

# Quantitative Risk Management by Demand Response in Distribution Networks

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**Abstract**—Demand response (DR) is a versatile tool capable of providing sophisticated solutions and competitive services. Currently, the utilities pursue such services, as the reliability improvement, by continuous infrastructure investment and maintenance. In many cases, DR can provide reliability benefits, as it allows distribution network operators to reshape the load profile when a contingency is imminent. The quantification of the DR benefits is necessary to understand its economic and financial impact on the power sector. Methodologies used in risk management can be adapted for this purpose. In this paper, we propose a method to build a detailed reliability model, to assess the expected reliability indices, and to manage the financial risk of the reliability performance by DR in distribution networks subject to performance-based regulation. The outcome of the proposed method is the quantification of the relation between the risk and return of DR portfolios, in terms of conditional value-at-risk and expected return, respectively. The results demonstrate that the method can be used as a decision support system for optimal DR allocation to trade off efficiently between the reliability performance risk and the expected return.

**Index Terms**—Demand response, distribution reliability, Monte Carlo simulation, quantitative risk management.

## NOMENCLATURE

### A. Sets and Indices

- $h$  ( $\mathcal{H}$ ) Index (set) of time intervals.
- $i$  ( $\mathcal{I}$ ) Index (set) of simulation iterations.
- $j$  ( $\mathcal{J}$ ) Index (set) of consumers.
- $n$  ( $\mathcal{N}$ ) Index (set) of network components.

### B. Parameters

- $\lambda_n^c$  Constant failure rate of the  $n$ th component during low loading conditions.
- $\lambda_n^{\max}$  Maximum failure rate of the  $n$ th component.
- $i_{\max}$  Maximum iteration number.
- $I_n^{\text{cr}}$  Current of the  $n$ th component.
- $I_n^{\max}$  Maximum current of the  $n$ th component.

### C. Variables

- $\lambda_n$  Failure rate of the  $n$ th component.

- $\text{CVaR}_\alpha$  Conditional Value-at-Risk, calculated for the worst  $\alpha$ -quantile of the simulation results.
- $I_n$  Current of the  $n$ th component.
- $U$  Random variable uniformly distributed in  $(0,1)$ .

### D. Abbreviations

- AMCHM Analytical/Monte Carlo hybrid method.
- AS Analytical Simulation.
- BS Base case.
- CDFR Condition-dependent Failure Rate.
- CPP Critical-Peak-Pricing.
- CVaR Conditional Value-at-Risk.
- DG Distributed Generation.
- DN Distribution Network.
- DNO Distribution Network Operator.
- DR Demand Response.
- EENS Expected Energy Not Supplied.
- ER Expected Return.
- LOLP Loss of Load Probability.
- MCS Monte Carlo Simulation.
- MTTR Mean Time to Repair.
- PBR Performance-based Regulation.
- RBTS Roy Billinton Test System.
- RMCS Random Monte Carlo Simulation.
- RPS Reward and Penalty Scheme.
- SAIDI System Average Interruption Duration Index.
- SAIFI System Average Interruption Frequency Index.
- SMCS Sequential Monte Carlo Simulation.
- ToU Time-of-Use.

## I. INTRODUCTION

### A. Motivation, Objective, and Solution

**P**OWER system reliability is an essential requirement for an effective electrical network operation, and occasional disrupting events emphasize its importance. The power supply continuity can be interrupted by various causes, attributed to events that occurred in any part of the grid, e.g., generation, transmission or distribution. Such interruptions can be sparked off by adequacy or security issues [1]. The former refers to the power system's ability to generate, transmit and distribute sufficient power to the demand under any static condition, whereas the latter describes the power system's ability to withstand disturbances.

In modern power systems, the distribution security events, also known as distribution reliability events, constitute the

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majority of the customer's annual interruption duration, i.e., about the 90% of the total sustained interruption duration [2].

The quantification of distribution reliability can be realized by the customer based reliability indices, such as SAIDI and SAIFI [3]. Regulating authorities consider the customer based reliability indices preferable to energy based reliability indices, e.g., LOLP, and EENS, since the customer based indices can fairly assess the interruption impact irrespective of the customer size or type. Therefore, SAIDI and SAIFI improvement is usually the objective of the cost allocation for reliability spending of DNOs [2], [4].

Historically, regulatory frameworks such as cost-of-service and rate-of-return were imposed to DNOs. Since DNO's profit was associated with their cost, there has been a negligible efficiency incentive. Nevertheless, in modern deregulated environment, more sophisticated mechanisms such as PBR are introduced to incentivize DNOs to increase their efficiency and quality of service [5]–[7].

The statistics of reliability events, which are provided by utilities, are very useful for predicting future risk and corrective actions to achieve a specific reliability level [8]. In such a way, historical performance is used increasingly by regulatory authorities with a view to set reliability standards by applying PBRs. The regulatory statutes can be materialized by an RPS contract between DNO and regulatory agency. Such contracts describe the DNO's reward or penalty based on the reliability performance, measured by SAIDI and SAIFI indices [9]. Currently, in Europe, RPSs have been applied to a certain extent in distribution systems of 17 countries [10].

The reliability improvement is usually pursued by continuous infrastructure investment and maintenance. However, in modern distribution systems, advanced technologies could be exploited as an alternative way to achieve reliability benefits. Accordingly, in this work, the proposed method implements various tools and concepts for reliability analysis, to reintroduce DR as an instrument for quantitative risk management in DNs.

## B. Literature Review

A straightforward path to increase the reliability in DNs is by investing in additional and/or upgraded infrastructures such as protection, reclosing, and sectionalizing devices. Automation is a key parameter for fast recovery time, and when it comes to manual operations, the need for rapid response by the crew is also crucial [2]. Other conventional reliability enhancement methods are the allocation of DG [11] and the network reconfiguration [12].

In recent works, the use of advanced technologies is taken into account. In [13], a detailed review study presents real world examples along with optimization methods for DR applications. In another recent review [14], a broad overview of the DR efforts happened throughout the world is presented. We observe in both works [13] and [14] that the DR state of the art regarding the efforts within the scope of reliability, reach only the quantification of the benefits in terms of improvement of reliability indices. The authors in [15] propose a smart grid architecture to use the smart grid technologies in reliability challenges. The authors in

[16] investigate the system and nodal reliability enhancement in terms of energy based reliability indices by DR, as well as in [17], where the authors deal with the contribution of DR and storage to the adequacy of supply. In [18]–[22], the authors investigate various impacts of DR on several DN characteristics, including reliability indices. In [23], the authors investigate the utility-demand interaction by taking into account a two-level game between residential users and utility companies. In [24], the authors propose a load management method utilizing multi-agent systems and considering the upstream grid, DG and DR for peak load reduction.

