Rearrangement of Electrical Distribution Networks With Optimal Coordination of Grid-Connected Hybrid Electric Vehicles and Wind Power Generation Sources

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ABSTRACT In this paper, a new model for distribution network rearrangement (DNR) with regard to plug-in electric vehicles (PEVs) is presented. The proposed model is a random model (random programming) in which scenarios corresponding to vehicle uncertainty are simulated by the Monte Carlo method. The distribution system was also mathematically modeled by an approximate linear model. This way of modeling helps us to derive a new design based on linear integer programming. The electricity market is considered to be the day-ahead electricity market. Uncertainties regarding the price of electricity as well as the load of the distribution network are also considered. The simulation results on a 24-bus distribution system showed that the proposed model has the required efficiency. Uncertainties related to PEVs are modeled by random programming using Monte Carlo Simulation (MCS). The DNR problem is formulated as a MILP problem. This problem is then solved by the Banders decomposition (BD) algorithm. Numerical results also showed that if the PEV is charged intelligently in the DNR issue, then the cost of purchasing electricity from above will be lower than in the case where the PEV is not controlled in a controlled way. We also see a different switching strategy in these two cases, which indicates that considering the electric vehicle in the DNR problem is inevitable. In addition, a method for rearranging distribution networks to transfer load from one feeder to another was presented. It has been observed that this reduces the load of high-capacity feeders well and causes the construction of new feeders to be delayed. It was also observed that rearrangement of the distribution network leads to a reduction in network losses. Also, with the help of rearrangement, the amount of interrupted load can be significantly reduced.

INDEX TERMS Distribution network reconfiguration, wind power, plug-in electric vehicle, uncertainty stochastic programming.

NOMENCLATURE

PEV Presence of Electric Vehicles
DNR Distribution network reconfiguration
BD Benders’ Decomposition
GA Genetic algorithm
BA Bat Algorithm
KHA Krill Herd Algorithm
ACA Ant Colony Algorithm
MILP mixed-integer linear programming
PL Parking-Lot
IGDT Information Gap Decision Theory
MCS Monte Carlo Simulation
MILP mixed-integer linear programming
DG Distributed Generation
CSA Cuckoo Search Algorithm
HAS Harmony Search Algorithm
BFOA Bacterial Foraging Optimization Algorithm
PSO Particle Swarm Optimization
MINLP mixed-integer nonlinear programming
GPL Grid-connected parking Lot
DS Distribution System
I. INTRODUCTION

