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An Efficient Stochastic Reconfiguration Model for Distribution Systems With Uncertain Loads

MEISAM MAHDAVI¹, HASSAN HAES ALHELOU², (Senior Member, IEEE),
AND MOHAMMAD REZA HESAMZADEH³, (Senior Member, IEEE)

¹Associated Laboratory, Bioenergy Research Institute (IPBEN), São Paulo State University, Campus of Ilha Solteira, Ilha Solteira 15385-000, Brazil

²School of Electrical and Electronic Engineering, University College Dublin, Dublin 4, D04 V1W8 Ireland

³School of Electrical Engineering and Computer Science, KTH Royal Institute of Technology, 11428 Stockholm, Sweden

Corresponding author: Hassan Haes Alhelou (alhelou@ieee.org)

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ABSTRACT Active power losses of distribution systems are higher than transmission ones, in which these losses affect the distribution operational costs directly. One of the efficient and effective methods for power losses reduction is distribution system reconfiguration (DSR). In this way, the network configuration is changed based on a specific power demand that has been already predicted by load forecasting techniques. The ohmic loss level in distribution system is affected by energy demand level, this is while an error in load forecasting can influence losses. Accordingly, including load uncertainty in DSR formulation is essential but this issue should not lead to change of the reconfiguration results significantly (i.e. the model should be robust). This paper presents a robust and efficient model for considering load uncertainty in network reconfiguration that is simple enough to implement in available commercial software packages and it is precise enough to find accurate solutions with low computational time. The analysis of results shows high efficiency and robustness of the proposed model for reconfiguration of distribution systems under demand uncertainty.

INDEX TERMS Distribution network reconfiguration, power losses reduction, robust model, uncertainty in demand.

I. INTRODUCTION

Distribution network has a prominent role in delivering the electricity provided by transmission system to individual electric energy customers [1]. Nonetheless, part of power supplied by transmission system is lost as thermal energy because of distribution line resistance. The distribution power losses are higher than transmission ones as they affect the system operational costs and voltage profile. Therefore, minimization of power delivery losses is important for distribution network operators [2].

Distribution system reconfiguration (DSR) is an efficient way to reduce the distribution losses, in which network topology is changed by opening normally closed sectional switches and closing normally open tie line switches in a specific load level [3]. Although loss minimization has been always important in DSR, voltage stability [4], load

balancing [5], reliability criteria [6], distributed generation (DG) costs [7], power restoration [8], and maintenance expenses [9] may be optimized beside losses.

Many approaches have been proposed for reconfiguration of radial distribution systems till now. Most of these approaches have solved the DSR as a deterministic problem [10]–[29]. Some of them included uncertainty issues in the DSR formulation without considering model robustness [7], [30]–[33], while some of them proposed robust models for uncertain DSR problems [34]–[37]. However, the proposed robust models are complex with high computational efforts. Therefore, the present paper intends to introduce a more efficient and simpler robust model with lower computational efforts. Simple implementation is important for practical applications.

A. DETERMINISTIC MODELS

Some approaches proposed for deterministic DSR problem have minimized estimated power losses using simple

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heuristic methods [10]–[13]. In spite of simple implementation of these methods, estimation of power losses reduces the efficiency of reconfiguration models. The linearized [14], simplified [15], and approximated [16] load flow techniques for loss minimization are discussed in the DSR literature. However, the introduced linearizations, simplifications, and approximations cause inaccurate solutions for DSR problem. Some other researchers have divided distribution network into several parts and minimized the power losses existing in these parts [17], [18]. However, partitioning large-size distribution systems is not an easy task.

In order to increase the accuracy of reconfiguration models, discrete ascent [19] and linear programming [20], [21], as well as Benders decomposition (BD) [22] were proposed to minimize network losses. Nonetheless, addition of loads as discrete steps to each bus in [19] and approximation of power losses using piecewise linear functions in [20] and [21], as well as linearization of non-linear terms in [22], degrade performance of the proposed models for reconfiguration applications. Therefore, more formal modeling proposals are required to represent DSR formulation in a precise way, as those presented in [23] and [24]. These works present increasingly complex mathematical models. Thus, nonlinear and quadratic programming approaches were proposed to minimize power losses in [25] and [26]. Although the nonlinear and quadratic programming could solve the DSR problem more efficiently than linear programming and BD, respectively, rewriting the nonlinear power flow equations in terms of rotated conic quadratic constraints in [25] and allocation of two continuous variables instead of binary ones to power flow direction of each line in [26] have decreased the efficiency of the proposed methodologies.

Recently, in [27], a fast decoupled Newton–Raphson power flow approach was employed to solve a DSR problem, showing its lower computing time compared to conventional power flow methods. Nevertheless, the efficiency of the proposed method in [27] is reduced in networks with high ratio of ohmic resistance to reactance (R/X) of distribution lines. Also, in [28], General Algebraic Modeling System (GAMS) was employed to solve multi-objective DSR problem in presence of demand response (DR). More recently, in [29], an approximated dynamic programming (ADP) approach was applied to minimize DG curtailment and load shedding in DSR, but uncertainty in power demand has not been considered in [29] and any above-mentioned models.

B. STOCHASTIC MODELS

Power demand is predicted by load forecasting techniques according to real consumption data of previous years and prediction of factors such as future climate changes, inflation rate, energy prices and policy, population immigration, load growth and so on. Every probable change in above factors and appearance of unpredicted events such as pandemic diseases (e.g. COVID-19 today) affect load amount and consumption pattern. Therefore, the electrical energy demand is uncertain in distribution systems. On the other hand, any increase or

decrease in load level can affect network loss level. For this, reference [30] proposed a probabilistic model for uncertain DSR problem using Monte Carlo simulation (MCS). The MCS is a probabilistic method for handling uncertainties, but it is computationally intensive. This difficulty is more evident in problems in which the main optimization algorithm is solved based on evolutionary methods [7]. In order to remove this drawback, the point estimate method (PEM) was used for calculation of uncertainties in [31]. In the proposed model, active power losses, voltage deviation, generation costs, and greenhouse gas emissions were minimized in a multi-objective framework using a particle swarm optimization (PSO) algorithm. The results show that the PEM is simpler and more flexible method than the MCS to analyze uncertainties in complex DSR problems. However, evolutionary algorithms such as PSO [7] cannot guarantee global optimality of the solutions. Therefore, in [32], a simultaneous network reconfiguration and DG allocation problem was solved by a classic optimization tool (GAMS) rather than evolutionary algorithms. In the proposed approach, uncertainties in demand and wind were formulated by a scenario-based technique. However, scenario-based approaches are time-consuming methods for solving uncertain DSR problems. Moreover, the accuracy of the proposed model depends on set of selected scenarios. In simple terms, solution accuracy and computation time are decreasing and increasing, respectively, by choosing improper scenarios. Furthermore, in [33], a DSR problem was solved in order to increase the hosting capacity of distribution network for DG by minimizing the number of switching operation. In this approach, fuzzy C-means (FCM) method was used to cluster different scenarios of switching operation and output uncertainties of DG units. Nevertheless, reference [33] and any model reviewed above has lack of robustness against uncertainties.

C. ROBUST MODELS

The uncertain DSR models should have high robustness against uncertainties, i.e. the reconfiguration plans should not be changed easily with every increase or decrease in load amount. Therefore, in [34] and [35], robust mixed-integer linear and nonlinear programming models were proposed for DSR considering load and generation uncertainties, respectively. The piecewise linear approximation model of [34] and nonlinear model of [35] were solved by master-slave decomposition algorithms implemented in the classic mathematical programming language, AMPL. However, linearizations and approximations used in [34] and high complexity of nonlinear model of [35] have decreased the efficiency of the proposed approaches for reconfiguration of large distribution networks. Furthermore, probabilities of uncertainties have not been considered in both formulations. In [36], a two-stage stochastic robust optimization model was proposed for optimal reconfiguration of distribution network under load uncertainty considering switching cost, DG operation expenses, and cost of power supplied by substation. However, determining the net load of each bus by processing nodal voltages and branch

current flows via a linear state estimation in the first stage and finding out the best configuration using second order conic programming in the second stage cause high computational efforts and accordingly hard implementation issue [36]. In order to remove difficulty of deriving accurate probability distributions (PD) of uncertain loads and DG outputs, first a deep neural network was used to learn the reference value of PD from historical data and then the optimal configuration under the worst case of load was determined. At this stage, the DG PDs were obtained by the proposed robust model in [37]. However, scenario decomposition-based method used in [37] adds more complexity to the problem.

