka arviointi ei aina ole mahdollista, koska joistain uhista ei esimerkiksi ole aikaisempaa tietoa. Herkkyysanalyysi auttaa ymmärtämään epävarmojen suojauskeinojen ja uhkien vaikutusta sähköverkkojen luotettavuuteen.

Tässä kandidaatintyössä tutkitaan suojauskeinojen optimaalisen yhdistelmän vakautta muuttamalla suojauskeinojen tehokkuutta ja uhkien haitallisuutta. Suojauskeinoyhdistelmän vakaus tarkoittaa optimaaliseen yhdistelmään sisältyvien suojauskeinojen vaihtumista mainittujen muutosten seurauksena. Tavoitteena on tunnistaa suojauskeinot, joita käytetään suurimmassa osassa suojausstrategioista. Optimaalisen suojauskeinoyhdistelmän vakauden tutkiminen auttaa sähköjärjestelmän operaattoria hylkäämään tarpeettomia suojauskeinoja, mikä tekee optimaalisen yhdistelmän ratkaisemisesta tehokkaampaa.

Tässä opinnäytetyössä tarkastellaan myös sähköjärjestelmän luotettavuuden herkkyyttä. Ensin olemassa olevaan tietoon pohjautuen valittiin suojauskeinojen yhdistelmä, minkä jälkeen joko suojauskeinojen tehokkuus tai uhkien haitallisuus muuttui. Alkuperäisen järjestelmän luotettavuutta verrattiin järjestelmän luotettavuuteen, jossa joko suojauskeinojen tai uhkien vaikutukset ovat muuttuneet. Näin pystyttiin tunnistamaan ne suojauskeinojen ja uhkien parametrit, joiden vaikutus järjestelmän luotettavuuteen on suurin. Tämä auttaa sähköjärjestelmän operaattoria valitsemaan ne parametrit, joiden tarkkuutta on hyödyllisintä parantaa.

Avainsanat Päätösanalyysi, sähköverkot, herkkyysanalyysi, sähköverkkojen luotettavuus

Contents

1 Introduction

Electricity, as a secondary energy source, is more critical than ever. Many companies and countries are eager to achieve carbon neutrality, which requires reducing non-renewable energy sources and increasing electricity use. Because electricity is used in households and critical infrastructure like hospitals, the electrical distribution system must be as reliable as possible.

Rough weather conditions, overloading and possible cyber-attacks, among many others (Mahmoud et al., 2021) can threaten the system's functionality, directly affecting the end consumers. The distribution system operator (DSO) can overcome these external hazards by applying different reinforcement actions to the distribution grids. According to Wirtz (2007), improving the reliability of the distribution network generally results in higher costs for the DSO when reinforcing a reliable grid compared to an unreliable one. Adding new reinforcement actions does not improve reliability significantly when the system is already relatively reliable.

The problem of choosing reinforcement actions to provide as reliable a distribution grid as possible while minimizing the costs has been carried out by de la Barra and Salo (2023). The problem is represented using influence diagrams, and the optimal combination of reinforcement actions can be solved using Portfolio Decision Analysis (PDA) techniques (Salo et al., 2022).

Expert judgments and historical information can be used to determine the impact of different hazards and reinforcement actions on the reliability of the distribution grids. However, these estimates are rarely complete because some hazards have not occurred previously, and predictions and simulations might be inaccurate. For example, it can be difficult to estimate the impact of cyber-attacks that have not occurred before on the system's reliability. In addition, it might be challenging to predict how big a part of the distribution system they impact. Also, it is challenging to determine the effectiveness of reinforcement actions against those hazards. This can cause problems for the DSO as the reinforcement actions are chosen based on uncertain estimates.

This thesis aims to understand how optimal reinforcement actions change when reinforcement actions' effects on the system's reliability or hazards' severity are misestimated. We are also interested in how the system's reliability changes when an optimal portfolio of actions is first chosen following some changes in the effectiveness of reinforcement actions or severity of hazards. Sensitivity analysis on a small distribution system is used to achieve the aim of this thesis. The system consists of two distribution grids, three different possible hazards and five different reinforcement actions available.

Sensitivity analysis is conducted in two different ways. The stability of the optimal portfolio of reinforcement actions is examined under the influence of the changes in the effectiveness of reinforcement actions and hazards. In our context, a portfolio is stable if the actions in the portfolio do not change due to parameter fluctuations. Robust actions are identified, i.e., actions used in most reinforcement strategies. The sensitivity of the reliability is studied by comparing the reliability of the original system to the reliability of the system with the same reinforcement actions but modified effectiveness of actions or severity of hazards.

2 Literature review

There are multiple approaches to solving the problem of protecting distribution grids against external hazards. Dehghanian et al. (2018) present a restoration strategy to keep the distribution grids resilient in the case of facing high impact low probability threats. Movahednia et al. (2022) consider one specific type of hazard proposing a stochastic resource allocation approach against floods. Zhang et al. (2015) use multi-objective approach. They aim to maximize independent power suppliers' cost-benefit ratio while maximizing distribution companies' profits. de la Barra and Salo (2023) utilize a single-objective approach, where reliability is maximized subject to budget constraints. In this thesis, a single-objective approach will be used.

Many different hazards affect the reliability of distribution grids. Mahmoud et al. (2021) divide causes of faults in distribution grids into three categories: external factors, natural factors and improper maintenance. Hazards of those categories are further classified into subcategories. All subcategories combined, there are 14 different groups of threats.

The influence of different external threats on the reliability of distribution grids has been widely studied. Ji et al. (2016) examined the effect of extreme weather conditions. The study pointed out that extreme weather can exacerbate existing vulnerabilities in distribution grids. Dvorkin and Garg (2017) and Ding et al. (2022) review cyber threats on distribution grids and propose potential solutions. Bagheri et al. (2015) and Pan et al. (2019) study the impact of uncertainties in the demand for electricity on the grids' reliability.

After identifying relevant hazards, it is of interest to select suitable reinforcement actions and quantify risk mitigation of the actions. Ahmadi et al. (2019) propose simultaneous reconfiguration and distributed energy resources sizing to improve the functionality and reliability of the distribution grids. Similarly, Azizivahed et al. (2020) present an optimal charging/discharging scheme of batteries and network topology to improve the reliability of the grids. Also, the installation of protective devices has been a popular topic in literature (López et al., 2016); (de la Barra et al., 2021); (Falah et al., 2014). Osman et al. (2015) propose adaptive communication-based protection.