The rearrangement problem is known as a nonlinear optimization problem with multiple constraints. Some arrangements are not allowed to be selected due to violations of restrictions such as radial network, the voltage of all bus bars and violation of operating restrictions such as allowable voltage and current range. The problem of redistribution of distribution networks was first posed by two French researchers, Merlin and Beck, in 1975 to reduce distribution network losses in an innovative way. In this method, to achieve an optimal arrangement, after closing all the switches, the switches that have less current are opened, which ultimately leads to the formation of radial networks with the least losses [1]. After that, various techniques were proposed to rearrange the distribution network. In 1988, Sivanlar introduced a method in which branches are replaced, that is, as soon as one switch is closed, another switch is opened, leaving a radial arrangement, and this process until the losses are minimized. To be continued [2]. Subsequently, in 1989, Shirmohammadi developed this method and included the constraint related to the flow through the feeder. It also solved the network in a weak loop, resulting in less network losses. According to this method, first, all the normally open state switches of the network are closed, by doing this, the radial network is turned into a circular network, and then the network switches are opened one by one, to return the network to the radial state again. In the opening process, switches are opened to reduce the ohmic losses of the resulting lines [3]. After this method, glamocanin, which was formulated based on a transportation problem with square costs, was used for rearrangement [4]. Also in the following years, the rearrangement problem was implemented by Baran and Hu. In this way, first all the switches are considered closed and then the loop with the most losses is selected and opened by distributing the load. In addition to the innovative methods used in previous years to rearrange the problem, in recent years, intelligent algorithms have been used to find the optimal arrangement. It should be noted that these algorithms are also called meta-heuristic algorithms, which can include Genetic Algorithm (GA), Cuckoo Search Algorithm (CSA), Bat Algorithm (BA), Krill Herd Algorithm (KHA), Harmony Search Algorithm (HAS), Bacterial Foraging Optimization Algorithm (BFOA), Ant Colony Algorithm (ACA) and Particle Swarm Optimization (PSO) [5]–[12]. All of these algorithms, inspired by natural phenomena, have been able to arrive at a mathematical model to optimize problems such as distribution network rearrangement. Various objectives such as loss reduction, improving voltage profile, load balancing and improving reliability indicators for optimization are considered as objective functions in these algorithms. As mentioned, the rearrangement of distribution networks is a nonlinear optimization problem with complex numerical variables, so these problems cannot be solved by conventional methods, and most optimization algorithms are a good answer to solve these problems. Will not find and consider the local optimal point instead of the general optimal point as the output response. In the reference [13], a new approach to rearrange the electrical energy distribution networks using the ant colony optimization algorithm to achieve minimum power losses and increase the load balance coefficient in the electrical distribution network under study in the presence of power generation sources, scattered power is provided. To show the effectiveness of the proposed approach and solve the problem of optimal switching of the electricity distribution network, a 33-bus distribution test network has been used. The results obtained from the implementation of the above approach show that the network power losses and network load balance in the presence of distributed power generation sources have better values compared to the case where these resources are not present in the network. In the reference [14], the issue of rearrangement of electrical energy distribution systems, which is a complex optimization problem, is presented. The above problem aims to find an optimal radial configuration of the electricity distribution network that minimizes power losses in the electricity distribution network, while also meeting the operating limitations of the electricity distribution network. In the above reference, the harmonic search meta-heuristic algorithm is used to solve the problem of rearrangement of electrical energy distribution networks. In the reference [15], a new approach to solve the problem of rearrangement of electricity distribution networks in the presence of distributed power generation sources to minimize real power losses and improve the voltage profile in the electricity distribution network under study is presented. Meta-heuristic algorithms have been used to determine the optimal location of distributed power generation sources. Feeder voltage and current limits are also considered in modeling the proposed approach. In the reference [16], it solves the problem of rearrangement of electricity distribution networks with the aim of minimizing losses. Also, genetic algorithm has been used to solve the complex problem of rearrangement. In order to increase the productivity of the genetic algorithm, the operators of this algorithm have been improved. Also, graph theory has been used to study the radial structure of the distribution network. The simulation results show that the power losses obtained using the proposed approach are significantly lower compared to other approaches. In the reference [17], an improved version of the forbidden search meta-innovation algorithm is presented to minimize the losses of electrical distribution networks using rearrangement. In this reference, the parameters of the forbidden search algorithm have been improved in order to increase performance. Reference [18] presents a new approach to rearrange the electrical energy distribution networks based on the cuckoo search optimization algorithm. The purpose of the proposed approach is to minimize active power losses and maximize the voltage range in the electrical distribution network under study. In the reference [19], a new approach to rearranging the electrical distribution networks is presented. The above approach aims to minimize active power losses as well as maximize the reliability of the electricity distribution network under study while meeting the limitations associated with the operation.
of electricity distribution networks. In reference [20], a new method for rearrangement of electrical energy distribution networks based on a reverse search algorithm is presented to minimize active power losses and minimize voltage deviations. In reference [21], a new approach for optimizing the topology and location of distributed power generation sources in electrical distribution networks to reduce power losses and improve voltage stability is presented. In the reference [22], the importance of combining the harmonic search algorithm and the bee colony algorithm to solve the problem of rearrangement of electrical energy distribution systems along with the optimal placement and measurement of capacitive banks has been investigated. One of the most widely used methods is the genetic algorithm, which is based on the laws of evolution and natural selection. Since 1661, genetic algorithms have been widely used to solve the problem of rearrangement of distribution networks [23]–[26]. In addition to the many advantages of the genetic algorithm, this algorithm has a low convergence rate as well as many simulation steps to find the optimal point. The PSO algorithm has shown improvements in such optimization problems. Including the ability of local and public search to find the optimal point with low computation time. Particle Community Optimization Algorithm is a relatively new algorithm that, like the genetic algorithm, is a population-based algorithm that updates the population to find the optimal point by finding the optimal movement of fish species while finding food, but unlike the genetic algorithm, no operator it does not evolve [27]–[30]. It can be said that this algorithm suffers from falling at the local optimal point and rapid convergence at the local optimal point despite having a fast search system for problems with complex objective functions. In [31] A robust formulation is employed to capture uncertain wholesale energy prices, renewable resource availability, and PEV flows. The resulting bilevel robust optimization model is transformed into an equivalent single-level optimization problem by replacing the lower level problem with Karush-Kuhn-Tucker optimality conditions. A new planning framework for the optimal allocation of parking-Lot (PL) based charging infrastructure is proposed to facilitate the efficient integration of plug-in electric vehicles (PEVs) in [32]. Are considered and taken by the proposed PL planning model using an appropriate scenario generation method. In the reference [33], a study is presented to investigate the potential role of parking connected to the electric vehicle grid-connected parking lot (GPL) in improving the stability of the power supply as virtual energy storage in the municipal network. Extraction of corresponding capacity value indicators is made. The specificity of the proposed method has been confirmed through implementation in both the standard test case and the actual distribution system in China. In Ref [34] evaluated the scheduling problem for energy hub system consisting of wind turbine, combined heat and power units, auxiliary boilers, and energy storage devices via hybrid stochastic/information gap decision theory (IGD) approach in this method, it is proposed to minimize the expected operating cost of the energy hub in which

