Intl. Trans. in Op. Res. xx (2021) 1–25

A variable neighborhood search simheuristic algorithm for reliability optimization of smart grids under uncertainty

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Received DD MMMM YYYY; received in revised form DD MMMM YYYY; accepted DD MMMM YYYY

Abstract

A fundamental part of the self-healing grid is reducing disturbances and automatically responding to problems. Towards this goal, smart grid operators would be of great use to ensure stability after a potential overload for a planning horizon, as the electrical values are unknown. To evaluate the robustness of the topology reconfiguration after a disturbance, like an overload, reliability analysis through simulation can be employed. However, the simulation approach we propose in this paper, except for the excessive time it consumes, cannot assure the quality of its solutions. To achieve a more robust configuration, we, additionally, propose a single-stage stochastic program to optimize the grid topology configuration after a potential overload to ensure stability for the next day. We suggest a simheuristic approach based on a Variable Neighborhood Search metaheuristic to solve the above stochastic optimization problem. We evaluate the two approaches for this real-world problem, together with Creos Luxembourg S.A., the leading grid operator in Luxembourg. We show that our method can quickly suggest countermeasures to operators facing potential overloading incidents, ensuring the smart grid's stability for the next day.

Keywords: Simheuristic; Variable Neighborhood Search; Stochastic Optimization; Simulation

1. Introduction

The increased complexity of the energy grids motivates the idea of a smarter grid. There is a way that they can deal with the growing demand for energy and providing innovative services (Antoniadis et al., 2020).

One of the most critical issues in power grids is overloading cables as they can harm distribution power lines. By using fuse switches, an overload trips the fuse, causing the circuit to open, and, consequently,

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stopping flow and heating. Grid operators usually assume that the load rate above a predefined level on a cable entails a significant chance of overload. Long-term overloads, however, can also damage cables even within the security limits and may cause energy grids to malfunction (Zhang et al., 2013).

Specific counteractions can then be applied to reduce cable loads, preventing overload, including the curtailment of over-production or over-usage by individual users.

Some consumers, however, have contracts that prohibit the operator from controlling its power capacity. In these cases, therefore, a restriction is not a choice. More generally, when such constraints do not effectuate a stable state, i.e., without the possibility of a surge, operators need to reconfigure the grid topology by swapping fuses to transfer reserves between networks even when the intertrip for the meshed low voltage network is complicated.

Technicians, if remotely switching is not possible, have to physically visit the correct cabinets if the fuse states are to be changed. The minimization of the number of visitor booths is, therefore, an area of considerable concern for the grid operator, which minimizes the recovery time of a possible incident.

It is a matter of significant interest for grid operators to avoid disconnecting users, especially important ones, such as hospitals. However, if there is an inadequate operating reserve, this will happen to prevent cascading overloads to avoid harm to the line as a last resort. In this case, there will still remain a small number of disconnected users.

The above countermeasures, including user curtailments and reconfiguration of the grid's topology, are generally applied in a short time, i.e., less than an hour. Although, even if the above counteractions are applied immediately after the detection of a risky overloading incident, the recovery response solution could lead to another overloading incident, as the future demands are not known beforehand. Moreover, there is ongoing demand from the grid operators for more reliable smart grids towards the "self-healing" grid (Sun et al., 2018), in the sense of automatically respond to problems and minimize disturbances. Therefore, if the recovery response solution could be tested for its efficacy over the next day, the smart grid operators would be of great use to ensure the solution applied is as robust as possible.

1.1. Contribution

This paper presents two methods capable of calculating a smart grid's short-term expected reliability after an overloading event. We first present, correspondingly to the aforementioned IEEE reliability indices, three customer-based, three cable-based, and two load-based reliability indices, estimating overloading incidents. After a potential overload event, the optimal and sub-optimal solutions are calculated, as described in (Antoniadis et al., 2020). For every solution, using Monte Carlo simulation, the eight reliability indices could be estimated. Along with the number of fuses' changes, a Unified Overload Index (UOI) is calculated as a normalized weighted sum of the values. By using different vectors of weights, the decision-maker could investigate different aspects of the reliability assessment.

As the simulation is not an optimization tool (Juan et al., 2015), we propose a single-stage stochastic program to optimize the reconfiguration of the grid topology and to ensure the smart grid could remain stable for the next 24 hours. We propose to solve it through the simheuristics method, which combines simulation with metaheuristics (Ribeiro et al., 2020) to solve stochastic combinatorial optimization problems. For the metaheuristic part, we use Variable Neighborhood Search, in which the intensification of search and the diversification of local optimum solution is based on the systematic change of neighborhoods. Additionally, we apply the control variate reduction technique to the Monte Carlo Simulation (MCS) to reduce the number of simulations.

The remainder of this paper is structured as follows. Section 2 discusses related work, while the Section 3 provides the mathematical model for the stochastic program of this work. Then, in Section 4, we detail the implementation of our proposed solution method, which is evaluated in Section 5. Finally, we conclude in Section 6.

2. Background and related work

This section presents the technical background related to reliability analysis, simulation-based optimization methods and Variable Neighborhood Search (VNS). Along with the background, this section provides an overview of works on related research topics. Special care was taken to exhaustively cover all the published studies until the time of writing.

2.1. Reliability analysis

Generally, the term *reliability* is used to denote the overall ability of a system to perform its intended function (Billinton and Li, 1994; Singh et al., 2018; Brown, 2017; Chowdhury and Koval, 2009). In a quantitative sense, reliability can deal with understanding and decisions making while dealing with complex situations. The term *reliability* is used, in this paper, to denote, quantitatively, the ability of the smart grid to avoid overloading events.

Different models have been proposed to determine the effects of random disturbances, like overloads, on the reliability assessment of a smart grid system. The above models can be grouped into either *analytical methods* or *Monte Carlo simulation* methods (Brown and Hanson, 2001; Singh et al., 2018; Celli et al., 2013).

Analytical methods include (Singh et al., 2018; Todinov, 2007):

- *State space* method using Markov processes, where all possible system states are enumerated; consequently, this approach can be regarded as the most direct approach to calculating reliability indices (Singh et al., 2018).
- *Network reduction* method, where the serial and parallel elements of a system are reduced to a single equivalent element; hence the reliability of the reduced system equals the reliability of the initial system (Todinov, 2007).
- *Conditional probability* method, where the complex, not serial, or parallel, elements of a system are simplified, via the conditional probability concept, to a combination of serial and parallel structures; then the network reduction method can be used to find the reliability of the system (Singh et al., 2018).
- *Cut-set* and *tie-set* method. The minimal cut set contains a set of system components that, when they fail, would cause the failure of the system. On the opposite, the minimal tie set consists of a set of system components that, when successful, would lead to system success. Then, the reliability indices can be calculated by the probabilities of failures or successes (Hongbin Li and Qing Zhao, 2005; Singh et al., 2018).

The above analytical approaches could be used when the problems are relatively easy to be modeled and solved. However, in complex models, Monte Carlo Simulation should be employed to determine the effect of random failures on the reliability of the system, as it is more flexible in dealing with challenging operating conditions and system considerations (Singh et al., 2018). Thus, using simulation, we can estimate the reliability indices by constructing realizations of the stochastic values. Monte Carlo simulation (MCS) can be categorized as non-sequential (Pereira and Balu, 1992), and sequential (Peng Wang and Billinton, 2002). In non-sequential Monte Carlo simulation (NSMCS), the states of the system are randomly sampled, while in sequential MCS (SMCS), the system states are simulated in chronological order, providing statistically more reliable information (Hadjsaïd et al., 2013).

Reliability, as defined above, is concerned with the ability of a power system to avoid overloading incidents. To quantify the expected reliability, indices are used to express the probabilistic measures of the examined system. Some of the most common reliability indices (Falaghi and Haghifam, 2005; Brown, 2017; Chowdhury and Koval, 2009), introduced by IEEE (2012), are the System Average Interruption Frequency Index (SAIFI), the System Average Interruption Duration Index (SAIDI), the Customer Average Interruption Duration Index (CAIDI), the Average System Interruption Frequency Index (ASIFI), and the Average System Interruption Duration Index (ASIDI). Moreover, Weighbull (Wang et al., 2019, 2016) and lognormal (Chiodo et al., 2016; Subban and Awodele, 2013) distributions can be used in reliability analysis, by modelling the failure and restoration processes.

