

Improved Binary Particle Swarm Optimization Based TNEP Considering Network Losses, Voltage Level, and Uncertainty in Demand

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ABSTRACT

Transmission network expansion planning (TNEP) is an important component of power system planning. It determines the characteristics and performance of the future electric power network and influences the power system operation directly. Different methods have been proposed for the solution of the static transmission network expansion planning (STNEP) problem till now. But in all of them, STNEP problem considering the network losses, voltage level and uncertainty in demand has not been solved by improved binary particle swarm optimization (IBPSO) algorithm. Binary particle swarm optimization (BPSO) is a new population-based intelligence algorithm and exhibits good performance on the solution of the large-scale and nonlinear optimization problems. However, it has been observed that standard BPSO algorithm has premature convergence when solving a complex optimization problem like STNEP. To resolve this problem, in this study, an IBPSO approach is proposed for the solution of the STNEP problem considering network losses, voltage level, and uncertainty in demand. The proposed algorithm has been tested on a real transmission network of the Azerbaijan regional electric company and compared with BPSO. The simulation results show that considering the losses even for transmission expansion planning of a network with low load growth is caused that operational costs decreases considerably and the network satisfies the requirement of delivering electric power more reliable to load centers. In addition, regarding the convergence curves of the two methods, it can be seen that precision of the proposed algorithm for the solution of the STNEP problem is more than BPSO.

KEYWORDS: STNEP; network losses; voltage level; uncertainty in demand; IBPSO.

1. INTRODUCTION

Transmission network expansion planning (TNEP) is an important part of power system planning that its main objective is to acquire the most optimal plan for the network expansion. TNEP should satisfy the required adequacy of the lines for delivering safe and reliable electric power

to load centers along the planning horizon [1, 2]. Determination of investment costs for power system expansion is a very difficult task, because costs should be determined from grid owners with agreement of a customer and considering the various reliability criteria [3]. The long-term TNEP is a hard, large-scale, and non-linear combinatorial optimization problem that generally could be classified as static or

dynamic. Static expansion determines where and how many new transmission lines should be added to the network up to the planning horizon. If in the static expansion the planning horizon is categorized in several stages, then it becomes dynamic planning [4, 5].

Most of power systems, generating plants are located far from the load centers. In addition, the planned new projects are still so far from completion. Due to these situations, the investment costs of transmission network are huge. Thus, the STNEP problem acquires a principal role in power system planning and should be evaluated carefully, because any effort to reduce the cost of transmission system expansion by some fraction of a percent allows saving of a significant amount of capital.

Garver proposed one of the first approaches for solving the STNEP problem in 1970 [6]. He formulated the problem as a power flow problem and used a linear programming algorithm to find the most direct routes from generation to loads. After his paper, much research has been done on the field of static transmission network expansion planning. Some of them are related to problem solving method. Some others proposed different approaches for the solution of this problem considering various parameters such as uncertainty [7, 8], reliability criteria [3, 9], and economic factors [10]. Also, some of them investigated this problem and generation expansion planning together [11, 12].

Chanda and Bhattacharjee [13] solved static transmission expansion planning problem in order to obtain a maximum reliable network. Reliability criteria are related to actual systems that considering them help to maintain a higher degree of

reliability of the system. Later, they [14] proposed a new method for designing a maximum reliable network when failure probabilities of the lines are fuzzy in nature instead of deterministic as mentioned in Ref. [13]. However, voltage level and uncertainty in demand have not been considered in their literatures.

Grandville et al. [15] were formulated the STNEP problem by a linearized power flow model and used the Benders decomposition for its solution. However, classical decomposition approaches, e.g., Benders decomposition may fail to converge to optimal solutions due to the non-convex nature of the TNEP problem. In order to handle these non-convexities difficulties, a Benders hierarchical decomposition approach (HIPER) was proposed by Romero and Monticelli [16], where, a chain of three models represented the power network constraints. The two first models relax all the non-convexities constraints, which results in the optimal solution. Then, the non-convexities are introduced (third model). Nevertheless, the non-convexities still exist in the mathematical model used and application of this approach to networks with a large number of candidate circuits is limited by computational limitations. Binato et al. [17], presented a heuristic approach, called greedy randomized adaptive search procedure (GRASP) to solve the static transmission expansion planning problem. GRASP is an expert iterative sampling technique that due to its generality and simplicity, is a useful alternate approach that can be applied to many other kinds of decision problems. However, this technique is the most time consuming and the local search procedure used in this approach leads to some difficulties related to pruning

by comparison. Lee et al. [18] adopted branch and bound (B&B) algorithm in a way to preserve the discrete nature of investments for solution of STNEP problem. However, some problems such as being too slow the convergence of algorithm regarding the problem complexity and difficult implementation are when a planner uses this algorithm. Periera and Pinto [19] proposed a technique based on sensitivity analysis for static expansion of the transmission network. But the difficulty of the proposed method is that, if the number of nodes or number of participants is large, the planning for expansion is combinatorial complicated and that makes it very difficult to find reasonable solutions within short computational time.