II. RECONFIGURATION OF DISTRIBUTION NETWORK

This section presents a new plan for the problem of rearrangement of the distribution network in the presence of electric vehicles (PEV). The proposed model takes into account the cost of power generation and specifies which distribution feeders should be switched on. Due to the increasing number of electric vehicles in distribution networks, traditional models for network development need to be updated to manage the new uncertainties that have increased with the presence of electric vehicles. In this regard, a scenario-based strategy is proposed in this chapter in which PEV-related uncertainties are modeled by random programming using Monte Carlo Simulation (MCS). Taken from the type of electricity market the next day. Uncertainty about the price of electricity and cargo is also considered. The DNR problem is formulated as a MILP problem. This problem is then solved by the Banders decomposition (BD) algorithm. The proposed method is implemented on a 24-bus distribution system.

A. FORMULATION OF THE PROPOSED MODEL IN THE DISTRIBUTION NETWORK

The mathematical model of the scenario-based DNR problem is formulated in this section. The distribution network is
represented by a linear approximation model:

\[
\begin{align*}
\text{Minimize } & \quad OF = \sum_{i \in \Omega^W} SC_i^F \times y_i^F + \sum_{s \in \Omega^S} \pi_s \\
& \quad \times \left( \sum_{i \in \Omega^{SS}} \sum_{h \in \Omega^H} \left( \lambda_{SS} x_i^h \times g_{s,h,i}^{SS} \right) + \sum_{i \in \Omega^{DGN}} \sum_{h \in \Omega^H} \lambda_{DG}^i \times g_{s,h,i}^{DG} \right) \\
\end{align*}
\]

(1)

Restrictions that apply to radial operation in the distribution network.

\[
\begin{align*}
n_{\text{Load}} - n^SS = \sum_{i \in \Omega^F} y_i^F \quad \forall t \in \Omega^T \\
\end{align*}
\]

(2)

Power balance constraint on each bus:

\[
\begin{align*}
g_{s,h,i}^{SS} + g_{s,h,i}^{DG} - D_{s,h,i}^{\text{Load}} - D_{s,h,i}^{\text{PEV}} = \sum_{i \in \Omega^F} f_i^{s,h,i} \\
- \sum_{i \in \Omega^F} f_i^{s,h,i} \quad \forall s \in \Omega^S, \forall h \in \Omega^H, \forall i \in \Omega^N
\end{align*}
\]

(3)

Distribution network technical constraints:

\[
\begin{align*}
-M \left( 1 - y_i^F \right) & \leq f_i^{s,h,i} \times Z_i^F \times l_i^F \\
& \quad - \left( V_{s,h,i} - V_{s,h,i}^H \right) \leq M \left( 1 - y_i^F \right) \\
& \quad \forall s \in \Omega^S, \forall h \in \Omega^H, \forall l \in \Omega^F \\
V_{\text{min}} \leq V_{s,h,i} \leq V_{\text{max}} & \quad \forall s \in \Omega^S, \forall h \in \Omega^H, \forall i \in \Omega^N \\
0 \leq g_{s,h,i}^{SS} \leq g_{s,h,i}^{\text{max},SS} & \quad \forall s \in \Omega^S, \forall h \in \Omega^H, \forall i \in \Omega^{SSN} \\
0 \leq g_{s,h,i}^{DG} \leq g_{s,h,i}^{\text{max},DG} & \quad \forall s \in \Omega^S, \forall h \in \Omega^H, \forall i \in \Omega^{DGN} \\
0 \leq f_i^{s,h,i} \leq y_i^F & \quad \forall s \in \Omega^S, \forall h \in \Omega^H, \forall l \in \Omega^F \\
\end{align*}
\]