2.2. Simulation-based optimization

Simulation techniques can model complex systems, although they cannot be used by themselves as an optimization tool (Juan et al., 2015). If we combine simulation approaches with optimization techniques, like metaheuristics, the hybrid simulation-optimization can handle the uncertainty in stochastic optimization problems (Figueira and Almada-Lobo, 2014; Amaran et al., 2016). There are many ways to combine simulation with optimization in simulation-optimization approaches; the major categories are (Figueira and Almada-Lobo, 2014):

- *Solution Evaluation* approaches. In these approaches, a representing simulation model of the system is developed, and different solutions are evaluated. Thus, these approaches are focused on the optimization of a simulation model, while the purpose of a simulation is to evaluate the performance of solutions (simulation optimization). The drawback of these approaches is that evaluating various solutions through simulation can be computationally intensive.
- *Solution Generation* approaches. In some problems, the solution could be chosen without the simulation outcome be needed. In such approaches, a representing analytical model of the system is formulated and solved, and different solutions simulated (optimization-based simulation). The purpose of a simulation is to compute all the interesting variables and not to evaluate the solutions. Although these methods can be very effective in the above problems, they may not be effective in other problems.
- *Analytical Model Enhancement* approaches. In these approaches, usually, the analytical model is hybridized with Solution Evaluation approaches. Simulation results could be another enhancement of the analytical model.

Simheuristics (Juan et al., 2015; Chica et al., 2020), as a simulation-optimization approach, combine simulation with metaheuristics to solve stochastic combinatorial optimization problems. Application areas of simheuristics include transportation and logistics (Reyes-Rubiano et al., 2017; Juan et al., 2019, 2018; Gruler et al., 2020; Juan et al., 2014; Raba et al., 2020; Villarinho et al., 2021; Mara et al., 2021), finance (Panadero et al., 2020; Saiz et al., 2021), healthcare (Fikar et al., 2016), waste collection (Gruler et al., 2017b,a), and cloud computing (Mazza et al., 2018). For real-worlds complex stochastic optimization problems, simheuristics should be considered as a "first-resort" method (Chica et al., 2020), as it can handle reality in uncertain problems by simulation modeling, it can assess risk with ease, and a post-run simulation output analysis can be made. In our approach, simulation drives the optimization in a sense that, after adaptive sampling, each candidate solution is evaluated, and the optimization algorithm can drive the search process.

2.3. Variable Neighborhood Search

Variable Neighborhood Search (VNS) (Mladenović and Hansen, 1997; Hansen et al., 2017; Benmansour et al., 2020; Sifaleras et al., 2019; Urrutia-Zambrana et al., 2021; Brimberg et al., 2021) is an efficient and straightforward metaheuristic method for solving various types of optimization problems. The intensification of search and the diversification of local optimum solution is based on the systematic change of neighborhoods. VNS selects a neighbor solution from the current solution and applies a local search to get a local (neighborhood) optimum. This procedure continues for all the neighborhood structures until a better global solution is found. If an improved solution is not found, a perturbation procedure is applied to perform a new search. The use of VNS in a simheuristic has been used in many recent projects (Gruler et al., 2018, 2020; Panadero et al., 2020; Quintero-Araujo et al., 2019).

3. Materials and Methods

The scope of our work is to predict the stability of a smart grid after a potential overload. The outline of the procedure is presented in Figure 1. From the given electrical values that have been read by the smart meters, if a potential overload has occurred, our proposed methods suggest the proper actions that have to be applied by the smart grid technicians. Our goal is to propose a robust solution for the next day under uncertainty, as the future electrical values are unknown. To do so, we propose two methods. The first one extends the work presented in (Antoniadis et al., 2020) by including an MCS step for predicting the electrical values after a potential overload. As the simulation is not an optimization tool, in the second method, we use a single-stage stochastic program to optimize the reconfiguration of the grid topology to ensure the smart grid could remain stable for the next 24 hours by hybridizing simulation with a metaheuristic. To evaluate the quality of the solutions, we propose a Unified Overload Index as described in the following subsection 3.1.

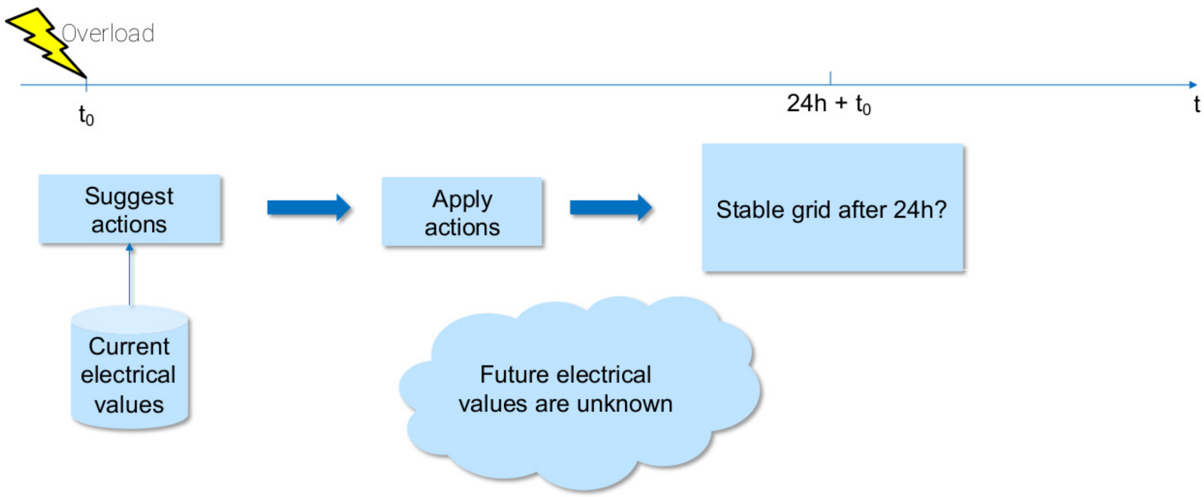

Fig. 1. Check for stability over time.

3.1. Unified Overload Index

In order to estimate the reliability after a potential overloading situation, we propose, in accordance with the state-of-the-art IEEE reliability indices (IEEE, 2012) the following eight indices (Appendix A):

- System Average Overload Frequency Index (SAOFI), like SAIFI (IEEE, 2012). It expresses how often a *customer* experiences a sustained overload over a predefined period of time *(overloads/day)*.

$$SAOFI = \frac{co}{m} \tag{1}$$

$$co = \sum_{i=0}^{n} \sum_{t=0}^{T} fail_{it} cust_i \tag{2}$$

$$fail_{it} = \begin{cases} 1 & (u_{i(t-1)} = 0 \wedge u_{it} = 1 \wedge t > 0) \vee (u_{i0} = 1 \wedge t = 0) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$u_{it} = \begin{cases} 1 & ld_{it} > \lambda \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

- System Average Overload Duration Index (SAODI), like SAIDI (IEEE, 2012). It expresses the total duration of overload for a *customer* during a predefined period of time *(mins/day)*.

$$SAODI = \frac{cmo}{m} \tag{5}$$

- Customer Average Overload Duration Index (CAODI), like CAIDI (IEEE, 2012). It expresses the average time required to restore service on a *customer (mins/day)*.

$$CAODI = \frac{cmo}{co} \tag{6}$$

$$cmo = \sum_{i=0}^{n} \sum_{t=0}^{T} downt_{it} cust_i \tag{7}$$

$$downt_{it} = 15u_{it} \tag{8}$$

- Cable System Average Overload Frequency Index (CBLSAOFI), like SAIFI (IEEE, 2012). It expresses how often a *cable* experiences a sustained overload over a predefined period of time *(overloads/day)*.

$$CBLSAOFI = \frac{cblo}{n} \tag{9}$$

$$cblo = \sum_{i=0}^{n} \sum_{t=0}^{T} fail_{it} \tag{10}$$

- Cable System Average Overload Duration Index (CBLSAODI), like SAODI (IEEE, 2012). It expresses the total duration of overload for a *cable* during a predefined period of time *(mins/day)*.

