

Robust restoration of distribution systems considering DG units and direct load control programs

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Abstract: This paper presents a new method for restoration of distribution networks after a fault occurrence. This problem is solved from the viewpoint of the distribution system operator with the main goal of minimizing the operating cost during the fault clearance period. The effects of distributed generation (DG) units and direct load control (DLC) programs are considered in designing the proposed restoration procedure. Moreover, the uncertainties associated with the predicted loads of different nodes and the availability of DG are modeled here. Robust optimization is used to model the uncertainties of restoration problems and manage their associated risks. Finally, a robust reconfiguration plan is obtained solving a bilevel problem using a genetic algorithm (GA). The upper-level problem is concerned with evaluating the optimum configuration by GA and the lower-level problem obtains the optimum schedules of DG and DLC with an AC optimal power flow. A 32-bus test system is used to demonstrate the applicability of the proposed method.

Key words: Direct load control, distributed generation, reconfiguration, robust optimization

1. Introduction

A distribution system is one of the most important parts of power systems, because it is the last part of servicing customers. Numerous outages of power system loads are due to failures of distribution system components. Hence, backup plans should be investigated to be quickly performed after contingencies occur in these systems. This procedure, known as restoration, has been widely discussed in the literature [1–5]. Changing the network configuration by an optimized switching procedure, the load points placed in the faulted areas can be restored by connecting them to other feeders. For this purpose, the backup plan for every possible failure is evaluated. The proposed method of this paper is designed to evaluate the offline restoration plans associated with the failure of distribution elements.

Previous works have considered different objective functions for the associated optimization problem of restoration problems. Minimization of energy not supplied [2], minimizing the switching actions [1], loss reduction [3], reliability improvement [5], and a combination of these [5] are largely used as the objectives of restoration problems. The objective function of the restoration problem is highly dependent on the organization that performs it. For example, if the restoration problem is being solved from the perspective of the distribution system operator (DSO), which is the concern of this paper, reconnecting the maximum amount of loads in the out-of-service area can be introduced as the associated objective function.

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The restoration problem is highly related to determining the binary variables associated with distribution switches. On the other hand, DC power flow approximation cannot be used in the problems of distribution systems since the distribution lines have a high level of resistance. Therefore, the restoration optimization problem is faced with hard nonlinear terms of AC power flow equations and nonconvexity due to the existence of binary variables in the model. In this way, pure mathematical programming is not proper for this optimization problem [1,2]. Heuristic search algorithms [1,5–7], the minimal path and search technique [8], the branch and bound method [9], dynamic programming [10], and multiagent systems [11] are examples of optimization methods used in solving restoration problems. This paper implements a genetic algorithm (GA) to solve the proposed restoration model.

Once a fault occurs it will be impossible to recover all of the disconnected loads. This is because of the flow limits in the backup feeders. In order to increase the ability of recovering different loads during the restoration process, various remedial solutions have been discussed in the literature such as distributed generation (DG) [12] and direct load control (DLC) programs [13]. The authors in [7,8] and [12] discussed that the presence of DG units in the restoration process can significantly improve the obtained results. DG units can supply some part of disconnected loads and reduce the flow of backup feeders. Interruptible loads (ILs) can also play the same role as DG during contingencies [13]. In this regard, the DSO can employ IL programs such as DLC during a contingency and therefore reduce the tie lines' current. Therefore, reconfiguration in the presence of DG and ILs needs determining the optimum schedule for DG and ILs in addition to other variables.

On the other hand, this problem involves many uncertainties. For example, the predicted level of demands and availability of DG are sources of uncertainty in this problem. Different methods are used in the literature to model the uncertain parameters and control their related risks. Stochastic programming [14–17], fuzzy methods [18], and interval-based optimization methods such as information gap decision theory [19,20] and robust optimization [21–23] are examples of these methods. Among them, interval-based optimization methods are appropriate for handling the high level of uncertain parameters [22–25]. Moreover, interval-based optimization methods make no assumption on the probability density function (PDF) of uncertainties, which makes them a good choice for uncertainties where their PDF could not be evaluated straightforwardly, such as predicted nodal distributed demands or availability of DG. Therefore, robust optimization would be a suitable choice in reconfiguration problems.

