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# Robust Switch Selection in Radial Distribution Systems Using Combinatorial Optimization

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***Abstract*—Selecting the best type of equipment among available switches with different prices and reliability levels is a significant challenge in distribution system planning. In this paper, the optimal type of switches in a radial distribution system is selected by considering the total cost and reliability criterion and using the weighted augmented epsilon constraint method and combinatorial optimization. A new index is calculated to assess the robustness of each Pareto solution. Moreover, for each failure, repair time is considered based on historical data. Monte Carlo simulations are used to consider the switch failure uncertainty and fault repair time uncertainty in the model. The proposed framework is applied to an RTBS Bus-2 test system. Furthermore, the model is also applied to an industrial system to verify the proposed method's excellent performance in larger practical engineering problems.**

***Index Terms*—Combinatorial optimization, Monte Carlo Simulation, multi-objective optimization, radial distribution system, reliability, robustness.**

## NOMENCLATURE

### A. Indices

| | |
|---|---|
| $s$ | Index for scenarios. |
| $sw$ | Index for switches. |
| $y$ | Index for switch types. |
| $f$ | Index for faults. |
| $i$ | Index for busses. |
| $l$ | Index for intervals in Monte Carlo simulation. |
| $t$ | Index for uncertain parameters. |
| $q$ | Index for Pareto optimal solutions in a Pareto front. |
| $u$ | Index for objective functions. |

### B. Parameters

| | |
|---|---|
| $rr_y$ | Reliability of switch type $y$. |
| $\lambda_{sw}$ | Failures Rate for location $sw$. |
| $r_f$ | Repair time for fault $f$. |
| Load$_i$ | Load at bus $i$. |
| $d_y$ | Dependability of switch type $y$. |
| $F_{sw,y}$ | Switch price. |
| $\alpha_{l,t}$ | The probability of selecting interval $l$ in Monte Carlo simulation for uncertain parameter $t$. |
| $N_q$ | Number of objective functions. |
| $OW_u$ | The weighting factor for objective function $u$. |

### C. Variables

| | |
|---|---|
| ENS | Energy not supplied. |
| $u_{sw,y}$ | Binary decision variable for switch selection. |
| $W_{l,t,s}$ | Decision variable for constructing scenarios in Monte Carlo simulation. |
| Prob$(s)$ | probability of each scenario. |
| $PFR_S$ | Robustness of the whole Pareto front obtained in scenario $s$. |
| $RI_q$ | Robustness index for Pareto solution $q$. |
| $\mu_u^q$ | membership function for objective function $u$ Pareto solution $q$. |
| $f_u^q$ | Value of objective function $u$ for Pareto solution $q$. |
| $f_u^{SN}$ | Value of pseudo-Nadir point for objective function $u$ for Pareto solution $q$. |
| $f_u^U$ | Value of utopia point for objective function $u$ for Pareto solution $q$. |
| $\mu^q$ | membership function Pareto solution $q$. |
| POS | Code for each Pareto optimal solution. |

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## I. INTRODUCTION

THE occurrence of outages is widespread in distribution systems [1]. Equipment failure usually occurs due to improper maintenance or environmental situations. Most of the outages occur in distribution systems because the amount of equipment is enormous in these systems compared to the generation and transmission sectors. This makes the maintenance in distribution systems much harder. In addition, since distribution systems' failures are not as critical as in transmission/generation systems, reliability is often not seriously considered. However, reliability improvement in distribution systems may considerably improve the overall power system reliability. Therefore, it is essential to find an economically feasible way to improve distribution system reliability.

In previous research, the main objective of distribution system planning was to minimize the total cost [2]. However, this approach is not acceptable from a social viewpoint. In an optimal distribution system, reliability assessment, the interruption costs that the industrial and residential customers pay due to interruption in production or decrease in welfare, should be considered. In [3], the interruption costs are considered as an objective function to solve the switch selection problem in a radial system. In [4], the effects of using remote switches instead of regular disconnecting switches is presented. In [5], a reliability model based on Monte Carlo simulation is presented to measure the system's reliability indices. The system failures are categorized into temporary and permanent faults.

