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Investigation of Wind Power Uncertainty on Transmission Network Expansion Planning

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Abstract- The main goal of transmission expansion planning (TEP) is to develop or reinforce the electrical network to fulfil the future electrical load requirement and to integrate new equipment added to the network. TEP is a major subject in smart grid development, where Demand Response Program (DRP) affect long- and short-term power system decisions and these in turn, affect TEP. First, this paper discusses the effects of Non-Linear Demand Response Program (NDR) on reducing the final costs of a system in TEP. In order to approach real behaviour of the loads, three different types of loads including residual, commercial and office-building have been considered. Real data for wind power is extracted from Khaf, Iran. Using Mont-Carlo and based on Empirical Cumulative Distribution Function (ECDF), 1000 scenarios are produced to study the uncertainty characteristic of wind. As there are a lot of scenarios which are time consuming, Radial Based Neural Network Clustering (RBNNC) is used for decreasing the run-time significantly. Then TEP problem is solved using the Teaching-Learning-Based Optimization (TLBO) and Gray Wolf Optimization (GWO) algorithms in order to minimize the costs of generation, losses, and lines. Simulation results show the optimal effect of NDR and wind on postponing the additional cost of investments for supplying peak load.

Keywords Transmission expansion planning, Non-linear demand response program, TLBO, GWO, Wind power, Mont-Carlo, Uncertainty.

1. Introduction

The main goal of transmission expansion planning (TEP) is to develop or reinforce the power system to accomplish the future electrical load requirement and to integrate new equipment added to the network considering stability and reliability of the electrical network [1].

From mathematical point of view, TEP is a discrete, non-linear, and large-scale optimization problem with many equality and inequality constraints. TEP studies can be divided to three main categories including evolutionary techniques [2-7], mathematical techniques [8-10], and meta-heuristic techniques [11-13].

Garver [2], as one of the pioneers in solving TEP problems, formulated the TEP as a load distribution problem and considered the objective function and the constraints by linear functions. Ohmic power losses was neglected by Garver and by considering the newly added lines, new linear load flow was calculated, and the operation continued until no overload found in the system. The other example for evolutionary technique is the Lattore's studies [3] which TEP problem was separated into two different problems: the first one was investment which solved by an evolutionary technique, and the second one was generation which solved by a known optimization technique. In another studies of evolutionary technique [4-7], sensitivity analysis was used to solve TEP problem. In these publications, sensitivity index was used to determine the added lines. Different algorithms such as minimum depletion, load feeding [4], lowest criteria [5], a lighter version of its own mathematical model, or the optimal load flow [6] was used to generate sensitivity index.

The most famous mathematical technique for TEP problem is linear programming where constraints and the objective function are linear [8-9]. The linear TEP problem was separated into two different problems including investment and generation problems, which were defined by a linear planning model and Monte Carlo, respectively, based on DC load flow. The other mathematical technique for TEP problem is nonlinear planning where some constraints and the objective function was formulated as nonlinear equations. The objective function was considered minimizing the investment costs, Ohmic losses and corona. The main disadvantage of this technique is that the output result may get stuck in the local solution, in other word, initial values of load flow has great impact of output results. Pereira's studies [10] is another example for mathematical technique which mathematical decomposition was used.

To use the benefits of evolutionary and mathematical techniques, meta-heuristic techniques were used. A parallel SA algorithm was implemented by Gallego [11] that significantly reduced the computation burden and improved quality of the SA solution. A greedy randomization adaptive search procedure was proposed by Binato [12]. Maghouli [13] presented a multi-stage TEP using a multi-objective optimization framework with internal scenario analysis for handling uncertainties.

In recent years, Demand response programs (DRPs) are becoming popular because of delaying additional apparatus costs for delivering the peak load. It is proved that implementing DRPs in TEP problem can be useful [14–18]. These programs affect short-term and long-term decision-making strategies for an electrical network.

Renewable energy penetration in power system has been increased over the recent decades because of the great attention to climate change, environmental pollution and so on. In this among, wind energy has attracted more attention in the world and its usage is increasing [19]. Due to intermittent nature of wind farms, some publications are focused to investigate the wind power generation on TEP problem [20-26].

TEP problem considering load management and wind power uncertainties is a relatively new research topic which is the aim of this paper. In our previous research [27], decreasing the total costs of a power system in TEP using the linear DRPs has been studied. Then the TEP program investigated using TLBO algorithm in order to minimize the total costs including costs of power generation, power loss, and line construction. In this paper, the effect of a non-linear DRP (NDR) on decreasing the total costs of a system in TEP has been studied. In order to approach real behaviour of the loads, three different types of loads including residual, commercial and office-building have been considered. Real data for wind power is extracted from Iranian network. Using Mont-Carlo and based on Empirical Cumulative Distribution Function (ECDF), 1000 scenarios are produced to study the uncertainty characteristic of wind. As there are a lot of scenarios which are time consuming, Radial Based Neural Network Clustering (RBNNC) is used for decreasing the run-time significantly. Then TEP problem is solved in such a way that the costs of generation, losses, and lines to be minimized. It is used two different optimization algorithm; TLBO and Gray Wolf optimization (GWO) algorithms; to find the effectiveness of them.

The investigations are performed on different scenarios including:

1. Without consideration of TEP and DRP: this scenario is base;
2. Without consideration of TEP and consideration of DRP: in this scenario the effect of DRP is investigated;
3. TEP without wind: in this scenario the effect of TEP is investigated;
4. TEP with wind: in this scenario the effect of wind is investigated;
5. TEP with wind and wind uncertainty: in this scenario the effect of wind uncertainty is investigated;

The proposed method is applied on the IEEE 57-bus test system. This method is a bi-step optimization problem where in the first step, a DRP is applied for reducing the peak load and costs of TEP. TLBO and GWO algorithms are used to solve the TEP problem in the second step to understand the simultaneous effects of non-linear DRP, wind and wind uncertainty. The flowchart of the proposed method is shown in Fig.1. As can be seen, after applying NDR and TEP, the total cost is calculated. If the system's normal operation cost is lower than the total cost of TEP (Before NDR and TEP), NDR is applied to increase the customer participation in NDR. This can be done by increasing (decreasing) the price of energy in peak hours (valley and off-peak hours) or decreasing the constraints of customer cooperation in NDR.