(4)

PEV-related restrictions:

\[
\begin{align*}
SOC_{P_{x,h,v}}^{\text{PEV}} = SOC_{P_{x,h,v}}^{\text{PEV}}(x, b-1, v) + \eta \times P_{x,h,v}^{C,\text{PEV}} & \quad \forall s \in \Omega^S, \\
& \quad \forall v \in \Omega^V, \forall h \in \left[ \mu_{\text{arr}}^h, \mu_{\text{dep}}^h \right] \\
SOC_{x,h,v}^{\text{min,PEV}} \leq SOC_{x,h,v}^{\text{MAX,PEV}} & \quad \forall s \in \Omega^S, \\
& \quad \forall v \in \Omega^V, \forall h \in \left[ \mu_{\text{arr}}^h, \mu_{\text{dep}}^h \right] \\
AV_{x,h} \times P_{x,h,v}^{C,\text{min,PEV}} \leq P_{x,h,v}^{C,\text{MAX,PEV}} & \quad \forall s \in \Omega^S, \\
& \quad \forall v \in \Omega^V, \forall h \in \Omega^H \\
SOC_{x,h,v}^{\text{des,PEV}} \leq SOC_{x,h,v}^{\text{PEV}}(x, h) & \quad \forall s \in \Omega^S, \\
& \quad \forall v \in \Omega^V, \forall h \in \Omega^V \\
D_{x,h,v}^{\text{PEV}} = \sum_{i \in \Omega^F} P_{x,h,v}^{C,\text{PEV}} & \quad \forall s \in \Omega^S, \\
& \quad \forall h \in \Omega^H, \forall i \in \Omega^N
\end{align*}
\]

(5)

The set of decision variables are:

\[
\Omega^{\text{DV}} = \left\{ g_{s,h,i}^{SS}, g_{s,h,i}^{DG}, f_i^{s,h,i}, V_{s,h,i}, D_{x,h,v}^{\text{PEV}}, SOC_{x,h,v}^{\text{PEV}}, P_{x,h,v}^{C,\text{PEV}} \right\} \cup \left\{ y_i^F \right\}
\]

(14)

Equation (3) shows the objective function of the problem, which includes the cost of switching and the cost of purchasing electricity from the transmission network plus the cost of generating electricity by distributed generation sources. Equations (11) to (14) constrain the distribution network to operate radially. In a radial distribution network, the number of active nodes minus the number of posts must be equal to the number of feeders.

### III. NUMERICAL RESULTS

A 20 kV distribution network is intended to implement the proposed method. CPLEX solver is used in GAMS software to solve the problem. The topology of the distribution network is shown in Figure (1) where the distribution feeders with no line switchable capability and the dotted line switchable feeders are shown. The simulation was performed on a computer with Windows operating system, 2.5 GHz processor and 8 GB of RAM. The dual gap is considered 0.5%. The voltage range is limited to 0.95 per unit to 1.05 per unit. The maximum charging power and PEV battery capacity are considered to be 4 kW and 20 kWh, respectively.

The duality gap is considered 0.5%. The voltage range is limited to 0.95 per unit to 1.05 per unit. Battery efficiency is assumed to be 90%. The daily consumption curve and electricity price are shown in Figure (2). The number of days attributed to each curve is 58, 191, and 116 days. (58 for the upper curve and 116 for the lower curve). The data for the electric vehicle are given in Table (1).

Maximum charging power and PEV battery capacity are 4 kW and 20 kWh, respectively. The SOC value is assumed to be 90% for all-electric vehicles. The number of PEVs per node is shown in Table (2).

The number of PEVs per node is shown in Table (2). Note that in nodes 17, 18, 19, and 20 there is no PEV in the first period. Distribution network information is shown in Table (3). Load data are shown in Table (4).