Several methods are presented in literature to address the distribution system reliability. In [6], remote switches' number and location are selected in a distribution system and DG sources. The presented model is solved using an oppositional differential search algorithm. In addition to DG placement, in [7], a capacitor placement is suggested to improve the radial distribution system. To solve this problem, a heuristic algorithm, called fish electro-location optimization, is introduced. In [8], a service restoration strategy is presented for service restoration in distribution systems with DG sources. An efficient Matrix-based reliability evaluation method is used in [9]. In the proposed method, each fault event's influence is shown on each load interruption, providing beneficial insight when dealing with reliability improvement in distribution systems.

The optimal selection of equipment in the planning sector's distribution systems is essential to improve system reliability. Nonoptimal device selection will force the distribution system operator to change the equipment before their useful remaining life (URL) is finished, which significantly increases the total operational costs.

One of the most crucial pieces of equipment that should be selected in a distribution system is switches, since they have a considerable effect on distribution system reliability. An extensive study on circuit breaker reliability is presented in [10]. The sectionalizing switches are essential in an automated distribution network. In [11], a genetic algorithm is used to determine the optimal location for sectionalizers and tie points in distribution systems. The goal is to minimize the cost of switches and outage costs and simultaneously improve the reliability criterion.

The optimal switch placement in distribution systems with high penetration of a DG source is addressed in [12] to achieve a certain level of reliability while considering investment and operational cost. It is shown that DG can be used to provide improvement in reliability indices. In [13], the optimal placement of sectionalizing switches and protective devices in distribution networks is used as a successful strategy to enhance system reliability in DG units' presence.

In [14], a novel method is presented to select the switches that should be upgraded in the distribution systems to improve their reliability and decrease their losses. The variations in daily and hourly demand are incorporated into the model to make the model more realistic.

Another model is presented in [15] to determine the remote switch location to enhance the distribution system reliability. A PSO-based multi-objective optimization technique is introduced in [16] to solve the switch placement problem in radial distribution systems, reducing capital costs, and simultaneously improving reliability. The selection of a switch type despite its considerable impact on total cost and reliability criterion is not addressed thoroughly in the technical literature. An appropriate switch selection should simultaneously minimize the total cost and improve the reliability index. Reliability and cost are usually in conflict with each other, which means an improvement in one of them results in a decrease in the other, and vice versa. This calls for the usage of multi-objective optimization techniques [17].

Since it is impossible to forecast the exact time and location of faults in the system, the distribution system planner should take some measures to guarantee that the solutions he/she has made are optimal for a wide range of credible scenarios. In other words, the results should be robust against inaccuracy in forecasted parameters of the system, such as equipment failure rate, etc. In [18], the information gap decision theory is used to develop a robust framework for short-term hydrothermal scheduling to deal with severe load uncertainties. In [19], the authors use a flexible virtual power plant to increase the system robustness against uncertainty in distributed energy sources output. In [20], a new technique to improve the distribution system's robustness against extreme weather events is presented. The paper aims to minimize the total load shedding cost and damage repair cost in the case of low probability, and high impact extreme weather events.

In the published papers, the optimal switch selection to simultaneously minimize cost and improve reliability is not considered. Furthermore, robustness analysis in switch selection in distribution systems is not addressed.

Optimal switch selection considerably decreases the operational costs in the long-term horizon, especially during the design stage of large manufacturing plants or distribution systems. It also increases the system reliability and reduces the load shedding and its consequent expenses. In this paper, a new model is presented, determining the optimal type of switches considering the total cost, reliability, and robustness. The model obtains the system data, and the candidate switches data as input.

The main contributions of this paper are as follows:

- A multi-objective framework for optimal switch selection in distribution systems is proposed using the augmented weighted epsilon constraint method and fuzzy decision-making and combinatorial optimization to simultaneously optimize the total cost and reliability index.
- A new index is proposed to assess Pareto optimal solutions' robustness and the robustness of the entire Pareto front. The decision-maker uses this index in order to quantify the robustness of each solution. This index is used together with the total cost and reliability index in the fuzzy decision-making method to find the final solution.
- The uncertainty in the reliability of the switch and repair time of the fault is considered using the Monte Carlo simulation. The repair time uncertainty is usually neglected in the technical literature, although it significantly affects the final solutions' optimality.