The wide-ranging content of risk management of power systems, and the large overlap of risk and reliability is presented in [25]. It is assumed that higher risk means lower reliability, and vice versa. Regarding the risk management in DNs, the work in [26] evaluates risk management strategies from a resource planning point of view and classifies them by their flexibility and robustness. In [27], [28] the authors present a framework for the assessment of the reliability and risk of using post-fault DR to pursue DN capacity increase. In [29], a financial risk management is proposed for electric energy contract evaluation. In [30], the authors introduce hedging strategies to mitigate the exposure to real-time price volatility risk. The work in [31] proposes a framework to estimate the electricity sale price based on time-of-use rates and to manage a portfolio of contracts for optimal procurement and hedge against risks.

In a more relevant work in [32], the authors formulate an optimal portfolio framework to analyze the DR impact on the profit-risk trade-off for load serving entities. The above work uses the mean-variance analysis developed by Markowitz [33] and focuses on the use of DR instead of purchasing energy from wholesale markets to cover supply shortfall in peak-hour loads.

What is missing from the literature is a calculation tool which could enable a DNO to make an educated decision to select a specific desired amount of risk and expected return, regarding the reliability performance of his DN.

## C. Contributions

This paper focuses on the financial risk of the reliability performance with regard to DN. The proposed method evaluates the reliability of a DN using the concepts of SMCS, AS, CDFR, and network reconfiguration. Subsequently, the method formulates DR programs as assets of DR portfolio, to calculate the maximum ER for any desired level of risk, for the specific network under study. The maximum ER as a function of risk constitutes an efficient frontier which is a guideline for the optimal allocation of DR programs while trading-off between risk and ER. Therefore, the method can be used as a decision support system for the balance of the expected rewards or penalties, according to the risk tolerance of the DNO. The contribution of this paper is twofold.

- (1) The paper reintroduces DR as a quantitative instrument for risk management in DNs subject to PBR regulation.
- (2) The paper proposes a method for tailor-made optimal DR programs allocation within a DR portfolio, as a tool for risk management in terms of financial benefit.

#### D. Paper Organization

The remainder of the paper is organized as follows. Section II describes the modules of the simulation framework to evaluate the impact of the failure events to the consumers. Section III describes the reliability and risk framework which formulates the quantitative risk management process. Section IV is a case study on Bus 2 of the Roy Billinton test system. Finally, Section V concludes the paper.

## II. SIMULATION FRAMEWORK

The distribution reliability study requires an accurate reliability model, which should predict the expected DN performance. According to [34], the reliability model becomes increasingly significant among stakeholders, and it could even surpass the power flow model in terms of importance and usage. Additionally, a thorough reliability model, allows the engineer to design, test, and assess effectively a distribution system from the reliability perspective. It is the bedrock in the process to meet reliability targets, to identify problems, to assess improvement in projects' effectiveness, to determine system expansion impact, and to design for different reliability levels [35].

In this paper, the reliability model takes into account all the network failures that can trigger circuit breakers. There are various basic modeling methods in the literature used in simulation environment: network modeling, Markov modeling, AS, and MCS [35]. In this work, the AMCHM is used, as presented in [2], which can produce a useful statistical output of mean values, variance and confidence intervals of the reliability indices, which in turn could be further analyzed to conduct quantitative risk management.

The reliability model is designed to handle the input data comprising grid topology, loading condition, and component reliability data, i.e., CDFR and MTTR. According to the AMCHM, the occurrence of reliability event is randomly determined by a MCS. More specifically, a SMCS is used to take into account time-varying parameters. Subsequently, when a reliability event is determined, an AS is initiated to calculate the system's response and the impact on customers.

Fig. 1 outlines the structure of the method. The developed modules, which apply the AMCHM, are explained in the following subsections.

#### A. SMCS

Monte Carlo algorithms are a versatile class of solvers relying on repeated random sampling for a broad spectrum of physical and mathematical problems. MCS is flexible and parallelizable and is widely applied in distribution reliability analysis. It can be found in the literature in three variants namely random, sequential, and pseudo-sequential [36]. All variants are performed by the aggregate result of an iterative random input, which is applied to specific time intervals of the time series.

The RMCS variant, samples the time intervals randomly. The reliability indices can be estimated efficiently by simulating system's random behavior over a sample of the total time intervals. But when it comes to time-varying parameters, the RMCS

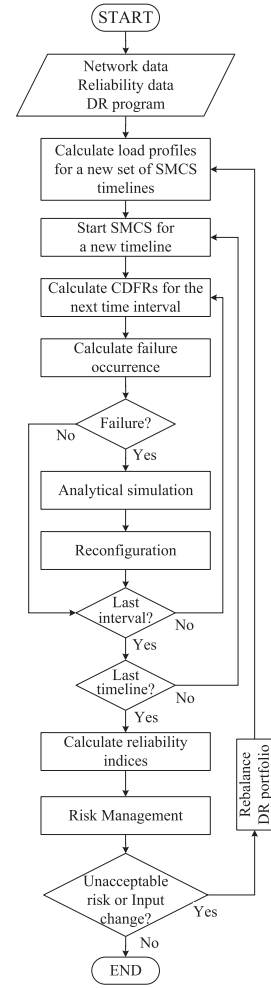


Fig. 1. The flowchart of the proposed method.

sampling may ignore a part of the system's activity. In such cases, the SMCS variant can assess the distribution system reliability more accurately. The sequential time interval handling from start to end, like a sliced timeline, inherits a memory concept to the process. Therefore, the SMCS is suitable in studies of rewards and penalties for DNOs subject to PBR, which are based on time-variable and seasonal parameters [37]. However, the preciseness of the SMCS comes with a heavy computational burden. There is also a later variant, the pseudo-SMCS [38], which is a hybrid approach that melds the RMCS and SMCS advantages. The pseudo-sequential simulation employs an RMCS-type subroutine to determine a failure occurrence, and subsequently, it explores the neighboring time intervals sequentially.