$$CBLSAODI = \frac{cblmo}{n} \tag{11}$$

$$cblmo = \sum_{i=0}^{n} \sum_{t=0}^{T} downt_{it} \tag{12}$$

- Cable Average Overload Duration Index (CBLAODI), like CAODI (IEEE, 2012). It expresses the average time required to restore service on a *cable (mins/day)*.

$$CBLAODI = \frac{cblmo}{cblo} \tag{13}$$

- Average System Overload Frequency Index (ASOFI), like ASIFI (IEEE, 2012). It is similar to SAOFI but it is based on load *(overloads/day)*.

$$ASOFI = \frac{lo}{lt} \tag{14}$$

$$lo = \sum_{i=0}^{n} \sum_{t=0}^{T} fail_{it} ld_{it} \tag{15}$$

$$lt = \sum_{i=0}^{n} \sum_{t=0}^{T} ld_{it} \tag{16}$$

- Average System Overload Duration Index (ASODI), like ASIDI (IEEE, 2012). It is similar to SAODI but it is based on load *(mins/day)*.

$$ASODI = \frac{lmo}{lt} \tag{17}$$

$$lmo = \sum_{i=0}^{n} \sum_{t=0}^{T} downt_{it} ld_{it} \tag{18}$$

In accordance with our industrial partner Creos Luxembourg S.A., the weighted mean of the above indices is defined as the Unified Overload Index (UOI). UOI can be used as a standard metric for the decision-makers to help them understand the impact of every proposed solution to the grid.

$$\begin{aligned} UOI = {} & w_{SAOFI} \frac{SAOFI}{\frac{T}{2}+1} + w_{SAODI} \frac{SAODI}{15(T+1)} + w_{CAODI} \frac{CAODI}{15(T+1)} \\ & + w_{CBLSAOFI} \frac{CBLSAOFI}{\frac{T}{2}+1} + w_{CBLSAODI} \frac{CBLSAODI}{15(T+1)} + w_{CBLAODI} \frac{CBLAODI}{15(T+1)} \\ & + w_{ASOFI} \frac{ASOFI}{\frac{T}{2}+1} + w_{ASODI} \frac{ASODI}{15(T+1)} \end{aligned} \tag{19}$$

$$\begin{aligned} & w_{SAOFI} + w_{SAODI} + w_{CAODI} + w_{CBLSAOFI} \\ & \qquad + w_{CBLSAODI} + w_{CBLAODI} + w_{ASOFI} + w_{ASODI} = 1 \end{aligned} \tag{20}$$

3.2. Simulation approach

In our first method, after a potential overload, at most five best solutions are picked from the method suggested in (Antoniadis et al., 2020), the proposed actions are applied, and the future electrical values are simulated, from the corresponding historical Gaussian distribution, for the next 24 hours. From the current and the simulated electrical values, the UOI is calculated to denote the quality of each proposed solution.

The Mixed Integer Quadratically Constrained Program (MIQCP) formulation of the overloading prevention problem (Antoniadis et al., 2020), is as follows:

$$\max \sum_{i=1}^{n} r_i \sum_{k=1}^{m} uc_{ki} \tag{21}$$

$$\min \sum_{b=1}^{o} dfcab_b \tag{22}$$

$$\min \sum_{f=1}^{2n} |x_f - x_f^0| \tag{23}$$

subject to:

$$A \cdot wp = P \tag{24}$$

$$A \cdot wq = Q \tag{25}$$

$$l_i < \lambda, \forall i \in \{1, \dots, n\} \tag{26}$$

The first objective (Equation (21)) maximizes the serviced users of the grid by defining the fuses' state, while the second objective (Equation (22)) minimizes the number of visiting cabinets. At the same time, the third objective (Equation (23)) minimizes the number of visiting fuses. Equations (24) and (25) approximate the current loads, while Equation (26) constraint the current load percentage on each cable under the predefined threshold. The notation used is presented in the Appendix A.

3.3. Simheuristic approach

Instead of hoping to find a good solution, after applying the proposed actions, in our second method, using the UOI, we try to find the actions to increase the expected reliability for the next 24 hours. The UOI is calculated as a normalized weighted mean of the aforementioned reliability indices, as presented in Section 3.1. If we denote the random electrical data that is available only after the decision is made with ξ, we need to minimize the random UOI function $UOI(x, \xi)$. Since we cannot directly minimize $UOI(x, \xi)$, we alternatively minimize the expected value, $\mathbb{E}[UOI(x, \xi)]$. The notation used is presented in the Appendix A, while the corresponding single-stage stochastic optimization problem (Shapiro and Philpott, 2007) becomes:

$$\min \mathbb{E}[UOI(x, \xi)] \tag{27}$$

If in equation (20) we set all the weights equal to $\frac{1}{8}$, UOI is the arithmetic mean of the normalized indices:

$$\begin{aligned} UOI^a = \frac{1}{8} \Bigg[& \frac{SAOFI}{\frac{T}{2}+1} + \frac{SAODI}{15(T+1)} + \frac{CAODI}{15(T+1)} + \frac{CBLSAOFI}{\frac{T}{2}+1} + \frac{CBLSAODI}{15(T+1)} \\ & + \frac{CBLAODI}{15(T+1)} + \frac{ASOFI}{\frac{T}{2}+1} + \frac{ASODI}{15(T+1)} \Bigg] \end{aligned} \tag{28}$$

We can also calculate UOI as the geometric mean of the normalized indices as:

$$UOI^g = \left[\frac{SAOFI}{\frac{T}{2}+1} \cdot \frac{SAODI}{15(T+1)} \cdot \frac{CAODI}{15(T+1)} \cdot \frac{CBLSAOFI}{\frac{T}{2}+1} \cdot \frac{CBLSAODI}{15(T+1)} \cdot \frac{CBLAODI}{15(T+1)} \right. \\ \left. \cdot \frac{ASOFI}{\frac{T}{2}+1} \cdot \frac{ASODI}{15(T+1)}\right]^{\frac{1}{8}} \tag{29}$$

We suppose that the random variable ξ, which represents the realizations of the electrical values, has a given Gaussian distribution, i.e., it takes values ξ_1, ..., ξ_K, with respective probabilities p_1, ..., p_K, where the K considered scenarios represent historical data. We assume that the random variables follow a Gaussian probability distribution as it occurs very often in real-world data. Although they are only approximately normal, they are generally quite close. Moreover, the normal distribution maximizes information entropy, i.e., measuring the uncertainty associated with a random variable, among all distributions with known mean and variance. This feature makes it the natural choice for describing the distribution of data summarized in terms of mean and variance. For the case under study, possible sudden variations of the energy consumption or production are filtered if the normal distribution is employed to describe the energy consumption/production trend. Additionally, by describing the energy consumption/production trend by a Gaussian distribution, it is possible to manage a series of sampled data by a continuous function with continuous derivative, defined by two parameters. Our methodology is not dependent on this assumption, as with a slight change, we could assume that the random variables follow another distribution. In the case of finitely many scenarios, it is possible to model the stochastic program as a deterministic optimization problem by writing the expected value $\mathbb{E}[UOI(x, \xi)]$ as the weighted sum:

$$\mathbb{E}[UOI(x, \xi)] = \sum_{k=1}^{K} p_k UOI(x, \xi_k) \tag{30}$$

Our simheuristic approach is aimed to solve the problem (Equation (27)) using the general solving scheme that has been proposed by Juan et al. (2015). We use the following simheuristic algorithm (Algorithms 1 and 2). For the metaheuristic part of the simheuristic, we picked the Reduced VNS (RVNS), a VNS variant. It could quickly reach reasonable quality solutions for large instances, without applying an iterative improvement procedure, as the basic VNS, but it only explores randomly different neighborhoods. The most computationally intensive part of our algorithms is the fitness calculation, in which MCS is used. Therefore, we keep a tabu list to avoid calculating any candidate solution's fitness more than once. In the first step (Algorithm 1), our Sim-RVNS algorithm takes as input the initial state of the fuses when the potential overload has occurred. The number of neighborhoods, and the maximum number of iterations without change of the best solutions, and the maximum number of the elite solutions are also given, initially. After that, the RVNS procedure continues until the stopping criterion, i.e., the maximum number of iterations is reached. In the end, Algorithm 1 returns the list of the elite solutions found after fast simulations.