It is also useful to estimate the probabilities and correlations of different hazards. However, this is not always possible because of the lack of information about rare hazards, the lack of time to elicitate experts or the unavailability of suitable experts. The possible combinations of hazards are represented through scenarios. If there are many different hazards, the number of scenarios may become excessively large to perform calculations (Carlsen et al., 2016). de la Barra and Salo (2023) use only three different kinds of hazards to avoid computational complexity. Hazards to be considered are extreme weather conditions, overload and cyber-attacks. All possible combinations of the hazards are captured in 12 different scenarios.

Uncertainty of the model parameters presents a significant challenge for optimizing the reliability of distribution grids. Xiu-Ren Lei et al. (2005) tackle this problem using fuzzy numbers. These fuzzy numbers are similar to confidence intervals, and they represent the uncertain input parameters and evaluate the system's reliability. The probability distribution of the system reliability can be presented, but more demanding calculations are required compared to the regular methods. Another way to take the uncertainty into account is to perform robustness and sensitivity analysis for the model parameters, which is suggested by de la Barra and Salo (2023).

3 Methodology

Expert estimations and existing data are used to determine relevant hazards, reinforcement actions and interdependencies between different hazards and actions. In our case study, these are not determined but taken as input. Then, scenarios are developed. A scenario consists of different hazard types' realizations. In this thesis, scenarios cover all possible combinations of hazards. There are three severity levels of weather conditions and two severity levels of overloading and cyber-attacks, resulting in 12 scenarios. We sample the scenario probabilities. Then, the reliability of the distribution grids in different scenarios is estimated using reliability models. Reliability models aim to capture the effect of the hazards and reinforcement actions as accurately as possible. Afterwards, the optimal portfolio of reinforcement actions is provided, which maximizes the reliability. These results help the DSO select portfolios of reinforcement actions that optimally contribute to achieving reliability objectives while staying within a certain budget limit. (de la Barra and Salo, 2023)

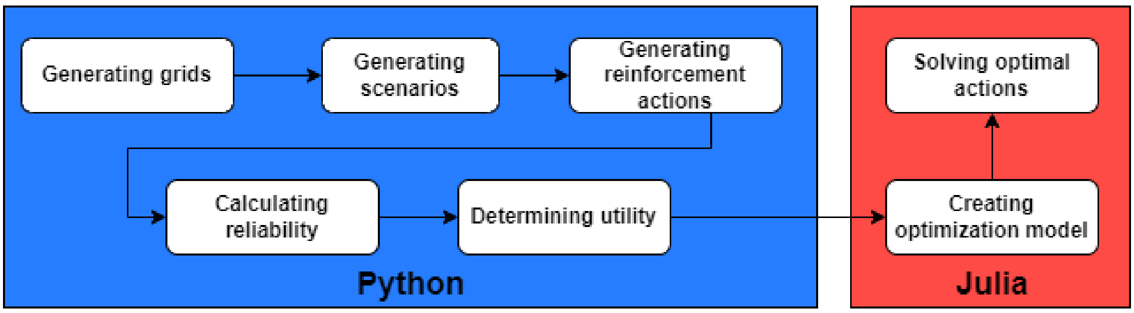

Figure 1: Steps to find a portfolio of optimal actions for distribution grids

Figure 1 is a diagram which illustrates the process of solving an optimal portfolio of reinforcement actions. At first, the distribution grids are generated. Scenarios are then created based on the hazards. After that, reinforcement actions are generated. Based on the reinforcement actions, the grid's reliability is calculated for every possible combination of grids, scenarios and portfolios of reinforcement actions. Utility functions are employed to determine utilities for each of those combinations based on the reliability values. Next, an optimization model is constructed and solved with the Julia package DecisionProgramming.jl by Salo et al. (2022) and Gurobi Optimizer.

3.1 Influence diagram

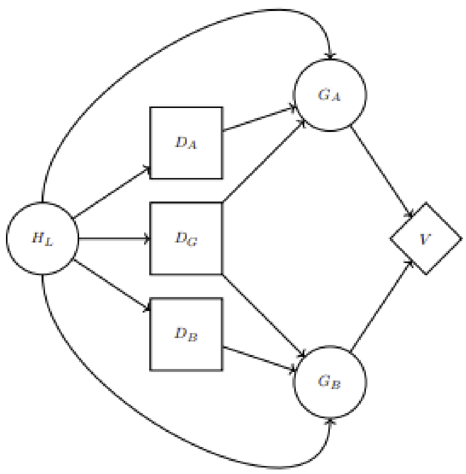

Figure 2: The problem of reinforcing distribution grids is represented using influence diagrams. (de la Barra and Salo, 2023)

The problem of choosing cost-efficient portfolios of reinforcement actions is represented as an influence diagram. Figure 2 is the influence diagram of our case study on two distribution grids. The diagram is a directed acyclic graph containing three different types of nodes. In influence diagrams, circles are chance nodes, C, which indicate random events. Squares are decision nodes, D, where the decision maker needs to make decisions. Each change and decision node $j \in C \cup D$ is associated with a set S_j of possible states. All states are discrete, and there is a finite number of states. Diamond-shaped nodes are value nodes, V. The directed arrows on the graph demonstrate the dependencies between nodes. The state of each change and decision node j is dependent on the information states $s_{I(j)} \in S_{I(j)}$ of the node, where the information state means the states of the direct predecessors of node j. The set of all information states $S_{I(j)}$ contains the possible combinations of states of the nodes in the information set $I(j)$ of node j. (Salo et al., 2022)

In our model, the node H_L represents the possible realizations of the hazards. Decision nodes D_A and D_B represent the decision to apply reinforcement actions locally in grids A and B, respectively. Global reinforcement action is decided at node D_G. Choosing the reinforcement action depends on the possible realizations of the hazards in H_L. The reliabilities of grids A and B are determined in G_A and G_B, respectively. The states of nodes G_A and G_B depend on the realization of hazards and chosen reinforcement actions. A utility function maps the reliability states in nodes G_A and G_B into a single value in the interval [0,1]. In the value node V, one of these values is attained: 0.0, 0.25, 0.5, 0.75 or 1.0, where the most reliable system has a value of 1.0. The value in node V is the mean of the reliabilities of grids A and B, which are 0.0, 0.5 or 1.0.