- The undesired tripping of the circuit breaker is considered in the model. This will make the model more realistic.

## II. Model Characteristics

### A. Deterministic Optimal Switch Selection Formulation

Total energy not supplied is calculated using equation (1):

$$ENS = \sum_{y}\sum_{sw}\sum_{i\in \text{LEM}_s} rr_y \times \lambda_{sw} \times u_{sw,y} \times r_f \times \text{Load}_i + \sum_{y}\sum_{sw}\sum_{i\in \text{LEM}_s^2} (1-rr_y) \times \lambda_{sw} \times u_{sw,y} \times r_f \times \text{Load}_i + \sum_{y}\sum_{sw}\sum_{i\in \text{LEM}_s} d_y \times r_f \times u_{sw,y} \times \text{Load}_i \quad (1)$$

where ENS is the total energy not supplied during one year, $rr_y$ is the reliability of switch type $y$, $\lambda_{sw}$ is the number of failures per year for the line, where switch $sw$ is located, $r_f$ is the repair time for fault f in hours, and $u_{sw,y}$ is a binary decision variable, which is 1 when the model decides to select type $y$ for switch $sw$. In this paper, the switch's location is considered to be known, and the problem is solely focused on determining the type of switches.

The utmost important characteristic of a radial power distribution network is that the power flow is in only one direction. In this condition, when a switch is operated, its entire downstream loads will be de-energized. In (1), ENS consists of three components. The first term calculates the total energy not supplied when a fault has occurred, and the switch has operated to clear the fault. The second line considers the situation when the fault has occurred, but the switch has failed to operate, and therefore the upstream switch has to clear the fault, which means in this case that more loads are disconnected. In this paper, the simultaneous failure of two switches is not considered. Consideration of simultaneous failures can be easily added to the model but is very unlikely to happen. The third line calculates the amount of ENS caused by the switch's incorrect operation, which means the operation of the switch when there is no command. This can happen because of the mechanical problems of a switch or an incorrect setting. $\text{Load}_{i,f}$ is the disconnected load in the bus $i$ during fault $f$. $\text{LEM}_s$ determines the disconnected loads when the switch $sw$ is opened. $\text{LEM}_s^2$ shows the disconnected loads when switch $sw$ is supposed to open but fails to work correctly, and its upstream switch operates. $d_{sw,y}$ determines the probability of the unintended operation of switch $sw$ with type $y$.

As mentioned earlier, there are different types of switches available with different reliability and prices. The total cost of switches can be easily obtained, as follows:

$$\cos t = \sum_{sw}\sum_{y} u_{sw,y} \times F_{sw,y} \quad (2)$$

where $F_{sw,y}$ is the price of switch $sw$ with type $y$. The switch price depends on several features, such as its level reliability, voltage level, current making, and breaking capability.

The single constraint of this optimization model is related to the capital cost of the selected switches. This capital cost should be less than the predetermined available investment.

### B. Stochastic Formulation

The reliability of each switch is assessed on its profound uncertainties and is usually predicted based on historical data. Neglecting the uncertainty will lead to divergence from the optimal solution due to forecasting error. To avoid this, a stochastic model is implemented using a Monte Carlo simulation. Another source of uncertainty is repair time. For example, the fault of a feeder in a transformer can vary from several hours to several weeks. It is necessary to consider this when modeling the distribution system.

To solve these stochastic problems, the problem is first converted to a set of deterministic problems called scenarios. This can be achieved by defining a discrete probability distribution function for each uncertain parameter. The procedure of scenario generation is described in the following Sub-Section.

### C. Robust Multi-objective Combinatorial Optimization

In this Section, the presented framework is described, and a new robustness index is introduced, as described in [21]. The procedure consists of the following steps:

#### 1) Generating the reference Pareto front

The deterministic multi-objective problem is solved, and the reference Pareto front is generated.