The DSR models should be adequately accurate (which requires proper linearization and approximation techniques), simple enough (without high computational burden and efforts), and relatively fast (with lower computational time) for practical applications. However, accuracy improvement may decrease the model simplicity and increase processing time of computations. On the other hand, simplicity improvement may reduce accuracy of the model.

D. CONTRIBUTIONS

Considering advantages and disadvantages of models proposed in [7], [30]–[37] and importance of including load uncertainty in network reconfiguration, this paper presents an efficient stochastic model for reconfiguration of distribution systems under demand uncertainty, which is simple to implement and is characterized by both high accuracy and short computational time. The simulation results show high efficiency and robustness of our proposed model for reconfiguration of distribution systems in uncertain environments. In summary, the current paper presents an efficient robust formulation for reconfiguration of radial distribution systems which is:

- Accurate and simple for implementation in commercial software packages.
- Efficient, as it requires short computing times without introducing decompositions and complexities.
- Providing only radial solutions during the whole optimization process (it guarantees network radiality).
- Prohibiting isolation of any buses from proposed radial topologies (it guarantees network connectivity).
- Applicable for reconfiguration of distribution networks of any size (from small to large systems).
- Considering uncertainty probability beside uncertain amounts in the objective function.
- Flexible to consider distributed generation uncertainty in the desired problem.

II. LOAD UNCERTAINTY MODELING

As mentioned earlier, electricity demand has a stochastic nature that its uncertainty should be considered in distribution network reconfiguration. In this way, uncertain demands as well as their possibilities should be included in DSR formulation. Unlike [31], [32], and [37], probability of uncertainties has not been considered in [34]–[36]. This fact

can decrease efficiency of the models for solving large-scale DSR problems under high uncertainty. Probability density function (PDF) is an efficient way for embedding probability of uncertainties in stochastic problems. Among different PDFs, normal one is used efficiently for handling uncertainties in power system operation studies [32]. In normal probability distribution, PDF can be generally described by (1).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{1}$$

Parameters μ and σ are expected value and standard deviation of probability variable x , respectively. Figure 1 shows normal probability density function ($f(x)$) for an uncertain load.

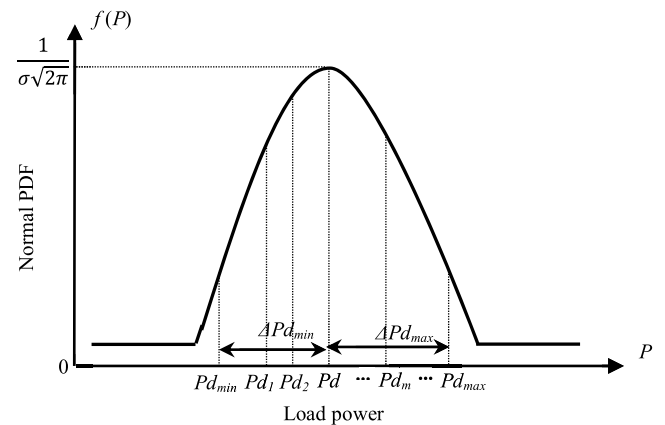


FIGURE 1. Normal probability density function of load.

In Fig. 1, Pd is nominal power demand that has been predicted by load forecasting (expected demand). Pd_{min} and Pd_{max} are minimum and maximum deviated load amounts, respectively. ΔPd_{min} and ΔPd_{max} are minimum and maximum deviations from expected (nominal) demand, respectively. According to Fig. 1, PDF in terms of load power can be written as follows.

$$f(P) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{P-Pd}{\sigma}\right)^2} \quad \forall Pd_{min} \leq P \leq Pd_{max} \tag{2}$$

In an uncertain DSR, value of P varies from Pd_{min} to Pd_{max} and should be determined by solution algorithm during reconfiguration. However this process can be computationally intensive because of wide range of real numbers in interval $[Pd_{min}, Pd_{max}]$. One way to resolve this issue is employing scenario-based methods [32], in which only specific discrete numbers between Pd_{min} and Pd_{max} are selected. In these methods, a set of possible scenarios (Ω^s) and their probabilities are defined as (3).

$$\begin{aligned} \Omega^s &= \{Pd_1, \dots, Pd_m, \dots, Pd_S\} \\ &\quad \forall Pd_1 \geq Pd_{min}, \quad Pd_S \leq Pd_{max} \\ f(\Omega^s) &= \{f(Pd_1), \dots, f(Pd_m), \dots, f(Pd_S)\} \end{aligned} \tag{3}$$

where, S is number of possible scenarios and $f(Pd_m)$ is calculated by (4).

$$f(Pd_m) = \frac{e^{-\frac{1}{2}\left(\frac{Pd_m - Pd}{\sigma}\right)^2}}{\sigma\sqrt{2\pi}} \quad \forall Pd_{\min} \leq Pd_m \leq Pd_{\max},$$

$$m = 1, \dots, S \quad (4)$$

Although search space of the solution algorithm can be reduced by using (3) and (4), choosing proper values for Ω^S and selecting proper number of scenarios are challenging tasks [34]. The computational burden and processing time of DSR problem is increased by selecting more scenarios. On the other hand, reducing the number of scenarios has an adverse effect on the accuracy of the reconfiguration model. In addition, choosing proper scenarios using probabilistic methods such as MCS and PEM [31] cannot lead to a realistic solution because selection of effective scenarios needs a precise evaluation of system behavior, while this analysis is really complex.

The whole deviated load can be represented by load deviation changes. In this case, zero expected demand deviation ($\Delta Pd = 0$) represents nominal demand for network consumption ($P = Pd + \Delta Pd$). Unlike minimum deviated load (Pd_{\min}), minimum load deviation change (ΔPd_{\min}) is a negative value. Therefore, Fig. 1 should be modified as Fig. 2.

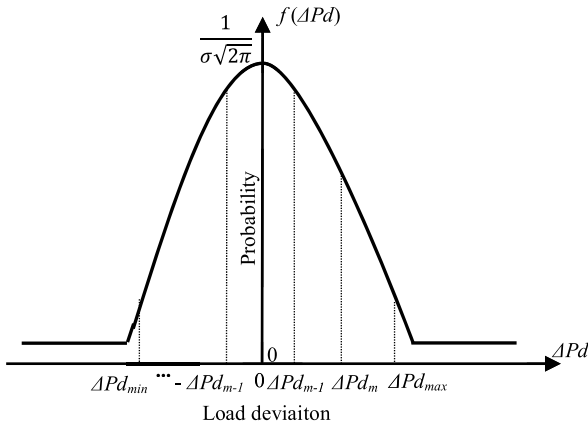


FIGURE 2. Normal probability density function of load deviation.

From Fig. 2, we have the following:

$$f(\Delta Pd) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}(\Delta Pd)^2} \quad \forall \Delta Pd_{\min} \leq \Delta Pd \leq \Delta Pd_{\max} \quad (5)$$

In power system studies, standard deviation (σ) value for load uncertainty is considered to be a small number (e.g. 0.05 [31]).