Romero et al. [20] presented simulated annealing (SA) for optimizing the investment costs and loss of load of the network in static transmission expansion planning. SA mimics the physical process of annealing in solids (i.e. heating up a solid, and cooling it down until it crystallizes). It is a point-to-point search method with a strong theoretical base that its ability to reach global, or near global, optimal solutions under certain circumstances (slow cooling schedules) makes it a robust optimization algorithm. However, in the hard combinatorial problems such as STNEP problem, both the number of alternatives to be analyzed and the number of local minimum points increase with the dimension of the network. This fact can negatively affect on computing time and solution quality of the problem. Later, Gallego et al. [21] in order to improve the performance of the SA, proposed parallel simulated annealing (PSA) approach. The objective function is

the same one of Ref. [20]. The simulation results show that the proposed method gives not only faster solutions but better ones as well. But, the implementation of this method for solving large-scale, hard and highly non-linear combinatorial problems like long-term STNEP problem is so hard.

Al-Saba and El-Amin [22] proposed a neural network based method for the solution of the STNEP problem with considering both the network losses and construction cost of the lines. Contreras and Wu [23] included the network expansion costs and transmitted power through the lines in the objective function and the goal is optimization of both expansion costs and lines loading. However, in these papers, voltage level and uncertainty in demand have not been studied.

Braga and Saraiva [24] considered the voltage level of transmission lines as a subsidiary factor but its objective function only includes expansion and generation costs and one of the reliability criteria i.e.: power not supplied energy. Moreover, expansion plan has been studied as dynamic type and the uncertainty in demand has not been considered.

Recently, Silva et al. [25] used a genetic algorithm (GA) for solving the proposed problem of Ref. [20]. GA is a random search method that has demonstrated the ability to deal with non-convex, non-linear, integer-mixed optimization problems like the STNEP problem. Later, Silva et al. [26] introduced a Tabu search (TS) based method for optimization of investment cost in static transmission expansion planning. TS is an iterative search procedure that moving from one solution to another looks for improvements on the best solution visited. The basic concepts of TS are

movements and memory. A movement is an operation to jump from one solution to another while memory is used with different objectives such as to guide the search to avoid cycles. The simulation results for two real-world case studies (Brazilian southern and Brazilian southeastern network) have been shown that TS is a feasible and powerful technique to be applied to STNEP problem. Also, the authors have shown that the performance of TS for finding the best solutions is almost similar to GA. Thus, it can be concluded that the most important advantage of GA is its simple implementation in addition to reach the respectively good solutions.

So, in [27, 28], the expansion cost of substations with the network losses have been considered for the solution of STNEP problem using decimal codification genetic algorithm (DCGA). The results evaluation in [27] indicated that the network with considering higher voltage level saves capital investment in the long-term and become overload later. In [28], it was shown that the total expansion cost of the network was calculated more exactly considering the effects of the inflation rate and load growth factor and therefore the network satisfies the requirements of delivering electric power more safely and reliably to load centers. But, the uncertainty in demand has not been included in the objective functions.

Shayeghi and Mahdavi [29] studied the effect of losses coefficient on static transmission network expansion planning using the decimal codification based genetic algorithm. They showed that this coefficient has not any role in determining of network configuration and arrangement. However, considering its effect in expansion planning of transmission

networks with various voltage levels is caused the total cost of the network (expansion and losses costs) is reduced considerably and therefore the STNEP problem is solved more exactly and correctly. Also, they [30] investigated the bundle lines effect on network losses in STNEP problem and indicated that these lines have an important role in reduction of network losses and subsequent operational costs. However, they have not investigated uncertainty in demand in their research.

Also, Zhao et al. [31] presented a multi-objective optimization model for static transmission expansion planning considering DG impacts, uncertainties of generation and load. But, they solved the problem regardless of network losses and voltage level. Finally, Mahdavi et al. [32] investigated the effect of bundle lines on static expansion planning of a multiple voltage level transmission network by DCGA. They concluded that considering the effect of bundle lines on static transmission expansion planning caused that the total expansion cost of network (expansion and operational costs) is considerably decreased and therefore the capital investment significantly saved. Moreover, it was shown that construction of bundle lines in transmission network with different voltage levels caused that the network lines is overloaded later and the network would have higher adequacy. Later they [33] considered the network losses in the problem of Ref. [32] and showed that network losses play an important role in transmission expansion planning and subsequent determination of network arrangement and configuration. However, they have not studied the uncertainty in demand in their literatures.