The vehicle charge profiles for all three strategies are shown in Figure (3). As can be seen in the figure, the smart charging strategy is effective in transferring the electric charge of vehicles from high electricity hours to low electricity hours, which leads to a reduction in operating costs.

It is also observed that smart charging with simultaneous optimization has a lower peak than smart charging with separate optimization.
FIGURE 2. Daily load curve and electricity price.

FIGURE 3. Daily PEV charge curve in three different strategies.

A. RESULTS WITHOUT DG

The optimal results for the distribution network development are shown in Figure (4). DG has been omitted for better comparison. Mode (a) is for when non-smart charging is intended. This means that PEVs are connected to the network and charged every time they get home. Mode (b) is when intelligent charging and network development are solved together in one format. Mode (c) is also for when smart PEV charging is intended. However, this smart charge is specified in a separate issue and then the amount of charge specified is considered as the electric charge in the DEP issue. In Figure (4), red indicates that type one should be built and blue indicates that type two should be built. As can be seen, the development strategy is different for all three modes. The investment, production and maintenance costs for these three modes are shown in Table (5).

A comparison of mode (a) and mode (b) shows that since electric vehicles are charged during the hours when electricity is more expensive, the cost of production is also higher in this mode. In both cases (b) and (c) the vehicles are intelligently charged. But in case (b) the vehicles and the DNR problem are solved simultaneously, while in case (c) the electric charge associated with the electric vehicle is determined before solving the DNR problem and then this time as a constant load in this problem is considered. As shown in Table (5), the cost of feeder investment in mode (c) is higher than the cost of investment in mode (b). The reason for this is that in mode (c) the PEV charge is determined only based on the price of electricity and the capacity of the feeders is ignored. Therefore, in this case, when solving the DEP problem, in which the amount of electric charge related to the vehicle is considered constant, it may be necessary to build a feeder with a higher capacity. It should be noted that the cost

**TABLE 1. Information on PEV.**

|                     | Average | Standard deviation | minimum | maximum |
|---------------------|---------|--------------------|---------|---------|
| arriving time       | 19      | 2                  | 16      | 1       |
| Time to leave       | 7       | 2                  | 5       | 12      |
| Primary SOC         | 75      | 25                 | 25      | 95      |

**TABLE 2. Information on the number of PEVs per node.**

| Number of PEVs | Node | Number of PEVs | Node | Number of PEVs | Node |
|----------------|------|----------------|------|----------------|------|
| 47             | 8    | 218            | 6    | 91             | 5    |
| 16             | 12   | 14             | 13   | 13             | 11   |
| 60             | 12   | 80             | 152  | 90             | 53   |
| 24             | 12   | 23             | 22   | 21             | 20   |
| 10             | 12   | 10             | 10   | 9              | 9    |
| 25             | 12   | 25             | 25   | 95             | 95   |

**TABLE 3. Post and feeder capacity information.**

| Z (Ω/km) | Capacity (MW) |
|----------|---------------|
| N.A.     | 15            |
| 0/557    | 6/28          |

**TABLE 4. Information on electrical charge in each node.**

| Node | Load | Node | Load |
|------|------|------|------|
| 1    | 5/42 | 11   | 2/80 |
| 2    | 1/21 | 12   | 2/29 |
| 3    | 3/98 | 13   | 1/87 |
| 4    | 2/43 | 14   | 3/16 |
| 5    | 0/47 | 15   | 1/62 |
| 6    | 1/81 | 16   | 1/22 |
| 7    | 4/36 | 17   | 2/40 |
| 8    | 0/94 | 18   | 2/10 |
| 9    | 1/77 | 19   | 1/81 |
| 10   | 2/40 | 20   | 3/79 |
TABLE 5. Production cost for three different modes.

| Mode (c): Smart Charging (Separate optimization) | Mode (b): Smart Charging (Simultaneous optimization) | Mode (a): Non-smart charging |
|-----------------------------------------------|--------------------------------------------------|-------------------------------|
| $10^3x1/087620$                              | $10^3x1/088630$                                  | $10^3x1/119570$               |

TABLE 6. Information on DG.

| Capacity (MW) | PC ($/MWh$) |
|---------------|-------------|
| 2             | 45          |

of investing in distribution posts is the same in both cases (b) and (c). Also, the cost of production in mode (c) is less than the cost of production in mode (b), because in mode (b) the PEV battery charge is transferred to the hours when the price of electricity may be higher. The reason for this transfer is the technical limitations of the distribution network. Total cost in case (b) means the total cost of investment, production and maintenance is less than the other two cases. It is emphasized that for the lower penetration coefficient of the electric vehicle in the network, the results of modes (b) and (c) will be exactly the same.

