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Active Distribution Network Expansion Planning considering the Uncertainty of Electric vehicles' load

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Abstract

Integrating Electric vehicles into distribution systems introduce new challenges both in operation and planning of electric distribution systems. In the planning process, these vehicles mainly affect load uncertainty in the grid. A new method for Active Distribution Network (ADN) expansion planning is proposed considering the uncertainty of bus loadings because of electric vehicles (EVs) integration. The approach taken in this paper includes the initial cost of investment and operation. A probabilistic model is proposed for extracting the effect of electric vehicles integration on future loading of network buses. Different scenarios are defined based on electric vehicle entrance time, charging delays and their overall penetration level. Particles colony algorithm is used for handling the proposed mixed integer and nonlinear optimization model. Also a graph theory based method for detecting radial structures is implemented for faster convergence. Finally, the effectiveness of the proposed algorithm is examined by implementing it on the modified IEEE 33 bus standard distribution network.

Keywords: Distribution system expansion planning, uncertainty, plug-in electric vehicles, graph theory.

Symbols:

S: scenario set
i,j: bus number
T: time duration of operation (24 hours)
Ψ^{L} : Candidate feeders sets
Ψ^{L} : sets of all existing and candidate feeders in the network
Ψ^{SC} : sets of candidate substations
Ψ^{s} : scenarios sets of Plug-in electric vehicle load uncertainty
c_i^{SC} / c_{ij}^{L} : investment cost of per length/ capacity of feeders/ substations
y_i^{SC} / x_{ij}^{L} : the binary decision variable for candidate feeders/ substations
l_{ij}^{L} :the feeder length between two buses i and j
k^{L} / k^{Sub} : flat annual Cost ratio of substations / network feeders
i : Rate of capital return of network feeders and substation extension
n^{L} / n^{Sub} : Substations / network life expectancy
γ_s : Probability of scenario s
G_{ij} / B_{ij} : The imaginary part / real admittance of the feeder between bus i and j
$V_{i,t,s}$:the voltage of the bus i, at hour t, in scenario s
$\theta_{ij,t,s}$:voltage phase difference between the buses i and j at hour t in scenario s
a : number of days in each month

c^E / c^{opr} : unit cost of network Energy / losses

$P_{i,t,s}$ / $Q_{i,t,s}$: Active/ reactive power injection to the bus i at hour t and scenario s

$P_{i,t}^D$ / $Q_{i,t}^D$: Active/ reactive power consumption of bus i at hour t and scenario s

$P_{i,t,s}^{PEV}$: Estimated power of plug-in electric vehicle load in bus i at hour t in scenario s

S_i^0 : Existing capacity of the substation connected to the bus i

$S_{ij}^{L,\max}$: The capacity of the feeder between the buses i and j

$V_i^{\min}$ /$V_i^{\max}$:maximum and minimum allowable voltage range of bus i

erv_n :energy required by each vehicle

BC :battery capacity of the plug-in electric vehicle (KWh)

e_n :the energy required by nth PEVs (KWh)

erf_i :the average energy required by the fleet of PEVs at bus i

N :total number of vehicles in the sample data

X^{pen} :PEV penetration level

TN_i : total number of PEVs at bus i

ChL : charging level (KW)

ChE :charging efficiency

ChD :average charging duration (h)

λ :the mean of the PDF which represents the charging delay time

1. INTRODUCTION

Increasing the penetration of electric vehicles will introduce new challenges in operation and planning of power systems. Recent studies show that if fifty percent of vehicles in North America become electric, the country's electric power consumption will increase by about 8% [1]. EVs have aroused extensive attention due to the increased social awareness of environmental issues and the desire to relieve reliance on fossil fuels. Plug-in electric vehicles (PEVs) produce less pollution than current fossil fuel cars. That's why in recent years scientists pay more attention to them. The widespread use of plug-in electric vehicles capable to be connected to the power network is causing a lot of uncertainty, and thus brings new challenges for strategies of planning and studies of the traditional method of distribution system expansion planninig [2].

Ignoring the uncertainties of electric vehicles' load in the expansion of network feeders and substations could results in an inefficient network. Because a large number of vehicles may be connected to the power source at the same time and create a large sudden shock imposed on the network and cause sudden. So far, this issue has been studied by many researchers. In [3] a method of dynamic expansion planning based on genetic algorithm for active distribution networks is offered which enables integration of distributed generation sources with conventional options for expansion, including the new feeders, network reconfiguration, Installation and launching new protection devices, and etc. In references [4-7] dynamic expansion methods have been used for the expansion of active distribution networks. Flexible expansion model is used taking into account the impact of plug-in electric vehicle uncertainties for the expansion of substations in [8] and the expansion of the feeders in [9-12]. In [13 to 15] the effect of plug-in electric vehicle on substations is investigated and some models for estimating the load of plug-in electric vehicle is proposed and according to that, distribution network expansion strategy is determined considering the effect of the plug-in electric vehicle charge / discharge in [16 - 20]. So far, many planning and investment strategies for distribution networks were developed, however the widespread use of PEVs, has challenged the philosophy of traditional planning approaches. There have been research efforts mainly on the potential impacts of PEV on residential distribution systems and also on their general charging profile [21].However many researchers believe planning methods for distribution systems with respect to the extensive integration capacity of PEVs have not been still systematically examined. In general, most uncertainty in distribution network planning is due to PEV multiple aggregations. These may include normal load level; the penetration level of plug-in electric vehicles capable of connecting to the network, and PEV successful or unsuccessful coordinated charging. Simulation of these uncertainties and then developing of an appropriate model for distribution network planning is of particular importance [21].