In this paper a new method is proposed for reconfiguration of the distribution network operated by a DSO. It is supposed here that the DSO has the ability of controlling some of the loads directly. In addition to DLC, DG is also assumed in the structure of this paper. A robust optimization method is used here to hedge the risk of uncertain parameters, i.e. predicted levels of demand and the availability of DG. Thus, this paper presents a conservative plan for reconfiguration of a distribution network in the presence of DG and DLC.

From a practical point of view, most distribution systems still operate in the traditional way and use offline plans for their restoration programs. The main aim of this paper is to provide a practical restoration plan for recovering loads after a fault occurrence. Thus, an offline restoration program is chosen in this paper. The uncertain parameters and their effects on the offline restoration program are still questionable in power system studies. This paper tries to find a proper way to model and control the effect of uncertain parameters on the offline restoration plan evaluation. The uncertainties involved in this problem are the predicted demand and the unavailability of DG. From a practical perspective, the PDF of distribution loads cannot be evaluated node by node, because of the lack of measured data in many distribution systems. The problem associated with the lack of measured data is common in traditional distribution systems. To solve this problem, robust

optimization is implemented here. Robust optimization does not need the PDF of uncertain parameters and it could be a good choice for this purpose.

The rest of this paper is organized as follows. The problem structures and the assumptions are presented in Section 2. The risk-neutral and the robust formulations are proposed in Section 3 and Section 4, respectively. The numerical results are provided in Section 5 followed, by the conclusion in Section 6.

2. Problem structure

Two kinds of decision variables should be defined in the restoration problem. The first category of decision variables is the set of switches whose statuses should be changed during the restoration process. These variables are binary and they should be defined in such a way as to create a new radial configuration serving a maximum level of disconnected loads. After determining the optimum configuration, the optimum schedule of DG and DLC should be evaluated as the second category of decision variables.

Based on the above explanation, the reconfiguration problem of this paper is modeled as a bilevel optimization problem. As depicted in Figure 1, the first level is concerned with determining the optimum radial configuration of the distribution network. This is followed by setting the status of switches. The lower level evaluates the optimum schedule of DG and DLC related to the evaluated configuration obtained from the upper-level optimization problem. In this level, an AC optimal power flow (OPF) should be implemented to ensure that the determined structure and schedules meet the operational constraints of the network, i.e. the maximum flow of feeders and limitations on bus voltages.

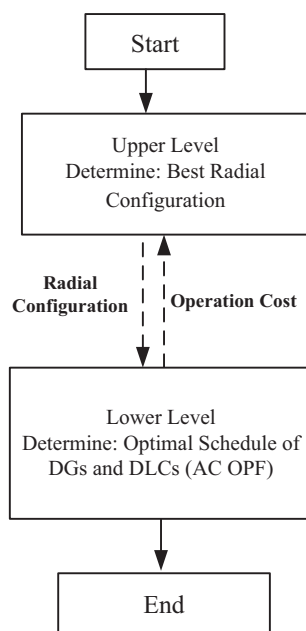


Figure 1. Flowchart of the reconfiguration problem.

As can be seen from the flowchart presented in Figure 1, the problem is solved iteratively. The heuristic algorithms are a proper option for solving this bilevel nonlinear nonconvex optimization model. In this paper, a GA is used due to its ability of handling binary variables [26]. In this way, the process of solving a bilevel optimization problem would be as follows:

1. Generating random radial configurations as the first generation of chromosomes.
2. Evaluating the optimum schedule of DG and DLC for the created configurations in the lower level.
3. Calculating the operating cost associated with the proposed radial structures evaluated by the upper level optimization (GA).
4. Generating the next generation by applying mutation and crossover operators considering the fitness value of the first generation, i.e. operating costs of chromosomes.
5. Checking the convergence criterion; if the procedure has not converged, go to step 2.

For more clarification about the bilevel optimization problem of this paper, each level is described in the following section.