Comparing mode (a) and mode (b) with each other shows that the total cost of investing in smart charging mode is less than when charging is done non-intelligently. This is because, in non-intelligent charging mode, PEVs are charged during peak hours, so more capacity is needed for the feeder and substation to be able to provide electrical charge. In addition, since electric cars are charged at times when electricity is more expensive, the cost of production is also higher in this case.

B. RESULTS WITH DG

Candidate DGs are located in nodes 1, 3, 4, 7, 9, 10, 14, 17, 18, 19. Information on DG such as investment and production costs is given in Table (6).

In non-smart charging, it is assumed that PEVs will be charged when they reach home. As shown in Figure (5), the switching strategy is different in these two cases. The cost of production for both strategies is shown in Table (7).

The vehicle charge profiles for all three strategies are shown in Figure (6). As can be seen in the figure, the smart charging strategy is effective in transferring the electric charge of cars from high electricity hours to low electricity hours, which leads to a reduction in operating costs. It is also observed that smart charging with simultaneous optimization has a lower peak than smart charging with separate optimization.

The CPLEX solver is able to generate various possible solutions. Figure (6) shows this figure. As can be seen, in smart charging mode it takes about 20 minutes to reach the final optimal solution and in non-smart charging mode it takes about 10 minutes. Note that the internal BD algorithm of this solver is also used.
IV. LOAD TRANSFER BETWEEN DISTRIBUTION NETWORK FEEDERS

Basically, in load distribution studies, the load connected to these two feeders is considered fixed. But in the case of distribution network rearrangement, since these two feeders are connected by power switches Figure(7), the distribution network arrangement can be changed with the aim of shifting the load from a high-capacity feeder to a low-capacity feeder to reduce losses.

By resetting the network, you can change the status of the switches $S_1$, $S_2$ and $S_3$. For example, in one situation the first and second switches can be closed and the third switch left open. In this case, the first to third loads are fed by feeder A and feeder B feeds only the fourth load. In another arrangement, the first and third switches are closed and the second switch is open, in which case the first and second loads are fed by feeder A and the third and fourth loads by feeder B.

A. FORMULATION OF NETWORK REARRANGEMENT PROBLEM

The optimal load distribution problem in AC mode is formulated as follows:

$$\begin{align*}
\text{min } OF &= \left( \sum EP_i \times pg_{is} \right)_{\text{cost of purchased energy}} \\
&+ \left( \sum C^\text{loss} (V_{is}^2 + V_{js}^2 - 2V_{is} V_{js} \cos \delta_{isj}) \times G_{ij} \right)_{\text{Network losses}} \\
&+ \left( \sum C^\text{LSH} \times \sum LSH_{is} \right)_{\text{Cost of load shedding}} \\
&+ \left( C_{gi} \times P_{w_{is}} \right)_{\text{Cost of wind disturbed generation}}
\end{align*}$$

Equation (15) shows the objective function. Equations (16) and (17) are the balance of active and reactive power in each bus. Equations (18) and (19) are linear powers whose...
constraint is applied by (20). Equation (21) is the voltage amplitude limit. Generating power by generators is limited by the two equations (22), (23). Equation (24) limits the power output of a wind farm, depending on the intensity of the wind. The switching operation is also explained by the following equations (25)–(29):

\[
\begin{align*}
    P_{AB}^{Transfer1} &= (2 * Z_3 + Z_2 - 1) * K_1 * P_{Old}^A \\
    P_{AB}^{Transfer2} &= (2 * Z_3 + Z_1 - 1) * K_2 * P_{Old}^A \\
    P_{NEW}^A &= P_{Old}^A - P_{AB}^{Transfer1} - P_{AB}^{Transfer2} \\
    P_{NEW}^B &= P_{Old}^B + P_{AB}^{Transfer1} + P_{AB}^{Transfer2} \\
    Z_1 + Z_2 + Z_3 &\leq 2
\end{align*}
\]

V. WIND UNCERTAINTY MODELING

Wind energy is inherently uncertain. This uncertainty is due to the lack of accurate wind speed prediction. Since the number of load and wind scenarios is large, we use the k-means clustering technique. Clustering places a large number of observations that have common characteristics or are relatively homogeneous within a group as shown in Figure 8.