Our contribution in this paper is as follow:

1. Find the effect of NDR on TEP for combination of residual, commercial and office-building loads.
2. Scenario reduction by RBNNC to study the uncertainty characteristic of wind.
3. Find the simultaneous effect of non-linear DRP, wind and wind uncertainty on TEP problem.
4. Probability calculation of the objective function occurrence (loss, Costs of generation and line constructions)
5. Find the objective function related to the defined confidence level in order to provide better decision making.

In section 2, briefly the modelling of NDR is proposed. In the following, TEP model is illustrated in section 3. TLBO and GWO algorithms are provided in section 4 and 5, respectively. Study of network and simulation results are presented in section 6. Finally and in section 7, the conclusion is provided.

2. Modelling the Non-Linear Demand Response Program

Three different models are used to model the customer response including power, exponential and logarithmic non-linear models. These models are studied carefully in [28]. It has been proved that logarithmic non-linear model is more effective than the others in most cases and on this basis, it is used in this paper. In the following the final customer's demands are provided:

$$d(i) = d_o(i).\{1 + \sum_{j=1}^{24} E(i,i).\ln(\frac{P(i)}{P_0(i)})\} \quad (1)$$

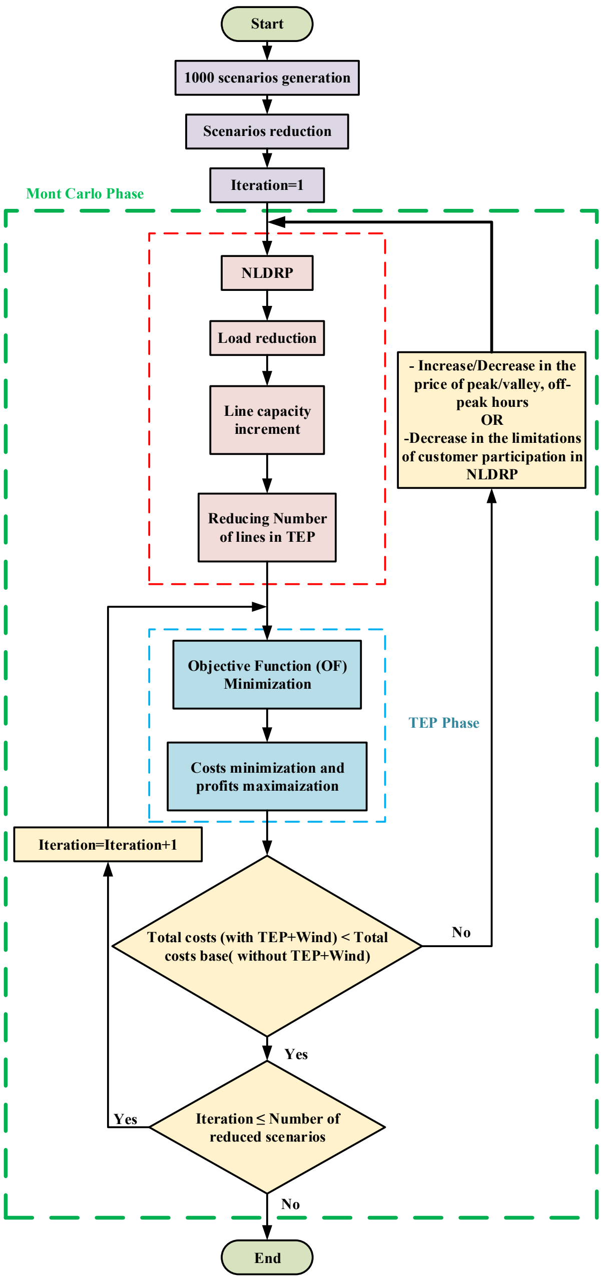

Fig. 1. Flowchart of the proposed method.

where *d(i)* is the customer demand, *E(i,j)* is the cross-elasticity, *P(i)* is the electricity price.

3. Problem Formulation

The TEP problem is formulated to minimize the total cost including cost of generation, cost of line construction and cost of loss. The TEP formulas are as [27]:

$$\min F = \sum_{i=1}^{m} K_i n_i + C_l[\sum_{i=1}^{m^0} e_i I_i^2 R_i d + \sum_{i=1}^{m} (e_i + n_i) I_i^2 R_i d] + \sum_{i=1}^{N_{DG}} (c_i P_i^2 + b_i P_i + a_i) d \quad (13)$$

$$\sum p_{ij} = P_{Gi} - P_{Di}, \; j \omega i, \; i \in N \quad (14)$$

$$-p_i^{\max} \le p_i \le p_i^{\max}, \; i \in m + m^o \quad (15)$$

$$o < n_i < n_i^{\max}, \; n \in Z, i \in m \quad (16)$$

where n_i is the number of circuits added to the right-of-way i; K_i is the candidate circuit cost for addition to the right-of-way i; d is the system runtime which is considered here as 4830 hours [27]; C_l is the loss cost per kWh; e_i is the number of circuits in the main base system; I_i is the electrical current in the ith circuit; R_i is the resistance of ith circuit; m is the right-of-way allowed to be the added line; m^0 is right-of-way not allowed to be the added line; a_i, b_i, and c_i are the cost coefficients; P_i is the active power generated from ith generator. Equation (14) is the constraint of power equation which is resulted from calculating power flow, where P_{ij} is the active power in line i to j; and PG_i and PD_i are the active power generation and load on ith bus. Equation (15) is the constraint of overload that can be introduced as a penalty for the overload of each circuit, where P_{imax} is the maximum active power flow in ith circuit. Equation (16) is the upper and lower constraint of the number of circuits that can be added to right-of-way i.