In this work, the SMCS is selected to investigate thoroughly the failure potential within the overall simulation horizon, in high accuracy. The duration of the time intervals is a critical trade-off between accuracy and execution speed. Hourly resolution is considered satisfying, as it provides, on the one hand, with sufficient variability, and on the other hand with satisfying execution time. We divide the annual simulation horizon into 8760 sequential hourly intervals. During each hourly interval, we consider that the network loading condition remains constant

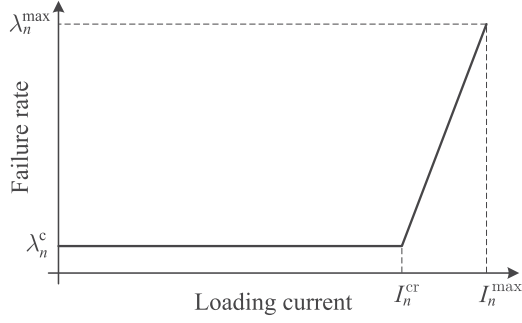


Fig. 2. Condition-dependent failure rate model. For light-loading conditions, the failure rate is considered constant  $\lambda_n^c$ . For loading current higher than a critical value of current  $I_n^{cr}$ , the failure rate increases linearly up to  $\lambda_n^{\max}$ .

and we calculate the failure occurrence taking into account the CDFR. In addition, the SMCS is executed iteratively to ensure convergence in the calculation of the reliability indices before the method proceeds to the risk analysis. Each execution of the SMCS handles a timeline of time intervals where the hourly load profile is assigned to every load point. The CDFR model determines the failure occurrence in a given time interval; hence a power flow is solved to calculate the exact loading condition of each network component during every time interval.

### B. Condition-Dependent Failure Rate

Many power system reliability studies assume the failure rate of the system components to be constant, ignoring the impact of their loading condition or other external parameters. According to [2], [39]–[42] the failure rate should be considered as a function of loading, especially in power lines and power transformers. Currently, there is no standard method for the modeling of the CDFR of a component. In practice, CDFRs can be acquired by historical data analysis. A punctilious DNO should log the scarce failure data for several years, which in turn can be analyzed to derive or to update the components' CDFRs. The CDFR model used in this work is shown in Fig. 2, and it represents a fusion between a constant failure rate  $\lambda_n^c$  for light loading conditions of the  $n$ th component and a linear increase up to  $\lambda_n^{\max}$  for loading greater than a critical value of current  $I_n^{cr}$ . In order to calculate the current  $I_n$  in Amperes for the  $n$ th component, an AC power flow problem is solved for every time interval. In the following process, each  $I_n$  is used by (1) to calculate the respective CDFRs  $\lambda_n$ :

$$\lambda_n(I_n) = \begin{cases} \lambda_n^c, & I_n \leq I_n^{cr} \\ \lambda_n^c + \frac{\lambda_n^{\max} - \lambda_n^c}{I_n^{\max} - I_n^{cr}} (I_n - I_n^{cr}), & I_n^{cr} < I_n \leq I_n^{\max} \end{cases} \quad (1)$$

The outcome of the above process is the  $\mathbf{P}$  vector which hosts the hourly CDFR probability  $\lambda_n$  for the  $n$ th component:

$$\mathbf{P} = [\lambda_n], \text{ for } n = 1, 2, \dots, n_{\max}. \quad (2)$$

In the following process, the method feeds the contents of the  $\mathbf{P}$  vector to a binomial random generator. The function of the binomial generator simulates a coin tossing experiment. The result, i.e., heads or tails, represent the operation or failure of the  $n$ th component, decided in each time interval by the respective

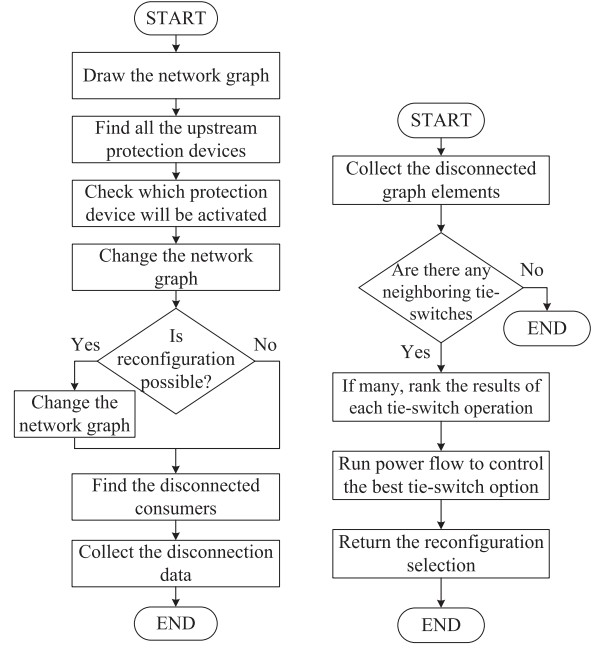


Fig. 3. Flowcharts. (a) Analytical simulation. (b) Reconfiguration.

probabilities  $(1 - \lambda_n)$  and  $\lambda_n$ . In more detail, for a  $U$  random variable uniformly distributed in  $(0, 1)$  given as input to the binomial random generator, the output is a binomial random variable  $X$  as:

$$X = \begin{cases} 1, & U \geq \lambda_n \\ 0, & U < \lambda_n \end{cases} \quad (3)$$

The above random trial is repeated  $n$  times, once for each component, for every time interval to produce the failure occurrence matrix  $F$ . The  $F$  matrix is expected to have in the majority of its elements ones, and sparsely zeros. A zero occurrence in the  $F_{(n,h)}$  element, is translated as a failure of the  $n$ th component during the  $h$ th time interval. Consequently, an AS is used for the calculation of the impact of the failure.

### C. AS

The AS is designed to estimate the protection system response and to calculate its impact<sup>1</sup> on the consumers. The normal sequence of events in a generic AS [2] is: contingency, reclosing, automatic sectionalizing, lockout, reconfiguration, and repair. In our work, since only the permanent failures having MTTR  $\geq 1$  h are taken into account, the reclosing and automatic sectionalizing processes haven't been incorporated into the algorithm, as they are applied in momentary interruptions. Additionally, in the reconfiguration subroutine, an overloading control process has been added, to forbid any inappropriate switching action. Fig. 3(a) depicts the flowchart of the modified variant of the AS which is used in this work.

<sup>1</sup>The impact usually extends to the following time intervals. The method is designed to take this into account.