Therefore, the normal PDF curve of load deviation is really sharp (see Fig. 3) and can be efficiently approximated by piecewise linear functions as (6) and (7).

$$f(\Delta Pd) = f(\Delta Pd_m) + \frac{f(\Delta Pd_m) - f(\Delta Pd_{m-1})}{\Delta Pd_m - \Delta Pd_{m-1}}$$

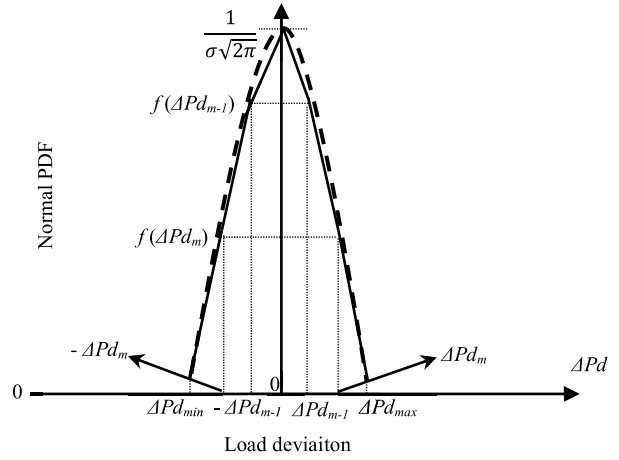


FIGURE 3. Normal PDF of load deviation for small standard deviations.

$$\times (\Delta Pd - \Delta Pd_m)$$

$$\forall 0 \leq \Delta Pd_{m-1} \leq \Delta Pd \leq \Delta Pd_m \leq \Delta Pd_{\max} \quad (6)$$

$$f(\Delta Pd) = f(\Delta Pd_m) - \frac{f(\Delta Pd_m) - f(\Delta Pd_{m-1})}{\Delta Pd_m - \Delta Pd_{m-1}}$$

$$\times (\Delta Pd + \Delta Pd_m)$$

$$\forall \Delta Pd_{\min} \leq -\Delta Pd_m \leq \Delta Pd \leq -\Delta Pd_{m-1} \leq 0 \quad (7)$$

High sharpness of PDF curve (dashed lines) and steep linearized functions shown by Fig. 3 indicate the following important notes:

- 1) Considering probability of load uncertainty is essential in real DSR applications because of significant difference between start and end points of each line on vertical axis. However, this important issue has been neglected in [34]–[36].
- 2) Equations (6) and (7) can accurately model the probability of load uncertainty without any concerns about selection of scenarios [32], [37], formulation complexity [31], [36] and need for the real analysis of the network.
- 3) Choosing appropriate values for m is simple due to curve shape symmetry, little difference in slopes of each two consecutive lines, and the small interval $[\Delta Pd_{\min}, \Delta Pd_{\max}]$.

Moreover, (6) and (7) present a flexible formulation because of their applications for both linear and nonlinear models and possibility of optimization of parameter m during reconfiguration.

III. PROBLEM FORMULATION

In this section, conventional and proposed robust and deterministic DSR models are described.

A. CONVENTIONAL DSR MODEL

The DSR problem for balanced distribution networks, aiming minimization of power losses (P_{Loss}) and considering a

certain load demand can be formulated by (8) to (18).

$$\text{Min } P_{Loss} = \sum_{ij \in \Omega^l} R_{ij} |I_{ij}|^2 \quad (8)$$

$$\text{subject to : } Ps_i + \sum_{ki \in \Omega^l} P_{ki} - \sum_{ij \in \Omega^l} P_{ij} - \sum_{ij \in \Omega^l} R_{ij} |I_{ij}|^2 = Pd_i$$

$$\forall i \in \Omega^b \quad (9)$$

$$Qs_i + \sum_{ki \in \Omega^l} Q_{ki} - \sum_{ij \in \Omega^l} Q_{ij} - \sum_{ij \in \Omega^l} X_{ij} |I_{ij}|^2 = Qd_i \quad \forall i \in \Omega^b \quad (10)$$

$$|V_i|^2 - |V_j|^2 = 2 [R_{ij} P_{ij} + X_{ij} Q_{ij}] + |Z_{ij}|^2 |I_{ij}|^2 + b_{ij} \quad \forall i \neq j \in \Omega^b, ij \in \Omega^l \quad (11)$$

$$|S_{ij}|^2 = P_{ij}^2 + Q_{ij}^2 \quad \forall ij \in \Omega^l \quad (12)$$

$$|S_{ij}|^2 = |V_j|^2 |I_{ij}|^2 \quad \forall j \in \Omega^b, ij \in \Omega^l \quad (13)$$

$$\sum_{ij \in \Omega^l} y_{ij} = |\Omega^b| - 1 \quad (14)$$

$$V_{\min}^2 \leq |V_i|^2 \leq V_{\max}^2 \quad \forall i \in \Omega^b \quad (15)$$

$$0 \leq |I_{ij}|^2 \leq (I_{ij}^{\max})^2 y_{ij} \quad \forall ij \in \Omega^l \quad (16)$$

$$|b_{ij}| \leq M (1 - y_{ij}) \quad \forall ij \in \Omega^l \quad (17)$$

$$y_{ij} \in \{0, 1\} \quad \forall ij \in \Omega^{sw} \quad (18)$$

where: sets Ω^l , Ω^{sw} , and Ω^b include normal branches (distribution lines and transformers), switches, and network buses, respectively. $|Z_{ij}|$ and $|S_{ij}|$ are magnitudes of impedance and complex power for branch ij , respectively. P_{ij} and Q_{ij} are active and reactive power flows of branch ij , respectively. Ps_i and Qs_i are active and reactive powers of substation and Pd_i and Qd_i are nominal active and reactive demands of bus i , respectively. $|I_{ij}|$ and I_{ij}^{\max} are magnitude of current flow and its maximum value for branch ij . $|V_i|$, V_{\max} , and V_{\min} are the voltage magnitude of bus i and its maximum and minimum amounts, respectively. b_{ij} is a variable for representing the Kirchhoff's voltage law (KVL) in the loop formed by line ij . Also, y_{ij} is a binary variable, indicating the operation status of switch located on line ij (0 for open and 1 for closed switches).

Equations (9) and (10) express active and reactive power balances of each bus (Kirchhoff's current law, KCL). Equation (11) describes the net summation of voltage drops of all branches in a planar loop, which must be equal to zero (KVL). In this equation, b_{ij} will be zero, when the switch of line ij is closed (KVL must be established) and will be a real number for open switches (KVL is not necessary). Also, (12) represents the line power flow in terms of its active and reactive components. Equation (13) shows relationship between power flow of each branch and its current and end bus voltage. Equation (14) models the radiality constraint. Accordingly, the total number of branches under operation (total number of closed switches) has to be equal to the total number of buses minus one (according to graph theory). Constraints (15) and (16) represent voltage and current

limits, respectively. It should be mentioned that (15) provides an acceptable voltage level for network buses in order to compensate voltage drop. (17) makes sure that the value of b_{ij} will be zero, if the switch of line ij is closed ($y_{ij} = 1$) and a real number between M and $-M$ when the corresponding branch is disconnected ($y_{ij} = 0$). In order to determine the value of M , let's consider that the switch of branch ij is open. From (16), it is obtained that $|I_{ij}|$ will be zero because of $y_{ij} = 0$, and therefore $P_{ij} = Q_{ij} = 0$ due to (12) and (13). Thus, the maximum value of M is $V_{\max}^2 - V_{\min}^2$ because $b_{ij} = |V_i|^2 - |V_j|^2$ from constraint (11) and the maximum difference between lower and upper voltage limits from constraint (15).

B. OUR PROPOSED ROBUST MODEL

In order to consider demand uncertainty in DSR using the proposed idea, active and reactive load deviations (ΔPd and ΔQd) have to be embedded in constraints (9) and (10), in which the deviation amounts should not exceed their permissible intervals (e.g. $[\Delta Pd_{\min}, \Delta Pd_{\max}]$ for active and $[\Delta Qd_{\min}, \Delta Qd_{\max}]$ for reactive demand deviations). The strategy should be maximization of load deviations because the zero (certain load situation) or negative values are suggested for ΔPd and ΔQd in minimization process, while the network users have more concerns about demand increment. On the other hand, maximization strategy has to be considered correctly, otherwise the solution algorithm tries to find the maximum values for load deviations and this issue raises the power losses considerably. Therefore, the best strategy is maximization of total demand deviation as it cannot increase the power losses significantly (minimum possible losses besides maximum probable deviations), i.e. the proposed model has to be robust enough. Also, the probability of uncertainties should be included in the problem formulation. Regarding the relationship between active and reactive demands at each bus through load power factor, maximization of active load deviation is adequate [35].