4. TLBO Algorithm

Recently TLBO has attracted more attention in electrical engineering [29]. TLBO is a population-based method where teacher and students are the main elements of this algorithm. In two steps, the students increase their level:

- Teacher step: in this step, teacher tries to increase the class level;
- Student step: in this step, by interaction through other students, students increase their scores;

The best answer or most knowledgeable student is called the teacher. The two steps of TLBO algorithm are explained in below:

3.1. Teacher Step

The best answer or teacher tries to increase the student class level from M_i to M_T (his own level), but in reality, it is impossible. Therefore, teacher tries to increase M_{mean} (average level of the class) to a M_2 (higher level). Good teacher or suitable answer performs better for the students.

To understand this step, the difference between M_T and M_{mean} is calculated as:

$$differ\_mean_i = r_i\,(\mathrm{M}_T - \mathrm{T}_f\,\mathrm{M}_{mean}) \tag{2}$$

where T_f is the teacher factor between 1 and 2 and r_i is a random variable in [0 1]. Based on *differ_mean*, the answer will be updated as follows:

$$X_i^{new} = X_i^{old} + differ\_mean_i \tag{3}$$

3.2. Student Step

A comparison is made between two different students (X_i and X_j). If the first student (X_i) has more knowledge against the second student (X_j), this will learn new things, otherwise, the second will learn new things. On this basis, X_i will be updated as the following equations:

$$\begin{gathered} X_i^{new} = X_i^{old} + r_i\,(X_i - X_j) \\ if \;\; f(X_i) < f(X_j) \end{gathered} \tag{4}$$

$$\begin{gathered} X_i^{new} = X_i^{old} + r_i\,(X_j - X_i) \\ if \;\; f(X_j) < f(X_i) \end{gathered} \tag{5}$$

5. Gray Wolf Optimization Algorithm

Gray wolf optimization algorithm is one of the new introduced meta-heuristic optimization algorithms [30]. This algorithm is inspired by the wolves pack where α is leading the group. In the next level β wolves are existed where their role are helping α to make better decisions. Scout, sentinel, elder, hunter and caretakers are the next duty of δ wolves. The end level wolves are ω where their duty is scapegoat.

In the gray wolf optimization algorithm, α is considered the best solution. α is followed by β and δ and the reminder solutions are considered ω. When the wolves go hunting, they want to circle their pray. This behaviour can be modelled by the following equations:

$$\vec{D} = \left| \vec{C}.\vec{X}_p(t) - \vec{X}(t) \right| \tag{6}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{7}$$

where $\vec{X}$ is the vector position of gray wolf, $\vec{X}_p$ is the vector position of the prey and t is the current iteration. $\vec{A}$ and $\vec{C}$ are coefficient vectors which obtained by the following equations:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{8}$$

$$\vec{C} = 2.\vec{r}_2 \tag{9}$$

where $\vec{a}$ is set to reduced from 2 to 0 over the optimization period, and r_1 and r_2 are random vectors in [0,1].

The three best solutions (α, β, δ) are saved and other solutions (ω) update their positions based on current best positions. The related equations are provided as below:

$$\begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1.\vec{X}_\alpha - \vec{X} \right|, \\ \vec{D}_\beta &= \left| \vec{C}_2.\vec{X}_\beta - \vec{X} \right|, \\ \vec{D}_\delta &= \left| \vec{C}_3.\vec{X}_\delta - \vec{X} \right| \end{aligned} \tag{10}$$

$$\begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1.\vec{X}_\alpha - \vec{X} \right|, \\ \vec{D}_\beta &= \left| \vec{C}_2.\vec{X}_\beta - \vec{X} \right|, \\ \vec{D}_\delta &= \left| \vec{C}_3.\vec{X}_\delta - \vec{X} \right| \end{aligned} \tag{11}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{12}$$

6. Simulation and Results

In this paper, proposed method has been studied on IEEE 57-Bus System in order to investigate the effects of NDR and TEP on network's total cost. The information of the case study can be found in [31].

Load profile for residual, commercial and office-building load has been shown in the Fig. 2, Fig. 3 and Fig. 4, respectively. There are two thresholds, 0.55 and 0.8. The load values lower than first threshold (0.55) is considered as valley. The load values between first threshold (0.55) up to second threshold (0.8) is considered as off-peak. The load values higher than second threshold (0.8) is considered as peak. Peak, off-peak and valley times for different load types are summarized in Table 1.

The electricity price in Iran is 150 Rials/kWh as the flat rate, 40 Rials/kWh in valley periods, 160 Rials/kWh in the off-peak period and 400 Rials/kWh for the peak period [32]. Self- and cross-elasticity for residual load have been shown in Table 2. Considering equal elasticity matrix for commercial and office-building loads, self- and cross-elasticity have been tabulated in Table 3.

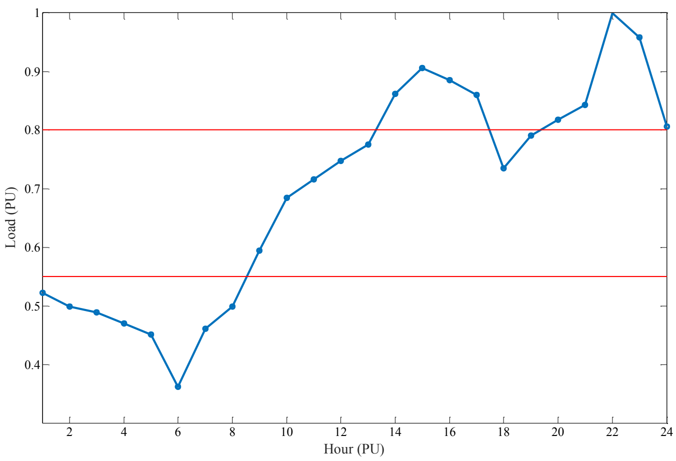

Fig. 2. Residual load profile.