3. Risk-neutral formulation

After specifying the problem structure, the optimization formulation and modeling is presented in this section. First the formulation of the restoration problem ignoring the uncertainties is introduced and then the uncertainties will be involved in the formulation in order to manage the risk level of the decision-making problem.

3.1. Upper level optimization problem

The upper level optimization problem can be simply explained by Eqs. (1) and (2).

$$\min_{SW} OP(P^{DG}, P^{UP}, U^{DG}, U^{DLC}) \quad (1)$$

$$\text{NewConfigurationRadiality} \quad (2)$$

Here, SW is the set of switches whose statuses should be changed in order to reach a new radial configuration. $OP(P^{DG}, P^{UP}, U^{DG}, U^{DLC})$ is the operating cost of the distribution system during the repair time of the element, which is a function of other decision variables, i.e. scheduled power of DG P^{DG} , purchased power from upstream node P^{UP} , and binary variables U^{DG}, U^{DLC} that represent the commitment status of DG and ILs, respectively.

This optimization problem is constrained to the radiality constraint, which guarantees the radiality of the new configuration introduced for the distribution networks. A GA is used here to solve this problem. For this purpose, a binary chromosome is used in which each switch is associated with a bit of chromosome. The value of Eq. (1) indicates that the related switch should be closed and vice versa. The radiality of the created chromosome is checked in this step using a lookup table. For this purpose, by implementing a preanalysis process, all of the possible radial configurations are recognized and saved in a lookup table. Once a GA generates a chromosome, its feasibility is checked by this lookup table. If it is recognized as a nonradial configuration, it will be removed from the optimization process. In this way, all of the structures provided by the upper level would be radial.

3.2. Lower level optimization problem

In this step, the configuration of the network is defined by the upper level and sent to the lower-level optimization problem. In the lower-level optimization, the operating cost associated with the generated configuration provided

by the GA-based upper level is defined. The lower-level optimization problem level is explained as follows.

$$\min_{\substack{P_i^{DG}, U_i^{DG} \\ P^{UP}, U_i^{DLC}}} OP = \left(\lambda^{UP} P^{UP} + \sum_{i \in D} a_i (P_i^{DG})^2 + b_i P_i^{DG} + c_i U_i^{DG} + \sum_{i \in L} U_i^{DLC} \lambda_i^{DLC} + \sum_{i \in I} \lambda_i^{Int} \right) \quad (3)$$

$$|I_l| \leq I_l^{\max} \quad \forall l \in F \quad (4)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad \forall i \quad (5)$$

$$(P_i^{DG})^2 + (Q_i^{DG})^2 \leq (S_i^{\max})^2 \quad \forall i \in D \quad (6)$$

$$U_i^{DG} P_i^{\min} \leq P_i^{DG} \leq U_i^{DG} P_i^{\max} \quad \forall i \in D \quad (7)$$

$$U_i^{DG} Q_i^{\min} \leq Q_i^{DG} \leq U_i^{DG} Q_i^{\max} \quad \forall i \in D \quad (8)$$

$$P_i^{DG} - U_i^{DLC} P_i^{DLC} - P_i^D = \sum_k V_i V_k Y_{ik} \cos(\theta_i - \theta_k) \quad \forall i \quad (9)$$

$$Q_i^{DG} - U_i^{DLC} Q_i^{DLC} - Q_i^D = \sum_k V_i V_k Y_{ik} \sin(\theta_i - \theta_k) \quad \forall i \quad (10)$$

The lower-level optimization is an AC OPF in which the operating cost is minimized with respect to the set of decision variables, i.e. $P_i^{DG}, U_i^{DG}, U_i^{DLC}, P^{UP}$. In Eq. (3), the operating cost has four terms. In other words, the DSO has four sources to feed the distribution system’s load during contingency events. The first term distinguishes the cost of purchasing power from the upstream network, i.e. $\lambda^{UP} P^{UP}$, in which λ^{UP} is the average price of energy. The next source is installed DG whose operating cost is modeled through the second term of the objective function of Eq. (3), i.e. $\sum_{i \in D} a_i (P_i^{DG})^2 + b_i P_i^{DG} + c_i U_i^{DG} \alpha_i (P_i^{DG})^2 + \beta_i P_i^{DG} + \gamma_i U_i^{DG}$. The set of buses including DG is denoted by D. The other option of the DSO to operate the network after the contingency is utilizing the DLC sources with the cost of $\sum_{i \in L} U_i^{DLC} \lambda_i^{DLC}$. L is the set of nodes with DLC capacity. The cost of activating DLC of node i is considered to be λ_i^{DLC} . Finally, the last choice of the DSO is interrupting the loads with cost of $\sum_{i \in I} \lambda_i^{Int}$, in which i is the set of load points interrupted during contingency operation.