#### D. Network Reconfiguration

The primary objective of the network reconfiguration is to protect feeders from overload or abnormal voltage. In other cases, a DNO may use this tool for loss minimization [43]. In this work, the network reconfiguration is employed, as described in [2], to reconnect the largest possible part of the disconnected customers. To this purpose, during contingency analysis, after the fault isolation, the reconfiguration algorithm inspects if there is any tie-switch available to divert disconnected consumers to the active part of the grid. If such a tie-switch is found, it will be activated during the analyzed contingency. The flowchart of the developed algorithm is shown in Fig. 3(b).

#### E. Convergence Criterion

In order to have satisfactory SAIDI values, it is necessary to decide the number of SMCS iterations. Theoretically, for infinite iterations, the expected value of the simulation equals to the average of the results. In practice, the occurrence of rare events, e.g., an extreme failure expected to happen once per 100 years or more, can be considered out of the scope of the paper. Thus, in this work we propose 500 iterations, to have a high probability of simulating several failures expected to happen as sparsely as once every 50 years.

### III. RELIABILITY AND RISK FORMULATION

#### A. Distribution Reliability Index Calculation

The formulation of distribution reliability indices is introduced in [1]. Usually, they are measured over the course of a year. In the current work, we designed the method to handle an annual simulation horizon for several iterations to produce SAIDI statistics.<sup>2</sup> Considering that the simulation applied in  $i_{\max}$  MCS iterations for a distribution network with  $N$  total consumers, where in the  $i$ th iteration, the  $j$ th consumer sustain  $U_j^i$  annual outage time, we collect the annual SAIDI results in an  $\mathbf{S}$  vector with elements as follows:

$$S_i = \frac{\sum_{j=1}^N U_j^i}{N}, \text{ for } i = 1, 2, \dots, i_{\max}. \quad (4)$$

#### B. Risk Management

As previously mentioned in the Section I, regulatory agencies may impose performance-based incentives to DNOs, to motivate for reliability enhancement. This motivation takes place by an RPS as it is shown in Fig. 4, which in turn causes a financial risk to the DNO. Consequently, it is for the interest of a DNO to apply a risk management process, which in general consists of risk identification, risk assessment, risk response, and monitoring.

Regarding the risk identification, in this work, we focus on the financial risk as a function of SAIDI performance. The  $\mathbf{S}$  vector, which is calculated according to the Section III-A, contains a pool of  $i$  annual SAIDI reliability indices of the distribution network. In this process, the algorithm will calculate the financial impact, taking into account the rewards and penalties, i.e., the

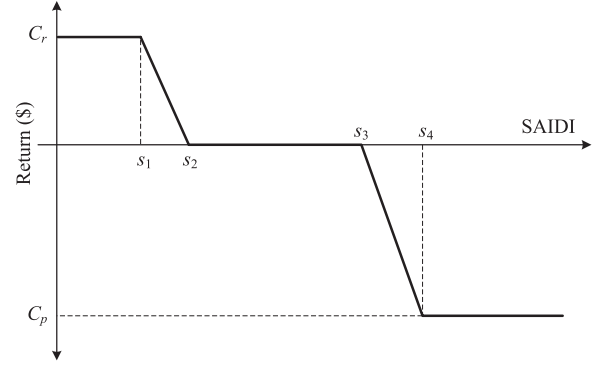


Fig. 4. Diagram of a capped reward-penalty scheme. Reward and penalty are capped:  $C_r$  for SAIDI  $< s_1$  and  $C_p$  for SAIDI  $> s_4$  respectively, and they are zeroed in the dead zone between  $s_2$  and  $s_3$ .

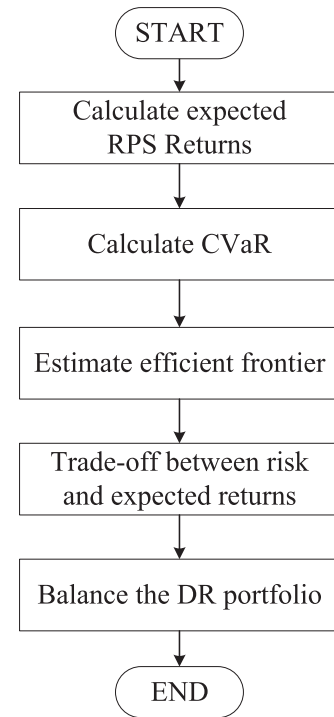


Fig. 5. Flowchart of the risk management algorithm.

return, as a function of SAIDI, dictated by the respective RPS. Fig. 4 shows a typical capped RPS.

Regarding the risk assessment, as it is shown in Fig. 5, we analyze the returns, which are stored in an  $\mathbf{R}$  vector. The positive or negative sign of the  $i$ th value indicates that the annual reliability performance of the network during the  $i$ th MCS is expected to generate reward or penalty respectively. If the  $i$ th value of  $\mathbf{R}$  vector equals to zero, the reliability performance is expected to fall within the target of the RPS regulation, i.e., the dead zone between reward and penalty.

In financial terms, since the implementation of a DR program results in a specific risk–return pair, we can consider DR program as a risky asset. Furthermore, we can consider the  $\mathbf{R}$  vector values as the Monte Carlo simulated returns of a portfolio comprised of various risky assets. Now the problem is

<sup>2</sup>In a similar way, we could produce and use SAIFI statistics.

transformed into estimating which asset allocation minimizes the variance, i.e., the risk, for the desired level of return. In such optimization problems, we can calculate the efficient frontier as introduced by Markowitz in modern portfolio theory [33] using the mean-variance analysis. In this work, we derive the return under the influence of CDFR and RPS, so we can easily assume that the return will follow a non-parametric distribution. Since the variance is calculated by the standard deviation, a metric not applicable in non-parametric distributions, we cannot follow the mean-variance analysis process. According to [44] and [45], we can overcome this problem using, instead of variance, the CVaR, also known as expected shortfall. The  $CVaR_\alpha$  as a risk measure in a non-parametric framework is defined as the average portfolio loss for the worst  $100(1 - \alpha)\%$  of MCSs, where  $\alpha$  is a number between 0 and 1. Usually, the  $CVaR_{0.95}$  is taken into account in the risk management processes.