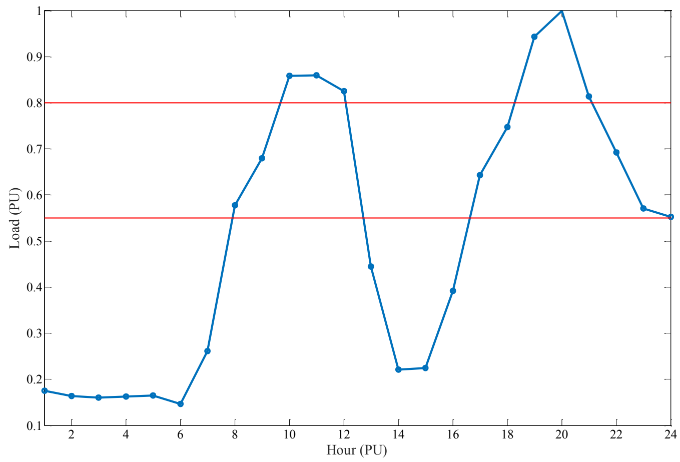

Fig. 3. Commercial load profile.

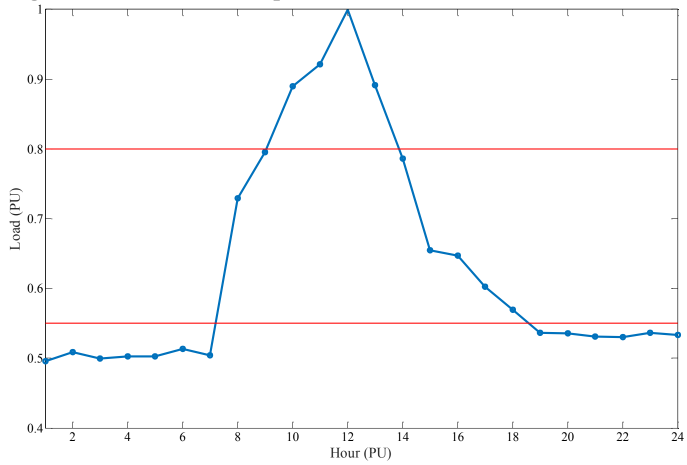

Fig. 4. Office-building load profile.

Non-linear demand response program discussed in section 2 has been implemented on three different load types and the results have been depicted in Fig. 5, Fig. 6 and Fig. 7. It is easily understood that the load values have been shifted from peak hours to valley and off-peak hours. In other words, load reduction in peak hours can help lowering system stresses.

Table 1. Peak, off-peak and valley times for different load types

Load Type	Valley	Off-peak	Peak
Residual	1-2-3-4-5-6-7-8	9-10-11-12-13-18-19	14-15-16-17-20-21-22-23-24
Commercial	1-2-3-4-5-6-7-13-14-15-16	8-9-17-18-22-23-24	10-11-12-19-20-21
Office-building	1-2-3-4-5-6-7-19-20-21-22-23-24	8-9-14-15-16-17-18	10-11-12-13

Table 2. Self- and cross-elasticity for residual load

	Valley	Off-Peak	Peak
Valley	−0.10	0.01	0.012
Off-Peak	0.01	−0.10	0.016
Peak	0.012	0.016	−0.10

Table 3. Self- and cross-elasticity for commercial and office-building loads

	Valley	Off-Peak	Peak
Valley	−0.07	0.006	0.0072
Off-Peak	0. 006	−0. 07	0.0096
Peak	0. 0072	0. 0096	−0. 07

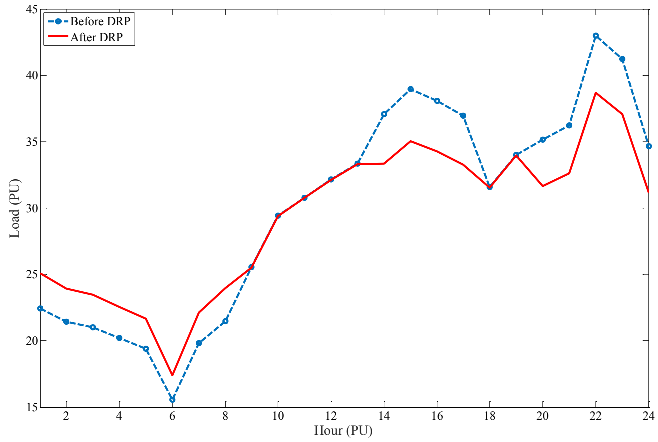

Fig. 5. Residual load diagram before and after the NDR.

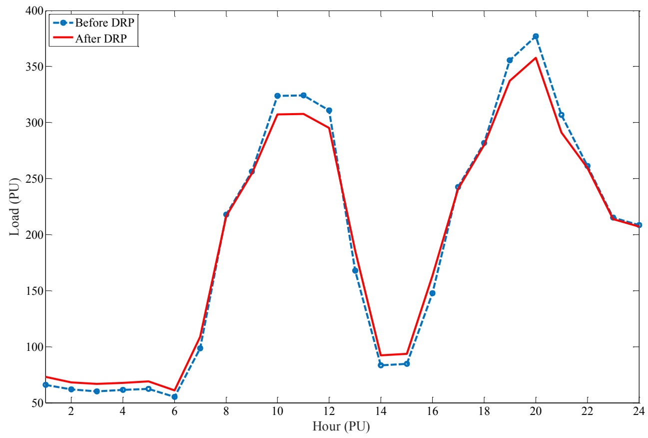

Fig. 6. Commercial Load diagram before and after NDR.

