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Selecting combinations of reinforcement actions to improve the reliability of distribution grids in the face of external hazards

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Decisions concerning reinforcing distribution grids are complicated by the interaction of multiple hazards and reinforcement actions. This creates a need for a systemic approach to assessing how the system's reliability depends on these interactions.
In this paper, we develop a systemic framework to support a distribution system operator to reinforce and protect multiple distribution grids. We address the problem of choosing between alternative combinations of reinforcement actions under budget constraints, minimum reliability standards, and different hazards. In the framework, this problem is structured as an influence diagram containing scenarios representing different combinations of hazards. The optimization problem is solved using techniques of Portfolio Decision Analysis (PDA) from a mixed integer linear problem which incorporates risk measures such as conditional value at risk (CVaR) to maximize reliability. We showcase the framework with an illustrative study case in which the operator considers several reinforcement actions to mitigate the risks posed by different hazards in two distribution grids.
The proposed approach is novel in combining the strengths of the PDA with existing reliability models and expert judgments to account for interactions between hazards and reinforcement actions. In particular, it exploits synergies to propose cost-efficient combinations of reinforcement actions.

Keywords: Decision analysis, Influence diagrams, System reliability, Risk management, Distribution grids.

1. Introduction

The electrification of industrial processes, reconversion of heating systems, and the integration of electromobility have made electricity one of the primary energy sources in most countries. While society expects a fully reliable system, this is impossible due to the inherent failure rates of technical components and the possibility of excessive loads due to harsh external conditions. As shown by de la Barra et al. (2021) and Wirtz (2007), the extent to which high-reliability levels are guaranteed directly impacts the system's total cost.

Power interruptions can occur due to failures in generation, transmission, and distribution systems, Billinton and Allan (1984). Interruptions affecting end consumers are primarily due to problems at the distribution level, Ji et al. (2016). This has motivated the development of approaches to reinforce distribution grids so that safety and reliability requirements can be met while keeping the costs as low as possible. The grids' reliability is quantified through global or local reliability indexes. Total costs consist of energy losses, acquisition of new components, and penalties for violating reliability requirements, among others. Single-objective approaches minimise cost, subject to reliability requirements or maximise reliability subject to budget constraints. Shang et al. (2021) and Zhang et al. (2015) propose multi-objective methods to minimise cost and losses while maximising reliability. One of the main challenges is that the problem is not deterministic due to uncertainty associated with potential hazards, fault events, and growth in electricity demand and generation capacity, Lei et al. (2005).

It is crucial to identify relevant hazards and to quantify their impacts when designing and implementing reinforcement actions to mitigate them.

Mahmoud et al. (2021) categorize hazards according to their magnitude, duration, and likelihood, among others. It can be challenging to quantify risks due to the large number of hazard and the complexity of their interactions with the systems, Doguc and Emmanuel Ramirez-Marquez (2012).

Many well-established models have been developed to estimate the reliability performance of the grids in the face of different hazards. For instance, Ji et al. (2016) show that extreme weather exacerbates the existing vulnerabilities of the distribution grids. Atrigna et al. (2021) study the effect of heatwaves on power distribution grid failures and propose a fault prediction system. Dvorkin and Garg (2017) study the reliability impact when several controlled loads of a distribution grid are hacked. Ding et al. (2022) provides a broad review of cyber threats. Bagheri et al. (2015); Fan et al. (2016); Pan et al. (2019) explore the effect of demand uncertainty and renewable generation on the distribution grid's reliability.

Elicitation of expert judgments can help identify potential risks and their impact on critical infrastructures. Such judgements are beneficial when there is a lack of data or when the grids must be prepared against hazards such as intentional attacks that have not occurred in the past. For instance, Interior (2019) contains a wealth of expert judgments on Finland's national risk assessment. Taken together, computational models and elicitations provide complementary sources of relevant information in support of reinforcement decisions.

Once the risks caused by hazards have been characterized, reinforcement actions need to be selected and implemented to prepare distribution grids against them. Depending on their design and characteristics, reinforcement actions can be local, affecting just a portion of the grid, or systemic, in which case they benefit a more significant part of the grid or even different grids. Amjady et al. (2018); Muñoz-Delgado et al. (2018) propose capital-intensive solutions to replace and upgrade infrastructure equipment. Ahmadi et al. (2019); Azizivahed et al. (2020) present operational approaches such as the reconfiguration of the grid. de la Barra et al. (2021); Franco et al. (2016) propose less intensive capital solutions by installing protective devices, which has become a timely topic with the integration of distributed generation, and the availability of more sophisticated communication systems, Osman et al. (2015). Detailed surveys on alternatives to improve the reliability of the grids, the algorithms developed, and the objective of the studies can be found in Ganguly et al. (2013); Kennedy et al. (2016).