Regarding the  $CVaR_\alpha$  calculation in a discrete distribution  $X$ , whose cumulative distribution function is  $F_X$ , the authors in [46] and [47] propose the following formulation:

$$CVaR_\alpha(X) := \kappa VaR_\alpha(X) + (1 - \kappa) CVaR_\alpha^+(X), \quad (5)$$

where:

$$VaR_\alpha(X) := \min\{c : P(X \leq c) \geq \alpha\}, \quad (6)$$

$$\kappa := \frac{\psi - \alpha}{1 - \alpha}, \quad (7)$$

$$\psi = F_X[VaR_\alpha(X)], \quad (8)$$

$$CVaR_\alpha^+(X) := E[X | X > VaR_\alpha(X)]. \quad (9)$$

By following the above formulation, the efficient frontier of the DR portfolio is calculated, which indicates the portfolio compositions that yield minimum CVaR for each ER.

Regarding the next processes of risk management, namely risk response and monitoring, we propose that the DNO should rebalance his DR portfolio according to the calculated efficient frontier, to achieve the desired ER with minimum CVaR. Moreover, the portfolio rebalancing should be studied periodically, to ensure the long-term efficiency of the proposed asset allocation.

#### IV. CASE STUDY

##### A. Test System

We applied the above method to the Roy Billinton test system – Bus 2 (RBTS–Bus 2) [48], a typical distribution network with four main distribution power lines, and 22 load points, as shown in Fig. 6. In addition, the RBTS–Bus 2 test system, has also tie-switches, which have been taken into account by the reconfiguration algorithm during network failures. We complemented the original topology by the additional reliability data from [49], and we considered the upstream transmission grid to be fully reliable.

##### B. Load Profiles

The simulation horizon, in this work, is set to one year. Initially, we built a standard hourly load profile, extracted by the hourly, daily, and seasonal statistics given in [50]. The above

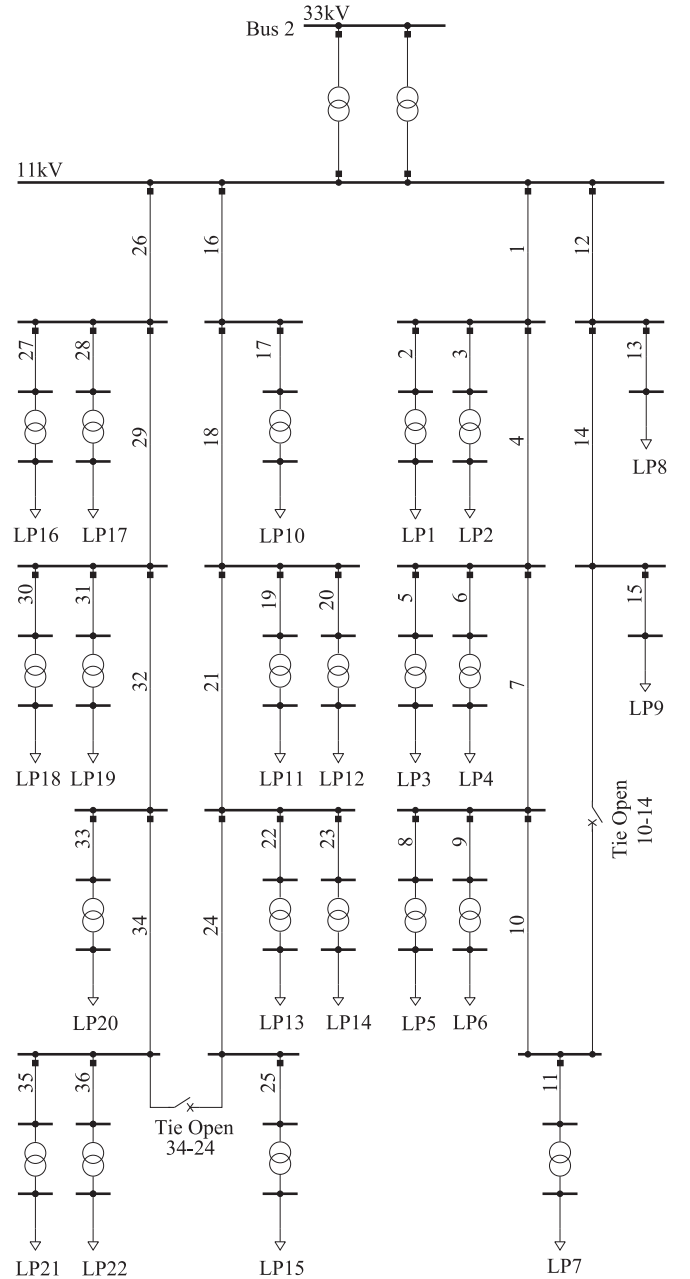


Fig. 6. Topology of the RBTS-Bus 2 test system.

load profile is expressed in 8760 hourly percentage values of the annual peak and it is shown in Fig. 7, transformed in load duration form. Subsequently, every load point acquires a specific hourly load profile, by multiplying its peak load with the above 8760 hourly percentage values. Finally, we apply a normally distributed uncertainty factor  $\pm 5\%$  in every hourly load value. The load profiles regarding the DR programs are explained in the following subsection.

##### C. DR

DR is a multipurpose tool which can be used for many objectives, e.g., reliability enhancement, investment deferral [51],

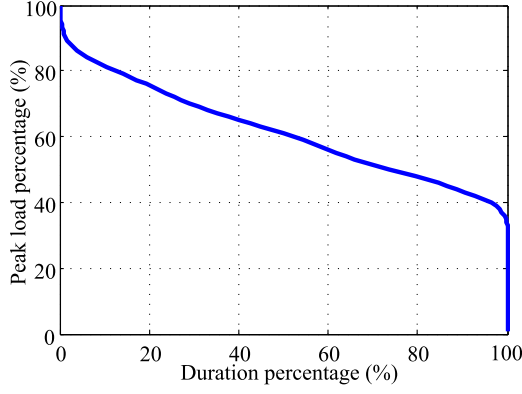


Fig. 7. Load duration curve.

**Algorithm 1:** Load profile calculation for ToU DR program.

**Input:** The annual load profile of all load points  $P_{in}$   
**Output:** The annual load profile for all load points  $P_{ToU}$

- 1: **for** every load point **do**
- 2:   **for**  $t = 1$  to 8760 **do**
- 3:     **if**  $(13h \leq t < 15h \text{ and } 19h \leq t < 22h)$  **then**
- 4:        $P_{ToU,t} = r_{ToU} \times P_{in,t}$
- 5:     **end if**
- 6:   **end for**
- 7: **end for**
- 8: **return**  $P_{ToU}$

and electricity bill savings [52]. A DNO could exploit the DR flexibility for efficient load balancing during peak hours. The typical DR availability, as it is stated in [53] can reduce the peak loads of 810 GW in the U.S.A. and 63 GW in the U.K., by 38–188 GW and 8–11 GW respectively. In percentage values, the above peak load reductions are translated into 4–20% in the U.S.A. and 13–17% in the U.K.