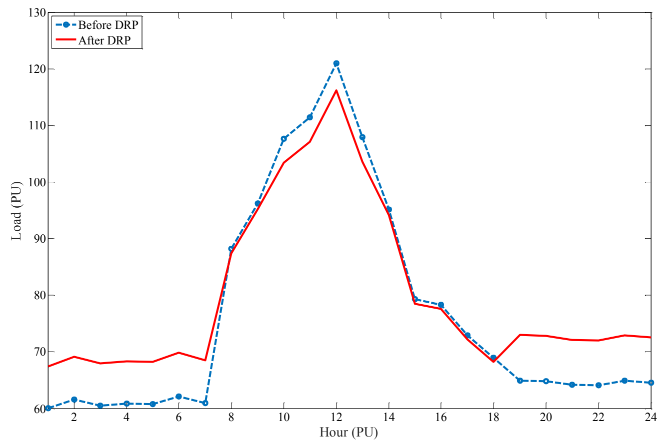

Fig. 7. Office-building load diagram before and after the NDR.

As loads have different characteristics, for example the peak of office-building occurs at 12 mid-day, it is better to consider the worst case for transmission expansion planning. For this purpose and on this basis that the loads in the network are one of residual, commercial and/or office-building type, these three loads are summed up and the time of peak are obtained. Therefore, 8 p.m. is derived as the peak time (worst time). In this paper, it is assumed that the only loads of buses 9, 12, 16 and 18 are responsive. Also, the types of them are office-building, commercial, residual and residual, respectively.

Two scenarios are considered to evaluate the effectiveness of the demand response program in reducing the total costs including generation, loss and line construction costs. The first scenario is optimal load flow before applying the NDR. In the second scenario, the optimal load flow is running considering NDR. The results of the first and second scenarios including loss, cost of loss, cost of generation, cost of line construction and total cost are presented in Table 4. It is worth to mention that loss per MWh for IEEE 57 bus network is 3.48 \$/MWh. As can be seen, NDR makes the cost of generation and cost of loss to be decreased and consequently, the total cost to be reduced. Reduction percentage of loss, cost of loss, cost of generation and total cost has shown in Fig. 8. As can be shown, 7.48, 7.47, 8.7 and 8.6% reduction on loss, cost of loss, cost of generation and total cost has been seen by NDR.

Table 4. Results of OPF before and after the NDR

Scenario	Loss (MW)	Cost of Loss (\$/h)	Cost of Generation (\$/h)	Cost of Line construction (\$/h)	Total Cost (\$/h)
Before DR (1)	16.5132	57.4660	41738	481.1636	42277
After DR (2)	15.2784	53.1690	38109	481.1636	38643

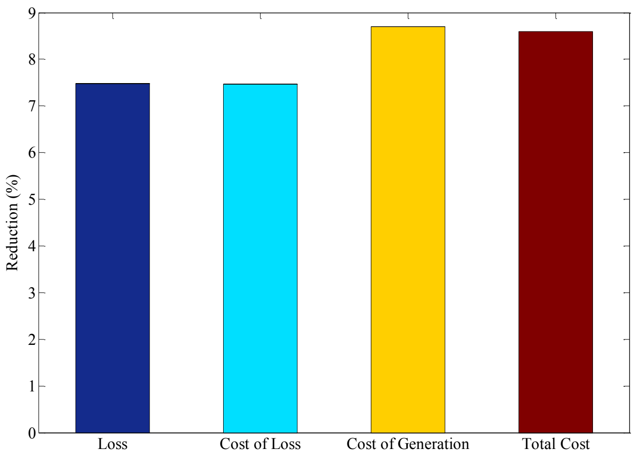

Fig. 8. Reduction percentage after the NDR.

As stated before, wind energy has attracted more attention in the world and its usage is increasing. Wind energy can provide local loads and it is expected to increase lines capacities. Therefore, it causes a delay in adding new lines. Moreover, loss and generation costs are decreased. In the following, the effect of wind energy on TEP will be investigated. Wind output power can be stated by the below equation [32]:

$$
\begin{aligned}
&P_w = 0 && for\, v < v_{cut\,in}\; or \;\; v > v_{cut\,out} \\
&P_w = P_r\left(\frac{v - v_{cut\,in}}{v_r - v_{cut\,in}}\right) && for\, v_{cut\,in} \le v \le v_r \\
&P_w = P_r && for\, v_r \le v \le v_{cut\,out}
\end{aligned}
\tag{17}
$$

where v_{cutin}, v_{cutout}, v_r, P_r and P_w are low wind speed, high wind speed, rated wind speed, rated power and wind power, respectively.

Due to intermittent nature of wind energy, the results of TEP have uncertainties. In this paper, Mont-Carlo method is used to study the uncertain nature of the wind energy. Investigations have shown that wind behavior does not follow Weibull distribution. Therefore for providing Mont-Carlo scenarios, it is better used the real data and empirical cumulative density function (ECDF) [33-34]. Wind speed data was provided from Khaf in Iran. The data were collected as 1-hour time-stamped values for a period of 3 years. Empirical cumulative density function (ECDF) was applied for the recorded data in each hour. Then, sets of uniformly distributed samples on [0, 1] was provided by applying a random number generation algorithm. The generated uniform samples were converted to sets of simulated variables having the same uncertain nature as the recorded data using inverse ECDF transformation.

Using 1000 randomly generated values in the range [0,1] and using ECDF of wind, Fig. 9, 1000 scenarios for wind speed and wind power are generated. As TEP is time-consuming simulation, using Radial Based Neural Network Clustering, these 1000 scenarios are decreased to 30 scenarios [35-38]. In the Fig. 10, the nature of 1000 scenarios against 30 scenarios is shown. As can be seen, these have similar nature and it is possible to use 30 scenarios based on Mont-Carlo to investigate TEP program considering wind uncertainty.