Algorithm 1 Sim-RVNS for the reliability optimization problem

Step 1: RVNS with fast MCS

Input: initial state
k_{max} : number of neighborhoods
$maxIter$: maximum number of iterations without change of the best solution
$maxEliteSolutionsSize$: number of elite solutions

```
bestSol ← initial state
TabuList ← {bestSol}
EliteSolutions ← ∅
iter ← 0
Fast ← true
repeat
   k ← 1
   while k ≤ k_max do
      newSol ← shake(bestSol, k)
      if newSol ∉ TabuList then {if newSol has been already checked}
         TabuList ← TabuList ∪ newSol
         if size_of(EliteSolutions) < maxEliteSolutionsSize then
            if newSol ∉ EliteSolutions then {if newSol not in the EliteSolutions}
               EliteSolutions ← EliteSolutions ∪ newSol
            end if
         else
            if fitness(newSol, Fast) < fitness(worstSol(EliteSolutions), Fast) then
               if newSol ∉ EliteSolutions then {if newSol not in the EliteSolutions}
                  EliteSolutions ← EliteSolutions \ worstSol(EliteSolutions)
                  EliteSolutions ← EliteSolutions ∪ newSol
               end if
            end if
         end if
         if fitness(newSol, Fast) < fitness(bestSol, Fast) then
            bestSol ← newSol
            iter ← 0
            break
         else
            k ← k + 1
         end if
      else
         k ← k + 1
      end if
   end while
   iter ← iter + 1
until iter > maxIter
return EliteSolutions
```

In the second step, Algorithm 2 takes as an input the elite solutions are found in the first step (Algorithm 1). For every elite solution, a long simulation is performed, and the tuple of the best solutions is updated. In the end, Algorithm 2 returns the tuple of the best solutions, containing the configuration with the corresponding, expected UOI.

Algorithm 2 Sim-RVNS for the reliability optimization problem
Step 2 : Long MCS for the elite solutions

Input: $EliteSolutions$ from the Algorithm 1

```
1: BestResults ← ∅
2: Fast ← false
3: for all sol ∈ EliteSolutions do
4:     BestResults ← BestResults ∪ (sol, fitness(sol, Fast))
5: end for
6: return BestResults
```

As time is a determinant factor for our problem, we need to reduce the number of simulations needed. Therefore, we use a variance reduction technique, the control variate (Ross, 2013). The variance reduction techniques minimize the Monte Carlo estimator's standard error by making the estimator more deterministic. A raw yet insightful approximation achieves this by the control variate method. As the covariance between the UOI^a (Equation 28) and UOI^g (Equation 29) is high, we pick the geometric mean as our control variate (Algorithm 3). Additionally, we use a modified adaptive sampling method, described in (Pasupathy and Song, 2020), by introducing a geometrically increasing sample size schedule having a dynamic rate to reduce the number of samples needed for our experiments (Algorithm 3). The fitness function is described in Algorithm 3.

4. Experimental evaluation

We evaluate the capability of the two methods we propose to calculate the short-term expected reliability of a smart grid after an overloading event. We consider a real-world topology from a neighborhood in Luxembourg city and real prosumption data, which are used to estimate future energy demands and supply. Both of the approaches deploy the above dataset to simulate the electrical values for the day-ahead from a given date and time. Our research question concerns the comparison of the expected reliability, in quantitative measures, of each approach, for the next day. The proposed methodology, as well as the details on the dataset and its features, are provided below.

4.1. Prosumption data and topology

The dataset covers 711 different customers' profiles, average and standard deviation of active and reactive consumption demand, as well as active and reactive production supply data, is provided by Creos Luxembourg S.A. The data consisted of 12 months of values, with 96 measurements per day. The topology dataset consisted of 23 cabinets, 3 of which are substations, 31 cables, and 219 smart meters, ex-

Algorithm 3 Function `fitness`$(sol, Fast)$

Fitness function with adaptive simulations and control variates

Input: sol : solution to check, $Fast$: flag for fast simulations, N_{quick} : number of fast simulations
c_0 : minimum multiplier (1.05), c_h : maximum multiplier (3), c_1 : default multiplier (1.1)
UOI_s^a : Arithmetic mean of UOI (Equation (28)) for experiment s, based in sol
UOI_s^g : Geometric mean of UOI (Equation (29)) for experiment s, based in sol
$maxiter$: Maximum iterations for the same number of simulations, e.g. 5

if $Fast$ **then**
  $innerError \leftarrow relaxedFastStoppingCriterion$
  $outerError \leftarrow fastStoppingCriterion$
else
  $innerError \leftarrow relaxedLongStoppingCriterion$
  $outerError \leftarrow longStoppingCriterion$
end if
Calculate initial load (from current electrical values)
$amean \leftarrow \frac{1}{N_{quick}} \sum_{s=1}^{N_{quick}} UOI_s^a$
$gmean \leftarrow \frac{1}{N_{quick}} \sum_{s=1}^{N_{quick}} UOI_s^g$
$cov \leftarrow \frac{1}{N_{quick}-1} \sum_{s=1}^{N_{quick}} [(UOI_s^a - amean) \cdot (UOI_s^g - gmean)]$
$var \leftarrow \frac{1}{N_{quick}-1} \sum_{s=1}^{N_{quick}} (UOI_s^g - gmean)^2$
$c^* \leftarrow -\frac{cov}{var}$
$\tau \leftarrow 0$; $N \leftarrow N_{quick}$
$\mathbb{E}(interval) \leftarrow \infty$
while $\mathbb{E}(interval) < outerError$ **do**
  if $\tau = 1$ **then**
    $c_1 \leftarrow \min(2c_1 - 1, c_h)$
  else
    if $\tau = maxiter$ **then**
      $c_1 \leftarrow \max(c_0, \frac{c_1+1}{2})$
    end if
  end if
  $N \leftarrow \lceil c_1 N \rceil$
  $\tau \leftarrow 0$
  while $(\tau < maxiter) \wedge (\mathbb{E}(interval) < innerError)$ **do**
    $gmean \leftarrow \frac{1}{N} \sum_{s=1}^{N} UOI_s^g$
    $\mathbb{E}(UOI) \leftarrow \frac{1}{N} \sum_{s=1}^{N} [UOI_s^a + c^* (UOI_s^g - gmean)]$
    $\mathbb{E}(interval) \leftarrow z_a \cdot \frac{\sqrt{\frac{1}{N-1} \sum_{s=1}^{N} [UOI_s^a + c^* (UOI_s^g - gmean) - \mathbb{E}(UOI)]^2}}{\sqrt{N}}$
    $\tau \leftarrow \tau + 1$
  end while
end while
return $\mathbb{E}(UOI)$

tracted from a real neighborhood in Luxembourg, which is also provided by Creos Luxembourg S.A.

As it is unlikely we have more than 25% of overloaded prosumers on a grid and, if a curtailment policy can be applied, it is also unlikely we could curtail home residents, we created four different case realistic scenarios as a combination of different percentage of overloaded and curtailed prosumers:

Table 1
Case scenarios.

Scenario	Percentage of overloaded prosumers	Percentage of curtailed prosumers
1	10%	0%
2	10%	25%
3	25%	0%
4	25%	25%

For each one of the 219 smart meters, five random profiles are picked from the historical dataset. Depending on each scenario's percentage of overloaded and curtailed customers, the equivalent number of smart meters is picked uniformly randomly, and initial consumption and production energy data are created from the corresponding Gaussian distribution. Thus, our experimental dataset consists of 20 different energy data files. Five different initial consumption and production energy data are created for every smart meter. Curtailment policy to the customers is applied if a prosumer overpasses the threshold of 60A, i.e., 80% of 75A, the typical roof-top solar panel installation amperage, or if a consumer overpasses the threshold of 32A, i.e., 80% of 40A, the typical amperage supplied by residential meters. If a prosumer or a consumer is picked for curtailment, its active energy is limited to 20A; a value picked together with Creos Luxembourg S.A. The "good" UOI level is set to 0.006, meaning less than 0.25 overloads per day, 5 mins of interruptions per day, and 15 mins of restoration per day, while the "poor" UOI level is set to 0.013, meaning over than 0.5 overloads per day, 15 mins of overloads per day, and 30 mins of restoration per day, as suggested by Creos Luxembourg S.A.