#### 2) Determining the number of scenarios

The number of scenarios (S) is determined. This number is set based on a compromise between compilation time and accuracy in uncertainty modeling. A larger number of scenarios leads to more accurate uncertainty modeling, but a large value will make the problem very difficult to solve.

#### 3) Scenario generation

S scenarios are generated using the Monte Carlo simulation. First, the probability function is discretized, and the probability for each section is determined. This can be seen in Fig. 1 [23]. The probability of each interval is calculated according to Fig. 2. Scenario generation is performed using the roulette wheel method [22]. In this method, for each parameter, a random point in Fig. 2. is selected [23], and based on the position of the point, the percentage of forecast error is determined.

This is done for all the uncertain parameters of the problem. By knowing the forecasting error for each parameter and its forecasted value, each scenario's parameters are calculated. Finally, to generate the scenario S, the calculated values of

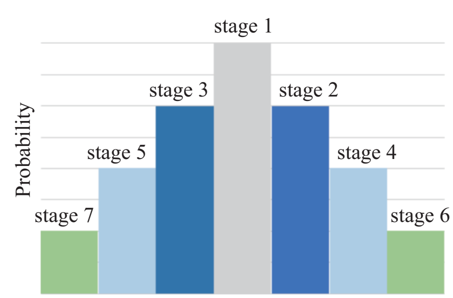


Fig. 1. Dividing the probability distribution function into several intervals.

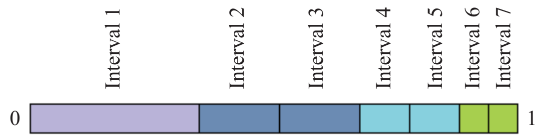


Fig. 2. Calculation of accumulative distribution function.

uncertain parameters are selected as shown in (3):

$$S = \{W_{1,t,s}, \cdots, W_{7,t,s}\} \tag{3}$$

where $W_{l,t,s}$ is a binary variable determining which interval is used for uncertain parameter $t$ in scenario $s$.

The mentioned steps are repeated for the determined number of scenarios (S) in step 2. The probability of each scenario is calculated using Eq. (4).

$$\text{Prob}(s) = \frac{\prod_{t=1}^{\text{T}} \left(\sum_{l=1}^{7} (W_{\text{l, t, s}} \alpha_{l,t})\right)}{\sum_{s=1}^{\text{S}} \prod_{t=1}^{\text{T}} \left(\sum_{l=1}^{7} (W_{\text{l, t, s}} \alpha_{l,t})\right)} \tag{4}$$

From Fig. 2, the following equation can be induced:

$$\sum_{l=1}^{7} \alpha_{l,t} = 1 \quad \forall t \tag{5}$$

where $T$ is the total number of uncertain parameters in the model.

*4) Solving the deterministic multi-objective problem*

For each scenario, a deterministic bi-objective optimization problem is solved to simultaneously minimize the total cost and ENS, which is calculated using (1) and the total cost is calculated using (2). The augmented weighted Epsilon constraint method is used in this paper to find the Pareto front for each scenario. This method is well described in [24].

*5) Calculation of robustness indices*

To consider the robustness during switch selection, a robustness index should be calculated for each solution [21]. Using this index, the solutions with high sensitivity to forecasting errors will be less likely to be selected in the decision-making process.

After solving multi-objective optimization problems for S times, S Pareto fronts and S×QPareto optimal solutions (POS) are generated where Q is the size of each Pareto front. For each POS in the reference Pareto front, its frequency over S Pareto fronts is counted ($N_q$). This shows that each POS has appeared in how many Pareto fronts. Then the robustness index (RI) is calculated for each POS as follows [21]:

$$RI_q = \frac{N_q}{S} \tag{6}$$

After calculating RI for each POS, the whole Pareto front's robustness can be calculated as the average $N_q$ of Pareto optimal solutions [21].

$$PFR_S = \frac{\sum_{q=1}^{Q} RI_P}{Q} \tag{7}$$

These indices are used as an additional criterion in the decision-making process.