3.2 Reliability

Reliability indices are used to quantify the reliability of distribution grids (IEEE-Std-1366, 2012). There are multiple reliability indices, but in this thesis, only SAIDI is considered to prevent the problem from becoming too broad. SAIDI is an abbreviation for the System Average Interruption Duration Index. SAIDI $= \frac{\sum D_i N_i}{N}$, where N_i is the number of customers exposed to power outage i of duration D_i in hours. N is the total number of customers, and the sum includes all power cuts within a year. SAIDI is a continuous index discretized into reliability states.

Reliability models use reliability parameters to compute the reliability indices. We consider two reliability parameters that characterize the fault events of every line in a distribution grid. The expected failure rate λ of a line indicates the number of failures per year, and expected restoration time τ indicates the average time in hours per failure required to repair the line. (de la Barra and Salo, 2023)

3.3 Hazards and reinforcement actions

Different types of hazards, denoted by h, affect the reliability of the grids differently. This thesis has three types of hazards: extreme weather conditions, cyber-attacks and overloading. H denotes the set of all types of hazards. Hazards can affect the expected failure rate, the expected restoration time of the lines, or both. Depending on the type of hazard, they can affect only some or all of the lines in the grid. For example, the factors associated with the base state of weather conditions are (1.0, 1.0, all). This implies that all the lines in the grid would be affected. However, the λ and τ factors are equal to one, which means that they would not affect the reliability of the lines. Weather2 state of weather conditions has factors (1.4, 1.4, all), which indicates that it affects both the failure rate and restoration time of the target lines.

The total failure rate of a line is $\lambda = \sum_{h \in H} \lambda_h$, where λ_h is the failure rate of the line associated with a hazard of type $h \in H$. The expected restoration time of a line is not dependent on the type of hazard but rather on the specific hazards affecting it. The total restoration time of a line is calculated by multiplying the line's failure rate with the restoration time.

Depending on their type, reinforcement actions can modify either the failure parameters λ or τ or protective devices of the target lines. They affect either some or all lines in the grid. Depending on the type of reinforcement action, specific λ_h of the target line associated with the target hazard $h \in H$ is decreased. (de la Barra and Salo, 2023)

3.4 Evaluating robustness of the selection process

Figure 3 presents the steps to evaluate the robustness of the selection process. Due to small fluctuations in model parameters, the optimal actions may change. Thus, it is useful to determine the robust actions that are in every or almost every non-dominant portfolio of actions. The more robust the selection process, the less the optimal portfolio of actions changes due to changes in model parameters.

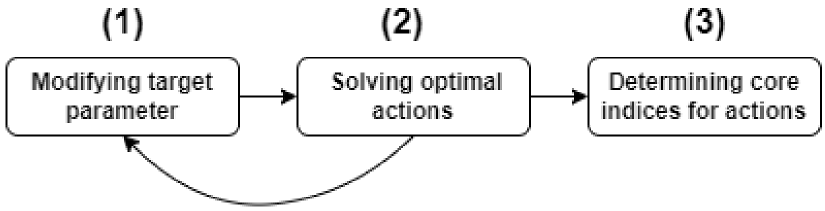

Figure 3: Steps to evaluate the robustness of the selection process

In step 1, either the reinforcement action's effectiveness or the hazard's severity is modified. Depending on the target hazard or action, either the factor λ, which affects the failure rate, or the factor τ, which affects the reparation time of the target lines, can be modified. The original grids, scenarios and scenario probabilities remain unaltered to guarantee the comparability of the results. In step 2, the optimal actions are solved for the changed parameters of step 1.

Steps 1 and 2 are repeated until all the desired parameter modifications are done and the corresponding optimal actions are solved. In step 3, the robustness of each action is determined using a core index. A core index of action is the proportion of non-dominated portfolios, which include the specific action (Liesiö et al., 2007). A portfolio is non-dominated if no other portfolio improves the reliability of the system more. Core indices are calculated separately for each budget.

3.5 Evaluating sensitivity of the reliability

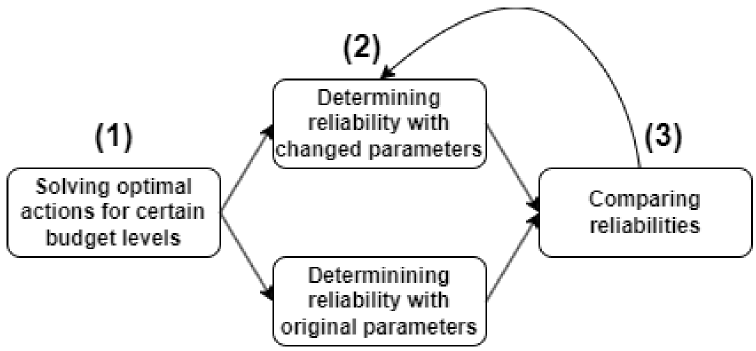

Figure 4: Steps to evaluate the sensitivity of the reliability

Figure 4 presents the steps to evaluate the sensitivity of the reliability. The benefit of performing the reliability sensitivity analysis is that the parameters that affect the reliability most can be identified. The optimal portfolio of actions is solved for certain budget levels in step 1. In step 2, the system's reliability is determined with the original model parameters and with either changes in the factors of actions or hazards. In step 3, the reliability with original parameters is compared to that with changed parameters. Steps 2 and 3 can be repeated in order to evaluate the effect of different parameter changes on the reliability. Cumulative distribution functions of the SAIDIs are used to compare system reliabilities in step 3.

3.6 Formulation of the optimization problem

The formulation of this optimization problem is based on the MILP (mixed-integer linear programming) formulation by Salo et al. (2022). This formulation was applied to the problem of selecting an optimal portfolio of reinforcement actions by de la Barra and Salo (2023). We define a path $s = (s_1, s_2, ..., s_n)$ as a sequence of states $s_i \in S_i$ of all chance and decision nodes in an influence diagram. $p(s)$ is the probability of a path s. $\pi(s)$ represents the probability of scenario path s, and compared to $p(s)$, it ensures that the path s is compatible with the global decision strategy Z.