In this paper we develop a comprehensive planning method for expanding feeders and substations with the presence of plug-in electric vehicles for distribution systems to deal with the future uncertainties. The approach taken in this paper involves the initial investment and operational costs. In the proposed model, expansion of feeders and substations and, probabilistic uncertainty of plug-in electric vehicle load is considered. Probabilistic scenarios in the probabilistic model of plug-in electric vehicle load is generated based on three factors: uncertainty of plug-in electric vehicle arrival time, uncertainty of delay in plug-in electric vehicle charging, and power required to charge. To search for required power to charge, the urban travel data in [22] is used. And also to solve the proposed model of distribution expansion planning, the particle colony algorithm is used. In heuristic algorithms, making network structures and substations is taken into account as stochastic and no observing provision is made.

In this paper the problem of distribution expansion planning is formulated as a nonlinear stochastic optimization problem and presented in section 3 and PEVs load modeling is presented in section 4. Section 5 is allocated to the proposed optimization method. Numerical studies come in the sixth and finally conclusions are presented in Section 7.

2. The Proposed Model For Distribution Expansion Planning

In this paper, the planning of feeders and substations expansion in distribution network is formulated as a nonlinear optimization problem. The objective function is total investments and network operation costs, which should be optimized, constrained to network constraints. New feeders and substations are considered as expansion candidates and also the status of switched along feeders are among decision variables. Based on the above assumptions, the optimization model for expansion of distribution network feeders and substations are presented as following [21].

$$\begin{aligned}\min \quad & k^{L} \sum_{(ij)\in\Psi^{L}} c_{ij}^{L} x_{ij}^{L} l_{ij}^{L} + k^{Sub} \sum_{i\in\Psi^{SC}} c_{i}^{SC} y_{i}^{SC} S_{i}^{SC} \\ & + \sum_{s\in\Psi^{s}} \gamma_{s} \left(ac^{E} \sum_{t\in T} \sum_{(ij)\in\Psi^{L'}} \frac{G_{ij} x_{ij}^{L}}{\left(V_{i,t,s}^{2} + V_{j,t,s}^{2} - 2V_{i,t,s} V_{j,t,s} \cos\theta_{ij,t,s}\right)} \right) \\ &) \\ & + \sum_{s\in\Psi^{s}} \gamma_{s} \left(ac^{opr} \sum_{t\in T} \sum_{i\in\Psi^{SC}} y_{i}^{SC} \sqrt{(P_{i,t,s}^{sub})^{2} + (Q_{i,t,s}^{sub})^{2}} \right)\end{aligned} \tag{1}$$

$$k^{L} = \frac{i(1+i)^{n^{L}}}{(1+i)^{n^{L}} - 1}, k^{Sub} = \frac{i(1+i)^{n^{Sub}}}{(1+i)^{n^{Sub}} - 1} \tag{2}$$

S.t :

$$P_{i,t,s} = P_{i,t}^{D} + P_{i,t,s}^{PEV} + V_{i,t,s} \sum_{j} V_{j,t,s} x_{ij}^{L} (G_{ij} \cos\theta_{ij,t,s} + B_{ij} \sin\theta_{ij,t,s}) \tag{3}$$

$$Q_{i,t,s} = Q_{i,t}^{D} + V_{i,t,s} \sum_{j} V_{j,t,s} x_{ij}^{L} (G_{ij} \sin\theta_{ij,t,s} - B_{ij} \cos\theta_{ij,t,s}) \tag{4}$$

$$(P_{i,t,s})^{2} + (Q_{i,t,s})^{2} \le S_{i}^{0} + \sum_{i\in\Psi^{SC}} c_{i}^{SC} y_{i}^{SC} S_{i}^{SC} \tag{5}$$

$$(P_{ij,t,s})^{2} + (Q_{ij,t,s})^{2} \le x_{ij}^{L} S_{ij}^{L} \tag{6}$$

$$V_{i}^{\min} \le V_{i,t,s} \le V_{i}^{\max} \tag{7}$$

$$\sum_{(ij)\in\Psi^{L'}} x_{ij}^{L} = n^{DS} - n^{Sub} \tag{8}$$

The objective function is offered in accordance with equation (1) in four terms. The first and second terms of the objective function is related to the network expansion costs, respectively including the annual investment cost of feeder expansion and the annual investment cost of new substation expansions in the network. On the contrary, the third and fourth terms of the objective function is related to the annual costs of operation. The third term of objective function is related to the expected cost of losses and finally, the fourth term includes the average cost of the operation of the substation in the network. Based on different life expectancy of feeders and substations, different annualized factors π_{Sub} و π_{L}, is calculated according to the equation (2). Equations (3) and (4) are related to nodal active and reactive balance at each bus. Certainly, the change in the network structure at the time of expansion causes the change in power flow equations included in equations (3) and (4). According