*6) Decision making*

In multi-objective optimization, the final step is to find the most preferred solution among Pareto optimal solutions. Fuzzy Decision Making (FDM) is one of the most popular tools to perform this task [25]. In FDM, a linear fuzzy membership function is calculated for each objective function, which indicates the degree of optimality for the $u^{\text{th}}$ objective function in the $q^{\text{th}}$ Pareto-optimal solution. The membership function is calculated as follows for objective functions that should be minimized [25]:

$$\mu_u^q = \begin{cases} 1 & f_u^q \le f_u^U \\ \dfrac{f_u^q - f_u^{SN}}{f_u^{SN} - f_u^U} & f_u^U \le f_u^q \le f_u^{SN} \\ 0 & f_u^{SN} \le f_u^q \end{cases} \tag{8}$$

where $f_u^{SN}$ and $f_u^U$ are the worst and best values for the $u^{\text{th}}$ objective as obtained in the payoff table. It should be noted that values of $f_u^{SN}$ and $f_u^U$ are different for each scenario. In addition to objective functions, the RI of each solution is also considered to find the final solution in decision-making. The total membership function ($\mu^q$) of each solution is computed using the relative importance of the criteria ($OW_u$) as follows:

$$\mu^q = \left(\sum_{u=1}^{2} OW_u \times \mu_u^q\right) + OW_3 \times RI^q \tag{9}$$

The best compromise solution is the solution with the maximum total membership function. A higher membership function for a solution means the closer an objective function value is to its utopia value.

## III. Numerical Results

In this Section, the presented model is implemented on a RBTS Bus-2 [26]test system and in a real industrial plant to verify the proposed robust multi-objective stochastic model's excellent performance.

Load data and failure rates are taken from [27]. The reliability of the fuses is considered 100 % for the sake of simplicity. It can be easily added to the model. Six types of switches with different failure rates and prices are considered in this paper. The results for different situations are presented in the remainder of this section.

All simulations are performed using the CPLEX 12.3 solver of the general algebraic modeling system (GAMS) software package.

### A. RTBS BUS-2

In this Section, the proposed model is implemented on a simple RTBS bus-2 system, and the obtained results are discussed. The test system includes 22 load points and ten switches. The candidate switch data are presented in Table I.

The reference Pareto front is shown in Fig. 3. The results are shown in Table II. In the last column, the type of selected switches in each POS is presented. For example, 6666616666 means that SW6 is type 1, and other switches are type 6. This can be mathematically formulated as follows:

$$POS = \sum_{y=1}^{y=Y} \left(u_{s,y} \times \text{Ord}(y) \times \sum_{s=1}^{S} 10^{(\text{Ord}(s)-1)}\right) \tag{10}$$

TABLE I
CANDIDATE SWITCH PROPERTIES

| Type | Cost ($) | Failure Rate |
|---|---|---|
| 1 | 6419 | 0.9999 |
| 2 | 5000 | 0.99 |
| 3 | 3600 | 0.98 |
| 4 | 2469 | 0.97 |
| 5 | 2393 | 0.96 |
| 6 | 1280 | 0.95 |

TABLE II
LOAD CURTAILMENT IN MW FOR EACH SWITCH FAILURE

| SW No. | Load curtailment (MW) | SW No. | Load curtailment (MW) |
|---|---|---|---|
| SW1 | 2.575 | SW6 | 1.586 |
| SW2 | 1.474 | SW7 | 0.454 |
| SW3 | 0.454 | SW8 | 2.486 |
| SW4 | 1.15 | SW9 | 1.586 |
| SW5 | 2.571 | SW10 | 1.02 |

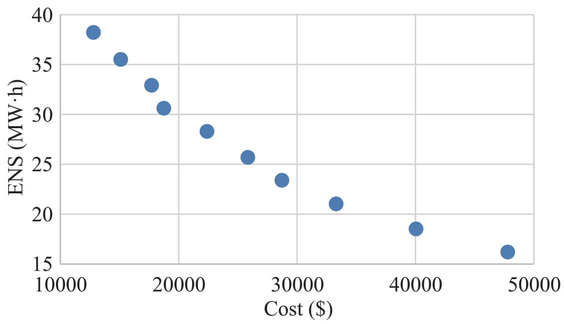


Fig. 3. Reference Pareto front.