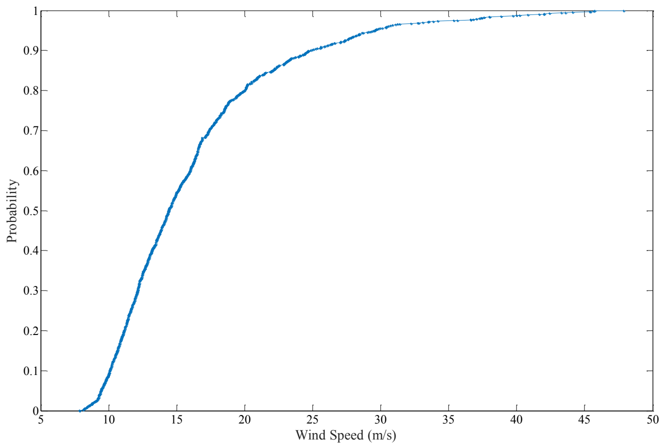

Fig. 9. ECDF of wind speed at 8:00 p.m.

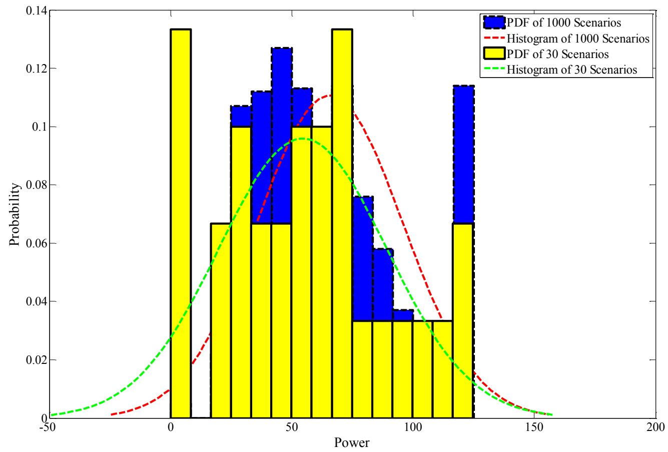

Fig. 10. Nature of 1000 and 30 scenarios.

In the next step after applying NDR, TEP was applied. The lines can be added between buses 1, 2, 3, 6, 8, 9, 12, 16, and 17 and the maximum allowable number of new lines permitted to be added is 3. The TEP is performed using TLBO and GWO algorithms in order to minimize total cost in the following scenarios:

- Scenario 3: TEP using TLBO without wind is studied;
- Scenario 4: TEP using GWO without wind is studied;
- Scenario 5: TEP using TLBO with wind is studied;
- Scenario 6: TEP using GWO with wind is studied;
- Scenario 7: TEP using TLBO with wind and wind uncertainty is studied;
- Scenario 8: TEP using GWO with wind and wind uncertainty is studied;

The results of above scenarios are summarized in Table 5.

In Fig. 11, the value of loss for scenarios 1 up to 8 has been shown. Before NDR, the value of loss is 16.5132 MW while after that; the value of loss is decreased to 15.2784 MW. Adding new lines by TEP using TLBO algorithm in scenario 3 resulted in reduction of the loss to 9.8771 MW while by TEP using GWO algorithm in scenario 4 resulted in reduction of the loss to 9.7438 MW. As wind provides local loads, it makes the loss to be decreased to 9.7276 MW in scenario 5 using TLBO algorithm and to 9.535 MW in scenario 6 using GWO algorithm. Because of uncertainty of the wind, the value obtained in scenario 5 and 6 are not precise and the value of loss considering uncertainty is 9.7738 MW in scenario 7 using TLBO algorithm and 9.5666 MW in scenario 8 using GWO algorithm.

Table 5. Results of TEP for different scenarios in a 57-bus network.

Scenario	Loss (MW)	Cost of Loss ($/h)	Cost of Generation ($/h)	Cost of Line construction ($/h)	Total Cost ($/h)
(3)	9.8771	34.3722	37854	515.6575	38404
	No. of Lines Added Between Two Different Buses : 1–8(3),1–12(3),1–17(3),2–3(3),2–8(3),2–16(3),3–8(3),6–8(3),8–9(3),8–12(3),8–16(3),8–17(3),12–16(3)				
(4)	9.7438	33.9084	37104	513.0041	37651
	No. of Lines Added Between Two Different Buses : 1–8(3),1–12(3),1–17(3),2–3(3),2–8(3),2–16(3),3–8(3),8–9(3), 8–12(3),8–16(3),8–17(3),12–16(3)				
(5)	9.7276	33.8521	34973	510.6861	35518
	No. of Lines Added Between Two Different Buses : 1–8(3),1–12(3),1–17(3),2–3(3),2–8(3),2–9(3),3–8(3),6–8(3),8–9(3),8–16(3),8–17(3)				
(6)	9.5350	33.1818	34253	508.0022	34794
	No. of Lines Added Between Two Different Buses : 1–8(3),1–12(3),1–17(3),2–3(3),2–8(3),2–9(3),3–8(3),6–8(3),8–16(3),8–17(3)				
(7)	9.7738	34.0128	34897	519.5612	35451
	No. of Lines Added Between Two Different Buses : 1–8(3),1–12(3),1–17(3),2–3(3),2–8(3),2–16(3),3–8(3),6–8(3),8–9(3),8–12(3),8–16(3),8–17(3),9–16(3),12–16(3),12–17(3)				
(8)	9.5666	33.2918	34171	515.7214	34720
	No. of Lines Added Between Two Different Buses : 1–8(3),1–12(3),1–17(3),2–3(3),2–8(3),2–16(3),3–8(3),6–8(3),8–9(3),8–12(3),8–16(3),8–17(3),9–16(3),12–16(3)				

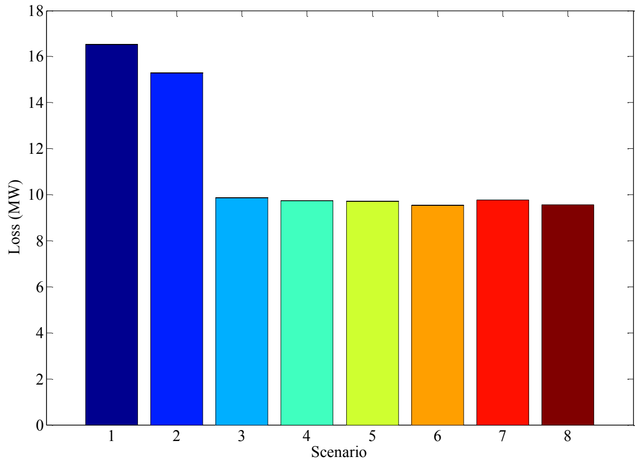

Fig. 11. Loss for different scenarios.