to the impact of the charge / discharge of plug-in electric vehicle in network power flow, the estimated power of plug-in electric vehicle is provided in equation (3). The amount is different in any scenario of plug-in electric vehicle load uncertainty. So in every scenario, the equation of power flow has changed and therefore, network loss changes too. In equation (5) capacity limitation for each substation is stated. Also equation (6) shows capacity limit of the network feeders. Voltage boundary limits of network buses are provided in equation (7). All restrictions of power flow should be fulfilled in all plug-in electric vehicle load scenarios. According to radial operation of distribution networks, expansion plan should not create a loop in the network. Indicating the next radial network, considering network expansion plan, is shown in equation (8). The logic of equation (8) is based on the graph cases and creating a comprehensive forest.
lso, the schematic of simulated system can be seen in Figure.

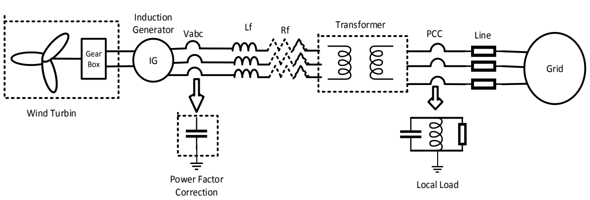

Fig. 1. Studied network in this paper

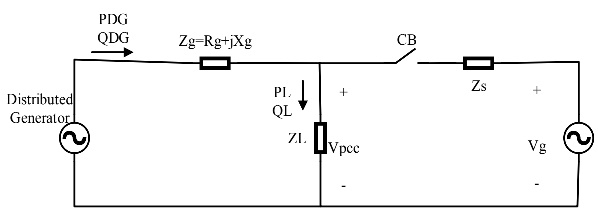

Fig. 1. the equivalent circuit of DG on islanding mode

The equivalent circuit on islanding mode has been shown in Figure 2. The power balance in network is based on Equ. 9,10.

$$P_{load} = P_{DG} + \Delta P \quad (9)$$

$$Q_{load} = Q_{DG} + \Delta Q \quad (10)$$

Where if $P_{load} = P_{DG}$ or $Q_{load} = Q_{DG}$, any power between island and network would be transferred. Also if the resonant frequency of RLC load is equal to the line frequency network, then linear load don't get any reactive power.
Reactive power is directly related to voltage. Also, after the network outage, active power of load get equal to reactive power of turbine. So:

$$V'_{pcc} = K.V_{pcc} \quad (11)$$

Where:

$$K = \sqrt{P_{DG}/P_{load}} \quad (12)$$

If $P_{Load} < P_{DG}$, The voltage domain increases and if $P_{Load} > P_{DG}$, the voltage domain decreases. Also, because of reactive power and voltage-frequency relation:

$$Q'_{load} = Q_{DG} = \left(\frac{1}{\omega'.L} - \omega'.C\right).V'^{2}_{pcc} \quad (13)$$

So in the islanding mode, the swing ω' calculated by the following equation:

$$\omega' = \frac{1}{2} \times -\frac{Q_{DG}}{C.V'^{2}_{pcc}} + \sqrt{\frac{Q_{DG}}{C.V'^{2}_{pcc}}^{2} + \frac{4}{L.C}} \quad (14)$$

So when changes in ΔP and ΔQ are higher, better and faster detection can be done. Because of the extent and success of passive methods, the main focus of this article is based on passive methods. Voltage unbalance is one of the methods in many networks that can show changes easily. According to the Figure 2 for the proposed method, voltage of point PCC have been expressed by the following expressions:

$$V_{pcc} = \frac{Z_L}{Z_L + Z_s} V_g + Z_L.I_L \quad \text{,When CB is on} \quad (15)$$

$$V_{pcc} = Z_L.I_L \quad \text{,When CB is off} \quad (16)$$

The impedance of each component are calculated according to the following equations:

$$Z_s = R_s + j\omega L_s \quad (17)$$

$$Z_g = R_g + j\omega L_g \quad (18)$$

$$Z_{islanding} = R_L \; || \; j\omega I_L \; || \frac{1}{j\omega C_L} || (R_g + j\omega L_g) \quad (19)$$

According to the new method, based on analysis of the voltage, if amount of voltage is greater than a contestant, the islanding detection.