$U^g(s)$ is the utility of path s in grid $g \in G$, where G is the set of all grids in the system. Generally, $U^g(s)$ can be composed by taking a weighted sum of utilities calculated using different reliability indices. However, in this thesis, $U^g(s) = U^g_{SAIDI}(s)$ because SAIDI is the only reliability index we are using. The overall utility of the system is $U(s) = \sum_{g\in G} w_g U^g(s)$. In this case study, the two grids are equally weighted. A binary variable $z(s_j \mid s_{I(j)}) \in \{0, 1\}$ equals one if decision s_j is made based on the information set $s_{I(j)}$ at decision node j. Otherwise, it equals zero. The formulation can now be presented as follows

$$\max_{z\in Z} \sum_{s\in S} \pi(s)U(s) \tag{1}$$

$$s.t. \sum_{s_j\in S_j} z(s_j \mid s_{I(j)}) = 1,\ \forall j \in D, s_{I(j)} \in S_{I(j)} \tag{2}$$

$$0 \leq \pi(s) \leq p(s),\ \forall s \in S \tag{3}$$

$$\pi(s) \geq p(s) + \sum_{j\in D} z(s_j \mid s_{I(j)}) - |D|,\ \forall s \in S \tag{4}$$

$$\pi(s) \leq z(s_j \mid s_{I(j)}),\ \forall s \in S, j \in D \tag{5}$$

$$z(s_j \mid s_{I(j)}) \in \{0, 1\},\ \forall j \in D, s_j \in S_j, s_{I(j)} \in S_{I(j)} \tag{6}$$

$$\sum_{j\in D} \sum_{s_j\in S_j} z(s_j \mid s_{I(j)})c_{sj} \leq \hat{\mathbf{B}} \tag{7}$$

Equation (1) is the objective function. The optimal strategy $z \in Z$ maximizes the expected utility. Equation (2) ensures that for each decision node, one decision is made. Equations (3) and (4) define boundaries for path probability. Equation (5) assures that the path probability of a path is zero if the path is incompatible with the decision strategy. Equation (7) ensures that the sum of the chosen reinforcement actions s_j is at most the budget limit $\hat{\mathbf{B}}$.

4 Case study

We illustrate the robustness and the sensitivity analysis with a case in which the DSO seeks to find robust actions to protect the distribution system and identify the parameters that affect reliability the most. The distribution system consists of two distribution grids. Hazards in this thesis are weather conditions, cyber-attacks and overloading. Reinforcement actions are spare transformer, maintenance crew, protective devices, underground line and communication system update. We also provide details of the iterations made in the robustness analysis and analyze results. Possible parameter modifications of the reliability sensitivity analysis are proposed, and the results of two of those cases are discussed.

4.1 Hazards and reinforcement actions

Table 1: Characteristics of the hazards.

Hazard	Type	Factors
Weather1	Weather conditions	1.0, 1.0, all
Weather2	Weather conditions	1.4, 1.4, all
Weather5	Weather conditions	3.0, 2.0, all
CA1	Cyber-attack	2.0, 1.0, 0
CA5	Cyber-attack	3.0, 1.0, 4
OL1	Overload	1.5, 1.0, 0
OL5	Overload	2.0, 1.0, 4

Hazards used in our case study are in Table 1. Each hazard type has different severity levels, e.g., weather conditions have three levels. Hazards are characterized by factors which indicate the severity of the hazard. From left to right, as in Table 1, factors are λ factor, τ factor and number of affected lines. The λ factor multiplies the failure rate, and the τ factor multiplies the restoration time of the affected lines. For example, the hazard OL5 increases the failure rates of four lines by a factor of two. The higher the reliability parameters of the line are, the less reliable the line is. Weather conditions affect all of the lines in the grid, while cyber-attacks and overloading affect only some of them. Weather1, CA1 and OL1 are the base states, which do not affect any reliability parameters of the lines.

Table 2: Characteristics of the global actions: Spare transformer (ST) and Maintenance crew (MC).

Action	Target Hazard	Factors	Cost
ST0	Weather, Overload	1.0, 1.0, 0	0
STA	Weather, Overload	0.5, 1.0, 1	200
MC0	All	1.0, 1.0, all	0
MCA	All	1.0, 0.8, all	200

Tables 2 and 3 contain lists of global and local actions used in this case study. For each reinforcement action, the type of the action, its target hazard, factors and cost are specified. Reinforcement actions are characterized similarly by factors as hazards are. The factors of the reinforcement actions are smaller or equal to one. The actions decrease their target lines' failure rate and/or restoration time. For example, the maintenance crew (MCA) does not affect the failure rate but decreases

Table 3: Characteristics of the local actions: Protective devices (PROT), Underground line (UL) and Communication system update (CS).

Action	Target Hazard	Factors	Cost
PROT0	All	-, -, 0	0
PROTA	All	-, -, 3	20
PROTB	All	-, -, all	120
UL0	Weather	1.0, 1.0, 0	0
ULA	Weather	0.0, 1.0, 1	50
ULB	Weather	0.0, 1.0, 2	100
CS0	Cyber-Attacks	1.0, 1.0, 0	0
CSA	Cyber-Attacks	0.5, 1.0, 1	30
CSB	Cyber-Attacks	0.5, 1.0, 5	150

the restoration time of all lines in all distribution grids. Protective devices have no factors associated because they do not directly affect the lines' failure rate or restoration time. Reinforcement actions affect the failure rates associated with one or more specific hazards, e.g., the underground line only protects against extreme weather conditions.

Labels 0, A and B represent different levels of investment. More expensive actions provide more effective protection. Reinforcement actions with label 0 represent the base state that does not affect the system's reliability. A portfolio of reinforcement actions consists of one global action of each type and one local action of each type for both of the grids. The overall cost of the portfolio is the sum of the individual actions. The overall cost cannot exceed the budget limit of the DSO.

4.2 Robustness of the selection process

Tables 1, 2, and 3 contain parameters for the original actions and hazards. To perform robustness analysis, we modify the original factors of each action and hazard type separately. After every modification, the model is solved to determine the optimal actions based on the changes in factors, as in Figure 3.