The experiments were conducted on a standard MacBook Pro with a 2.6 GHz Intel Core i7 processor, macOS Catalina 10.15.3 operating system, 16 GB 2133 MHz LPDDR3 memory using Java JDK 1.8.0-162 and Gurobi Optimizer 9.0.1 – Academic Version (Gurobi Optimization, 2020). Interested readers may find all the presented results along with the input data files from http://tiny.cc/SimheuristicRVNS.

4.2. Experimental setup

To estimate the reliability indices, for our first approach, we first apply, for each one of the 20 instances, the method described in (Antoniadis et al., 2020). For each one of the optimal and sub-optimal results and the next 96 quarters of an hour, i.e., 24h, we run adaptive simulations as described in Algorithm 3 to estimate the future electrical values of the customers. We then solve the corresponding linear systems to get the current load of each cable and calculate the indices and the UOI. The average time and the 95% confidence interval for the experiments were found to be equal to 444 sec +/- 448 sec. The minimum and the maximum time was found to be 0.5 sec and 14,930 sec, respectively.

In our second approach, we investigate a single-stage stochastic program that gives the impact of the solutions to the grid's reliability level. We apply the simheuristic algorithm, described previously in Algorithms 1 and 2. Neighborhood search or local search is considered a highly efficient metaheuristic mechanism for solving many problems of satisfaction with constraints and optimization. In defining a neighborhood and starting with an initial solution, local search is gradually exploring the current solution's neighborhood for improvement. In this way, one of its neighbors (often improving) replaces the current solution iteratively until a specific stop criterion has been met (Lü et al., 2010). We define five neighborhoods, based on the one-flip heuristic, where a flip means assigning the opposite state to a variable, i.e., negation, of the given solution in the algorithm's metaheuristic part as follows:

- N_1 *One-flip (substation)*. In this method, we flip each fuse that changes the substation, which powers every cable, if possible, in our current solution and appends that to the neighborhood list.
- N_2 *One-flip (parallel)*. In this method, we flip each fuse in parallel cables, in such a way that the cables become parallel or not, in our current solution and append that to the neighborhood list.
- N_3 *One-flip (end fuses)*. In this method, we flip each end fuse in every cable in our current solution and append that to the neighborhood list.
- N_4 *One-flip (start fuses)*. In this method, we flip each start fuse in every cable in our current solution and append that to the neighbourhood list.
- N_5 *One-flip (all fuses)*. In this method, we flip each fuse in every cable in our current solution and append that to the neighbourhood list.

The number of elite solutions is set to five, while the maximum number of iterations without change of the best solution, so far, is set to 80. We use a tabu list to avoid the possibility of recalculating the same solution, as it is very costly. For the fitness function, described in Algorithm 3, the number of fast simulations is set to 30, while the indices c_0, c_h, and c_1 are set to 1.05, 3 and 1.1, respectively. The tail area α for the standard normal distribution is set to 0.025, i.e., $z_{.025} = 1.96$.

We have focused on minimizing an expected value while reducing the confidence interval, as shown in Algorithm 3, line 29, and Table 2. Given that, we are 95% confident that the expected value's (UOI) margin of error is at most 0.001 for the three digits precision experiments and 0.0001 for the four digits precision experiments. The combination of precision and the stopping criteria we use is presented in Table 2.

Table 2
Stopping criteria.

Fast/Long	Significant digits	Relaxed	Normal
Fast	3	0.005	0.003
Long	3	0.002	0.001
Fast	4	0.001	0.0005
Long	4	0.0002	0.0001

In all of the following experiments, ten independent runs with different random seeds were conducted for each scenario and instance, to acquire statistically significant results. For each scenario and instance we pick the best solution. For the experiments with three decimal places precision, the average time and the 95% confidence interval for the experiments was found to be equal to 348 sec +/- 26 sec. The minimum and maximum time were found to be 185 sec and 694 sec, respectively.

For the experiments with four decimal places precision, the average time and the 95% confidence interval for the experiments was found to be equal to 1,350 sec +/- 372 sec. The minimum and maximum time were found to be 211 sec and 7,557 sec, respectively.

5. Results

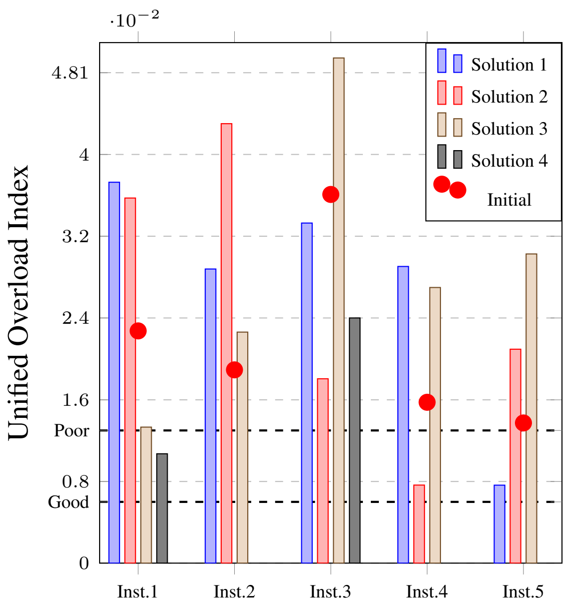

Fig. 2. First method - First scenario.

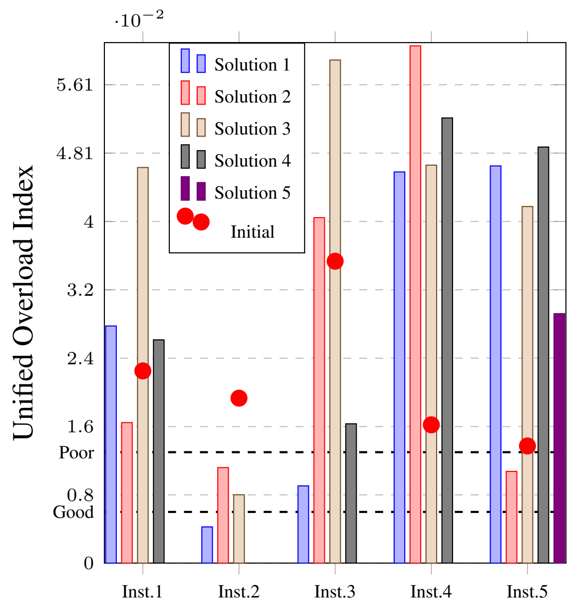

Fig. 3. First method - Second scenario.

We can see from the results that the first method, as expected, gives poor results. In Figures 2, 3, 4, and 5 we observe that about 44% of the cases, the calculated results are worse than the initial, i.e., when an potential overload incident is occurred, ones. In only three instances, the UOI is under the good UOI level. In Table 3, the standard deviation, the margin of error and the relative error at 95% confidence level for the top solutions found for each method and scenario are presented. The time to conclude the experiments also has a huge variance and, in the worst-case needed over four hours to finish.

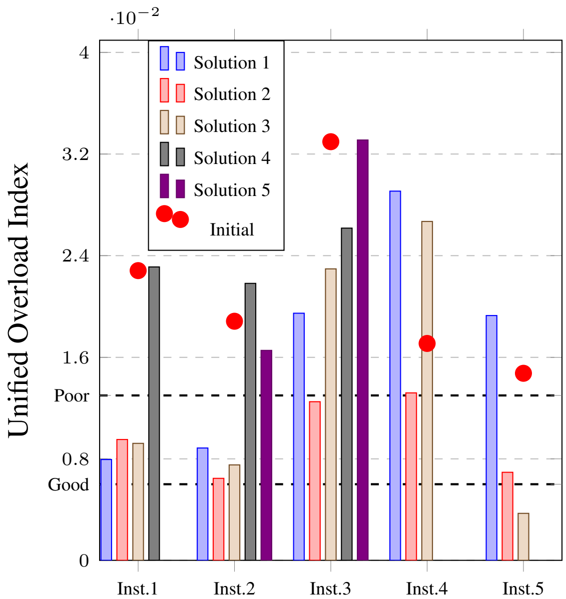

Fig. 4. First method - Third scenario.