3. Probabilistic Model Of Plug-in Electric Vehicle Load

In this paper, the probabilistic model, plug-in electric vehicle load dependent to parameters of time of arriving home, plug-in electric vehicle charging energy, and charging start time is determined. According to the existing information, the time of going back home after a trip, is distributed as a function at all hours of a day. Distribution function of probability of entering house is considered as discrete distribution function in accordance with the equation (9).

$$P^{FA}(x^{FA}) = \prod_{t=1}^{24} (P_t)^{x_t^{FA}} \tag{9}$$

The next parameter is the energy needed to recharge the plug-in electric vehicle after a trip. The amount of energy needed for plug-in electric vehicle to traverse a mile is calculated by the division of plug-in electric vehicle capacity into the total miles traveled in electric mode. Thus, the energy required to travel a special mileage is obtained by multiplying the distance by energy of length unit. In this paper, minimum and maximum of the value SOC of plug-in electric vehicle is considered respectively 20 percent and 92 percent. On this basis, the most energy needed for plug-in electric vehicle will be 72 percent of its battery capacity. Thus, the energy needed for each vehicle on the average is calculated as energy required traveling from bus i with charge time according to equation (10).

$$v_n = \begin{cases} 0.7BC & e_n \geq 0.8BC \\ 0 & e_n \leq 0.1BC \\ e_n & 0.1BC \leq e_n \leq 0.8BC \end{cases} \tag{10}$$

$$erf_i = \frac{\sum_{n \in N} erv}{N} X^{pen} TN_i \tag{11}$$

$$hD = \frac{\sum_{n \in N} erv}{N \times ChL \times ChE} \tag{12}$$

The third parameter is the starting time of plug-in electric vehicle charging. The parameter is dependent on the arrival of plug-in electric vehicle to home and subscriber behavior. Subscribers' behavior is considered in two different groups. The first group attempt to charge their plug-in electric vehicle when entering home. For the second group, the charging time and arrival time is considered as different. In this group the starting time of charging is modeled using a Poisson probability distribution function, according to the equation (13).

$$P^{SC}(T_o) = \frac{\lambda^{T_o}}{T_o!} e^{-\lambda} \quad T_o \geq 0 \tag{13}$$

In this equation, T_o can be a value between 0 to 24. Finally, the plug-in electric vehicle load is calculated based on the start time of charging, charge time and the energy required for each bus. Due to changes in displacement and plug-in electric vehicle trips in different seasons, probability distribution function of entering plug-in electric vehicles is different. On this basis in this paper, the estimated time for plug-in electric vehicle is calculated separately for different seasons. Considering the stochastic nature of the parameters of plug-in electric vehicles entering and latency time, the plug-in electric vehicle load profiles will be stochastic. To cover the stochastic nature of plug-in electric vehicle load, the scenario technique is used in this paper. On this basis, probability distribution functions of plug-in electric vehicle arrival and charging delay is considered as discrete in 5 cases. Thus, totally there are 25 scenarios per hour and the probability of occurring the scenario is determined in the previous section according to the calculated probability distribution.

4. The Proposed Approach

4.1. Optimization Algorithm

In this paper, the optimization algorithm is used based on particle assembly for expansion studies of feeders and substations. The proposed algorithm flowchart is shown in Figure 3.