In this work, we modeled in a deterministic way several DR cost-neutral programs of two types, ToU and CPP. For the first portfolio  $P_1$ , which is explained in detail in the results section, regarding the ToU and CPP programs, we choose in respect of the above typical DR availability the load reduction factors as  $r_{ToU} = 0.85$  and  $r_{CPP} = 0.95$ , to create realistic scenarios. That means, regarding the ToU program, we expect to have a load shaving during peak hours; therefore, by  $r_{ToU} = 0.85$ , we impose a load reduction of 15% between 13h00–15h00 and 19h00–22h00 in the load profiles. As for the CPP program, we applied, by  $r_{CPP} = 0.95$ , a 5% load reduction for peak loads higher than 90%. The application processes of the DR programs in the load profiles of the load points are shown in Algorithm 1 and 2. In Table IV we list the reduction factors of the additional DR programs that we studied in the Section IV-F for portfolios  $P_2$  and  $P_3$ , to show the performance of the proposed method.

**D. Other Input Data**

Table I contains the data of the RPS which is used in the case study. It represents a generic non-symmetric RPS scenario, with

**Algorithm 2:** Load profile calculation for CPP DR program.

**Input:** The annual load profile of all load points  $P_{in}$   
**Output:** The annual load profile for all load points  $P_{CPP}$

- 1: **for** every load point **do**
- 2:   **for**  $t = 1$  to 8760 **do**
- 3:     **if**  $P_{in,t} \geq 0.9 \times \max(P_{in})$  **then**
- 4:        $P_{CPP,t} = r_{CPPa} \times P_{in,t}$
- 5:     **else if**  $P_{in,t} \geq 0.85 \times \max(P_{in})$  **then**
- 6:        $P_{CPP,t} = r_{CPPb} \times P_{in,t}$
- 7:     **end if**
- 8:   **end for**
- 9: **end for**
- 10: **return**  $P_{CPP}$

TABLE I  
RPS DATA

$C_r$	$s_1$	$s_2$	$s_3$	$s_4$	$C_p$
50 000 (\$)	10 (min)	40 (min)	60 (min)	300 (min)	-200 000 (\$)

TABLE II  
CDFR DATA

Network element	$I_n^{cr} / I_n^{\max}$	$\lambda_n^{\max} / \lambda_n^c$
Powerline	0.8	10
Transformer	0.8	15

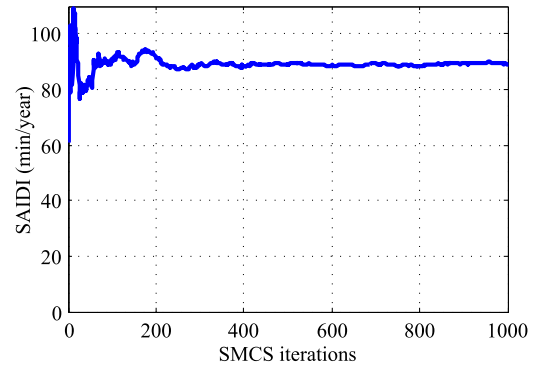


Fig. 8. Convergence of the algorithm results.

different reward and penalty caps. The CDFR data which were used in the simulation, are stored in Table II.

**E. Step-by-Step Execution**

In this subsection, an indicative execution of the methodology is described step by step.

- 1) Collect the input data (Network, Reliability, and DR).
- 2) Calculate load profiles for a new set of SMCS timelines.  
 In this step, a set of three hourly load profiles are calculated for an annual iteration of the BC, ToU, and CPP scenarios as explained in the Sections IV-B and IV-C.

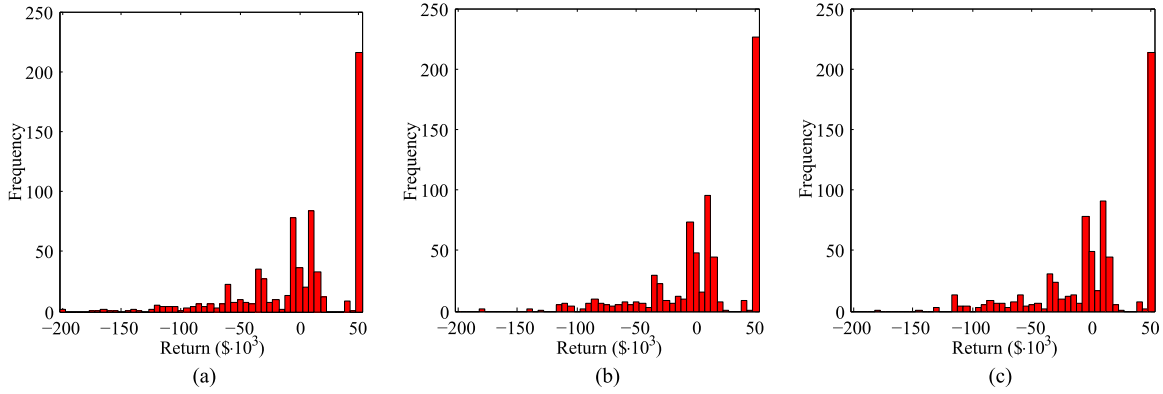


Fig. 9. Simulation results for the network. Higher frequencies are observed for the positive return values, due to the asymmetric cap setting of the RPS. (a) BC. (b) ToU program. (c) CPP program.

In the following steps, the execution of the three scenarios continues in parallel mode. For the step-by-step demonstration, we focus on the BC scenario.