It should be noted that, the model described by (8)–(18) is a hard nonlinear optimization problem with non-convexity (constraint (12)) and accordingly hard to solve. Also, (14) cannot guarantee radial topologies for large-sized distribution systems and networks with transfer nodes. Whereas real distribution networks often contain buses without substation and demand (transfer nodes). Moreover, additional constraints should be included in the problem formulation in order to increase the accuracy of the model and reduce its execution time. Consequently, following robust model is proposed for the DSR problem under uncertainty with the aim of active losses minimization.

$$\text{Min } \left(\sum_{ij \in \Omega^l} R_{ij} I_{ij}^{sqr} - \sum_{i \in \Omega^b} \Delta Pd_i Pd_i f(\Delta Pd_i) \right) \quad (19)$$

$$\text{where, } f(\Delta Pd_i) = \frac{f(\Delta Pd_{m,i}) - f(\Delta Pd_{m-1,i})}{\Delta Pd_{m,i} - \Delta Pd_{m-1,i}}$$

$$(\Delta Pd_i - \Delta Pd_{m,i}) + f(\Delta Pd_{m,i})$$

$$\begin{aligned} \forall 0 \leq \Delta Pd_{m-1,i} \leq \Delta Pd_i \leq \Delta Pd_{m,i} \\ \leq \Delta Pd_{\max} \end{aligned} \quad (20)$$

$$\begin{aligned} f(\Delta Pd_i) = \frac{f(\Delta Pd_{m-1,i}) - f(\Delta Pd_{m,i})}{\Delta Pd_{m,i} - \Delta Pd_{m-1,i}} \\ (\Delta Pd_i + \Delta Pd_{m,i}) + f(\Delta Pd_{m,i}) \\ \forall \Delta Pd_{\min} \leq -\Delta Pd_{m,i} \leq \Delta Pd_i \\ \leq -\Delta Pd_{m-1,i} \leq 0 \end{aligned} \quad (21)$$

$$\begin{aligned} \text{s. t. : } Ps_i + \sum_{ki \in \Omega^l} P_{ki} - \sum_{ij \in \Omega^l} P_{ij} - \sum_{ij \in \Omega^l} R_{ij} I_{ij}^{sqr} \\ = Pd_i + \Delta Pd_i Pd_i \quad \forall i \in \Omega^b \end{aligned} \quad (22)$$

$$\begin{aligned} Qs_i + \sum_{ki \in \Omega^l} Q_{ki} - \sum_{ij \in \Omega^l} Q_{ij} - \sum_{ij \in \Omega^l} X_{ij} I_{ij}^{sqr} \\ = Qd_i + \Delta Qd_i Qd_i \quad \forall i \in \Omega^b \end{aligned} \quad (23)$$

$$\begin{aligned} V_i^{sqr} - V_j^{sqr} = 2[R_{ij}P_{ij} + X_{ij}Q_{ij}] + |Z_{ij}|^2 I_{ij}^{sqr} + b_{ij} \\ \forall i \neq j \in \Omega^b, ij \in \Omega^l \end{aligned} \quad (24)$$

$$V_j^{sqr} I_{ij}^{sqr} \geq P_{ij}^2 + Q_{ij}^2 \quad \forall ij \in \Omega^l \quad (25)$$

$$y_{ij} = \beta_{ij} + \beta_{ji} \quad \forall ij \in \Omega^l \quad (26)$$

$$\sum_{ij \in \Omega^l} \beta_{ij} = 1 \quad (27)$$

$$\beta_{ij} = 0 \quad \forall i \in \Omega^0, ij \in \Omega^l \quad (28)$$

$$\beta_{ji} = 0 \quad \forall j \in \Omega^0, ij \in \Omega^l \quad (29)$$

$$V_{\min}^2 \leq V_i^{sqr} \leq V_{\max}^2 \quad \forall i \in \Omega^b \quad (30)$$

$$0 \leq I_{ij}^{sqr} \leq (I_{ij}^{\max})^2 y_{ij} \quad \forall ij \in \Omega^l \quad (31)$$

$$|b_{ij}| \leq (V_{\max}^2 - V_{\min}^2)(1 - y_{ij}) \quad \forall ij \in \Omega^l \quad (32)$$

$$\Delta Pd_{\min} Pd_i \leq \Delta Pd_i Pd_i \leq \Delta Pd_{\max} Pd_i \quad \forall i \in \Omega^b \quad (33)$$

$$\Delta Qd_{\min} Qd_i \leq \Delta Qd_i Qd_i \leq \Delta Qd_{\max} Qd_i \quad \forall i \in \Omega^b \quad (34)$$

$$P_{ij}^{\max} = V_{\max} I_{ij}^{\max} \quad \forall ij \in \Omega^l \quad (35)$$

$$Q_{ij}^{\max} = V_{\max} I_{ij}^{\max} \quad \forall ij \in \Omega^l \quad (36)$$

$$|P_{ij}| \leq P_{ij}^{\max} y_{ij} \quad \forall ij \in \Omega^l \quad (37)$$

$$|Q_{ij}| \leq Q_{ij}^{\max} y_{ij} \quad \forall ij \in \Omega^l \quad (38)$$

$$\beta_{ij} \in \{0, 1\} \quad \forall ij \in \Omega^{sw} \quad (39)$$

In above constraints, I_{ij}^{sqr} and V_i^{sqr} are square of branch current and bus voltage magnitudes, respectively ($I_{ij}^{sqr} = |I_{ij}|^2$, $V_i^{sqr} = |V_i|^2$, and $V_j^{sqr} = |V_j|^2$). Ω^0 is set of substation buses and β_{ij} is the binary variable to show direction of power flow in branch ij . P_{ij}^{\max} and Q_{ij}^{\max} are the maximum active and reactive powers of branch ij , respectively. $\Delta Pd_{m,i}$ and $\Delta Qd_{m,i}$ are m -th deviations of active and reactive power demands at bus i , respectively. Equations (26) to (29) guarantee network radiality and connectivity in large distribution systems with any number of substation and transfer nodes. Also, (37) and (38) show that active and reactive power flows of branches should be limited by their maximum values.

Although constraints (30) and (31) provide these conditions, (37) and (38) improve computation time and accuracy of solutions. Moreover, (25) indicates a convex constraint because it includes an area inside a circle with radius $|V_j| |I_{ij}|$ and center of (0, 0).

The main differences and similarities of our proposed model with models presented in [34]–[37] are:

- 1) In [34]–[36], probabilities of uncertainties have not been considered in the formulations, while this important issue has been considered in our proposed model.
- 2) In our proposed model similar to [34], the ratio of active and reactive load deviations at each bus is proportional to ratio of its active and reactive demands, while in [35]–[37], active and reactive demand deviations of each bus do not depend on their active and reactive loads.
- 3) Models of [34]–[37] do not include constraints (35) to (38).
- 4) Both load and generation uncertainties have been considered in [35]–[37], while just load uncertainty has been included in our proposed model and [34].
- 5) Objective functions of our proposed model and models presented in [34] and [35] include only power losses, while those of [36] and [37] consider switching and DG operational costs in addition to losses cost.