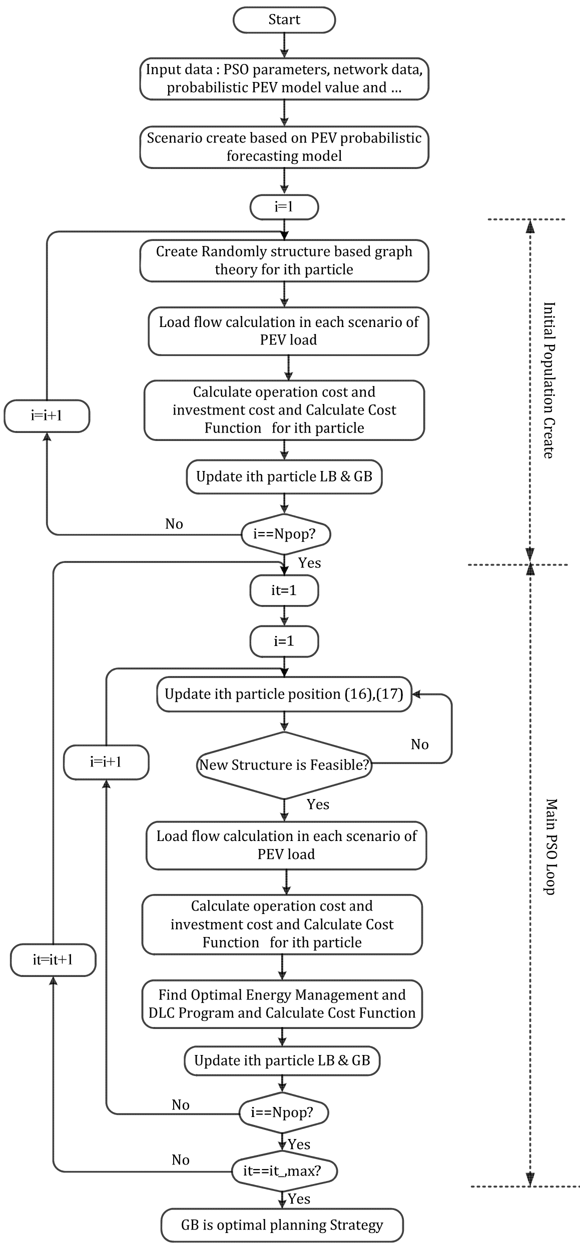

Figure 1: Optimization algorithm

According to figure 1, firstly the number of stochastic candidate substations is selected in expansion study. By creating a stochastic structure, it will be counted in the objective function. Initially, the adequacy of production in any part of the network is checked based on the level of load at peak hours and production levels according to the substations transformers capacity connected to upstream network and maximum production power of Network's DGs. On condition of violating production adequacy, the objective function will be fined. In case of existing the adequacy of production in any part of the network, the level of power consumption of active and reactive network buses in each scenario of uncertainty plug-in electric vehicle load is specified in any time of day, based on the hourly load profiles, plug-in electric vehicle stochastic profile and penetration of plug-in electric vehicles in each bus of the network. According to specified values, the power flow of called AC and network losses will be counted. In establishment of each power flow at any time of day every buses and feeders voltages of network is checked and in case of violation of provisions, the objective function will be fined. The process takes action for all scenarios of load uncertainty of plug-in electric vehicles in different seasons of year, and finally the amount of expected cost of operation is calculated with the equation (1). Also according to the present stochastic structure, other terms the objective function including cost of the feeder expansion and new substations are calculated and the objective function value will be obtained. With production of the initial population, speed and position of the particle updating process is calculated by the following equation:

$$X_i(it+1) = X_i(it) + round\,(v_i(it+1)) \qquad (14)$$

$$v_i(it+1) = wv_i(it) + c_1 r_1 (X^l(it) - X_i(it)) \\ + c_2 r_2 (X^g(it) - X_i(it)) \qquad (١)$$

In equation (14), *Xi* is the position of the particle *i*, *it* is the repeat number, and *Vi* shows speed of article *i*. Also in equation (15) *w*, *c1* and *c2* are respectively of weight coefficient of inertia, weight coefficient of cognitive component and the social component. In this paper, *w*, *c1*, and *c2* values are considered as 0.5, 1, and 2 respectively. Also *r1* and *r2* are a stochastic value in the range of zero to one. In addition, X1 and Xg are the best cognitive and social components. The cognitive component is the best answer that a particle gains by itself. On the contrary, the social component is the best solution accepted by the entire population. Recognition of social and cognitive components is based on objective function in each replication.

5-2- Creating stochastic structure algorithm

In metaheuristic algorithms, making network structures and substations are done stochastically and without observing any provision. In these conditions, it may happen that most cases in main provisions related to the network topology, like network radial, connection of all network buses to substation connected to upstream network will be violated. In this case, execution performance time of program significantly increases. In this paper, to solve this problem, the first level search of depth method is used. In first level search of depth method, the heads are examined deeply. That is, as far as possible, it goes into greater depth and withdraws in the face of deadlock; each head enters the stack after processing is complete. Algorithm starts with root (in graphs, a tree without roots, a node is chosen as the root arbitrarily) and at every step, neighboring heads are examined through the top edge of its output respectively, and when faced with a neighbor who has not been seen before, recursively runs to the current head. If all the neighbors have already seen, algorithm backwards, and the algorithm continues for the current head from which we have come. In the other words, the algorithm goes into greater depth as far as possible and when faced deadlock, it withdraws. This process continues as long as all heads of roots are met [23].

In this paper, to create stochastic and possible structures, we make network graph model assuming all candidate feeders and substations connected, using this methods. In graphs equivalent with network model, network buses are considered as nodes and network feeders are as branches. Then elected positions are randomly selected from the candidate substations. Then each of the selected posts is located, alongside the current network posts, as the node of root. Then, using algorithm of first level search of depth, stochastic structure of network feeder is made, including an inclusive tree. An inclusive tree includes several sets of subgraphs of a tree from a graph which contains all nodes in the original graph. In this algorithm, we randomly select a node from the attached nodes to the network then add it to the visited nodes. This process continues until all the nodes of network are visited and placed on the list. This algorithm ensures that the created structures have radial structure and are connected to the upstream network.

5. Numerical Results

5.1 The studied network structure

In order to evaluate the effectiveness of the proposed algorithm, 33 corrected IEEE buses of network is used. In Figure 2, the studied network structure is prepared. As shown in the figure, the network studied has 33 old and 5 new buses, based on network expansion studies. Also, due to the network geographical situation, two substations are considered as candidate substations. Candidate feeders and existing feeders of network are shown in the figure. In this paper it is assumed that every one of the feeders of previous network can be isolated. So, possible structures may dramatically increase. Data on candidate substation and micro turbine resources of network are mentioned in Table 1 and Table 2, respectively. Then in Table 3 and Table 4, the candidate feeders' information such as length, condition, and information of power flow are presented. Other network information including available feeders' information, network buses data, … are presented in [24]. Daily load curve is shown as a coefficient of power of each buses of network in Figure 3. Plug-in electric vehicle penetration level of loads is considered as a coefficient of total capacity of plug-in electric vehicle in the network, according to Figure 4. Different parameters of expansion model of network are presented in Table 5.