Although global optimization techniques like GA and TS seem to be good methods for the solution of TNEP problem. However, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then they have degraded efficiency to obtain a global optimum solution and simulation process use a lot of computing time. In order to overcome these drawbacks, Shayeghi et al. [34] applied the binary PSO (BPSO) for optimization of transmission lines loading in STNEP. They found that BPSO performance is better than GA from precision and convergence speed viewpoints. BPSO is a novel population based metaheuristic that is a useful tool for engineering optimization. Unlike the other heuristic techniques, it has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. However, the standard BPSO algorithm has also some disadvantages like premature convergence phenomenon similar to the GA. Thus, in this paper, to overcome these drawbacks and considering voltage level and uncertainty in demand, expansion planning has been investigated by including network losses cost, uncertainty in demand and also the expansion cost of related substations from the voltage level point of view in the fitness function of the STNEP problem using improved binary particle swarm optimization (IBPSO). This technique by introducing the mutation operator often used in genetic algorithm makes some particles jump out local optima and search in another area of the solution space. The proposed IBPSO method is tested on the real transmission network of the Azerbaijan regional electric company, in comparison with BPSO approach in

order to demonstrate its effectiveness and robustness for the solution of the desired STNEP problem. The results evaluation reveals that considering the role of network losses for the solution of the STNEP problem under environments with uncertainty in demand is caused that even for low load growth coefficients, configurations that have higher voltage levels be economic for network expansion and therefore the total expansion cost of network (expansion and operational costs) decreases considerably. Also, by comparing between the convergence curves of two methods (IBPSO and BPSO), it can be concluded that the precision of the proposed algorithm for the solution of the STNEP problem is more than BPSO.

2. PROBLEM FORMULATION

Due to considering the effect of the network losses on STNEP problem in a multi voltage level transmission network under uncertainty in demand and subsequent adding the expansion cost of substations to expansion costs, the proposed objective function is defined as follows:

$$OF = \sum_{k=1}^{NS} \left(EC_k + LC_k + \alpha \times \sum_{i=1}^{NB} r_i^k \right) \times PR_k \quad (1)$$

$$EC_k = \sum_{i,j \in \Omega} CL_{ij} n_{ij}^k + \sum_{i=1}^{NB} \sum_{c=1}^{ST} m_i^k SC_c \quad (2)$$

$$LC_k = \left(\sum_{i=1}^{NY} \sum_{t=1}^{NC} R_{ij}^k I_{ij,t}^k \right) \times K_{loss} \times 8760 \times C_{MWh} \quad (3)$$

Where,

EC_k : Expansion cost of network in scenario k .

LC_k : Annual losses cost of network in scenario k .

r_i^k : Loss of load for i -th bus in scenario k .

α : A coefficient for converting loss of load to cost (\$US/MW).

PR_k : Occurrence probability of scenario k .

CL_{ij} : Construction cost of transmission line in corridor $i-j$.

n_{ij}^k : Number of new circuits of corridor $i-j$ in scenario k .

SC_c : Cost of c -th type transformer (related costs are given in Appendix A).

m_i^k : Number of transformers that have been predicted for constructing in i -th bus under scenario k .

C_{MWh} : Cost of one MWh (\$US/MWh).

R_{ij}^k : Resistance of branch $i-j$ in scenario k .

$I_{ij,t}^k$: Flow of branch $i-j$ in t -th year under scenario k . It is varied with respect to annual load growth and therefore depends on the time.

K_{loss} : Losses coefficient.

Ω : Set of all candidate corridors.

NY : Number of years after expansion to calculate the network losses. It's rate in all scenarios has been considered 10 years.

NC : Number of expandable corridors of network.

NB : Number of network busses.

ST : Number of types for constructed transformers.

NS : Number of scenarios.

The calculation method of K_{loss} has been given in [27]. Several restrictions have to be modeled in a mathematical representation to ensure that the mathematical solutions are in line with the planning requirements. These constraints are as follows:

$$S^k f^k + g^k - d^k = 0 \quad (4)$$

$$f_{ij}^k - \gamma_{ij}^k (n_{ij}^0 + n_{ij}^k) (\theta_i^k - \theta_j^k) = 0 \quad (5)$$

$$|f_{ij}^k| \leq \beta \cdot (n_{ij}^0 + n_{ij}^k) \bar{f}_{ij} \quad (6)$$

$$0 \leq n_{ij}^k \leq \bar{n}_{ij} \quad (7)$$

$$N-1 \text{ Safe Criterion} \quad (8)$$

Where, $(i, j) \in \Omega$ and:

S^k : Branch-node incidence matrix in scenario k .

f^k : Active power matrix for each corridor in scenario k .

g^k : Generation vector in scenario k .

d^k : Demand vector in scenario k .