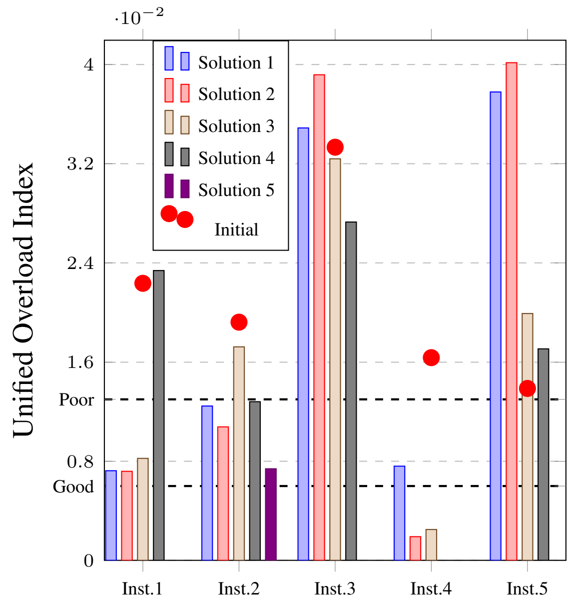

Fig. 5. First method - Fourth scenario.

Table 3
Statistics on the top solutions.

Method	Scenario	Standard deviation	Margin of error	Relative error
First	1	1.07×10^{-3}	3.84×10^{-4}	5.02%
	2	4.16×10^{-4}	1.49×10^{-4}	3.51%
	3	6.11×10^{-4}	2.19×10^{-4}	5.91%
	4	4.26×10^{-4}	1.52×10^{-4}	7.97%
Second - 3 significant digits	1	6.21×10^{-4}	2.22×10^{-4}	12.96%
	2	6.38×10^{-4}	2.28×10^{-4}	12.24%
	3	6.42×10^{-5}	2.3×10^{-5}	0.51%
	4	5.26×10^{-4}	1.88×10^{-4}	8.48%
Second - 4 significant digits	1	6.44×10^{-4}	5×10^{-5}	2.34%
	2	6.09×10^{-4}	4.76×10^{-5}	2.26%
	3	2.46×10^{-6}	8.8×10^{-7}	0.02%
	4	6.28×10^{-4}	3.33×10^{-5}	1.18%

As our first method tries to find a solution without concerning the future electrical values, the quality of the solutions is, understandably, poor. Our second method improves the results significantly. Even with 25% of overloaded customers, our method finds a proper plan to ensure a stable grid, with the minimum disturbances for the smart grid users and minimize the risk of overheating cables.

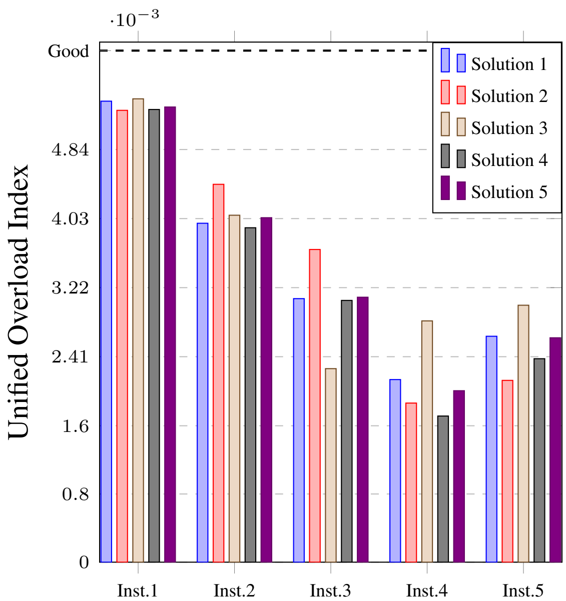

Fig. 6. Second method - First scenario - three decimal places.

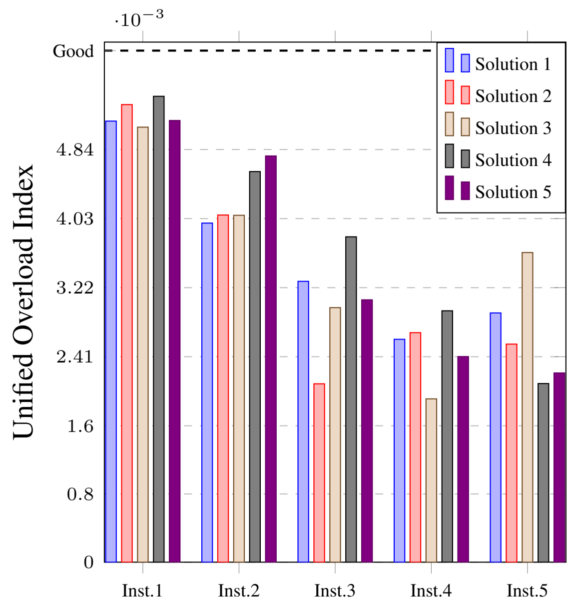

Fig. 7. Second method - Second scenario - three decimal places.

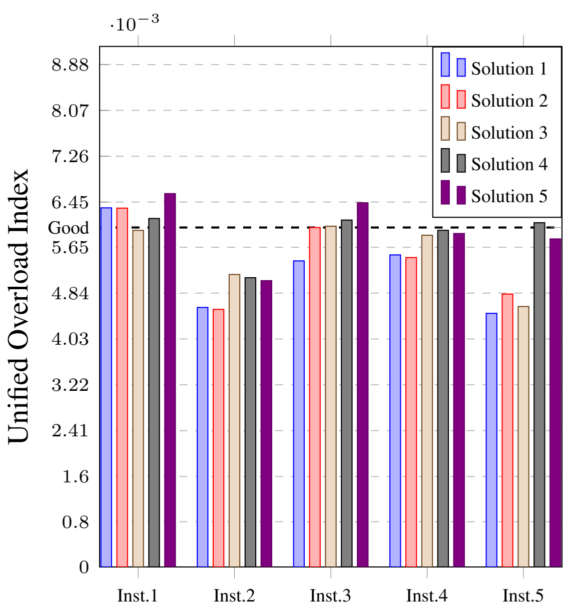

Fig. 8. Second method - Third scenario - three decimal places.

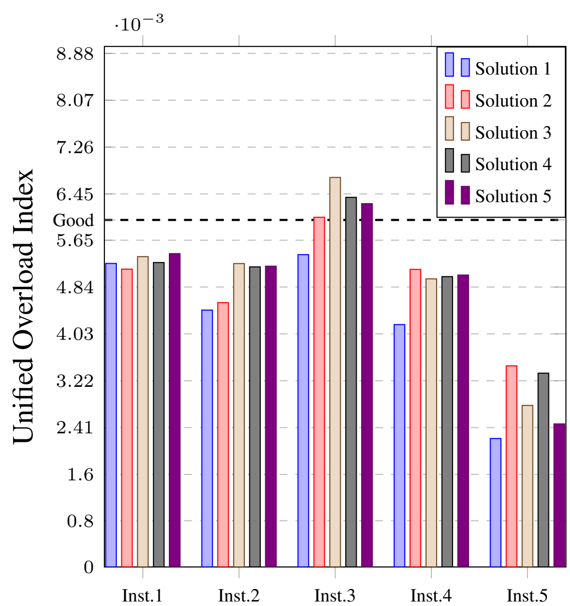

Fig. 9. Second method - Fourth scenario - three decimal places.

For the experiments that calculate the UOI with three digits precision, in the worst case, about 11.5 min are enough to find a solution, 3.5 min under the threshold of 15 min, which is the time interval between smart meter measurements, for the Creos Luxembourg SA case. In all scenarios and instances, the UOI is under the good UOI level, meaning that our method can be used as a robust reliability optimization tool for the smart grid companies, as can be seen in Figures 6, 7, 8, 9, 10, 11, 12, and 13.