Although each grid can be reinforced individually with the above procedures, there are benefits in reinforcing multiple grids simultaneously to select a *portfolio* (combination) of several reinforcement actions using approaches of Portfolio Decision Analysis (PDA), Salo et al. (2011). Selecting reinforcement actions by looking at one hazard at a time will not reveal how combinations of multiple reinforcement actions contribute to mitigating risks posed by several hazards. To achieve this, there is a need for a systemic approach that combines reliability models with expert judgements and provides a comprehensive framework within which the effectiveness of different portfolios of reinforcement actions can be assessed.

The selection of reinforcement actions for multiple distribution grids can be framed as an optimization problem under uncertainty in which the interactions between hazards, distribution grids, and reinforcement actions are capture. This systemic approach to the problem can be represented using influence diagrams which are solved using mixed-integer linear programming. The results are useful in guiding decision-makers in the selection of cost-effective portfolios of reinforcement actions that contribute optimally to the attainment of reliability objectives subject to budget constraints.

In this paper, we develop a framework to support the selection of reinforcement actions on distribution grids by structuring this problem as an influence diagram which is solved with Decision Programming, Salo et al. (2022). The framework accounts for the costs of reinforcement actions and their impacts on the grid's reliability. These impacts are assessed through conditional probabilities for different combinations of hazards and reinforcement actions. The framework identifies those portfolios of non-dominated reinforcement actions that are non-dominated in that they improve the system's reliability most at a given level of total costs. It is illustrated with a case study in which two adjacent distribution grids need to consider several alternative combinations of reinforcement actions to mitigate the risks posed by three kinds of external hazards.

This paper is structured as follows. Section 2 presents the framework and discusses relationships between reliability models and expert judgement elicitations. Section 3 specifies the structure of the reinforcement problem, presents the influence diagram, and the corresponding optimization model. Section 4 presents a study case in which two adjacent distribution grids are to be reinforced. Finally, Section 5 concludes by providing future guidelines.

2. Methodology

In our framework, the information provided by multiple reliability models and expert judgments is integrated to support the quantitative cost-effectiveness assessment of reinforcement actions for distribution grids. This integration captures how interdependencies between different combinations of hazards and reinforcement actions impact the grids' reliability. The Distribution System Operator (DSO) can exploit the results of this assessment to select combinations of cost-effective reinforcement actions that ensure the required reliability of the grids in the face of external hazards.

In the workflow in Figure 1, the risks caused by external hazards are first identified based on historical data, the use of statistical models, and the elicitation of expert judgments. The characterization of hazards is synthesized by formulating scenarios that represent combinations of realizations for these hazards. Probabilities are associated with the scenarios by drawing on all relevant sources of information.

Reliability models are employed to estimate the system's reliability and the impact that hazards and reinforcement actions have on it. These models can be either component-wise or systemic. The first of these consider the reliability of specific grid components, such as distribution transformers Lingfeng et al. (2022), or main feeders. They tend to be accurate regarding the physical representation of the electrical components whose reliability is quantified through failure rates and repair times. Systemic models consider these parameters to assess the reliability of the entire grid de la Barra et al. (2021). A systemic model can integrate the information of several component-wise models in order to provide a better representation of the system.

Expert judgements can be elicited to complement component and system reliability models. They are particularly useful in quantifying events with no history, such as cyber-attacks or extreme weather events due to global warming. Furthermore, they can be employed even when there is no data for reliability models due to lack of measurement systems, for instance.

The parameters of the influence diagram include probabilities of the hazard scenarios and the conditional probabilities, which are employed to measure the grid's reliability for different combinations of hazards and reinforcement actions. The influence diagram is converted into an optimization model to maximize the aggregate reliability of the grids for different budget levels. Specifically, the optimum gives the most reliable combination of reinforcement actions for the chosen budget level.