There are two types of clustering techniques: supervised clustering and unsupervised clustering. The difference is that in supervised clustering, centers are considered as input to the algorithm, whereas in unsupervised clustering, the algorithm determines the number of centers. In the K-means method, we do the following:

1. We select the primary centers of the clusters randomly.
2. Based on proximity to the centers, all data is transferred to the nearest center.
3. We calculate the distance between the cluster members and the centers. The center of each cluster is calculated according to the following formula (30).

\[
m_i = \frac{1}{|C_j|} \sum_{X_i \in C_j} X_i
\]

That \( |C_j| \) the number of data points is related to the \( C_j \) cluster. The distance of a \( X_i \) data point to the center of the clusters is calculated as follows.

\[
dist(X_i, m_j) = \sqrt{(X_{i1} - m_{j1})^2 + (X_{i2} - m_{j2})^2 + \ldots + (X_{ip} - m_{jp})^2}
\]

4. We calculate the Sum of Squared Error (SSE).

\[
SSE = \sum_{j=1}^{k} \sum_{X \in C_j} dist(X, m_j)^2
\]

VI. NUMERICAL RESULTS

The proposed model is applied to the system of Figure (9). There are several ways to reduce losses in the distribution system. The rearrangement method does not require the installation of new devices in the network, and with the same devices and switches available, they reduce losses in a simple and low-cost way. Closing some switches that are normally open and opening the same number of switches that are normally closed can change the power distribution path in the distribution network in a way that reduces system losses.

Given the high dispersion coefficient of wind energy production, it is not reasonable to consider rearranging the distribution network without considering wind energy. Therefore, much attention should be paid to wind energy modeling, which is inherently uncertain. Electric vehicles are also another emerging phenomenon in distribution networks that require charge and discharge management. In this paper, the topology of the distribution network changes in the presence of wind and electric vehicles.

A. REGARDLESS OF THE LOAD LIMIT OF LINES AND TRANSFORMERS

For simplicity, load limits from lines and transformers are not considered. In this case, the four components of the objective function are calculated in two modes of use and non-use of the load transfer method, the results of which are shown in Table (8). In this table, the last column represents the sum of the total value of the objective function. According to this table, using the proposed load transfer method will reduce the cost of purchasing energy from the transmission network by about 10%. On the other hand, the cost of losses in the above distribution network does not decrease significantly.

B. CONSIDERING THE LOAD LIMIT OF LINES AND TRANSFORMERS

In this case, the results are compared in the two modes of use and non-use of the proposed method of load transfer. Since considering scattered products in the above distribution network have different effects on the objective function components, therefore, according to Table 9 to 10, the results were examined in different cases. In Table 9, scattered products are omitted. According to this table, using the proposed method of load transfer, losses in the above distribution network are reduced by 6%, while the cost of purchasing energy from the
transmission network is reduced by 3.2%. But the interesting point that should be noted is that if the constraint related to the load limit of transformers and lines is taken into account if the proposed method of load transfer is not used, we will see a drop in load. However, the proposed method does not provide any report of load shedding. According to this table, we will
TABLE 7. Cost of electricity generation in both smart and non-smart charging modes.

| Mode                  | smart charging | Non-smart charging |
|-----------------------|----------------|--------------------|
| $PC_{CH}^E$ (S)       | 10037130       | 9975640            |
| $PC_{CH}^D$ (S)       | 216670         | 467528             |
| Total production cost $ | 15378712       | 15767823           |

TABLE 8. Objective function regardless of heat capacity.

| Scenario | Cost of electricity purchased | Cost of losses | Shipp ing cost | Scattered production cost | Final   |
|----------|-------------------------------|----------------|----------------|---------------------------|---------|
| Rearranging | 20034.916                     | 95.125         | 0              | 137.180                   | 20267.221 |
| No rearranging | 18653.864                     | 87.673         | 0              | 137.180                   | 18878.720 |