Table 4: Part 1 modifications

Action/hazard	target parameter	iterations	factors
ST	λ	20	0.1,0.2,...,2.0
MC	τ	20	0.1,0.2,...,2.0
CS	λ	20	0.1,0.2,...,2.0
Weather	λ	10	1.1,1.2,...,2.0
OL	λ	10	1.1,1.2,...,2.0
CA	λ	10	1.1,1.2,...,2.0

For each type of action, we perform 20 iterations, and for each type of hazard, we perform 10 iterations. Modifications are shown in Table 4. The original target factor of the target hazard or action is multiplied by the factors in the table. Compared to the base case, weaker and more powerful actions and more powerful hazards are considered.

For example, the maintenance crew only affects the reparation time, so the τ factor is modified, and the λ factor is not. Factors of protective devices are not changed because they do not directly affect τ or λ factors. Also, underground lines' factors are not modified because they directly decrease the failure rate of the target lines to zero with respect to weather conditions. Thus, it is not likely that there would be any fluctuations in the accuracy of the parameters of underground lines. Only changes in λ factors were taken into account for hazards.

4.3 Sensitivity of the reliability

When estimating the sensitivity of the reliability, we make a first-stage decision to apply reinforcement actions based on known information. Then, the model parameters change, and we are interested in how much the system's reliability can change (Figure 4). A range of parameter changes could be studied. Each global and local variable's effectiveness on reliability can be tested by making them either more or less powerful. Similarly, hazards' severity could be modified. Also, different combinations of previously mentioned changes could be applied. For example, all global actions, local actions or all hazards could be modified simultaneously. In Section 4.4.2, we provide two cases: 20% more effective global actions and 20% more severe weather conditions where the latter is more harmful to the DSO.

4.4 Results

4.4.1 Robustness of the selection process

The robustness analysis results of 90 different cases in Table 4 are summarized using core indices of the global and local actions in Figures 5 and 6.

From Figure 5, we conclude that none of the portfolios uses a spare transformer when the budget is below 560 because the core index of ST0 is one. For budgets above 560, STA is used in over 80% of the non-dominated portfolios. The core index of MCA is over 0.1 for budget 290, and the index starts increasing when moving to larger budgets. From budget 470 onwards, the maintenance crew is included in every non-dominated portfolio, making it clear a robust action. The maintenance crew increases the reliability of the system more than the spare transformer even though they are similarly priced, as seen in Table 2.

It can be concluded from Figure 6 that there are no clear core local actions with a core index of one. Especially for budgets 30, 200, 290 and 380, it is not clear which actions might be the most reasonable choice in the sense that they would be in the non-dominated portfolio of actions with high probability. For every budget, the core index of PROT0 is over 0.6. This means that protective devices are not widely used. Also, the more expensive underground line ULB and communication system CSB are preferred over ULA and CSA for budgets over 200.

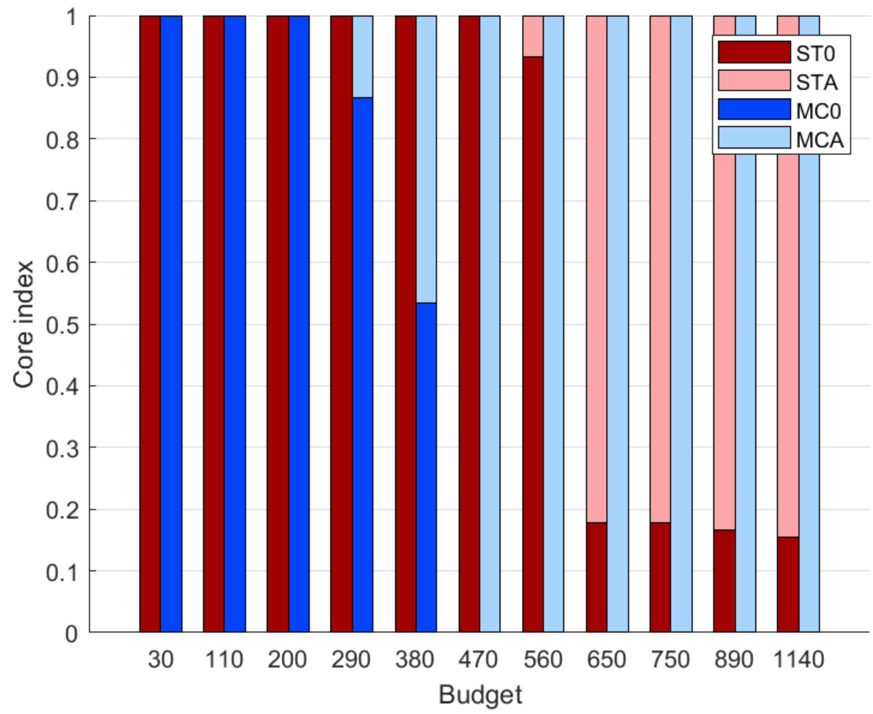

Figure 5: Recommendations for choosing global reinforcement actions.

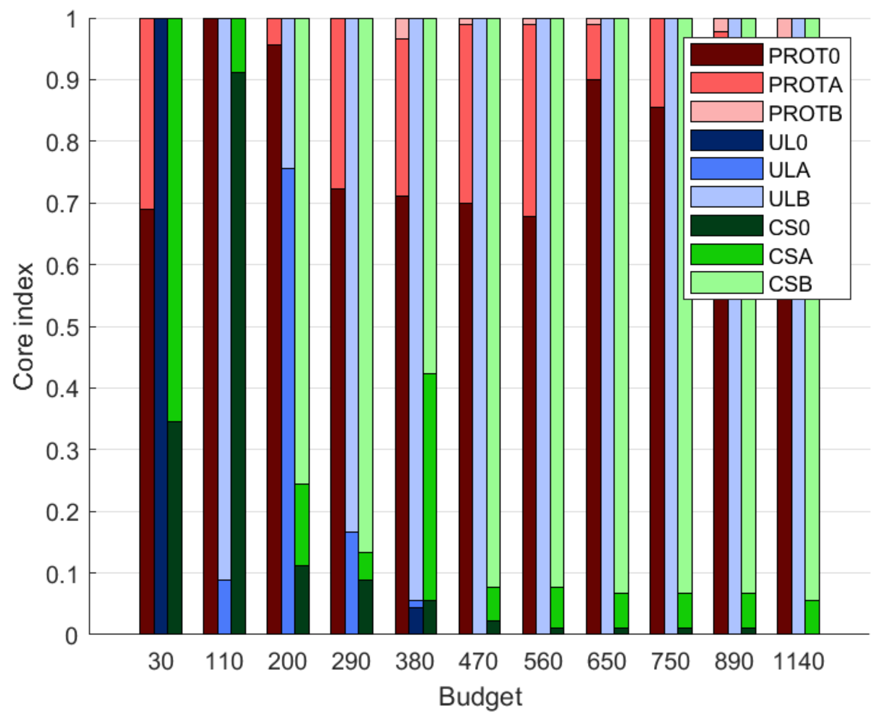

Figure 6: Recommendations for choosing local reinforcement actions.