3. Methodological Approach

3.1. *Influence Diagram*

The influence diagram in Figure 2 represents the problem of reinforcing grids A and B. It is a directed acyclic graph illustrating the probabilistic dependencies between events and decisions. The diagram contains three types of nodes: chance nodes C (circles) indicate random events, such as potential hazards or reliability performance; decision nodes D (squares) indicate possible reinforcement actions; and value node V (diamond) quantifies preferences for the consequences that are associated with different reliability levels. The set of all nodes is $N = C \cup D \cup V$. Dependencies between nodes states are represented by directed arcs $A \subseteq \{(i,j) \mid i,j \in N, i \neq j\}$, an arc (i,j) indicates that the state at node j is conditionally dependent on the state at node i. For details on influence diagrams, see Salo et al. (2022).

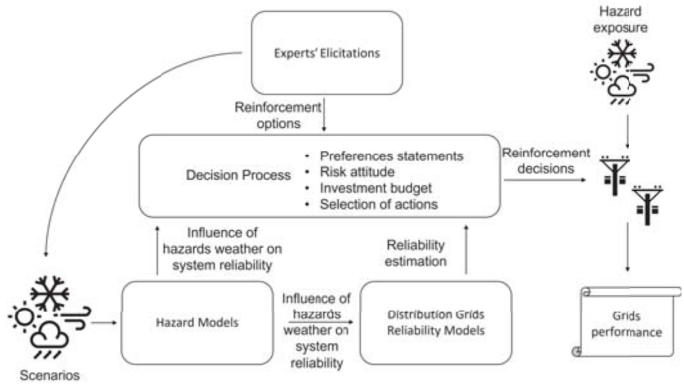

Fig. 1. Framework for selecting portfolios of reinforcement actions to improve the reliability of distribution grids.

In our context, the chance node H_L represents the chance event that depicts the realization of different hazards. Chance nodes G_A and G_B represent the reliability state of grids A and B, respectively. Local reinforcement actions are taken at decision nodes D_A and D_B, while the global reinforcement actions are chosen at decision node D_G. At value node V, there is a utility function defined on the reliability of the distribution grids. Arcs represent the impact that the reinforcement actions and the possible realization of hazards, taken together, have on the grids' reliability.

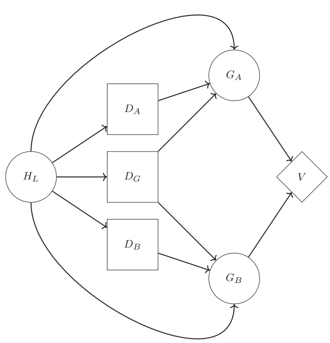

Fig. 2. Influence diagram for assessing reinforcement actions in the presence of external hazards.

3.2. *Optimization model*

Selecting reinforcement actions for distribution grids involves multiple objectives, most notably minimising the reinforcement costs or maximising reliability. We account for both objectives by formulating the problem to maximise reliability subject to constraints representing different budget levels. Budget levels indicate how much money is available to implement reinforcement actions.

When reinforcing multiple grids simultaneously, there may be a need to prioritise some, especially those that supply critical infrastructures such as hospitals, military facilities, or transportation systems. In our formulation, the reliability of each grid can be represented by a single utility function. By multi-attribute utility theory (MAUT), these grid-specific utility functions $\mathcal{U}_g$ of multiple grids $g \in G$ can be combined to an aggregate utility function $\mathcal{U} = \sum_{g \in G} w_g \mathcal{U}_g$ where the weights w_i represent preferences. We use the Decision Programming approach proposed by Salo et al. (2022) to maximise the single utility function subject to the budget constraints.

4. Case study

We showcase the framework with an illustrative case in which the DSO selects between several reinforcement actions to mitigate the risks arising from adverse weather conditions, potential cyber-attacks, and grid overloading that may affect two distribution grids. The aim is to maximise the reliability of the grids for different budget levels.

4.1. *Hazards*

We consider *simultaneously* three hazards: extreme weather, cyber-attacks, and overloading. Each of these has two possible states, representing normal and adverse conditions. We construct eight possible scenarios to capture all possible combinations of hazard states. Scenarios are enumerated so that those with a higher index lead to a more significant reduction of reliability unless reinforcement actions are taken.

The scenarios and their probabilities are in Table 1. Hazards are taken to be independent. This is not a restrictive assumption because these probabilities are input parameters. Thus, one could readily admit correlated hazards (e.g., weather conditions and grid overload could be correlated).

Table 1. Scenario probabilities.