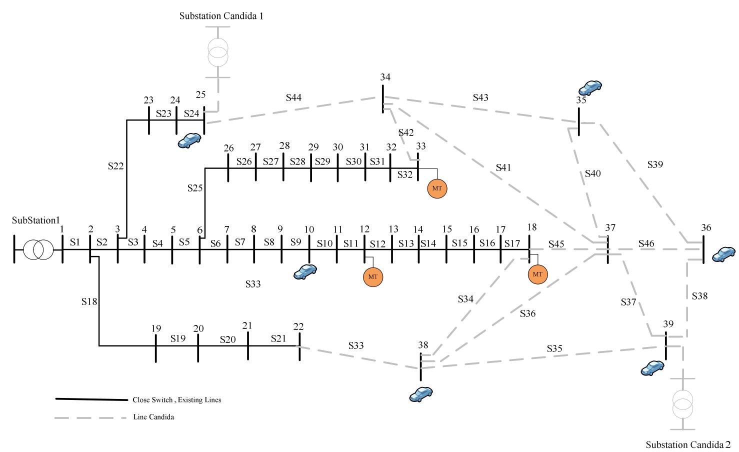

Figure 2: Structure of the modified IEEE 33 bus network

Table 1: candidate substations Information

Connection Bus	Planned[MVA]
25	13.3
39	16.7

Table 2: DGs network information

Connection Bus	Maximum active power(KW)	Maximum reactive power(KVar)	operating cost ($/kwh)
33	700	500	0.03
12	800	650	0.04
18	500	300	0.05

Table 3: candidate feeders' information

from	To	distance(km)	from	to	distance(km)
22	38	12	35	37	3.2
38	39	3	34	37	6.5

39	37	2	34	35	10
39	36	1.5	18	37	2
36	35	6	33	34	7
37	38	6	25	34	9

Table 4: Information of candidate feeders' power flow

Resistance(ohms of km)	Reactance (ohms of km)	capacity (KW)
0.2921	0.2466	1000

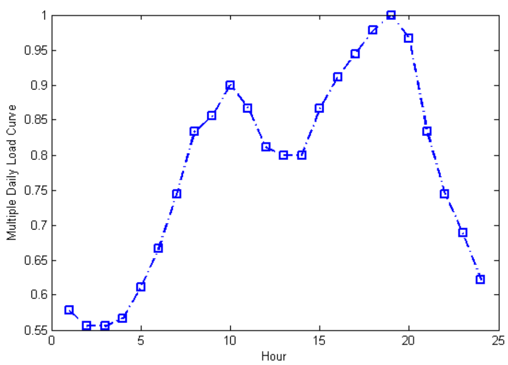

Figure 3: Normalized daily load curve

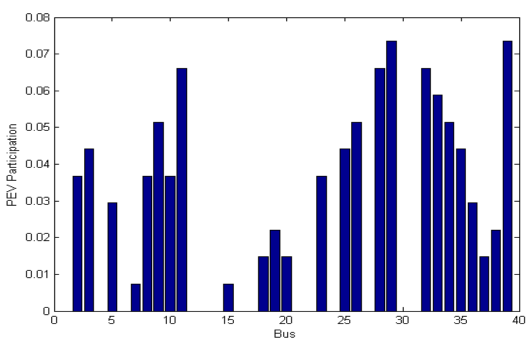

Figure 4: The level of electric car charge penetration in network buses

Table 5: Parameters of network expansion model

Parameter	Value	parameter	value
c^{opr}	10 \$/MWh	c^{E}	50 \$/MWh
$S^{\max}$	0.95	ζ	0.1
n^{L}	30	n^{Sub}	20
$U_i^{\max}$	1.05	$U_i^{\min}$	0.95

To estimate the plug-in electric vehicle load in each of network buses, exact information of transportation data in the study area is in hand. In [22] there is extensive information of urban transport data. Therefore,

NHTS 2001 urban transport data is used in this paper. The information contained in this reference is achieved based on the commute of 139,382 vehicles in 69817 house subscribers. This data includes comprehensive information such as vehicle type, purpose of travel, travel time and ... and is extracted based on daily trips in 42-hour period.

Probability distribution function of plug-in electric vehicle arrival time is shown based on the information in [22] Figure 5. It should be noted that 8% of plug-in electric vehicles have no travel during a day and therefore need no recharge.

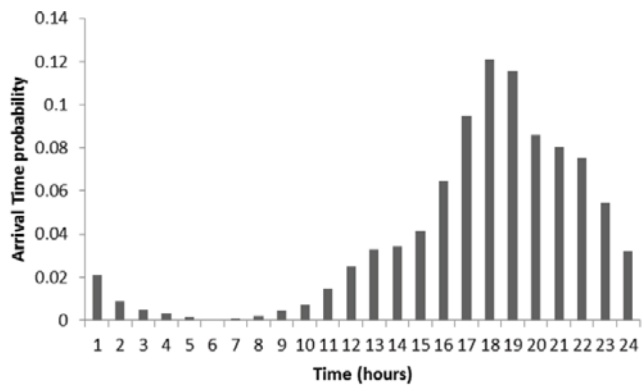

Figure 5: The probability distribution function of the arrival of the plug-in electric vehicle to home

The value λ is considered based on the energy price Ontario. The value λ is provided in 24-hour range in Figure 6.