θ_i^k : Phase angle of each bus in scenario k .

γ_{ij}^k : Total susceptance of circuits for corridor $i-j$ in scenario k .

\bar{n}_{ij} : Maximum number of constructible circuits in corridor $i-j$.

\bar{f}_{ij} : Maximum of transmissible active power through the corridor $i-j$ which will have two different rates according to the voltage level of candidate line.

β : A coefficient for providing security margin from the loading of lines view point. This coefficient guaranties required adequacy of lines to satisfy the all of network loads at years after expansion. The goal of the STNEP problem is to obtain the number of lines and their voltage level to expand the transmission network in order to ensure required adequacy of the network along the specific planning horizon. Thus, problem parameters are discrete time type and consequently the optimization problem is an integer programming problem. For solution of this problem, there are various methods such as classic mathematical and heuristic methods. In this study, the improved binary particle swarm optimization is used to solve the STNEP problem due to simple implementation and

high precision for finding the best solutions.

3. IMPROVED BINERY PARTICLE SWARM OPTIMIZATION (IBPSO) ALGORITHM

Particle swarm optimization algorithm, which is tailored for optimizing difficult numerical functions and based on metaphor of human social interaction, is capable of mimicking the ability of human societies to process knowledge [35]. It has roots in two main component methodologies: artificial life (such as bird flocking, fish schooling and swarming); and, evolutionary computation. It lies somewhere in between evolutionary programming and the genetic algorithms [28]. As in evolutionary computation paradigms, the concept of fitness is employed and candidate solutions to the problem are termed particles or sometimes individuals, each of which adjusts its flying based on the flying experiences of both itself and its companion. Vectors are taken as presentation of particles since most optimization problems are convenient for such variable presentations. In fact, the fundamental principles of swarm intelligence are adaptable, diverse response, proximity, quality, and stability [36]. It is adaptive corresponding to the change of the best group value. The allocation of responses between the individual and group values ensures a diversity of response. The population is responding to the quality factors of the previous best individual values and the previous best group values. As it is reported in [35], this optimization technique can be used to solve many of the same kinds of problems as GA and does not suffer from any of GAs difficulties. It has also been found to be robust in solving

problem featuring non-linear, non-differentiability and high-dimensionality. It is the search method to improve the speed of convergence and find the global optimum value of the fitness function.

PSO starts with a population of random solutions “particles” in a D-dimension space. The i th particle is represented by $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$. Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fitness for particle i is stored as $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$ that its best value is represented by ($pbest$). The global version of the PSO keeps track of the overall best value ($gbest$), and its location, obtained thus far by any particle in the population. PSO consists of, at each step, changing the velocity of each particle toward its $pbest$ and $gbest$ according to Eq. (9). The velocity of particle i is represented as $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward $pbest$ and $gbest$. The position of the i th particle is then updated according to Eq. (10) [35, 36]:

$$v_{id}(t+1) = \omega \times v_{id}(t) + c_1 r_1 (P_{id} - x_{id}(t)) + c_2 r_2 (P_{gd} - x_{id}(t)) \quad (9)$$

$$x_{id}(t+1) = x_{id}(t) + cv_{id}(t+1) \quad (10)$$

Where, P_{id} and P_{gd} are $pbest$ and $gbest$. It is concluded that $gbest$ version performs best in terms of median number of iterations to converge. However, $pbest$ version with neighborhoods of two is more resistant to local minima. The results of past experiments about PSO show that ω was not considered at an early stage of PSO algorithm. However, ω affects the iteration number to find an optimal solution. If the

value of ω is low, the convergence will be fast, but the solution will fall into the local minimum. On the other hand, if the value will increase, the iteration number will also increase and therefore the convergence will be slow. Usually, for running the PSO algorithm, value of inertia weight is adjusted in the training process. In Eq. (9), term of $c_1r_1 (P_{id} - x_{id}(t))$ represents the individual movement and term of $c_2r_2 (P_{gd} - x_{id}(t))$ represents the social behavior in finding the global best solution.