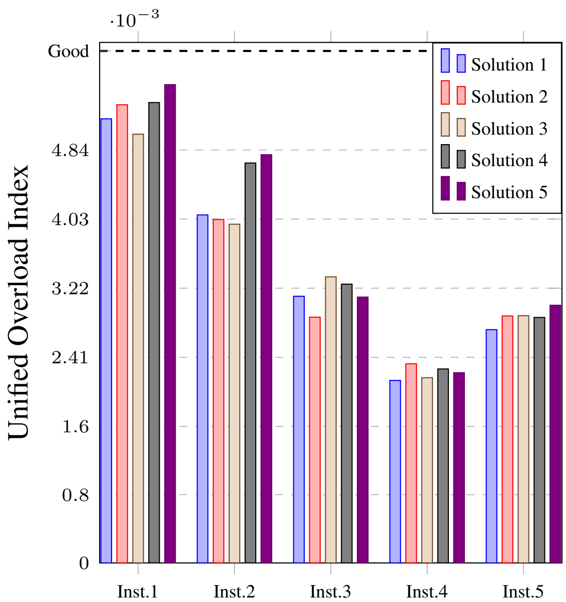

Fig. 10. Second method - First scenario - four decimal places.

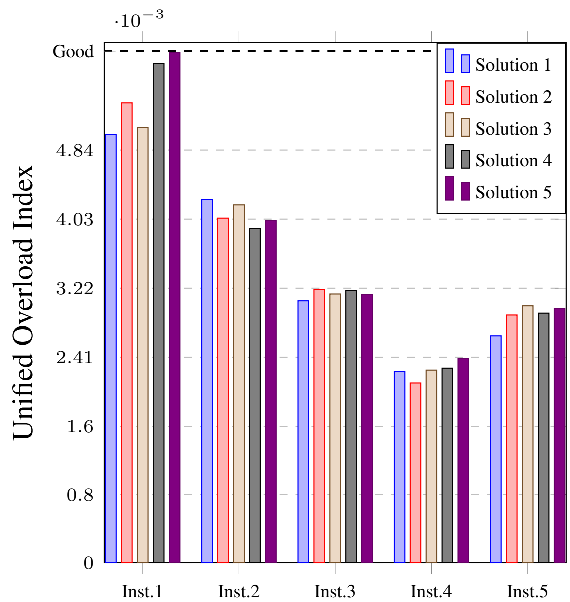

Fig. 11. Second method - Second scenario - four decimal places.

We also check the effect of the control variate technique. In comparison, the quality of the solutions is, on average, 5% better without variance reduction techniques, as it is shown in Figure 15, while the computational times are on average doubled as it is shown in Figure 14. Moreover, using the control variate technique, no experiment takes more than 15 min. On the opposite, 8.5% of the instances exceed the 15 min limit without using control variates.

We also conducted experiments with four digits precision to examine the practical significance of the risk in the results. The impact, as it can be seen in Figures 10, 11, 12, and 13, the difference between the results are given with the three decimal places precision and the four decimal places precision is negligible. Moreover, the four decimal places precision experiments last, on average, about 22.5 min, over the smart meter 15 min measurement threshold. Additionally, we compare the different methods concerning their computational time (Figure 16) and the quality of their solutions (Figure 17). From these boxplots, it is shown that the second method outperforms the simulation method concerning the quality of the solutions. Even the computational times in the simulation method are, on average, good, there are still 6.5% instances that exceed the limit of 15 min. Conversely, the second method with three decimal points precision has no instance over 15 min, while it has approximately the same quality of its results compared with the four decimal points precision alternative method.

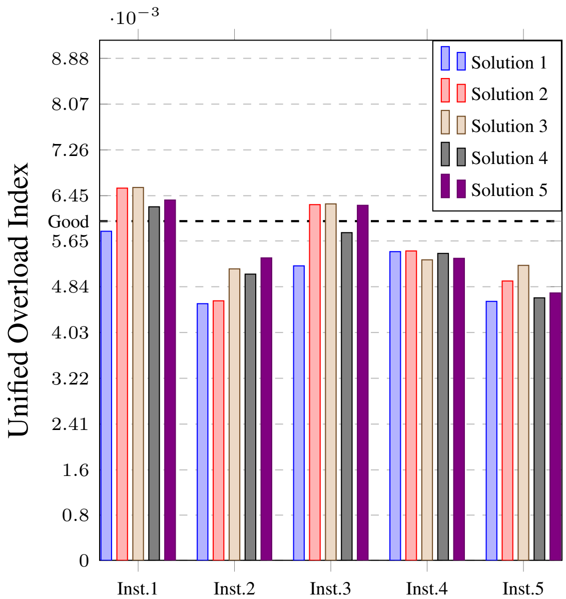

Fig. 12. Second method - Third scenario - four decimal places.

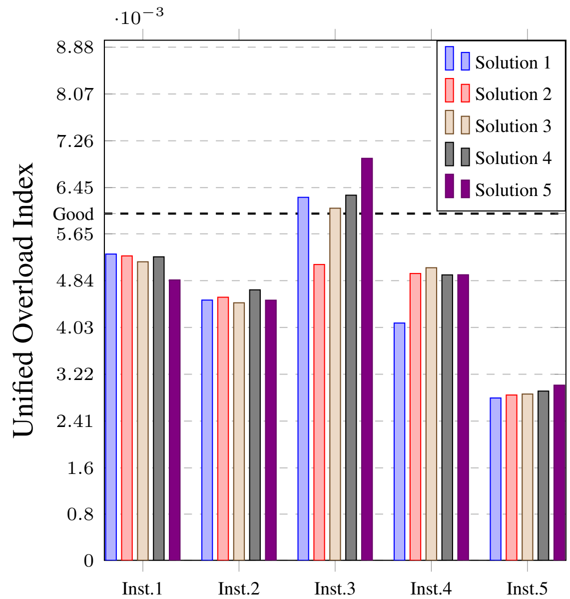

Fig. 13. Second method - Fourth scenario - four decimal places.

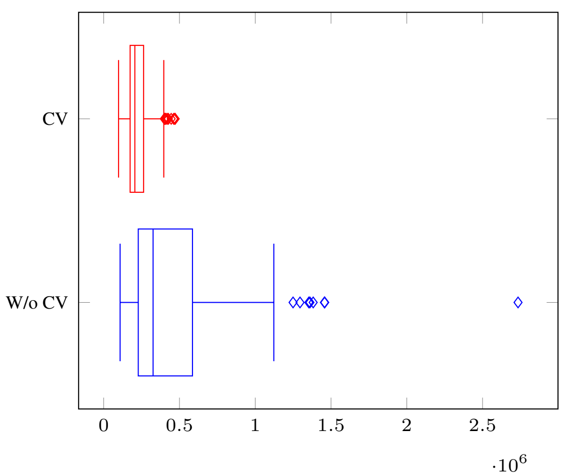

Fig. 14. Time (in msec).

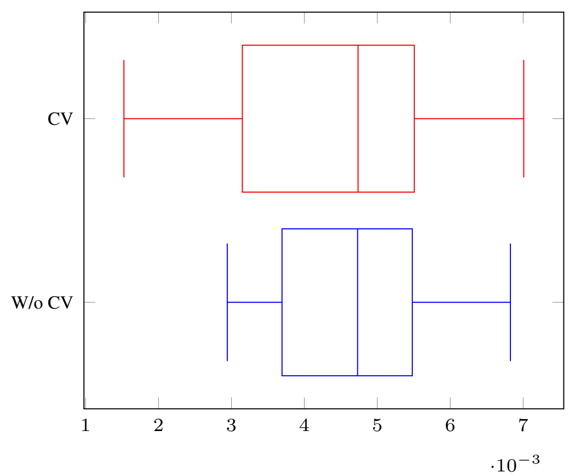

Fig. 15. Quality of solutions (UOI).

As the necessity of our method is to find fast such healing actions to ensure the stability of a smart grid after a potential overload, the three digits precision for the UOI is enough for the smart grid operators, according to Creos Luxembourg SA.

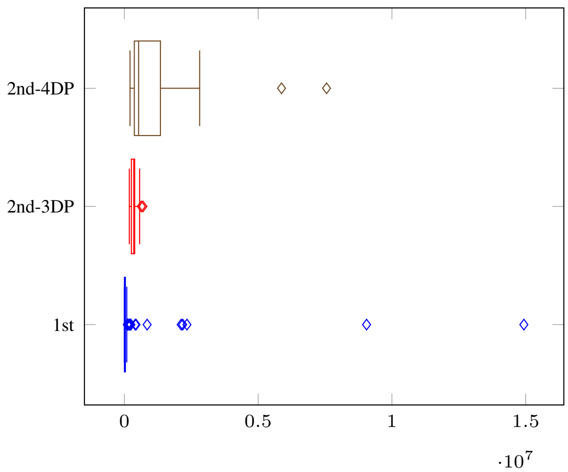

Fig. 16. Time (in msec).