- 3) The algorithm initiates the first iteration for the BC.
- 4) Calculate CDFRs. During the first time interval of the first iteration of the BC scenario, a load flow is solved by MATPOWER, to calculate the loading condition of all network components. The output of this process is the  $\mathbf{P}$  vector filled with the CDFRs as described in (2).
- 5) Calculate failure occurrence. In this step, the random process described in Section II-B is executed and the first column of the  $F$  matrix is calculated. If the elements of the first column of the  $F$  matrix are ones, it means that none component failure occurs in the current time interval. For demonstration purposes, let's assume that the  $F_{(32,1)}$  element which corresponds to the power line 32 is zero.
- 6) In this step, the AS is activated due to the above failure.
- 7) The protection devices which lay upstream of the power line 32 are searched. The nearest upstream protection device is selected to be activated, that is the switch at the upstream side of the power line 32.
- 8) The topology is modified due to the switching action which remains during MTTR duration of the above failure. The load points 20, 21, and 22 are now isolated from the rest of the network.
- 9) Check for reconfiguration. In this case, the tie-switch 34–24 is able to reconnect part of the disconnected load points. The reconfiguration algorithm is activated.
- 10) Collect disconnected load points, i.e., 20, 21, and 22.
- 11) Search for all the neighboring tie-switches. In this case, the tie-switch 34–24 is found.
- 12) If many tie-switches are found, a load flow is solved for every potential reconfiguration, to exclude any infeasible options which may lead to overloads. The feasible options are ranked in descending order in terms of the amount of the disconnected load that can recover.
- 13) Return the network reconfiguration selection, i.e., tie-switch 34–24, to the AS.
- 14) The topology is modified due to the activation of the tie-switch 34–24.

TABLE III  
CVaR AND ER FOR THE THREE SCENARIOS

Scenarios	BC	ToU	CPP
CVaR	\$128 600.0	\$107 410.0	\$111 170.0
ER	\$605.76	\$5592.17	\$2920.04

- 15) Find disconnected consumers. If any load point found disconnected in this step, the disconnection statistics are stored, for the calculation of the SAIDI at the end of the SMCS iteration. In this case, the load points 20, 21, and 22 are reconnected instantly by the reconfiguration.
- 16) All the processes of the first time interval are completed. The algorithm proceeds to the next time interval and recycles from the step 4.
- 17) When the last time interval is completed, the algorithm proceeds to the next iteration and recycles from step 3.
- 18) When the last iteration is completed, the algorithm proceeds to the SAIDI distribution calculation as described in (4). A similar calculation takes place after the completion of the ToU and CPP scenarios.
- 19) In the next step, the SAIDI distributions of the three scenarios are transformed point-by-point by the RPS into return distributions, as shown in Fig. 9.
- 20) In the next step, ER and CVaR are calculated for the three scenarios, as explained in the Section III-B. The values are stored in Table III.
- 21) The values of Table III are given as input in the PortfolioCVaR object in MATLAB [54], to estimate the efficient frontier and the respective asset allocations.
- 22) The results of the previous two steps are presented in a CVaR – ER diagram, as in Fig. 10 and in an asset allocation diagram, as in Fig. 11.
- 23) The DNO operator selects the desired CVaR – ER combination from the efficient frontier.
- 24) The CVaR selection is transformed to the optimal asset allocation by the diagram in Fig. 11.
- 25) The selected portfolio should be rebalanced if any of the input data change.



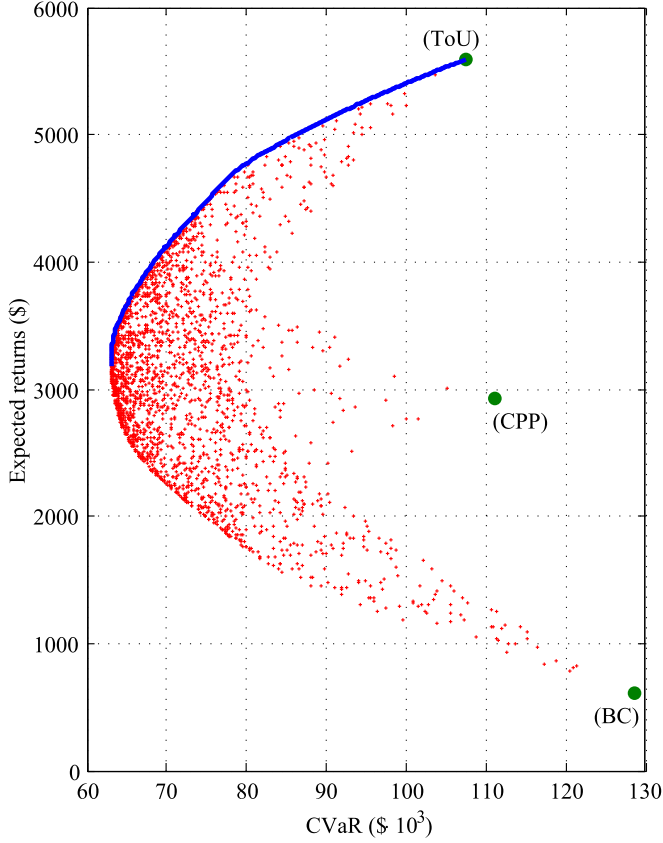


Fig. 10. Efficient frontier of the DR portfolio  $\mathcal{P}_1$  (blue line). The red crosses depict the locus of 1000 random and subefficient DR portfolio allocations. Every DR portfolio allocation shares its 100% in specific ratios between the three portfolio assets, namely the BC, the ToU, and the CPP. The green points represent the CVaR–ER results of the simulated scenarios, from Table III.

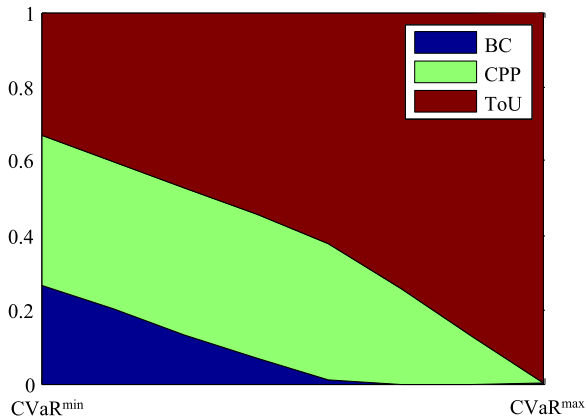


Fig. 11. Asset allocation diagram. The  $\text{CVaR}^{\min}$  to  $\text{CVaR}^{\max}$  range of the horizontal axis, corresponds to the respective CVaR values of the efficient frontier of Fig. 10.  $\text{CVaR}^{\min} = \$63\,025.53$  and  $\text{CVaR}^{\max} = \$128\,600.0$ .