4.4.2 Sensitivity of the reliability

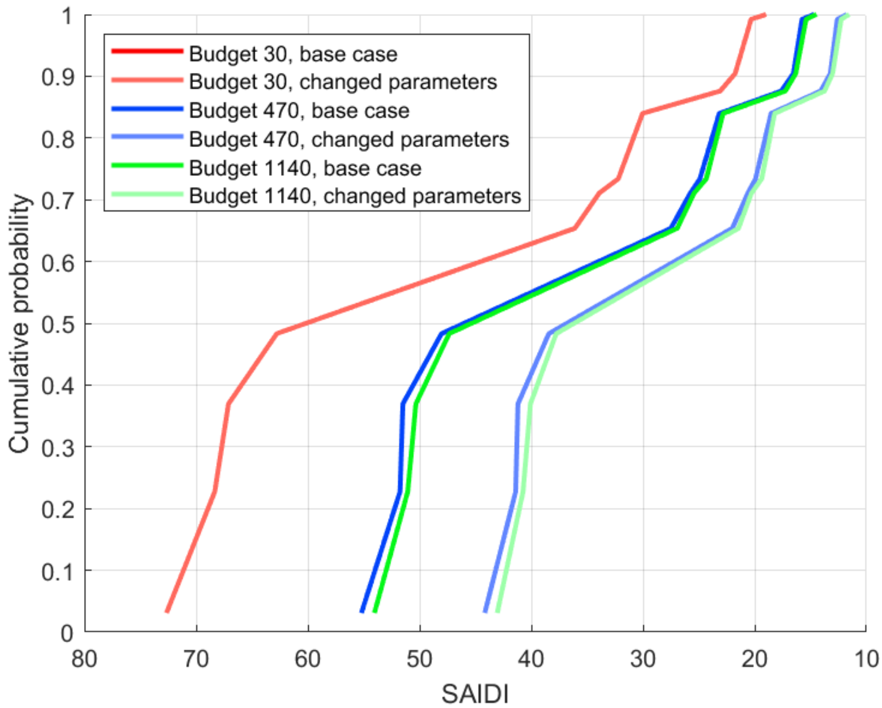

Figure 7: 20% smaller λ-factor of the STA and τ-factor of the MCA

Figure 7 illustrates the change in reliability after a 20% decrease in the STA and MCA factors. The actual shape of the plot depends on the scenario probabilities, which are random in our case study. Thus, we are interested primarily in the horizontal shift of the curves. These more effective global actions result in a significant improvement in the reliability of the grid, which is approximately 20%. With the lowest budget, global actions cannot be utilized. Thus, the change in parameters does not affect that budget.

In Figure 8, weather conditions are 20% more severe. That results in a 5% to 12% change in reliability. The relative change in reliability is almost identical for each budget, which indicates that more expensive actions do not provide better protection against uncertain severity of hazards. However, the larger the budget, the smaller the absolute change in reliability. The most severe scenarios expose the system to a bigger relative change in reliability compared to the more favourable scenarios.

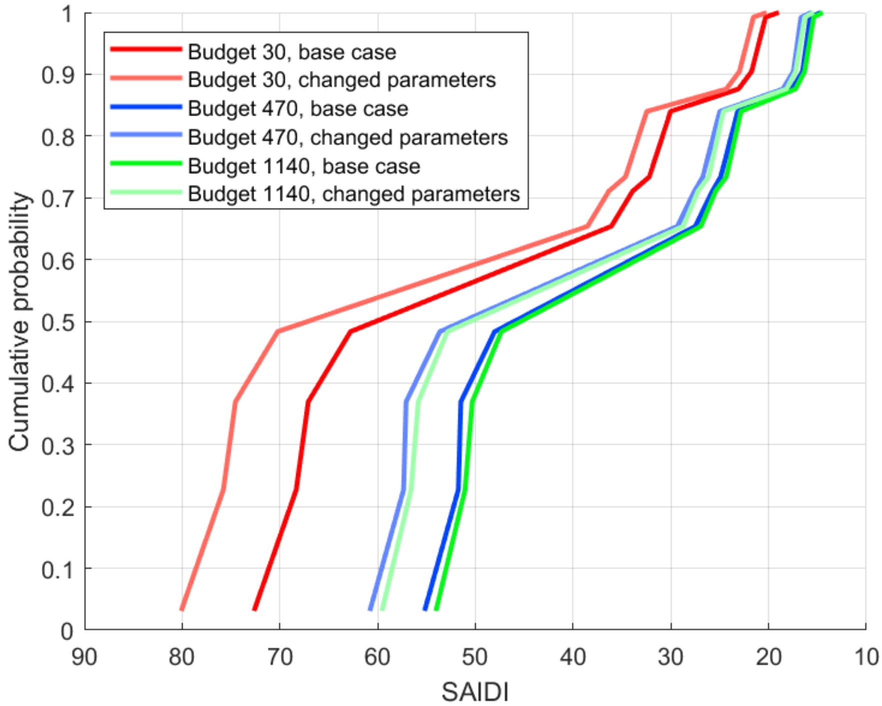

Figure 8: 20% bigger λ-factor of weather conditions

4.5 Discussion

The sensitivity and robustness analyses provide useful information to the DSO in protecting distribution grids against external hazards. There are more possible hazards in the real world, and the number of possible reinforcement actions may be greater than in our case study. Thus, computational efficiency becomes an important factor. Robustness analysis of the selection process can be used to exclude some of the reinforcement actions to limit the model size. For example, Figure 5 indicates that the spare transformer (STA) can be excluded from the possible set of global reinforcement actions for budgets below 560. Similarly, it can be assumed that ULB and CSB will be chosen for budgets over 380 in every portfolio. There is a small probability that other communication system updates or underground lines could be at least as effective. However, this assumption may be reasonable since it would significantly reduce the number of options, making the analysis more efficient. In general, the DSO can be confident that robust actions with a core index of one will be optimal even when the parameters vary. However, this will not always hold because some hazards may be excluded, and the estimation of the scenario probabilities might not be sufficiently accurate.