Scenario	WS	CA	OL	P
S_1	✓	✓	✓	0.432
S_2	✓	✓	×	0.108
S_3	✓	×	✓	0.288
S_4	✓	×	×	0.072
S_5	×	✓	✓	0.048
S_6	×	✓	×	0.012
S_7	×	×	✓	0.032
S_8	×	×	×	0.008

Notation: WS: weather state, CA: cyber-attacks, OL: overloading, ✓: normal conditions, and ×: adverse conditions.

4.2. *Reinforcement actions*

Reinforcement actions are in Table 2. The scope of the action refers to the ability to reinforce either one of the grids only (local) or both grids (global). Decisions about local actions are taken at decision nodes D_A and D_B, while global decisions are taken at the decision node D_G. The cost represents the annualized investment expenditure plus the annual maintenance and operation costs. The impacts of reinforcement actions on reliability depend on the hazards contained in the scenarios. For instance, line under-grounding improves the system's reliability, especially during bad weather conditions, compared to scenarios with normal weather conditions.

Table 2. Reinforcement actions.

Action	Scope	Cost (USD)	η_a	r_a
BG	Local	7500	0.6	0.8
CS	Local	7500	0.6	0.8
UL	Local	7500	0.6	0.8
ST	Global	5000	0.3	0.4
MC	Global	5000	0.3	0.4
BAU	-	0	0	0

Notation: BG: Backup generator, CS: Communication system, UL: Underground line, ST: Spare transformer, MC: Maintenance crew, BAU: Business as usual.

4.3. *Reliability of the grids*

Traditionally, the reliability of the power grids is quantified by reliability indexes. For instance, the System Average Interruption Duration Index (SAIDI) quantifies the duration of fault events, while System Average Interruption Frequency Index (SAIFI) quantifies their frequency.

We consider three reliability states R_1, R_2, and R_3, which are synthesized from such reliability indexes so that, for instance, each state can represent a range of SAIDI and SAIFI values. In our setup, R_1 is the most reliable state, and R_3 is the least reliable. The grid's reliability i is R_i with probability p_{R_i}, which depends on the scenario and the reinforcement actions.

Furthermore, each reinforcement action a has an effectiveness factor η_a and a distribution ratio r_a, in Table 2. The first quantifies how much the probability of state R_3 is reduced, while the second quantifies how this reduction is distributed to increment the probabilities of the other two states. The interaction between the scenario s and the global action g is accounted for by scaling the effectiveness factor η_{sg} by a factor θ_{sg}. The effectiveness factor for local action l depends on the global action g and scenario s; thus, it is scaled by θ_{sgl}. Factors θ_{sg} and θ_{sgl} are in Tables 4 and 3. The probabilities of the reliability states after the reinforcement action $p^*_{R_i}$ are given by (1) - (3), these equations are applied twice, first to account for the local actions and then for the global ones. These factors give a simple representation of the impact on reliability, and they can be obtained either by running computational models or eliciting expert judgements. Here, we assigned the same factor to every local and global action.

$$p^*_{R_1} = p_{R_1} + r_a \eta_a p_{R_3} \quad (1)$$
$$p^*_{R_2} = p_{R_2} + (1 - r_a)\eta_a p_{R_3} \quad (2)$$
$$p^*_{R_3} = p_{R_3} - \eta_a p_{R_3} \quad (3)$$

4.4. *Utility functions*

Because the grids need not be equally important, we introduce two utility functions, U_A, and U_B, that account for the reliability of the respective grids A and B. For each grid, the function is normalized so that it has a value of zero for the least reliable level and one for the most reliable one. The utilities of both grids are combined to obtain a single utility function $U_1 = 0.5U_A + 0.5U_B$ which, in the present context, has equal weights for both grids, thereby assuming that these grids are of equal importance. In general, different weights could be employed.

4.5. *Results*

We compute optimal portfolios of reinforcement actions at different budget levels for three choices of objective functions representing the maximization of expected utility; the maximization of expected utility in the 10% and 20% worst case tail of realized reliability, i.e., $CVaR_{0.1}$, and $CVaR_{0.2}$. The reinforcement actions are in Figure 3. Differences in proposed reinforcement actions for different objectives can be attributed to the fact that reinforcement actions have different impacts across scenarios and that global actions affect both grids. For instance, when the budget is 15000, and the objective is to maximize $CVaR_{0.1}$ and $CVaR_{0.2}$, it is optimal to invest in the Spare Transformer (ST), which contributes to the reinforcement of both grids.