C. PROPOSED DETERMINISTIC MODEL

The deterministic model obtained by choosing values of zero for ΔPd_i , ΔQd_i , and $\Delta Pd_{m,i}$ in the robust model.

$$\text{Min} \sum_{ij \in \Omega^l} R_{ij} I_{ij}^{sqr} \quad (40)$$

$$\text{s. t. (26) to (31) and :} \quad (41)$$

$$\begin{aligned} Ps_i + \sum_{ki \in \Omega^l} P_{ki} - \sum_{ij \in \Omega^l} P_{ij} - \sum_{ij \in \Omega^l} R_{ij} I_{ij}^{sqr} \\ = Pd_i \quad \forall i \in \Omega^b \end{aligned} \quad (42)$$

$$\begin{aligned} Qs_i + \sum_{ki \in \Omega^l} Q_{ki} - \sum_{ij \in \Omega^l} Q_{ij} - \sum_{ij \in \Omega^l} X_{ij} I_{ij}^{sqr} \\ = Qd_i \quad \forall i \in \Omega^b \end{aligned} \quad (43)$$

$$\begin{aligned} V_i^{sqr} - V_j^{sqr} = 2[R_{ij}P_{ij} + X_{ij}Q_{ij}] \\ + (R_{ij}^2 + X_{ij}^2) I_{ij}^{sqr} + b_{ij} \quad \forall i \neq j \in \Omega^b, ij \in \Omega^l \end{aligned} \quad (44)$$

$$|S_{ij}|^2 \geq P_{ij}^2 + Q_{ij}^2 \quad ij \in \Omega^l \quad (45)$$

$$|S_{ij}|^2 = V_j^{sqr} I_{ij}^{sqr} \quad \forall j \in \Omega^b, ij \in \Omega^l \quad (46)$$

$$\begin{aligned} (V_{\min}^2 - V_{\max}^2)(1 - y_{ij}) \leq |b_{ij}| \\ \leq (V_{\max}^2 - V_{\min}^2)(1 - y_{ij}) \quad \forall ij \in \Omega^l \end{aligned} \quad (47)$$

$$|P_{ij}| \leq V_{\max} I_{ij}^{\max} y_{ij} \quad \forall ij \in \Omega^l \quad (48)$$

$$|Q_{ij}| \leq V_{\max} I_{ij}^{\max} y_{ij} \quad \forall ij \in \Omega^l \quad (49)$$

where: R_{ij} is the resistance and X_{ij} is the reactance of branch ij .

IV. METHODOLOGY

The proposed robust mathematical model is a mixed-integer conic programming problem including binary variables y_{ij} and β_{ij} , real variables P_{ij} , Q_{ij} , P_i^S , Q_i^S , I_{ij}^{sqr} , V_i^{sqr} , ΔPd_i , ΔQd_i , and b_{ij} , a linear objective function (19), linear equations (20), (21), (24), (26)–(29), (35) and (36), linear constraints (22), (23), (30)–(34), (37) and (38), and convex restriction (25). The problem can be solved using analytical methods, heuristic techniques, and metaheuristic algorithms. It should be noted that heuristics and metaheuristics cannot guarantee the global optimum. Analytical methods, based on mathematical programming, are widely used to solve the DSR problem. For this purpose, AMPL as an algebraic modeling language has been designed for mathematical programming. The AMPL software is notable for the similarity of its arithmetic expressions to customary algebraic notation, and for the generality and power of its set and subscripting expressions. The AMPL also extends algebraic notation to express common mathematical programming structures, such as network flow constraints and piecewise linearities. This software offers an interactive command environment for setting up and solving mathematical programming problems. A flexible interface enables several solvers to be used simultaneously, so user can switch among solvers and select options that may improve solver performance. Once optimal solutions have been found, they are automatically translated back to the modeler's form, so they can be viewed and further analyzed. All of the general set and arithmetic expressions of the AMPL modeling language can also be used for displaying data and results; a variety of options are available to format data for browsing, printing reports, or preparing inputs to other programs [38]. The AMPL is a powerful optimization tool that can be used efficiently to solve the proposed problem. One of the most efficient solvers of AMPL is CPLEX. Therefore, in the current paper, the CPLEX solver in AMPL is used to solve our developed optimization problem in (19)–(39) and the one in (40)–(49).

V. MODEL ANALYSIS AND SIMULATION RESULTS

In order to show the efficiency of our proposed reconfiguration approach in uncertain environments, the proposed robust model was tested on several distribution systems and our results were compared with the ones presented by [34]–[37]. The models of [34]–[37] have been selected to verify our obtained results because of their robustness against uncertainties. The models in [34] and [35] have been implemented in AMPL and solved by CPLEX solver. Similarly, we used AMPL and CPLEX in our paper. The models of [36] and [37] have been simulated in GAMS and MATLAB, respectively. Also, only load uncertainty has been considered in reference [35] (similar to our model in the current paper), while in [34], [36], and [37], generation uncertainty has been taken into account in addition to uncertain demand. Moreover, for providing an accurate comparison between the obtained results and solutions proposed by [34]–[37], according to [35], the ratio of active and reactive load

deviations of each bus are assumed to be fixed and proportional to ratio of its active and reactive demands when the results are compared with those of [35]. Otherwise, according to [34], [36], and [37], load deviations are considered to be independent from active and reactive demands when the results are compared with solutions of [34], [36], and [37]. Also, the same load deviation limits as [35] ($\Delta Pd_{\max} = 5\%$ and $\Delta Pd_{\min} = -5\%$) were considered for our proposed robust model. Regarding ignorance of load uncertainty probability in [34]–[36], the standard load deviation used by [31] ($\sigma = 0.05$) was applied to our proposed formulation. The horizontal axis of Fig. 3 has been divided into 10 intervals of 0.01 step length ($m = 5$) between minimum and maximum load deviations. This partition can simulate efficiently the sharp curve of PDF by piecewise linear functions.

The models of [35], [36], and [37] have been performed on processors with CPUs of 2.53, 1.8, and 3.2 GHz and 8, 16, and 16 GB of RAM, respectively, while our proposed model in the current paper was run on a computer with a 3.6-GHz CPU and 16 GB of RAM. In order to have a fair comparison between computational times of all models, difference between CPU times of deterministic and robust models of [35]–[37] are compared with that of our proposed models.

A. 16-BUS TEST SYSTEM

A three-feeder 23 kV distribution system connected to substation buses 1, 2, and 3 including 13 sectional switches and three tie switches (dashed lines) is shown in Fig. 4. All data, such as resistances and reactances of branches, and nodal active and reactive power demands are reported in [39]. The maximum currents of branches 11, 16, and 18 are considered 500 A, 500 A, and 300 A, respectively, while those of all other branches are considered to be 250 A. Also, the network loss before reconfiguration is 511.4 kW. The model was applied to the 16-bus distribution system and proposed configurations, nominal and maximum power losses, and computing times are presented in Table 1.

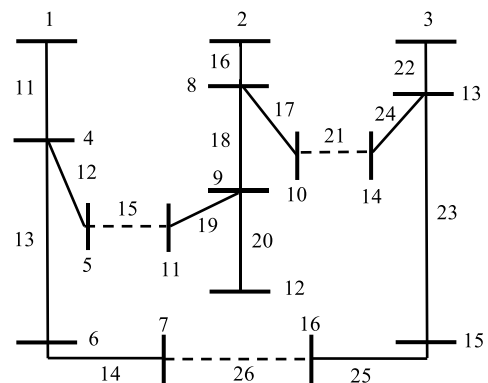


FIGURE 4. The 16-bus test system.

According to results presented in Table 1, our proposed robust model can find lower maximum power losses

TABLE 1. Numerical results for 16-bus test system.

Models	Open Switches	Power Losses (kW)		CPU Times (s)	
		Nominal	Maximum		
[35]	Deterministic	17,19,26	466.1	517.8	0.8
	Robust	17,19,26	466.1	517.8	17.18
Proposed	Deterministic	17,19,26	466.1	515.23	0.27
	Robust	17,19,26	466.1	515.23	0.31

(2.57 kW less) as compared to the models of [35]. This fact shows higher robustness of our proposed model compared to robust model of [35]. Also, comparing difference of CPU times between deterministic and robust models of [35] with the difference in CPU times of proposed models shows that the robust model presented by this article can solve the reconfiguration problem much faster than [35] in uncertain environments. Therefore, the proposed robust model is more efficient than that of [35] for reconfiguration of small distribution networks with uncertain loads.

B. 33-BUS TEST SYSTEM

The system shown in Fig. 5 includes two radial feeders with three 12.66 kV laterals, five tie switches, and 32 normal branches. The data of this test system are available in [12] and its initial loss (before reconfiguration) is 202.7 kW. The voltage of the substation bus (node 0) is assumed 1 per unit. The maximum current flow of each branch is 500 A. The proposed formulation was applied to this test system and the results in comparison with alternative models of [35] and [37] are listed in Table 2.