Some budgets have clear core actions, while others have borderline actions belonging only to some non-dominated portfolios. When the DSO's budget is 470, from the different types of actions, only protections lack a clear core choice that would be included in all non-dominated portfolios. Therefore, choosing actions for that budget should be a straightforward process. When the budget is 380, there are only two core actions, while the optimal investment level of the other three types of actions changes based on the fluctuations in model parameters. That implies certain budgets require more careful consideration than others.

It should be pointed out that the magnitude of the used factors in Table 4 is not carefully considered. For example, it may not be reasonable to assume that the mere existence of the maintenance crew makes the system less reliable. Parameter modifications should reasonably reflect real-world possibilities when performing a robustness analysis of the selection process with real data.

Studying the sensitivity of the reliability helps to identify the parameters that affect the reliability most. If these parameters can be identified, their accuracy could be improved to mitigate the system reliability fluctuations. When conducting the sensitivity analysis of the reliability, it was found that the impact of local actions' parameters on the system's reliability is small. On the contrary, as seen in Figure 7, changes in the parameters of global actions are reflected directly in the system's reliability. Even though it was clear which parameter's accuracy should be improved, it may still be challenging to improve parameter accuracy in practice. Some hazards have not occurred before, and consequently, determining the interaction between those hazards and reinforcement actions might be demanding. In addition, if the confidence intervals for the parameters are known, sensitivity analysis can be used to determine confidence intervals for the system's reliability. This can help the DSO identify worst-case scenarios of the reliability.

The model used in this case study has many limitations. It considers only two distribution grids and the number of hazards and reinforcement actions is small. Figures 7 and 8 indicate that budgets over 470 are redundant because they provide only marginal improvements in the reliability of the grids. Thus, in the future, the sensitivity and robustness analysis can be performed with real data. With real data, scenario probabilities should be carefully determined. Also, other reliability indices could be employed.

5 Conclusions

Distribution grids are an essential part of critical infrastructure. Thus, ensuring their reliability is important. In this thesis, we were interested in the impacts the uncertainties in the model parameters have on the portfolio of optimal reinforcement actions. Also, it sought to find out how the grid's reliability depends on the parameters of the chosen reinforcement actions.

When studying the robustness of the selection process, the parameters for the harmfulness of hazards and effectiveness of actions were modified, and the optimization model was solved to identify the optimal portfolio of reinforcement actions. Then, core indices for the actions were determined. Such analyses help the DSO identify robust actions and abandon exterior actions that are not part of any of the optimal portfolios.

When examining the sensitivity of the reliability, a first-stage decision based on the original information was made. After changes in the model parameters, the model performance was evaluated. Based on this analysis, the DSO can target attempts to improve the accuracy of the model parameters.

References

Seyed-Alireza Ahmadi, Vahid Vahidinasab, Mohammad Sadegh Ghazizadeh, Kamyar Mehran, Damian Giaouris, and Phil Taylor. Co-optimising Distribution Network Adequacy and Security by Simultaneous Utilisation of Network Reconfiguration and Distributed Energy Resources. *IET Generation, Transmission & Distribution*, 13(20):4747–4755, 2019. ISSN 1751-8695. doi: 10.1049/iet-gtd.2019.0824. URL https://onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2019.0824. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1049/iet-gtd.2019.0824.

Ali Azizivahed, Ali Arefi, Sahand Ghavidel, Miadreza Shafie-khah, Li Li, Jiangfeng Zhang, and Joao P. S. Catalao. Energy Management Strategy in Dynamic Distribution Network Reconfiguration Considering Renewable Energy Resources and Storage. *IEEE Transactions on Sustainable Energy*, 11(2):662–673, April 2020. ISSN 1949-3029, 1949-3037. doi: 10.1109/TSTE.2019.2901429. URL https://ieeexplore.ieee.org/document/8651379/.

A. Bagheri, H. Monsef, and H. Lesani. Integrated Distribution Network Expansion Planning Incorporating Distributed Generation Considering Uncertainties, Reliability, and Operational Conditions. *International Journal of Electrical Power & Energy Systems*, 73:56–70, 2015. ISSN 0142-0615. doi: https://doi.org/10.1016/j.ijepes.2015.03.010. URL https://www.sciencedirect.com/science/article/pii/S0142061515001453.

Henrik Carlsen, E. Anders Eriksson, Karl Henrik Dreborg, Bengt Johansson, and Örjan Bodin. Systematic Exploration of Scenario Spaces. *Foresight*, 18(1):59–75, March 2016. ISSN 1463-6689. doi: 10.1108/FS-02-2015-0011. URL https://www.emerald.com/insight/content/doi/10.1108/FS-02-2015-0011/full/html.

Joaquín de la Barra and Ahti Salo. Selecting Combinations of Reinforcement Actions to Improve the Reliability of Distribution Grids in the Face of External Hazards. In *Proceeding of the 33rd European Safety and Reliability Conference*, pages 3320–3327. Research Publishing Services, 2023. ISBN 978-981-18807-1-1. doi: 10.3850/978-981-18-8071-1_P248-cd. URL https://www.rpsonline.com.sg/proceedings/esrel2023/html/P248.html.

Joaquín de la Barra, Alejandro Angulo, and Esteban Gil. A Model for Simultaneous Location and Coordination of Protective Devices in Radial Distribution Networks. *IET Generation, Transmission & Distribution*, 15(19):2734–2746, 2021. ISSN 1751-8695. doi: 10.1049/gtd2.12211. URL https://onlinelibrary.wiley.com/doi/abs/10.1049/gtd2.12211. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1049/gtd2.12211.