This optimization problem is constrained to some physical constraints. In Eq. (4), the current limit of feeder l is enforced to the problem. Voltage limitation constraints explained by Eq. (5) and maximum and minimum generation capacity of active and reactive power of DG are also defined by Eqs. (7) and (8), respectively. The nominal power of the DG located at bus i is defined by Eq. (6). The other well-known AC power flow constraints are enforced for the problem by Eqs. (9) and (10).

By solving this bilevel optimization problem, the optimum configuration during contingency will be described as well as the optimum schedule power of DG and DLC.

4. Robust optimization formulation

The reconfiguration problem is faced with uncertain parameters. Some parameters are forecasted for this problem, such as demand of the load points. In addition, the behavior of some parameters is not well known for the decision maker, such as the availability of DG during a contingency. These uncertainties introduce some

level of risk to the problem. In order to model the uncertainties and control the related risk of them, robust optimization is utilized here [22,23,27].

Robust optimization is an interval-based optimization method considering an interval around the forecasted parameter. During the optimization process, the worst case of uncertainty occurrence in the assumed interval will be defined. In other words, this method tries to set the decision variables by considering the worst case of uncertain parameters. Therefore, the upper level will not change in robust format but the lower-level robust optimization formulation would be as follows:

$$\min_{\substack{P_i^{DG}, U_i^{DG} \\ P^{UP}, U_i^{DLC}}} \max_{\substack{\Delta P_i^{DG}, \Delta Q_i^{DG} \\ \Delta P_i^D, \Delta Q_i^D}} OP = \left(\sum_{i \in D} a_i (P_i^{DG})^2 + b_i P_i^{DG} + c_i U_i^{DG} + \lambda^{UP} P^{UP} + \sum_{i \in L} U_i^{DLC} \lambda_i^{DLC} + \sum_{i \in I} \lambda_i^{Int} \right) \tag{11}$$

$$U_i^{DG} P_i^{\min} \leq P_i^{DG} \leq U_i^{DG} (P_i^{\max} + \Delta P_i^{DG}) \quad \forall i \in D \tag{12}$$

$$U_i^{DG} Q_i^{\min} \leq Q_i^{DG} \leq U_i^{DG} (Q_i^{\max} + \Delta Q_i^{DG}) \quad \forall i \in D \tag{13}$$

$$P_i^{DG} - U_i^{DLC} P_i^{DLC} - (P_i^D + \Delta P_i^D) = \sum_k V_i V_k Y_{ik} \cos(\theta_i - \theta_k) \quad \forall i \tag{14}$$

$$Q_i^{DG} - U_i^{DLC} Q_i^{DLC} - (Q_i^D + \Delta Q_i^D) = \sum_k V_i V_k Y_{ik} \sin(\theta_i - \theta_k) \quad \forall i \tag{15}$$

$$-\alpha^{DG} P_i^{\max} \leq \Delta P_i^{DG} \leq \alpha^{DG} P_i^{\max} \quad \forall i \tag{16}$$

$$-\alpha^{DG} Q_i^{\max} \leq \Delta Q_i^{DG} \leq \alpha^{DG} Q_i^{\max} \quad \forall i \tag{17}$$

$$-\alpha^D P_i^D \leq \Delta P_i^D \leq \alpha^D P_i^D \quad \forall i \tag{18}$$

$$-\alpha^D Q_i^D \leq \Delta Q_i^D \leq \alpha^D Q_i^D \quad \forall i \tag{19}$$

(4) – (6)