The original and improved cumulative utility distributions in Figure 4 illustrate the aggregated reliability impact of optimal reinforcement actions for different objective functions in view of all scenarios at the budget level 15 000. The original case corresponds to the grid status before reinforcement actions. These results help the DSO give

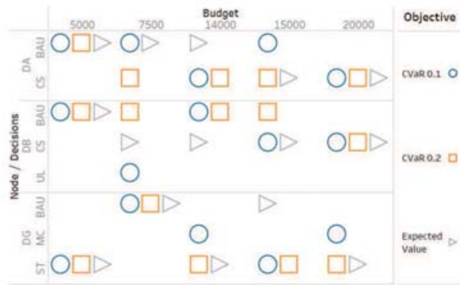

Fig. 3. Local and global reinforcement actions at different budget levels and objective functions.

more attention to the worst cases. For example, the curve for $CVaR_{0.1}$ (blue) lies below that for the Expected Value (red) for low utilities, indicating that the utility is less likely to fall below 0.3 when reinforcement actions are chosen to maximise $CVaR_{0.1}$. Nevertheless, these two curves cross between 0.3 and 0.4. While the expected utility is better for the red curve, neither solution dominates the other in the sense of first-order stochastic dominance.

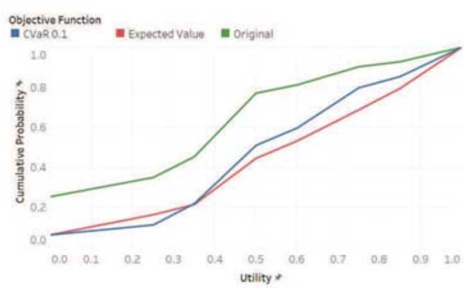

Fig. 4. Cumulative utility distribution for the maximization of $CVaR_{0.1}$ and Expected Value.

5. Conclusion

In this paper, we develop an optimization framework that integrates reliability models and expert judgments to support the process of reinforcing multiple and interdependent distribution grids in the face of multiple hazards. This framework helps identify portfolios of reinforcement actions that are cost-effective in mitigating the risks associated with the hazards. The DSO can use this

Table 3. Correlation factors between global actions, local actions and scenarios.

Global Action	Local Action	S1	S2	S3	S4	S5	S6	S7	S8
ST	BAU	1	1	1	1	1	1	1	1
ST	BG	0.72	0.81	0.92	0.78	0.84	0.95	0.81	0.97
ST	CS	0.75	0.84	0.72	0.86	0.88	0.89	0.91	0.89
ST	UL	0.75	0.77	0.94	0.84	0.88	0.96	0.72	0.84
MC	BAU	0.72	0.7	0.7	0.88	0.94	0.78	0.93	0.81
MC	BG	0.92	1	0.97	0.7	0.83	0.87	1	0.87
MC	CS	0.86	0.83	0.76	0.71	0.82	0.75	0.95	0.73
MC	UL	0.89	0.99	0.97	0.85	0.73	0.79	1	0.74

Table 4. Correlation factor between local actions and scenarios.

Local Action	S1	S2	S3	S4	S5	S6	S7	S8
BAU	1	1	1	1	1	1	1	1
BG	0.7	1	0.7	1	0.7	1	0.7	1
CS	0.7	0.7	1	1	0.7	0.7	1	1
UL	0.7	0.7	0.7	0.7	1	1	1	1

information to protect multiple grids, prioritizing some of them or considering different objectives, such as protecting against the worst case or maximizing the average reliability.

Our illustrative case study showcases the capabilities of the approach in the context of two distribution grids, local and global reinforcement actions with interdependent reliability impacts, and three types of hazards. For simplicity, we present our framework using only three levels of reliability. However, the use of alternative reliability levels can be readily extended to combine standard indexes such as SAIDI or SAIFI.

The proposed framework is viable as problems involving a much larger number of scenarios can be handled computationally, but challenges may be encountered when covering many distribution grids with a broad range of reinforcement actions. Still, there are benefits to considering the selection of reinforcement actions holistically, given (i) all the scenarios representing different combinations in which the hazards may occur and (ii) the local and global impact that portfolios of reinforcement actions have in these scenarios. In many cases, the parameters for such an analysis can be generated through computational reliability models. In other cases, it can be helpful to invite experts to think about the required parameters as this provides information about how well the scenarios or the impacts of reinforcement actions are understood. For future work, there is a potential to extend the model to cover multiple periods explicitly and to use a multi objective formulation rather than considering a single utility function.

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