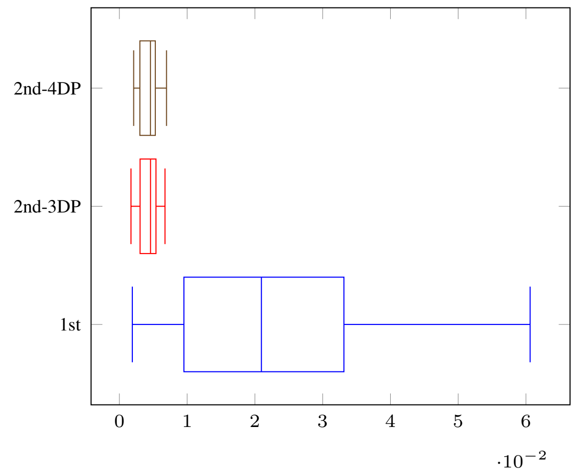

Fig. 17. Quality of solutions (UOI).

6. Conclusions

The demand for a "self-healing" grid requires novel tools to provide a resilient and reliable power grid to its users. One of the most critical issues in power grids is long-term overloads as they can harm distribution power lines, even within the security limits, and may cause energy grids to malfunction. Specific counteractions can then be applied to reduce cable loads, preventing overload, including the curtailment of over-production or over-usage by individual users. If such restrictions are not applicable, operators have to provide fast, recovery-response solutions to minimize the number of cabinets and fuses that technicians have to visit to change their state. Moreover, grid operators should avoid disconnecting users, critical ones, such as hospitals. Even if the above counteractions are applied immediately after detecting a risky overloading incident, the recovery response solution could lead to another overloading incident, as the future demands are not known beforehand. If this solution could be tested for its efficacy over the next day, the smart grid operators would be of great use to ensure the solution is as robust as possible. We presented two methods capable of calculating a smart grid's short-term expected reliability after an overloading event in this work. First, we presented a UOI which the smart grid's decision-makers can use to investigate the reliability assessment. After a potential overload incident, the UOI is estimated by calculating the optimal and sub-optimal solutions, using MCS as our first solution method.

Then, we defined and formulated the single-stage stochastic reliability optimization problem in smart grids, and suggested another solution method using simheuristics, which combines simulation with metaheuristics to solve stochastic combinatorial optimization problems, to optimize the reconfiguration of the grid topology and to ensure the smart grid could remain stable for the next 24 hours. For the simheuristic's metaheuristic part, we used VNS and applied the control variate reduction technique to the MCS to reduce the number of simulations. It is shown that this approach can be included in the grid operator's decision-making process as it can successfully and rapidly help to ensure the stability of a smart grid after a potential overloading incident of about the size of a neighborhood in Luxembourg.

As future work, we plan to extend our single-stage stochastic optimization problem into a multi-stage stochastic optimization problem, so that in every period, i.e., 15 min, considering the expected electrical values, new actions are calculated and, in the end, an action plan for the next 24 hours is calculated with more precision. This multi-stage stochastic optimization problem inevitably complexify the presented problem, increasing the size and its solution space. Thus, other metaheuristics, as part of our simheuristic algorithm, should be investigated. Hybrid and parallel metaheuristics may be a suitable solution method. As lognormal and Weibull distributions can reasonably model reliability data, it would be interesting to model, by using the above distributions, failure and repair times, and the number of overloads, and to answer critical questions about the robustness of the model. Control techniques as the ones explained in (Rabe et al., 2020) could also be of great use for an extension of our work.

Acknowledgments

The authors would like to thank Yves Reckinger and Robert Graglia from Creos Luxembourg S.A. for their support.

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Nomenclature

n	number of cables, $n \in \mathbb{N}^*$
r_i	reachability cable state; 1 if cable i is powered and 0 otherwise
m	number of users, $m \in \mathbb{N}^*$
uc_{ki}	user cable indicator; 1 if user k is connected with cable i, 0 otherwise
o	number of cabinets (including substations), $o \in \mathbb{N}^*$
$dfcab_b$	cabinet visit indicator; 1 if $\sum_{f=1}^{2n} cc_{bf}\|x_f - x_f^0\| \geq 1$, 0 otherwise
x_f	fuse state; 1 if fuse f is closed, and 0 otherwise; if $f = 2i$, x_f denotes the current state of the *start* fuse of cable i, else if $f = 2i + 1$, x_f denotes the current state of the *end* fuse of cable i
x	the vector of fuse states
x_f^0	initial fuse state
cc_{bf}	fuse cabinet indicator; 1 if fuse f belongs to the cabinet b, 0 otherwise
A_{jf}	coefficient matrix element; for equation j and fuse f, $A_{jf} \in \{-1, 0, 1\}$
wp_f	actual active energy vector energy element for fuse f; $wp_f \in \mathbb{R}$
P_j	active load vector element; $P_j = Pl_i \cdot r_i$, if equation j is describing the current flow of cable i, and 0 otherwise, $P_j \in \mathbb{R}$
Pl_i	initial active energy for cable i, $Pl_i = \delta \sum_{k=1}^{m} uc_{ki} RaE_k$

δ measurement frequency coefficient; e.g. $\frac{60}{15} = 4$, for 15 min interval

RaE_k real active energy consumption for user k, $RaE_k = aE_k$, if $cur_k < I_{LC}$, (consumer) or $cur_k < I_{LP}$ (producer), and $RaE_k = RGaE_k$ otherwise

aE_k active energy for user k, $aE_k = aEC_k - aEP_k$, $aE_k \in \mathbb{R}$

aEC_k active energy consumption for user k, $aEC_k \in \mathbb{R}_+$

aEP_k active energy production for user k, $aEP_k \in \mathbb{R}_+$

rE_k reactive energy for user k, $rE_k = rEC_k - rEP_k$, $rE_k \in \mathbb{R}$

rEC_k reactive energy consumption for user k, $rEC_k \in \mathbb{R}_+$

rEP_k reactive energy production for user k, $rEP_k \in \mathbb{R}_+$

cur_k amperage of user k, $cur_k = \frac{\sqrt{aE_k^2 + rE_k^2}}{\sqrt{3} \cdot 230}$

I_{LP} maximum allowed amperage for producers, e.g. 60A

I_{LC} maximum allowed amperage for consumers, e.g. 32A

$RGaE_k$ curtailed active energy for user k, $RGaE_k = \sqrt{|230^2 \cdot 3 \cdot I_R^2 - rE_k^2|}$, $RGaE_k \in \mathbb{R}_+$

I_R curtailed amperage for users, e.g. 20A

wq_f actual reactive energy vector energy element for fuse f; $wq_f \in \mathbb{R}$

Q_j reactive load vector element; $Q_j = Ql_i \cdot r_i$, if equation j is describing the current flow of cable i, and 0 otherwise, $Q_j \in \mathbb{R}$

Ql_i initial reactive energy for cable i, $Ql_i = \delta \sum_{k=1}^{m} uc_{ki} rE_k$

l_i actual current load percentage, at cable i; $l_i = \max(\frac{100\sqrt{wp_{2i}^2 + wq_{2i}^2}}{230 cl_i \sqrt{3}}, \frac{100\sqrt{wp_{2i+1}^2 + wq_{2i+1}^2}}{230 cl_i \sqrt{3}})$

l vector of the expected load percentages

ld_{it} expected current load percentage, at cable i at time t

λ maximum allowed current load percentage for all cables, e.g. 80%

i cable index, $i \in \{1, \dots, n\}$

co number of customers overloaded

cmo customer minutes of overload

$cblo$ number of cables overloaded

$cblmo$ cable minutes of overload

lo load of customers overloaded

lmo overload duration of customers

lt total load

t time period

T time horizon; e.g. $4 \cdot 24 = 96$, for 24 hours and 15 min measurement interval

$cust_i$ number of customers at cable i

$fail_{it}$ new overload at cable i on period t

$downt_{it}$ duration of overload at cable i on period t

u_{it} overload indicator at cable i on period t