As can be seen in Eqs. (11)–(19), the objective of the lower-level optimization problem of Eq. (11) is presented as a min–max optimization problem. The operating cost is minimized with respect to the main decision variables of the problem, i.e. $P_i^{DG}, U_i^{DG}, P^{UP}, U_i^{DLC}$, and it is maximized with respect to the uncertain variables, which are $\Delta P_i^{DG}, \Delta Q_i^{DG}, \Delta P_i^D, \Delta Q_i^D$. $\Delta P_i^{DG}, \Delta Q_i^{DG}$ are the deviation from the maximum active and reactive power of DG i . In other words, the availability of DG is modeled probabilistically. In the same way, the deviation from predicted levels of demands (P_i^D, Q_i^D) is modeled as $\Delta P_i^D, \Delta Q_i^D$.

In this way, the optimization problem of the lower level tries to find the worst case of the uncertain parameters in the confidence gap in Eqs. (16)–(19). In Eqs. (16)–(19) α^{DG} is the robustness parameter of the DG’s uncertainty, which is an input parameter defining the length of the confidence gap. α^D is the robustness parameter of demand uncertainty.

In order to solve this min–max problem, it should be noted that the problem is linear with respect to the uncertain variables, i.e. $\Delta P_i^{DG}, \Delta Q_i^{DG}, \Delta P_i^D, \Delta Q_i^D$. Thus, the inner maximization is a linear optimization problem and the worst case associated with these uncertainties happens on one of the bounds. As can be seen in Eqs. (12) and (13), $\Delta P_i^{DG}, \Delta Q_i^{DG}$ appeared with positive signs and hence their worst bounds are their lower bounds. By the same logic, the worst case of $\Delta P_i^D, \Delta Q_i^D$ will be their upper bounds. Therefore, the

maximization part of the min–max problem can be removed by replacing the worst bounds instead of uncertain variables. The final format of the robust lower level would be as follows:

$$\min_{\substack{P_i^{DG}, U_i^{DG} \\ P^{UP}, U_i^{DLC}}} OP = \left(\sum_{i \in D} a_i (P_i^{DG})^2 + b_i P_i^{DG} + c_i U_i^{DG} + \lambda^{UP} P^{UP} + \sum_{i \in L} U_i^{DLC} \lambda_i^{DLC} + \sum_{i \in I} \lambda_i^{Int} \right) \quad (20)$$

$$U_i^{DG} P_i^{\min} \leq P_i^{DG} \leq U_i^{DG} (P_i^{\max} - \alpha^{DG} P_i^{\max}) \quad \forall i \in D \quad (21)$$

$$U_i^{DG} Q_i^{\min} \leq Q_i^{DG} \leq U_i^{DG} (Q_i^{\max} - \alpha^{DG} Q_i^{\max}) \quad \forall i \in D \quad (22)$$

$$P_i^{DG} - U_i^{DLC} P_i^{DLC} - (P_i^D + \alpha^D P_i^D) = \sum_k V_i V_k Y_{ik} \cos(\theta_i - \theta_k) \quad \forall i \quad (23)$$

$$Q_i^{DG} - U_i^{DLC} Q_i^{DLC} - (Q_i^D + \alpha^D Q_i^D) = \sum_k V_i V_k Y_{ik} \sin(\theta_i - \theta_k) \quad \forall i \quad (24)$$

(4) – (6)

Based on this modeling procedure, the robust reconfiguration problem can be solved by implementing the GA on the upper-level problem of Eqs. (1) and (2). The lower-level problem can be easily solved by the mat power functions [28] in MATLAB to determine the operating cost of each radial configuration.

5. Numerical results

The applicability of the proposed method is investigated on the network initially presented by Baran and Wu [29]. It is assumed that DG is located at buses 7 and 16. Additionally, it is supposed that the load points of buses 6 and 31 have an interruption contract with the DSO. Based on this contract, the DSO can disconnect these loads during contingencies by billing them \$0.35/kWh and \$1/kWh, respectively. Moreover, the coefficients of generation cost of DG and their generation limits are provided in Table 1.