## F. Results

In a preliminary simulation, we tested the algorithm convergence for the SAIDI estimation in RBTS–Bus 2. Fig. 8 depicts the annual SAIDI estimation as a function of the number of SMCS iterations. It is obvious that 300 iterations can be considered sufficient to achieve convergence. In this paper, the iteration

TABLE IV  
REDUCTION FACTORS IN DIFFERENT SCENARIOS

Reduction factors	BC	ToU	ToU <sub>2</sub>	CPP	CPP <sub>2</sub>
$r_{\text{ToU}}$	1	0.85	0.90	1	1
$r_{\text{CPPa}}, r_{\text{CPPb}}$	1, 1	1, 1	1, 1	0.95, 1	0.90, 0.95

counter is set to 700, to secure a plethora of SAIDI values to have an accurate representation of the distribution statistics.

In this work, we executed three different annual scenarios, the BC, the ToU, and the CPP scenarios. In the BC scenario, the RBTS–Bus 2 was fed by the load profiles calculated in accordance to Section IV-B, whereas in ToU and CPP scenarios, the load profiles are modified by the respective DR program, as explained in Section IV-C. For each scenario, we applied 700 SMCS iterations, to estimate the SAIDI values and to fill the  $\mathbf{S}$  vector as defined in Section III. Subsequently, we transform the SAIDI performance into monetary return, based on the RPS program shown in Table I. The distributions of the annual return of the three scenarios are shown in the respective histograms of the Fig. 9.

The ER of the 5% worst (lowest return) scenarios, namely the CVaR of the  $\mathcal{P}_1$  portfolio, is calculated for BC, ToU, and CPP, by the process presented in (5)–(9), and the results are reported in Table III. In the same table, the respective ER values are also reported. The above two metrics constitute the input data for the mean-CVaR analysis to produce the efficient frontier for these three assets. We input the values of Table III to the MATLAB tool that implements the CVaR portfolio optimization, namely PortfolioCVaR object [54]. The outcome is shown in Fig. 10. In addition, PortfolioCVaR produces an asset allocation diagram as shown in Fig. 11 for all the range of CVaR values which belongs to the efficient frontier. A DNO could follow the above analysis to calculate the optimal DR program allocation to guide the reliability performance of his network to the desired level in order to have either minimum CVaR for the desired ER, or maximum ER for the desired CVaR, according to his risk tolerance.

For example, a risk-neutral DNO might choose the optimal DR portfolio allocation for a risk level of  $\text{CVaR} = \$71\,237.91$  which yields  $\text{ER} = \$4\,217.46$  according to the efficient frontier. Numerous asset allocations could provide such CVaR, but only the one which belongs to the efficient frontier can provide it under the maximum ER. The composition of this risk-neutral asset allocation is calculated by the Fig. 11 as follows: (BC, ToU, CPP) = (6.71%, 54.36%, 38.93%).

In a second example, a risk-averse DNO will choose the minimum risk, which is  $\text{CVaR}^{\min} = \$63\,025.53$ , that yields  $\text{ER}^{\min} = \$3\,186.43$ . The only asset allocation which can provide minimum risk lays in the left side of the Fig. 11, which is: (BC, ToU, CPP) = (26.55%, 32.96%, 40.49%).

We study two additional scenarios, namely ToU<sub>2</sub> and CPP<sub>2</sub> to compare the impact of different load reduction magnitude on both sides of the initial portfolio. Their respective reduction factors are stated in Table IV. We construct two additional

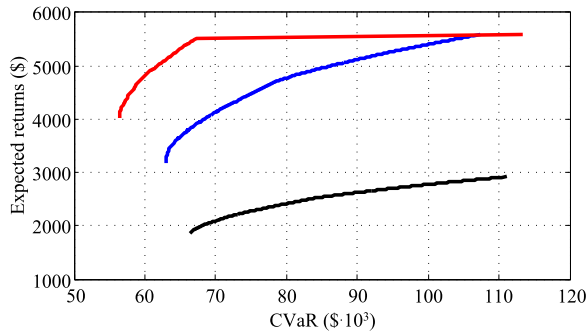


Fig. 12. Efficient frontiers of three DR portfolios. The blue line for  $\mathcal{P}_1$ , the black line for  $\mathcal{P}_2$ , and the red line for  $\mathcal{P}_3$ . The asset allocations on the efficient frontier of the  $\mathcal{P}_2$  yields less ER for the same CVaR in comparison to the  $\mathcal{P}_1$ . The exact opposite is the case between  $\mathcal{P}_3$  and  $\mathcal{P}_1$ .

TABLE V  
MINIMUM CVAR AND ER OF  $\mathcal{P}_1$ ,  $\mathcal{P}_2$ , AND  $\mathcal{P}_3$

Portfolios	$\mathcal{P}_1$	$\mathcal{P}_2$	$\mathcal{P}_3$
CVaR <sup>min</sup>	\$63 025.53	\$66 394.0	\$56 421.0
ER <sup>min</sup>	\$3 186.43	\$1 854.78	\$4 033.38

portfolios and we calculate their efficient frontiers by using these scenarios as follows:  $\mathcal{P}_2$ : (BC, ToU<sub>2</sub>, CPP) and  $\mathcal{P}_3$ : (BC, ToU, CPP<sub>2</sub>). As it is shown in Fig. 12, the smaller reduction factor of ToU<sub>2</sub> in  $\mathcal{P}_2$  produces an efficient frontier with smaller expected returns, while the exact opposite is the case with the larger reduction factor of CPP<sub>2</sub> in  $\mathcal{P}_3$ . We list in Table V the ER that is yielded under the minimum risk for the three cases.

## V. CONCLUSION

This paper proposes a method for quantitative risk management by DR in DNs subject to PBR regulation. The method evaluates the financial risk of the annual DN reliability performance and provides a specific efficient frontier depended on the characteristics of the DN and of the DR programs under study. The efficient frontier represents the optimal DR portfolio allocations which yield the maximum ER for any risk preference. Therefore, a DNO can use this method as a decision support system to trade-off efficiently between risk and ER.

The reliability assessment problem has been solved by the AMCHM, taking into account CDFR, and network reconfiguration. The risk management has been conducted by the mean-CVaR analysis for non-normally distributed return.

Finally, a case study has been presented to demonstrate the capability of the proposed method. In more detail, the test case which we applied in the RBTS-Bus 2 test system, shows that in a base case, without DR allocation, the DNO is expected to yield \$605.76 annually due to the rewards and penalties of RPS with a mean risk of \$128 600.0 in the worst 5% scenarios. On the other hand, the most risk-averse DNO could apply the proposed method to design a DR portfolio for minimum risk, which is calculated to yield \$3 186.43 with a mean risk of \$63 025.53 in the worst 5% scenarios.

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