The value of cost of line construction for different scenarios has been illustrated in Fig. 12. As no line is added in NDR, therefore NDR has not any influence on the cost of line construction. By adding new lines in TEP, cost of line construction is increased to 515.6575 MW in scenario 3 and to 513.0041 MW in scenario 4 against scenario 1 and 2. By postponing the construction of new lines in scenario 4 by wind, the cost of line construction is decreased in scenario 5 and 6 against scenario 3 and 4. In other words, wind power not only provides the demand of the local loads, but also can remove the congestion of the lines. Therefore the cost of line construction is decreased. The values obtained in scenario 5 and 6 are not precise due to wind uncertainty and the real values can be found in scenarios 7 and 8.

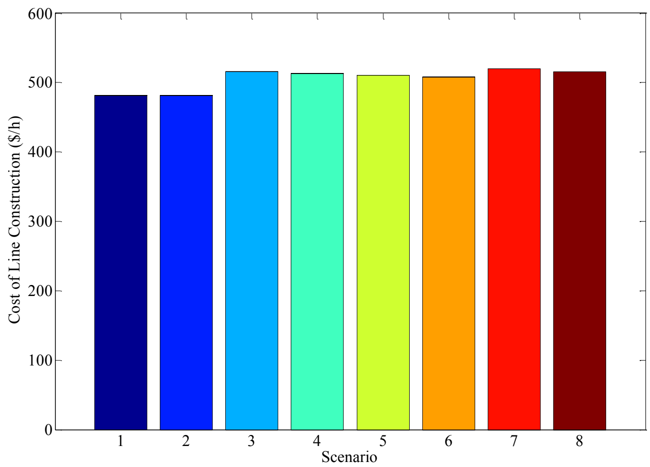

Fig. 12. Cost of Line Construction for different scenarios.

In Fig. 13, the cost of generation for scenarios 1 up to 8 has been provided. By shifting the load from peak hours to off-peak and valley hours, NDR decrease the cost of generation from 41738 $/h to 38109 $/h. By adding new lines and decreasing loss, the cost of generation is decreased to 37854 $/h and 37104 $/h in scenarios 3 and 4. Also, wind has great effect on the cost of generation and makes the cost of generation to be decreased to 34897 $/h and 34171 $/h in scenario 7 and 8.

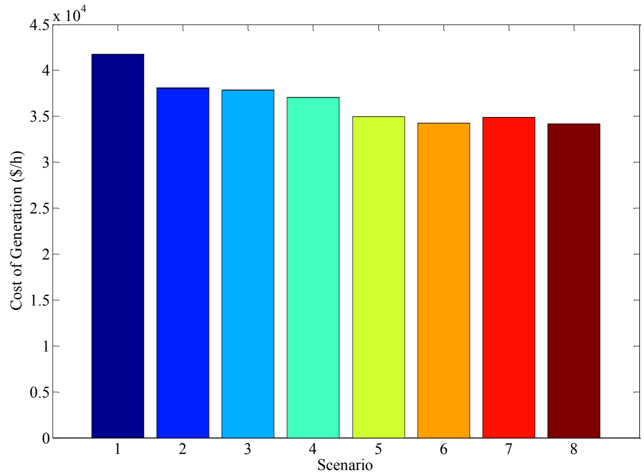

Fig. 13. Cost of Generation for different scenarios.

The value of total cost for different scenarios has been shown in Fig. 14. The effect of NDR can be easily found by comparing scenario 1 and scenario 2 results where total cost is decreased from 42277 $/h to 38643 $/h. By comparing scenario 2 with scenario 3 and 4 results, the effect of TEP can be found where the total cost is decreased to 38404 $/h and 37651 $/h. The effect of wind is found by studying the scenarios 5 up to 8.

By studying different scenarios, it is easily can be found that GWO algorithm gives better results than TLBO algorithms.

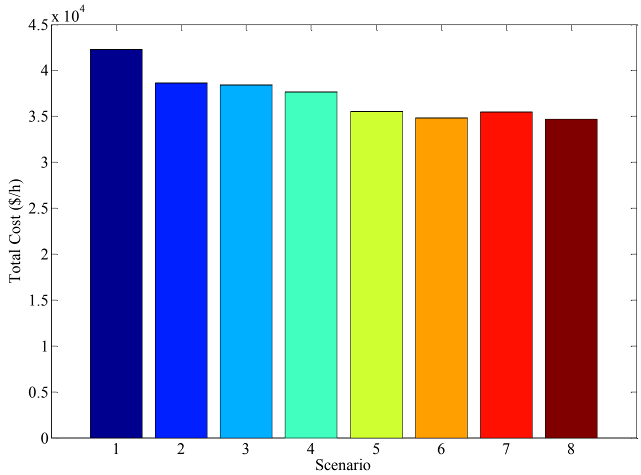

Fig. 14. Total Cost for different scenarios.