From Table 2, deterministic and robust models of [35] present non-radial solutions because opening switch 29 resulted in non-radial configurations and isolation of some buses such as 29, 30, and 31 from the network, while our proposed robust model finds the optimal radial solution in shorter computational time than the robust models of [35] and [37]. The same nominal losses and configurations found by both proposed models in current paper show high robustness of the presented formulation for reconfiguration of radial distribution networks in uncertain situations.

C. 70-BUS TEST SYSTEM

This test system is an 11 kV radial distribution network with two substations, four feeders, 68 load buses, 11 tie lines, and 68 sectional switches, as shown in Fig. 6. Data for this system are available in [5]. The initial power loss of the network is 227.5 kW. Table 3 shows proposed configurations, power losses amounts, and computation times of both deterministic and robust models.

Different radial topologies presented in Table 3 when the demand uncertainties are considered show non-robustness of all deterministic models. However, the proposed robust model is more efficient than those of [34] and [35] because

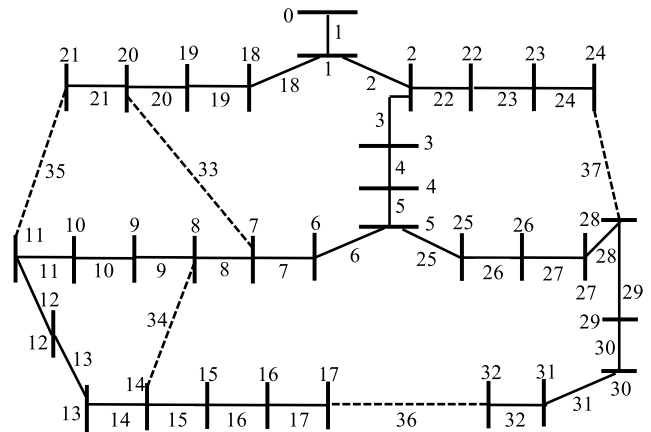


FIGURE 5. The 33-bus test system.

TABLE 2. Numerical results for 33-bus test system.

Models	Open Switches	Power Losses (kW)		CPU Times (s)	
		Nomi.	Max.		
[35]	Deterministic	7,9,14,29,32	129.9	Infeasible	3.90
	Robust	7,11,14,29,32	131.6	145.3	209.3
[37]	Deterministic	7,9,14,32,37	139.5	152.6	-
	Robust	7,9,12,17,28	149.7	162.4	71.06
Proposed	Deterministic	7,9,14,32,37	139.5	152.6	1
	Robust	7,9,14,32,37	139.5	152.6	1.92

it suggests a configuration with less nominal and maximum losses than the ones from configuration in [34] and [35].

Also, our proposed robust model can find better solution in shorter computational time than the one from robust model of [35]. These facts confirm higher efficiency of our proposed robust model compared to those of [34] and [35] for reconfiguration of 70-bus distribution system under load uncertainty.

D. 94-BUS TEST SYSTEM

As shown in Fig. 7, this real 11.4 kV network consists of two substations on buses 84 to 94, 11 radial feeders, 83 sectionalizing switches, and 13 tie lines, with data presented in [41].

The current-carrying capacity of each line (I_{ij}^{max}) is 410 A. The active power loss of initial network is 532 kW. Performance of the proposed models compared to alternative models of [35] is shown in Table 4 for this real distribution system.

Table 4 represents that the configuration found by our proposed robust model causes less nominal and maximum losses than switching sequences proposed by robust model of [35]. As we can see, our proposed deterministic model obtains less nominal power losses as compared to the nominal power losses in [35] (469.88 kW as compared to 471.9 kW). Our proposed robust model is much faster and more efficient

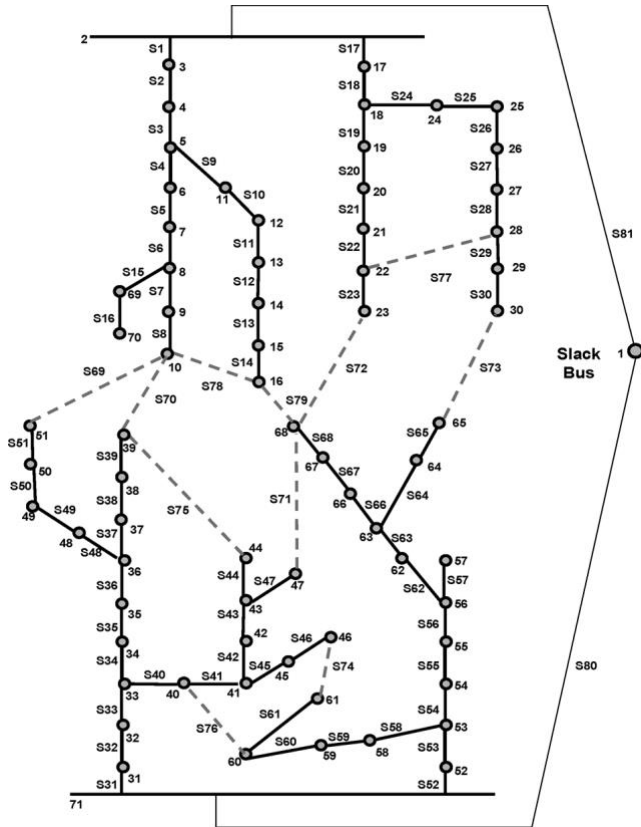


FIGURE 6. The 70-bus test system [40].

TABLE 3. Numerical results for 70-bus test system.

Models	Open Switches	Power Losses (kW)		CPU Times (s)	
		Nomi.	Max.		
[34]	Deterministic	7,13,22,39,46,63,64,72,75,76,78	237.5	296.9	-
	Robust	7,14,22,39,46,65,68,71,75,76,78	246.3	256.1	-
[35]	Deterministic	14,30,39,46,51,66,71,75,76,77,79	204.1	Inf.	13.3
	Robust	14,30,39,46,51,66,70,71,76,77,78	207.7	224.5	123.1
Proposed	Deterministic	13,30,45,51,66,70,75,76,77,78,79	201.4	Inf.	4.74
	Robust	14,30,51,66,70,74,75,76,77,78,79	203.4	223.5	25.53

than model of [35] in reconfiguration of real distribution networks.

E. 118-BUS TEST SYSTEM

An 11 kV distribution network, as shown in Fig. 8, with three radial feeders, one substation bus, 118 and 15 sectional and tie switches was chosen to show efficiency and robustness of the proposed formulation in large distribution systems. The parameters and related data of the system are available

TABLE 4. Numerical results for 94-bus test system.

Models	Open Switches	Power Losses (kW)		CPU Times (s)	
		Nomi.	Max.		
[35]	Deterministic	7,13,33,37,40,63,72,82,84,86,89,90,92	471.9	Inf.	3
	Robust	7,13,34,39,42,61,72,82,84,86,89,90,92	472.7	521.1	160.1
Proposed	Deterministic	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	Inf.	2.74
	Robust	7,13,34,39,55,62,72,83,86,89,90,92,95	470.01	515.5	3.69

TABLE 5. Numerical results for 118-bus test system.

Models	Open Switches	Power Losses (kW)		CPU Times (s)	
		Nomi.	Max.		
[34]	Deterministic	22,34,39,42,47,57,59,70,75,119,121,126,129-131	1145	Inf.	-
	Robust	22,34,39,42,43,46,57,59,69,75,119,126,129-131	1239	1367	-
Proposed	Deterministic	23,26,34,39,42,51,58,71,74,95,97,109,122,129,130	869.7	Inf.	62.08
	Robust	23,26,34,39,42,51,58,71,74,95,98,109,122,129,130	870.5	950.3	83.4

in [42], where the initial power loss is 1298 kW. Table 5 shows the relevant results compared to alternative model of [34].

Table 5 shows that the proposed deterministic and robust models find better configurations with lower power losses compared to configurations presented in [34]. As seen, proposed robust model could find a configuration with closer nominal losses to that of proposed deterministic formulation when compared to [34]. Also, the maximum power loss found by our proposed robust model is much lower than that found by robust model of [34]. Therefore, our proposed formulation is more efficient and robust than that of [34] for reconfiguration of 118-bus test system with uncertain loads.