As shown in Table III, in solution 1, the cheapest switches are selected for all locations. Since less expensive switches have lower reliability, solution 1 has the highest ENS. To improve reliability, e.g., decreasing the ENS, the total cost is increased. The increase in cost is because of selecting more expensive switches, as evident in Table III.

TABLE III
REFERENCE PARETO FRONT

| No. | Cost | ENS | POS |
|---|---|---|---|
| 1 | 12800 | 38.21858 | 6666666666 |
| 2 | 15102 | 35.5122 | 6666646665 |
| 3 | 17709 | 32.92297 | 6626646666 |
| 4 | 18745 | 30.61917 | 6446446664 |
| 5 | 22389 | 28.29563 | 6446426654 |
| 6 | 25840 | 25.69515 | 6436434652 |
| 7 | 28716 | 23.3976 | 6426424642 |
| 8 | 33298 | 21.03364 | 4326324632 |
| 9 | 40048 | 18.52557 | 4226223621 |
| 10 | 47795 | 16.20464 | 3214212421 |

Table II shows the amount of curtailed load caused by the failure of each switch. As seen in Table II, the effect of each switch on the system reliability is not identical. It is clear from Table II that failure in switches 1, 5, and 8 will lead to more load outage than other switches. Therefore, when deciding to improve the reliability of the system, these switches should be the priority. For example, in solution 10, the most expensive switches are selected for locations 1, 5 and 8, and for locations 3 and 7, less expensive switches of type 4 are selected.

In the next step, using a Monte Carlo simulation, 20 scenarios are generated as described above. The reference Pareto front with robustness information is presented below. As seen in Fig. 4, solutions 1–4 and 7 are more robust. Solution 10 is not shown in the results since it exists in none of the scenarios. It is clear from Fig. 4 that, in general, the results with low ENS are less robust against uncertainty in switch failure and repair time. This means increasing the system reliability is more vulnerable to inaccuracy in parameter forecasting.

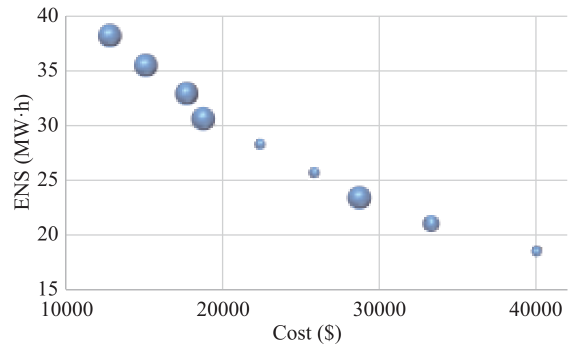


Fig. 4. Pareto front with robustness information.

It should be noted that fault repair time is independent of switch type and, therefore, does not influence the selection of switch types. In other words, if the fault repair time takes more than expected, the cost of the selected switch is not increased. On the contrary, repair time adversely affects reliability. Longer repair time causes more load shedding and more ENS.

After finding the Pareto front, FDM is used to find the best solution. Cost, reliability, and robustness are considered to find the final solution. The weighting factors are equal, because, without loss of any generality, the importance of cost, reliability and robustness are considered to be equal in this study. The total membership functions are presented in Table IV.

TABLE IV
MEMBERSHIP FUNCTION

| No. | MF | No. | MF |
|---|---|---|---|
| 1 | 0.667 | 6 | 0.699 |
| 2 | 0.686 | 7 | 0.739 |
| 3 | 0.7 | 8 | 0.715 |
| 4 | 0.725 | 9 | 0.672 |
| 5 | 0.692 | 10 | 0.333 |

The best solution is solution 7, with 23.4 MW·h ENS and a cost equal to $28,716. As seen in Fig. 4, the robustness of the selected solution is high. For more critical locations, i.e., locations 1, 5, and 8, switch type 2 is selected in this solution. For locations 3 and 7, which are less critical, according to Table III, the lower cost switches are selected.