Table 1. Operation data of DG.

	a (\$/(kW) ² h)	b (\$/kWh)	c (\$/h)	P _{max} (pu)	P _{min} (pu)	Q _{max} (pu)	Q _{min} (pu)
DG1 (bus 16)	0.01	0.35	0	3	0	2	-2
DG2 (bus 7)	0.01	0.4	0	2	0	1	-1

It has been assumed that a fault occurs at bus 3. After isolating the fault, subfeeders 2–3 and 3–4 will be out of service until the faulted element is repaired. In order to solve this reconfiguration problem, the GA is used with a population size of 100. The maximum generation number is also set to 100 and the stopping criterion is the maximum number of iterations in such a way that the tolerance of the objective is reduced to \$1. This condition is checked after the 70th generation. During the simulation process, the GA converged before reaching the maximum generation limit.

The effect of uncertainties on the operating cost is presented in Figure 2. In this figure, the operating cost is plotted versus the length of the robust gap of DG availability and demand prediction errors. As can be seen, the operating cost is increased by increasing the level of uncertainties. In addition, the uncertainties in demand prediction have more effect on the operating cost during reconfiguration. This figure also presents the relationship between the robust gap of uncertainties and the guaranteed level of operating cost.

In order to investigate the ability of the robust optimization method, an after-the-fact analysis is presented here. For this purpose, the risk-neutral reconfiguration is compared with the robust reconfiguration in after-the-fact analysis. For the robust-based reconfiguration, the point of $\alpha^{DG} = 0.2, \alpha^D = 0.2$ is chosen, which is related to the guaranteed level of \$6417. The expected operating cost of the risk-neutral model is obtained as \$5097. Three artificial scenarios are generated as after-the-fact scenarios. In the first scenario, the actual level of demand is generated by adding a 20% random error to the forecasted level. In a same way, the actual level of DG availability is generated by 20% error from the predicted level. In the second scenario, the error of the forecasted parameters is set to 30%, both for the demand and DG availability. Finally, in the last scenario, the prediction errors are increased to 40%. Figure 3 presents the operating cost of each scenario for the robust and risk-neutral restoration plans. Observe that the operating cost of the robust reconfiguration plan is less than the operating cost of the risk-neutral plan in all scenarios. Moreover, the ability of robust optimization in guaranteeing a prespecified level of cost can be seen in Figure 3. In the first scenario, the uncertain parameters, i.e. forecasted demand and the prediction of DG availability, surpass 20%, which is in the range of the robust plan. As can be seen the after-the-fact operating cost is below the guaranteed level. In the second scenario, however, the guaranteed condition is not met but it is still below the guaranteed level. This means that the robustness gap can be violated in the actual occurrence of uncertainties because the worst-case scenario is considered in the robust-based method. Finally, in the last scenario, the uncertainties' violation is 40%, resulting in the increase of operating cost higher than the guaranteed level.

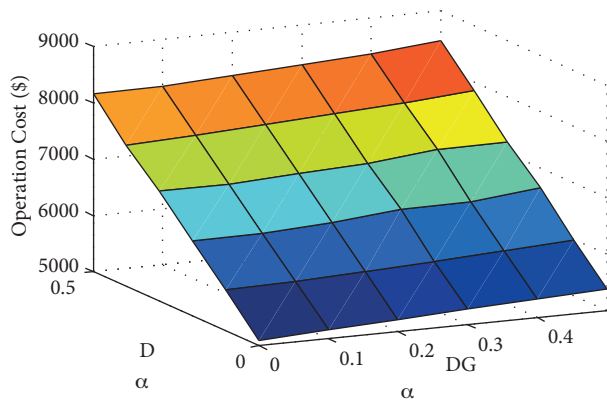


Figure 2. The impact of uncertainties on the operating cost of reconfiguration.