F. 136-BUS TEST SYSTEM

This real network is part of the Tres Lagoas distribution system in Brazil, with data available in [43] and configuration shown in Fig. 9. It has eight radial feeders, one substation bus, 135 sectionalizing switches and 21 tie lines, with nominal voltage and initial power losses of 13.8 kV and 320.37 kW, respectively. The results are presented in Table 6, showing that the robust model finds configurations with lower nominal and maximum losses than those of [35] and [36], while loss level of our proposed robust model in nominal scenario is

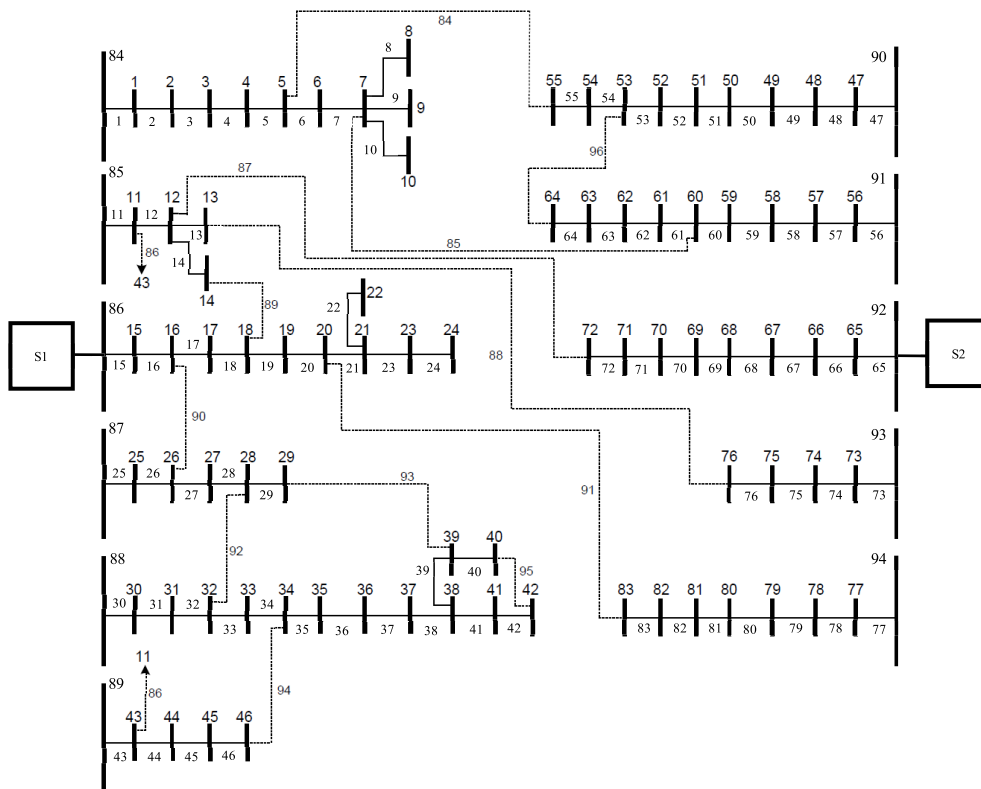


FIGURE 7. The 94-bus test system.

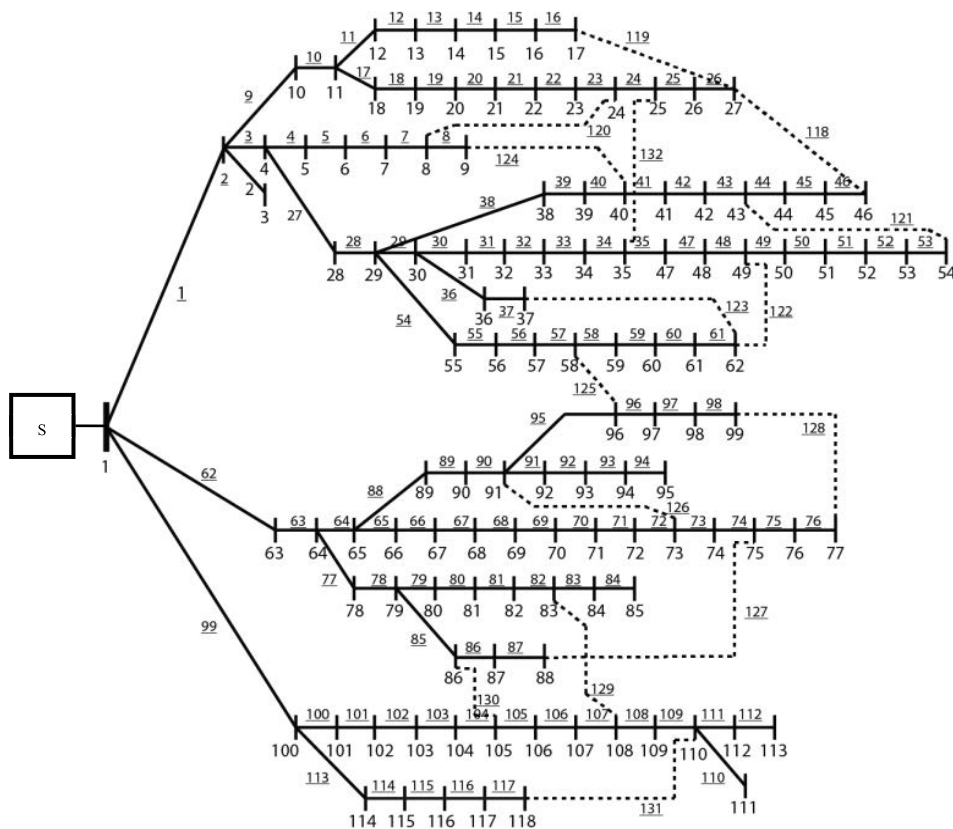


FIGURE 8. The 118-bus test system.

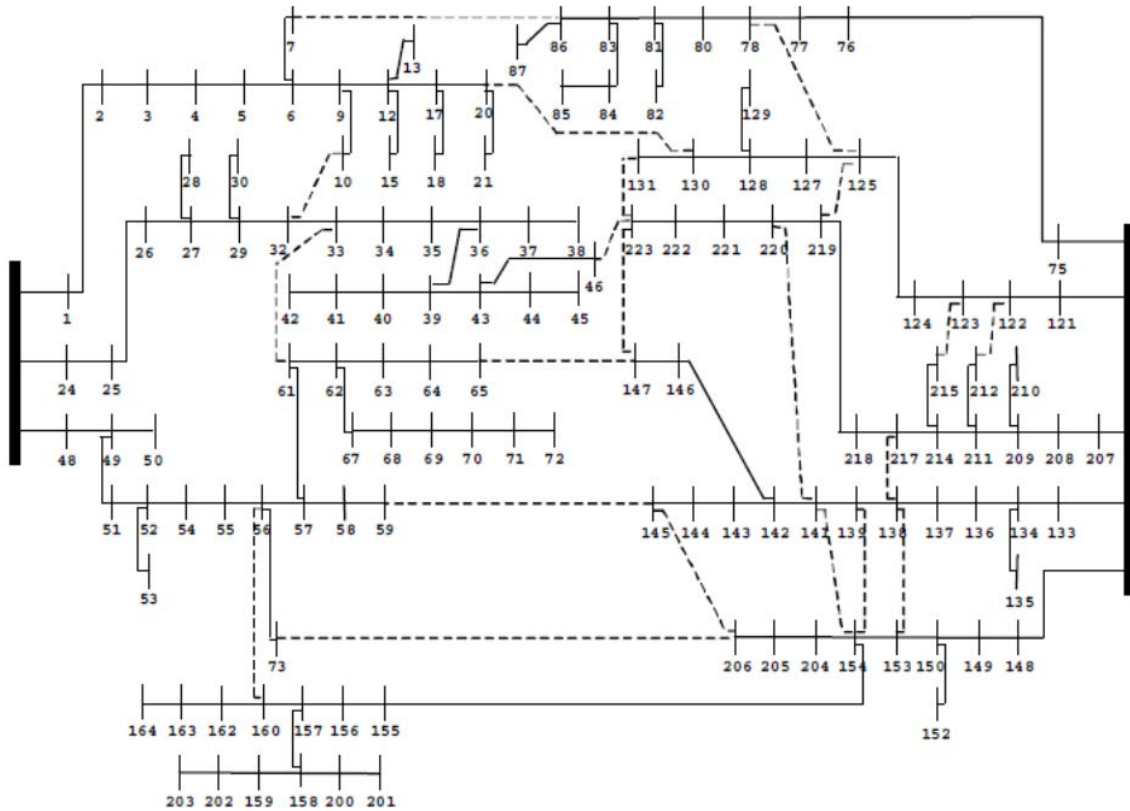


FIGURE 9. The 136-bus test system [43].