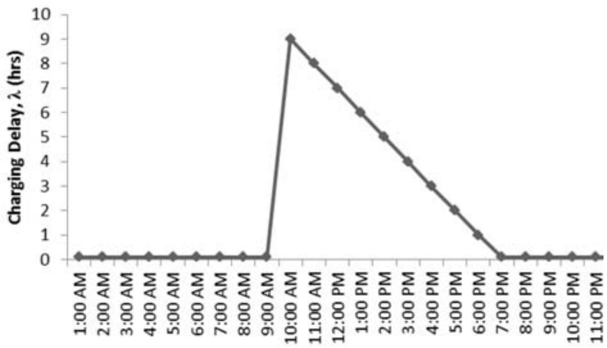

Figure 6: charging delay time per hour

6. Results of network expansion

According to the model used to estimate plug-in electric vehicle load in network, expected daily curve of plug-in electric vehicle load is calculated in accordance with Figure 7. It is necessary to note that in optimization process, different scenarios of the curve load is used to calculate the expected cost of operation and the expected cost of losses. However, due to the high number of scenarios of load uncertainty, is was not possible to show all scenarios in Figure 7, and just expected curves of plug-in electric vehicle load in each season are presented.

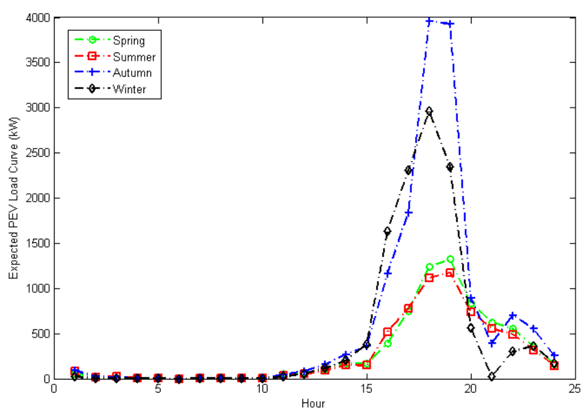

Figure 7: daily expected load curve of plug-in electric vehicle

To investigate the results, the proposed method is performed in three different cases study on the network. In the first case study, network expansion is done regardless of the plug-in electric vehicle load. In the second and third cases study, network expansion optimization has been calculated on the basis of the proposed method varying levels of influence of plug-in electric vehicle loads on the network.

6-1- The first case study

In this case study, network feeders and substation expansion is examined by the use of the proposed method in a condition without the presence of plug-in electric vehicle load. Optimal expansion plan in this case study is presented in Table 6. By selecting optimal expansion plan, network structure is shown in Figure 8. Also the amount of each terms of the objective function is shown in Table 7.

Table 6: optimal expansion plan with the implementation of the proposed algorithm in the first case study

substation expansion		feeders' expansion	
capacity (KW)	to	capacity (KW)	to
2000	25	39	36
1700	39	36	35
		35	34
		34	33
		34	37
		37	18
		39	38

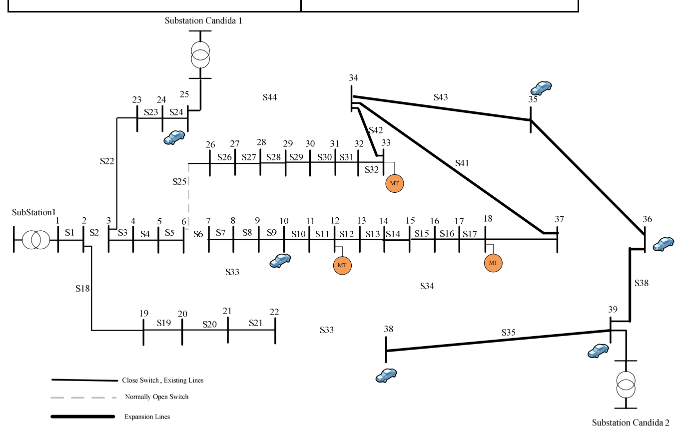

Figure 8: optimal structure expansion in the first case study

Table 7: different terms in the objective function in optimal expansion plan in the first case study

Expected annual losses(KWh)	the total length of feeders (Km)	the expected cost of operation ($)	the cost of network expansion*10^6($)
144520	36	2935.8	1308.3

6-2- The second case study

The second case study is examined by taking into account the plug-in electric vehicle penetration level of 50% in the network. In this case study, in accordance with estimated model of the expected load, the amount of the penetration rate of plug-in electric vehicle in the network is considered 50%. In this situation, network expansion studies are done using the proposed method. With the implementation of the proposed method, the optimal expansion plan in the second case study is presented in Table 8. By selecting optimal expansion plans, network structure is shown in Figure 9. The objective function in optimal status is shown in Table 9.