Pooria Dehghanian, Semih Aslan, and Payman Dehghanian. Maintaining Electric System Safety Through An Enhanced Network Resilience. *IEEE Transactions on Industry Applications*, 54(5):4927–4937, 2018. doi: 10.1109/TIA.2018.2828389.

Jianguo Ding, Attia Qammar, Zhimin Zhang, Ahmad Karim, and Huansheng Ning. Cyber Threats to Smart Grids: Review, Taxonomy, Potential Solutions, and Future Directions. *Energies*, 15(18):6799, September 2022. ISSN 1996-1073. doi: 10.3390/en15186799. URL https://www.mdpi.com/1996-1073/15/18/6799.

Yury Dvorkin and Siddharth Garg. IoT-enabled Distributed Cyber-attacks on Transmission and Distribution Grids, June 2017. URL http://arxiv.org/abs/1706.07485. arXiv:1706.07485 [cs].

Maryam Falah, Mohammad Hajivand, Reihaned Karimi, and Mohammad Karimi. Optimal Recloser Placement by Binary Differential Evolutionary Algorithm to Improve Reliability of Distribution System. *International Journal of Information, Security and System Management*, 3(2):332–336, 2014.

IEEE-Std-1366. IEEE Guide for Electric Power Distribution Reliability Indices. *IEEE Std 1366-2012 (Revision of IEEE Std 1366-2003)*, pages 1–43, May 2012. doi: 10.1109/IEEESTD.2012.6209381.

Chuanyi Ji, Yun Wei, Henry Mei, Jorge Calzada, Matthew Carey, Steve Church, Timothy Hayes, Brian Nugent, Gregory Stella, Matthew Wallace, Joe White, and Robert Wilcox. Large-scale Data Analysis of Power Grid Resilience Across Multiple US Service Regions. *Nature Energy*, 1(5):16052, April 2016. ISSN 2058-7546. doi: 10.1038/nenergy.2016.52. URL https://www.nature.com/articles/nenergy201652.

Juuso Liesiö, Pekka Mild, and Ahti Salo. Preference Programming for Robust Portfolio Modeling and Project Selection. *European Journal of Operational Research*, 181(3):1488–1505, 2007. ISSN 0377-2217. doi: https://doi.org/10.1016/j.ejor.2005.12.041. URL https://www.sciencedirect.com/science/article/pii/S0377221706002050.

Juan Camilo López, John Fredy Franco, and Marcos J. Rider. Optimisation-based Switch Allocation to Improve Energy Losses and Service Restoration in Radial Electrical Distribution Systems. *IET Generation, Transmission & Distribution*, 10(11):2792–2801, 2016. ISSN 1751-8695. doi: 10.1049/iet-gtd.2015.1509. URL https://onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2015.1509. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1049/iet-gtd.2015.1509.

Moamin A. Mahmoud, Naziffa Raha Md Nasir, Mathuri Gurunathan, Preveena Raj, and Salama A. Mostafa. The Current State of the Art in Research on Predictive Maintenance in Smart Grid Distribution Network: Fault's Types, Causes, and

Prediction Methods—A Systematic Review. *Energies*, 14(16):5078, August 2021. ISSN 1996-1073. doi: 10.3390/en14165078. URL https://www.mdpi.com/1996-1073/14/16/5078.

Mohadese Movahednia, Amin Kargarian, Celalettin E. Ozdemir, and Scott C. Hagen. Power Grid Resilience Enhancement via Protecting Electrical Substations Against Flood Hazards: A Stochastic Framework. *IEEE Transactions on Industrial Informatics*, 18(3):2132–2143, 2022. doi: 10.1109/TII.2021.3100079.

Ahmed H. Osman, Mohamed S. Hassan, and Mohamad Sulaiman. Communication-based Adaptive Protection for Distribution Systems Penetrated with Distributed Generators. *Electric Power Components and Systems*, 43(5):556–565, March 2015. ISSN 1532-5008, 1532-5016. doi: 10.1080/15325008.2014.992500. URL http://www.tandfonline.com/doi/abs/10.1080/15325008.2014.992500.

Jing Pan, Xiaogang Hou, Bin Xu, and Lingfeng Kou. Weaknesses Identification Using Reliability Tracking in Distribution System with Distribution Generation. In *2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, pages 3407–3412, Chengdu, China, May 2019. IEEE. ISBN 978-1-72813-520-5. doi: 10.1109/ISGT-Asia.2019.8881645. URL https://ieeexplore.ieee.org/document/8881645/.

Ahti Salo, Juho Andelmin, and Fabricio Oliveira. Decision Programming for Mixed-integer Multi-stage Optimization Under Uncertainty. *European Journal of Operational Research*, 299(2):550–565, June 2022. ISSN 0377-2217. doi: 10.1016/j.ejor.2021.12.013. URL https://www.sciencedirect.com/science/article/pii/S0377221721010201.

Frank Wirtz. Influence on Reliability of Supply and its Marginal Costs in Medium-voltage Networks. In *2007 IEEE Lausanne Power Tech*, pages 1623–1628, Lausanne, Switzerland, July 2007. IEEE. ISBN 978-1-4244-2189-3. doi: 10.1109/PCT.2007.4538558. URL http://ieeexplore.ieee.org/document/4538558/.

Xiu-Ren Lei, Zhen Ren, Wen-Ying Huang, and Bi-Yun Chen. Fuzzy Reliability Analysis of Distribution Systems Accounting for Parameters Uncertainty. In *2005 International Conference on Machine Learning and Cybernetics*, pages 4017–4022 Vol. 7, Guangzhou, China, 2005. IEEE. ISBN 978-0-7803-9091-1. doi: 10.1109/ICMLC.2005.1527640. URL http://ieeexplore.ieee.org/document/1527640/.

Limei Zhang, Wei Tang, Yongfu Liu, and Tao Lv. Multiobjective Optimization and Decision-making for DG Planning Considering Benefits Between Distribution Company and DGs Owner. *International Journal of Electrical Power & Energy Systems*, 73:465–474, December 2015. ISSN 01420615. doi: 10.1016/j.ijepes.2015.05.019. URL https://linkinghub.elsevier.com/retrieve/pii/S0142061515002240.