Since GWO algorithm gives better results than TLBO algorithm then results of this algorithm including the ECDF of loss, cost of loss, cost of generation and cost of line construction have been shown in Figs. 15 to 18. To find the probability of the values for scenario 8 in Table 5, the values shall be crossed with ECDF curve and appropriate probabilities are obtained (strict red lines). The value of loss in scenario 8 is 9.5666 MW, when this value is crossed related ECDF curve, 0.208 is obtained. This means with 20.8 % obtained loss is equal or lower than 9.5666 MW. It can be possible to look on the other view. Assume that the 85% is a suitable confidence level for system decision makers. The value 85% is crossed related ECDF, and the value of loss is obtained (dashed green lines). The loss of the network is equal or lower than 9.87 MW by probability of 85%. Similar to the loss, the cost of generation and cost of line construction are equal or lower than 36820 ($/h) and 523.3 ($/h), respectively.

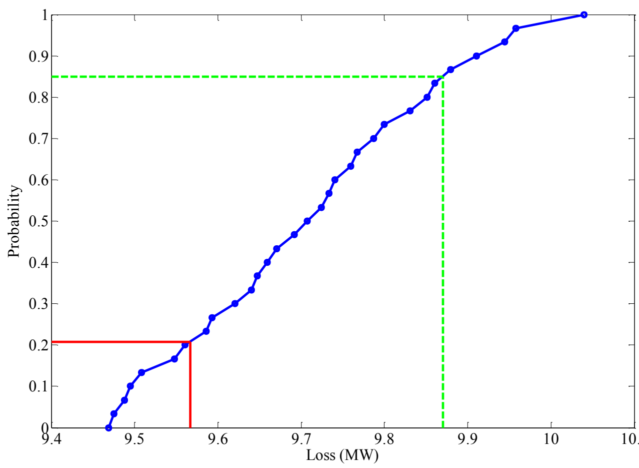

Fig. 15. ECDF of loss.

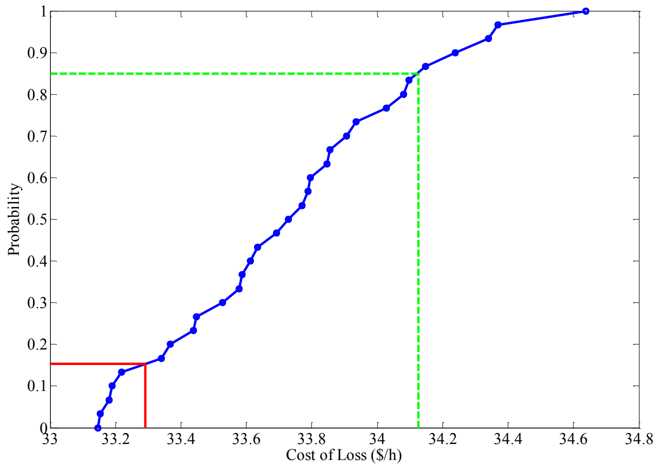

Fig. 16. ECDF of cost of loss

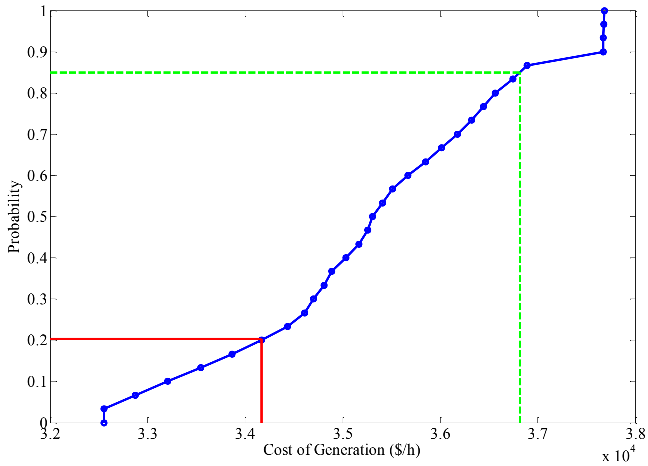

Fig. 17. ECDF of cost of generation

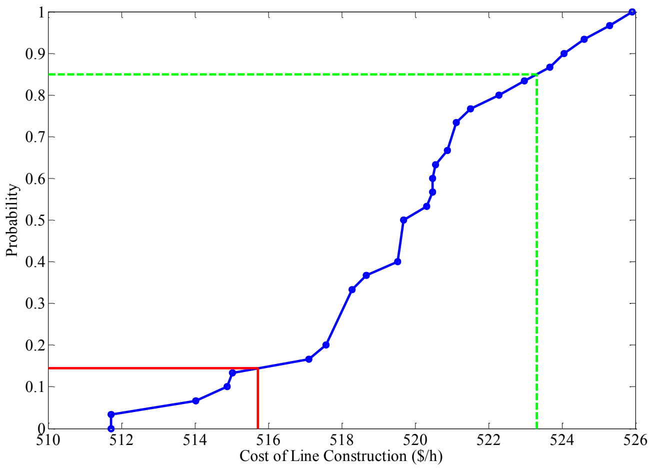

Fig. 18. ECDF of cost of line construction

7. Conclusions

In this paper, the effects of NDR on reducing the final costs of a system in TEP for three different types of loads including residual, commercial and office-building was investigated. Using Mont-Carlo and based on Empirical Cumulative Distribution Function (ECDF), 1000 scenarios were produced to study the uncertainty characteristic of wind. As there are a lot of scenarios which are time consuming, Radial Based Neural Network Clustering (RBNNC) was used for decreasing the run-time significantly. Then TEP problem was solved using the TLBO and GWO algorithms in order to minimize the costs of generation, losses, and lines. The NDR can reduce the peak of the loads in peak hours and costs of TEP as well. Finding the simultaneous effect of non-linear DRP, wind and wind uncertainty on TEP problem illustrated the reduction in the total costs. Probability of the objective function occurrence (loss, costs of generation and line constructions) has been calculated. Also, the occurrence probability of objective function related to the defined confidence level has been calculated in order to provide better decision making. Simulation results proved the optimal effect of NDR and wind on postponing the additional cost of investments for supplying peak load.

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