Table 8: optimal expansion plan by the implementation of the proposed algorithm in the second case study

substation expansion		feeders' expansion		
capacity (KW)	to	capacity (KW)	to	capacity (KW)
2000	25	25	34	100
1700	39	34	35	100
		34	33	100
		34	37	100
		39	36	100
		39	38	100
		22	38	100

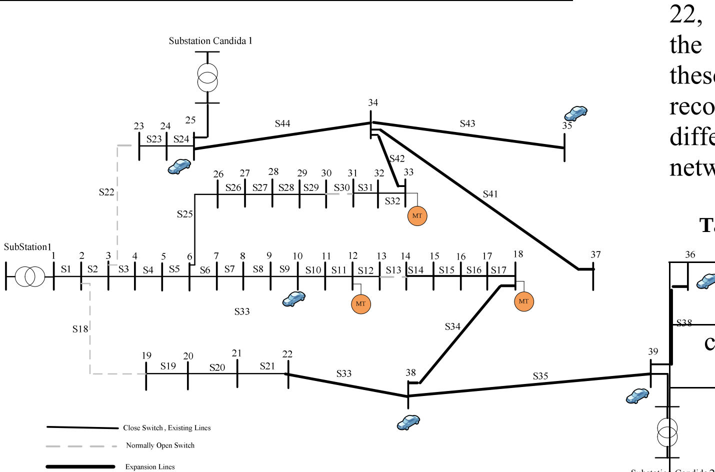

Figure 9: optimal structure expansion in the second case study

Table 9: different terms in the objective function in the optimal expansion plan in the second case study

The Expected annual losses(KWh)	the total length of feeders (Km)	the expected cost of operation ($)	the cost of network expansion*10^6 ($)
163416	53	3271.8	1371.4

6-2-3- The third case study

In this case study, according to the proposed model, the penetration level of plug-in electric vehicle is assumed 100%. With the implementation of the plan, the optimal structure is calculated in accordance with Table 10. Network structure in the network feeders and substation optimal expansion strategy is shown in Figure 10. In this case study, the optimal structure is similar to the first case study, but due to the changing influence level of loads of plug-in electric vehicle, the network optimal structure is different from the first case study. As specified, in the optimal structure both substations are selected in the optimal expansion plan. Network load increase and therefore violation of thermal limits of transportation lines and network voltage are reasons in optimal structure to include both substations in optimal plan. Selected lines in the optimal design are shown with bold lines in the figure below. In the optimal structure, the keys 22, 18 and 13 are opened to take advantage of the network in a radial manner. The presence of these maneuver keys will certainly facilitates recovery of loads at the time of event in different feeders of network and also enhances network reliability.

Table 10: optimal expansion plan by implementation of the proposed algorithm in the third case study

substation expansion		feeders' expansion		
capacity (KW)	to	capacity (KW)	to	capacity (KW)
2000	25	25	34	100
1700	39	34	35	100
		34	33	100
		34	37	100
		39	36	100
		39	38	100
		22	38	100
		38	18	100

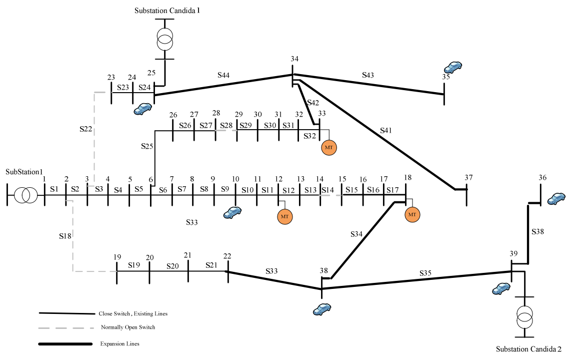

Figure 10: optimal structure of network expansion in the third case study

Using innovative method based on graph theory plays a significant role in the high speed of answer convergence. The objective functions in optima expansion plan is presented in Table 11.

Table 11: different terms of the objective function in optimal expansion plan in the third case study

Expected annual losses(KWh)	the total length of feeders (Km)	the expected cost of operation ($)	the cost of network expansion*10^6($)
۱۸۰۰۲۰	۵۳	۳۶۴۵,۸	۱۳۷۱,۴

7. Conclusion

In this paper we developed a comprehensive expansion planning of feeders and substations of network with the presence of plug-in electric vehicles for distribution systems to confront the future uncertainties. The approach taken in this paper includes the initial investment and operational costs. The effect of PEVs on network buses loadings are estimated through a set of scenarios based on three factors: uncertainty in plug-in electric vehicle arrival, uncertainty of delay in plug-in electric vehicle charging after reaching destination, and uncertainty in the required power for charging.

Also to solve the proposed model of feeders' and substations' expansion of the network, we have used the particle colony algorithm. To reduce the time of program performance, possible stochastic structures are used, benefitting the first level of depth search to create a comprehensive forest. Eventually, the effectiveness of the proposed algorithm was discussed by performing it on the modified IEEE 33 Bus distribution network. The result shows that using the graph theory-based method to create stochastic and possible structures and increases the speed of the algorithm. Also, the use of probabilistic models of plug-in electric vehicle load and creating various scenarios lead to resistant expansion operation plan of plug-in electric vehicle different optimal load scenarios.

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