## B. A Real Industrial Distribution System

The proposed model is applied to a real industrial distribution system to further investigate its performance. The under-study distribution system in Ahvaz city includes 37 Medium voltage loads, two 33/11 kV transformers, four 132/33 kV incoming transformers, and twenty-five 33/6.3 kV transformers. The 49 MV switches are used throughout the system. The total demand is about 152 MW. The layout of the system is shown in Fig. 5.

It should be noted that despite urban distribution systems, in industrial plants, each load's effect on the process should be considered. For example, in some cases, a trip in a small motor can result in a plant shut down. Therefore, it is crucial to consider the importance of each motor from the process operation point of view. This importance should be determined. Comparisons of Figs. 6 and 7 show that improving reliability is due to the process operator. The results are shown below in Fig. 6., which is in conflict with the robustness of the model. Also, it can be seen that in comparison to Fig. 4, the robust regions in the Pareto front are decreased.

The results obtained by the FDM method are shown in Table V. As made clear in Table V, solution 2 with $98,073 and 1,730 MW·h is selected as the final solution. Fig. 6 shows that the robustness of the selected solution is acceptable.

The model provides information about robustness for each solution. This information can be used for optimal switch selection. This is very important, usually during the design stage of large manufacturing factories or distribution networks. Such distribution networks include many switches with different ratings. Appropriate selection of these switches can reduce the costs associated with involuntarily load shedding [3]. In addition, it will lead to less operational costs in the long-term period.

## IV. Conclusion

This paper has presented a new model to incorporate uncertainty in multi-objective switch selection in distribution systems. The presented model considers uncertainty in repair time and uncertainty in switch failure as the primary uncertainty sources. Errors in the forecasting of uncertain parameters can lead to non-optimal solutions. Therefore, it is necessary to determine the robust areas of the Pareto front. To do this, a new robustness index is calculated for each Pareto