TABLE 6. Numerical results for 136-bus test system.

Models	Open Switches	Power Losses (kW)		CPU Times (s)
		Nomi.	Max.	
[35]	Deterministic 7,35,51,90,96,106,118,126,135,137,138,141,142,144-148,150,151,155	280.19	Inf.	68
	Robust 106,136-152,154-156	286.8	314.2	410
[36]	Deterministic 7,35,51,90,96,106,118,126,135,137,138,141,142,144-148,150,151,155	280.19	Inf.	68
	Robust 51,106,136-139,141-152,154-156	285.8	313.1	530
Proposed	Deterministic 7,35,51,90,96,106,118,126,135,137,138,141,142,144-148,150,151,155	280.19	Inf.	9.39
	Robust 7,38,51,54,84,90,96,106,119,126,135,137,138,141,144,145,147,148,150,151,155	281.02	307	20.44

very close to that of deterministic models. This indicates high robustness of our proposed model for reconfiguration of large and real distribution systems when compared to deterministic and robust models of [35] and [36].

TABLE 7. Changes of maximum power losses versus load deviation limits.

Load Deviation Limits	Maximum Power Losses (kW)					
	1%	2%	3%	4%	5%	6%
Robust Model of [35]	480	490	502	507	521.1	534
Proposed Robust Model	478.8	478.8	497	506	515.5	522.9

VI. DISCUSSION

In order to control overall load variations and reduce the search space of reconfiguration algorithm, a set of uncertainties have been designed and limited in [34]–[37]. As a result of this assumption, some buses cannot have uncertain loads and this issue decreases the efficiency of the models [34]–[37] for solving large-scale reconfiguration problems. Whereas our proposed robust model solves the DSR problem much faster and more accurate than models of [34]–[37] without imposing any uncertainty sets and limits. The limited uncertainty-set assumption and high complexity level are some weaknesses of the models proposed in [34]–[37]. The high complexity of the models presented in [34]–[37] compared to our proposed robust model causes their hard implementation for real applications. In addition, non-radial solutions found in [35] for 33-bus test system show that models of [35] may fail in reconfiguration of some distribution systems. For more analysis, robustness of both models versus different load deviation limits is demonstrated in Table 7 for 94-bus distribution system.

Table 7 shows better robustness of our proposed model compared to the model of [35] in all cases of load uncertainty. It can be seen that maximum power loss is increased by expanding load deviation limit. Also, it is observed that the performance of our proposed model becomes better in higher uncertainty levels as compared to robust model of [35]. This fact indicates high efficiency and robustness of our proposed model for reconfiguration of real distribution systems with severe uncertainties.

VII. CONCLUSION

Distribution networks are designed and operated based on an expected power demand predicted by load forecasting. The load consumption has an important impact on network operation conditions as every increase or decrease in its amount significantly affects network losses and operational costs. Reconfiguration of distribution systems is an effective way to reduce distribution losses, in which the states of switches are changed according to the expected (nominal) demand, while the technical and operational conditions have to be satisfied. Therefore, any change in power demand may affect the proposed reconfiguration topologies through its influence on operational costs, network losses, and operational conditions. On the other hand, load uncertainty should be considered in network reconfiguration in an efficient way such that the proposed switching sequences cannot be changed easily by any change in demand value (adequate robustness).

Accordingly, this paper presents an efficient robust model for reconfiguration of distribution systems with uncertain loads. The evaluation of the numerical results shows high efficiency and robustness of our proposed model when distribution networks are under load uncertainty. Main features of our proposed formulation compared to existing reconfiguration models are simple implementation, high computational efficiency, and adequate robustness. In our proposed approach, load uncertainty and its probability are embedded in the reconfiguration model effectively such that the deviation of maximum power loss from its nominal amount is small (sufficient robustness) while configuration of networks may be changed due to load uncertainties (high effectiveness). Our proposed model can be a good alternative for reconfiguration of real distribution systems because of its simple implementation, high computational efficiency, enough robustness, and low computational time compared to other proposed models in the relevant literature.

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also a Postdoctoral Fellow with the Department of Electrical Engineering, São Paulo State University, from 2017 to 2019. He is currently an Assistant

MEISAM MAHDAVI received the B.Sc. degree in electrical power engineering from IAU, in 2005, the M.Sc. degree in electrical power engineering from the University of Zanjan, in 2008, and the Ph.D. degree in electrical power engineering from the University of Tehran, in 2015. From 2011 to 2015, he was teaching electrical engineering courses at IAU. He was an Assistant Professor with the Faculty of Engineering, IAU, West Tehran Branch, from 2016 to 2017. He was

Researcher with the Associated Laboratory of IPBEN, São Paulo State University, Campus of Ilha Solteira. He is the author of three books, six book chapters, and more than 90 journal and conference papers. His research interests include distribution network reconfiguration, power system operation, power system expansion planning, renewable energies, distributed generation, bioenergy, network reliability, power system maintenance, and the applications of artificial intelligence and computational algorithms in optimization. He has performed reviews for high-quality journals, like IEEE ACCESS, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, IEEE SYSTEMS JOURNAL, IEEE LATIN AMERICA TRANSACTIONS, *IET Generation, Transmission & Distribution*, *Electrical Engineering, Energies, Electric Power Components and Systems, Applied Sciences, International Transactions on Electrical Energy Systems, Journal of Control, Automation and Electrical Systems, Journal of Ocean Engineering and Science*, and *Journal of Operation and Automation in Power Engineering*.



HASSAN HAES ALHELOU (Senior Member, IEEE) is currently with the School of Electrical and Electronic Engineering, University College Dublin, Ireland. He is also a Faculty Member with Tishreen University, Lattakia, Syria. He has participated in more than 15 industrial projects. He has published more than 120 research articles in high-quality peer-reviewed journals and international conferences. He has also performed more than 600 reviews for high prestigious journals, including IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON INDUSTRIAL POWER SYSTEMS, and *International Journal of Electrical Power & Energy Systems*. His research interests include power systems, power system operation, power system dynamics and control, smart grids, microgrids, demand response, and load shedding. He was a recipient of the Outstanding Reviewer Award from many journals, such as *Energy Conversion and Management (ECM)*, *ISA Transactions*, and *Applied Energy*. He was also a recipient of the Best Young Researcher in the Arab Student Forum Creative among 61 researchers from 16 countries at Alexandria University, Egypt, in 2011. He is included in the 2018 Publons list of the top 1% best reviewer and researchers in the field of engineering in the world.



MOHAMMAD REZA HESAMZADEH (Senior Member, IEEE) received the Ph.D. degree from the Swinburne University of Technology, Australia, in 2010, and the Docent (higher doctorate) degree from the KTH Royal Institute of Technology, Stockholm, Sweden, in 2013. From 2010 to 2011, he was a Postdoctoral Fellow with the KTH Royal Institute of Technology, where he is currently an Associate Professor. He is also a Faculty Affiliate with the Program on Energy and Sustainable Development (PESD), Stanford University, Stanford, CA, USA, and a Research Affiliate with the German Institute for Economic Research, DIW Berlin, Berlin, Germany. He is the author of the textbook *The Economics of Electricity Markets* (Wiley-IEEE Press) and also an Editor of the book *Transmission Network Investment in Liberalized Power Markets* (Springer). He has been providing advice and consulting services on different energy market issues to both private and government sectors over the last several years. He is a member of INFORMS, IAEE, and CIGRE. He also served as the Editor for the IEEE TRANSACTIONS ON POWER SYSTEMS and a guest editor for several other journals.

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