TABLE 9. Objective function considering heat capacity without considering scattered output (wind) and capacitor.

| Scenario | Cost of electricity purchased | Cost of losses | Shipp ing cost | Scattered production cost | Final   |
|----------|-------------------------------|----------------|----------------|---------------------------|---------|
| Rearranging | 19691.11                      | 95.667         | 7.1122E+6      | -                         | 7.1320E+6 |
| No rearranging | 19057.456                     | 90.287         | 0              | -                         | 19147.445 |

TABLE 10. Objective function considering heat capacity considering scattered output (wind) and capacitor.

| Scenario | Cost of electricity purchased | Cost of losses | Shipp ing cost | Scattered production cost | Final   |
|----------|-------------------------------|----------------|----------------|---------------------------|---------|
| Rearranging | 19286.252                     | 91.336         | 7.1122E+6      | 137.180                   | 7.1317E+6 |
| No rearranging | 18565.864                     | 87.673         | 0              | 137.180                   | 18878.720 |

have a load loss of about 71 MW, which can be concluded that about 2.75% of the total network load will be lost.

In Table 10, in addition to the pulsation transformers, the scattered products installed in the above distribution network are also included. According to this table, the cost of purchasing energy from the upstream grid will decrease by about 3.37%, which is a further decrease compared to Table 4, which excluded scattered generation. But as in the previous case, the load will drop as much if the proposed load transfer method is not used. According to Table 10, the cost of losses of the above distribution network in case of not using the proposed freight transfer method is $ 95,667, but according to Table 8, if the dispersed production is taken into account, it will be $ 91,336, i.e. a reduction of about 4.53%.

According to Table 10, if the proposed freight transfer method is used, the cost of losses will be $ 87,673, which represents a reduction of about 4% in addition to the reduction due to distributed generation. The proposed method of load transfer is a reduction of about 8.4% in the losses of the above distribution network. Observing these results, it can be said that the weight of the proposed load transfer method in reducing the losses of the above distribution network is equal to the weight of scattered products in reducing the losses of the same network, and this shows the high efficiency of this proposed method.

PEVs have time to go home and a time to leave home, which are uncertainty parameters modeled by the normal algorithm. Wind speed is measured at 8760 hours and relevant scenarios are generated. For example, 200 scenarios corresponding to different wind speeds are considered. The feature of the proposed algorithm includes considering the uncertainty of the electric vehicle to rearrange the network and considering the wind power plants and the related uncertainties and the resistance of the answer to the change of parameters.

In this section, a method for rearranging distribution networks to transfer load from one feeder to another is presented. It has been observed that this reduces the load of high-capacity feeders well and causes the construction of new feeders to be delayed. It was also observed that rearrangement of the distribution network leads to a reduction in network losses. Also, with the help of rearrangement, the amount of interrupted load can be significantly reduced.

VII. CONCLUSION

This paper presents a nonlinear mixed-integer model to solve the distribution network reconfiguration considering plug-in electric vehicles. Furthermore, regarding the increasingly growing penetration of wind power into the distribution network, wind-based distributed generation has been also incorporated into the model. Considering the intrinsic uncertainty of wind as well as the driving behavior of plug-in electric vehicles, it is inevitable to devise a scenario-based approach. Uncertainty of wind power is originated from errors in predicting the wind velocity while the uncertainty of plug-in electric vehicles is due to the random behavior of electricity owners. The corresponding scenarios are generated by the Monte Carlo simulation. The objective function includes the cost of energy purchased from the main grid plus the cost of energy production by DGs. The switching cost is also added to the objective function. Both smart and dumb charging are considered in this thesis and the results are compared together.

The mathematical model of the distribution network can be based on the exact approach (AC method) and the approximated approach (DC model). Both methods are formulated. The former one leads to mixed-integer nonlinear programming (MINLP), while the latter lead to mixed-integer linear programming (MILP). To verify the proposed methodology, it is applied to a 24-bus distribution network. The numerical results indicate that the optimal reconfiguration is efficiently able to reduce the operation cost as well as the required energy cost to charge the electric vehicles. In addition, the distribution reconfiguration can decrease the pressure on congested feeders which consequently can postpone the construction time of new feeders leading to saving money. The use of robust optimization in addition to random optimization or
simultaneously and in combination with each other in modeling existing uncertainties is proposed for future work.

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