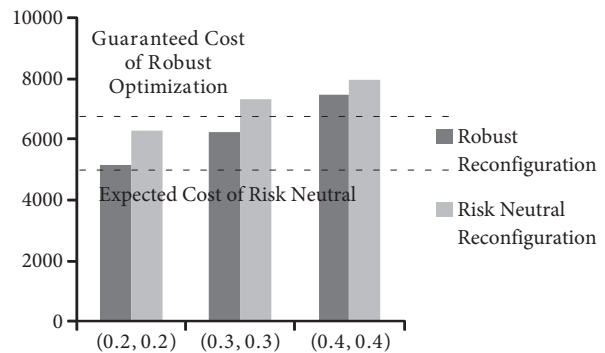


Figure 3. Comparing the operating cost of robust-based and risk-neutral reconfiguration methods for different levels of prediction errors (demand error, error of DG availability).

To better illustrate the effect of uncertainties on the reconfiguration plans, Figure 4 presents the optimum configuration of the restored network for different level of uncertainties, i.e. $\alpha^{DG} = 0, \alpha^D = 0$ in Figure 4a; $\alpha^{DG} = 0.2, \alpha^D = 0.2$ in Figure 4b; and $\alpha^{DG} = 0.5, \alpha^D = 0.5$ in Figure 4c. Moreover, the optimum schedules of DG and DLC are also presented in Table 2. As can be seen, in Figure 4 the uncertain parameters have no significant effect on optimum structure. In other words, as the amount of uncertainties increases from $\alpha^{DG} = 0, \alpha^D = 0$ in Figure 4a to $\alpha^{DG} = 0.2, \alpha^D = 0.2$ in Figure 4b, only the opened connection of 13–14 changes to the opened connection of 14–15, which is close to the previous one, and the other connections remain the same as before. The same thing happens when the uncertainties increase from $\alpha^{DG} = 0.2, \alpha^D = 0.2$ in Figure 4b to $\alpha^{DG} = 0.5, \alpha^D = 0.5$ in Figure 4c. The reason for this (uncertainties have no significant