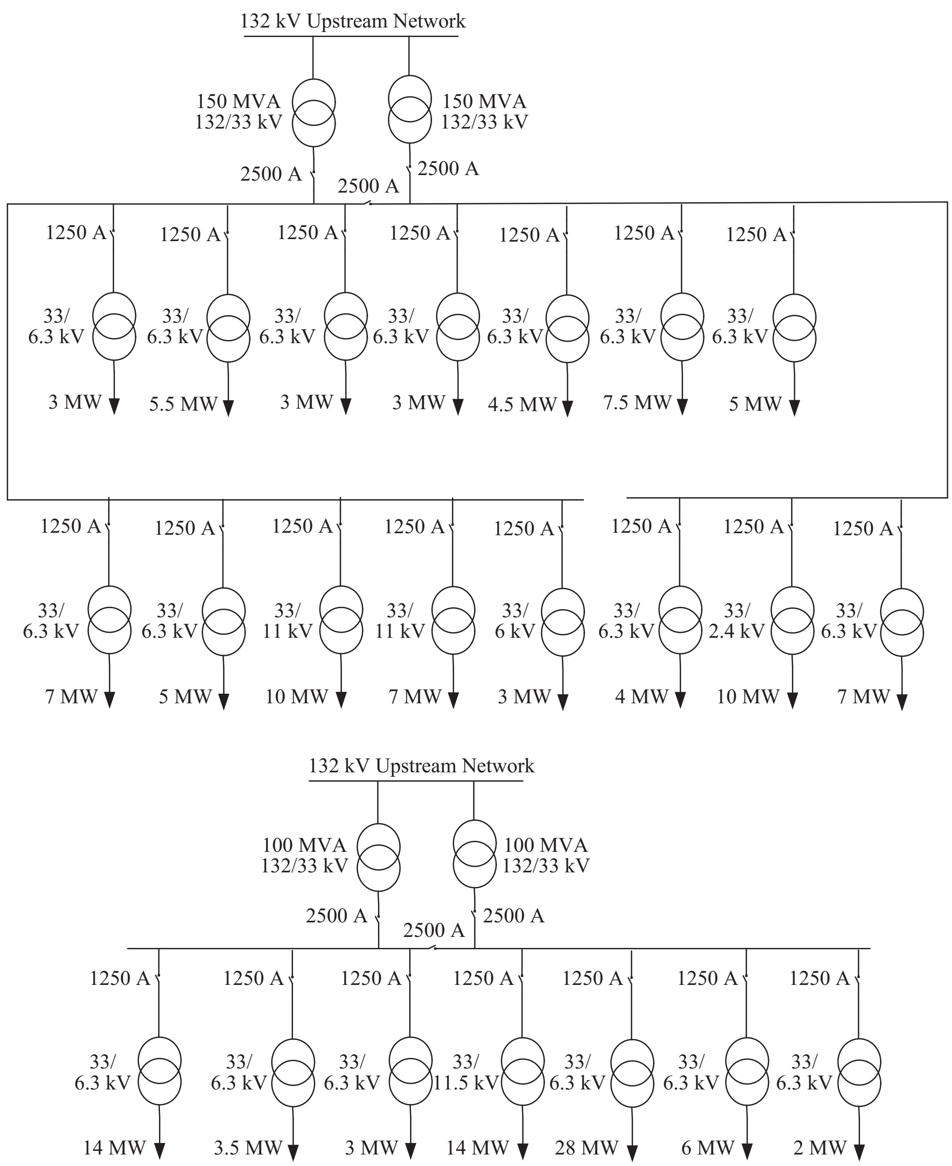


Fig. 5. The system layout of the real industrial distribution system in Ahvaz.

TABLE V
MEMBERSHIP FUNCTION FOR THE REAL INDUSTRIAL DISTRIBUTION SYSTEM IN AHVAZ

| No. | MF | No. | MF |
|---|---|---|---|
| 1 | 0.667 | 6 | 0.447 |
| 2 | 0.696 | 7 | 0.451 |
| 3 | 0.470 | 8 | 0.437 |
| 4 | 0.490 | 9 | 0.405 |
| 5 | 0.436 | 10 | 0.333 |

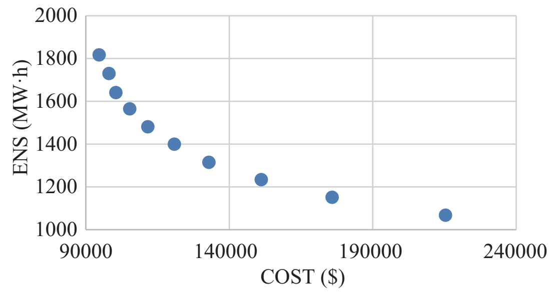


Fig. 6. Reference Pareto front for the real industrial distribution system in Ahvaz.

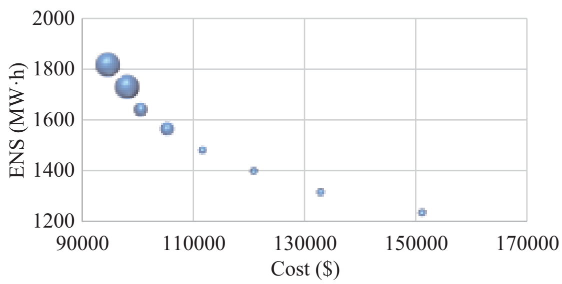


Fig. 7. Pareto front with robustness information for the real industrial distribution system in Ahvaz.

optimal solution. Using the proposed method, the solutions with high sensitivity to forecasting errors are neglected in the decision-making process. This will help the decision-maker to avoid non-robust solutions. The effect of uncertainty on model robustness is analyzed using two test cases.

The future study will be calculating the cost from the perspective of the whole life cycle and considering the anticipated future changes in the understudy distributions system, such as reconfiguration of the substation, load growth, etc.

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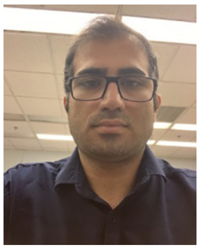

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