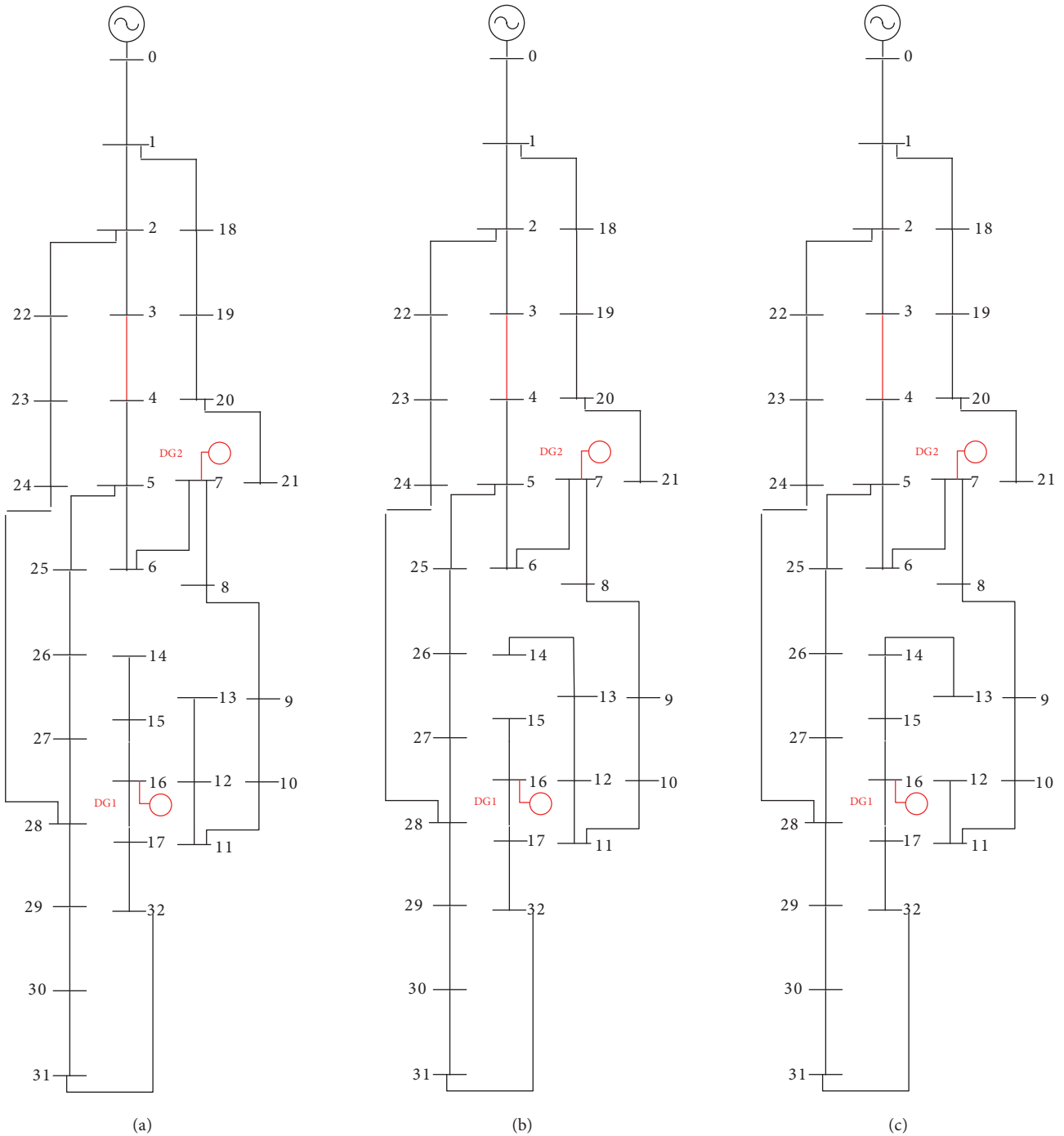


Figure 4. Restored network's configuration for the presented scenarios: a) $\alpha^{DG} = 0, \alpha^D = 0$; b) $\alpha^{DG} = 0.2, \alpha^D = 0.2$; c) $\alpha^{DG} = 0.5, \alpha^D = 0.5$.

effect on the optimum reconfiguration plan) is better explained by Table 2. As illustrated in this table, the optimum schedules of DG and DLC are largely changed by increasing the level of uncertain parameters. Hence, the uncertain parameters' effect better shows itself in the optimum schedule of DG and DLC rather than the optimum configuration of the network. In other words, implementing DG and DLC in the distribution network

makes the system flexible. Hence, the DG and DLC of the network makes reconfiguration problem robust against the uncertain parameters.

Table 2. Optimum schedule plan of DG and DLC for different levels of uncertainties.

		$\alpha^{DG} = 0$ $\alpha^D = 0$	$\alpha^{DG} = 0.2$ $\alpha^D = 0.2$	$\alpha^{DG} = 0.5$ $\alpha^D = 0.5$
DG1 (bus 16)	P	0	0	0
	Q	0.6	0.75	0.5
DG1 (bus 7)	P	0	0.15	1.35
	Q	0.67	0.86	1
DLC (Bus 6)	P	0.24	0.19	0.12
	Q	0.12	0.1	0.06
DLC (Bus 31)	P	0.25	0.2	0.13
	Q	0.12	0.1	0.06
Upstream node	P	3.23	3.97	4
	Q	0.81	1.01	1.86

6. Conclusion

A new method for reconfiguration of distribution systems was presented in this work. This paper modeled this problem with a bilevel optimization method. In the upper level, the best configuration of the faulted system was obtained through a GA and the optimum operating cost associated with the upper level was determined via the lower-level optimization problem. The AC optimal power flow of the second-level problem guaranteed the technical feasibility of the reconfiguration plan. In the numerical results, the effect of uncertain parameters was compared and it was shown that the forecasting error of distribution loads had a significant effect on the operating cost. Moreover, the capability of robust optimization in guaranteeing a prespecified level of operating cost was demonstrated through an after-the-fact analysis. In this analysis, it was shown that the operating cost of the faulted system was lower than the robust cost provided by the robust-based method of this paper, provided that the uncertain parameters fall into the prespecified robust gap or near it. Finally, it was shown that the proposed reconfiguration structure is significantly robust against uncertain parameters. This means that the optimum decided reconfiguration plan is not changed by changing the level of the uncertain parameters. The development of the proposed method for the purpose of implementation in the restructured systems or smart distribution systems can be considered as future work in line with this paper.

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