Regarding the fact that the parameters of the TNEP problem are discrete time type and the performance of standard PSO is based on real numbers, this algorithm can not be used directly for solution of the STNEP problem. Thus, in order to overcome this drawback a binary based particle swarm optimization (BPSO) algorithm is used for the solution of the STNEP problem. In this method, in a D-dimensional binary solution space, the position of i th particle can be expressed by a D-bit binary string as $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, where, $X_i \in \{0,1\}$. Since each bit X_i is binary-valued, the term of $(P_{id} - x_{id}(t))$ or $(P_{gd} - x_{id}(t))$ has only three possible values 0, 1 and -1. Where,

$$\begin{aligned} P_{id} - x_{id}(t) &= 1; & \text{if } P_{id} = 1, x_{id} = 0 \\ P_{id} - x_{id}(t) &= 0; & \text{if } P_{id}, x_{id} = 0 \text{ or } P_{id}, x_{id} = 1 \\ P_{id} - x_{id}(t) &= -1; & \text{if } P_{id} = 0, x_{id} = 1 \\ P_{gd} - x_{id}(t) &= 1; & \text{if } P_{gd} = 1, x_{id} = 0 \\ P_{gd} - x_{id}(t) &= 0; & \text{if } P_{gd}, x_{id} = 0 \text{ or } P_{gd}, x_{id} = 1 \\ P_{gd} - x_{id}(t) &= -1; & \text{if } P_{gd} = 0, x_{id} = 1 \end{aligned}$$

In Eq. (11), t is the number of algorithm iterations, t_{\max} is the maximum number of iterations, and ω_{\max} and ω_{\min} are the

maximum and minimum values of the inertia weight respectively. Also, the velocity $v_{id}(t+1)$ is a real number in $[-V_{\max}, V_{\max}]$. According to Eq. (10), for updating the position of the i th particle, the real value $v_{id}(t+1)$ must be added to the binary value $x_{id}(t)$, but this is not possible mathematically. So an intermediate variable $S(v_{id}(t+1))$ via the sigmoid limiting transformation is defined as Eq. (12) [37]:

$$S(v_{id}(t+1)) = \frac{1}{1 + e^{-v_{id}(t+1)}} \quad (12)$$

Eq. (12) maps the domain of $[-V_{\max}, V_{\max}]$ into the range of $[1/(1+e^{V_{\max}}), 1/(1+e^{-V_{\max}})]$, which is a subset of $(0, 1)$. The value of $S(v_{id}(t+1))$ can be therefore interpreted as a probability threshold. A random number with a uniform distribution in $(0, 1)$, R , is then generated and compared to $S(v_{id}(t+1))$. Thus, the position of the particle i can be updated as follows:

$$\begin{aligned} x_{id}(t+1) &= 1; & \text{if } R < S(v_{id}(t+1)) \\ x_{id}(t+1) &= 0; & \text{if } R \geq S(v_{id}(t+1)) \end{aligned} \quad (13)$$

The probability that $x_{id}(t+1)$ equals to 1 is $S(v_{id}(t+1))$ and the probability that it equals to 0 is $1-S(v_{id}(t+1))$. From Eq. (11), the velocity update of the particle consists of three parts: The first term is its own current velocity of particles; the second term is cognitive part which represents the particle's own experiences; the third term is social part which represents the social interaction between the particles. With respect to Eq. (11), it is realized that best position of particles take places proportional to $pbest$. It can be seen that: when a particle's current position coincides with the global best position ($gbest$), the particle will only leave this point if the

inertia weight and its current velocity are different from zero. If the particles' current velocities in swarm are very close to zero, then these particles will not move once they catch up with the global best particle. This means that the particles have been converged to the best experience of particles and are far from the group. At this moment if these positions corresponding fitness is not the problems expected global optimal, then the premature convergence phenomenon appears. In this situation, the convergence speed will be decreased [38]. In order to overcome this drawback and improve optimization synthesis, an improved binary particle swarm optimization (IBPSO), by introducing the mutation operator often used in genetic algorithm is proposed in this paper. This process can make some particles jump out local optima and search in another area of the solution space. In this method, the mutation probability (P_M) is dynamically adjusted according to the diversity in the swarm. The goal with mutation probability is to prevent the BPSO to converge prematurely to local minima. It should be noted the P_M is considered 0.01 in this study. Fig. 1 shows the flowchart of the improved BPSO algorithm. In this study, in order to acquire better performance of the proposed algorithm, parameters that are used in the improved BPSO algorithm have been initialized according to Table 1. It should be noted that IBPSO algorithm is run several times and then optimal results are selected.

4. SIMULATION RESULTS

The transmission network of the Azerbaijan regional electric system is used to test and evaluation of the proposed

method. This actual network has been located in northwest of Iran and is shown in Fig. 2. All details of this network have been given in [32].

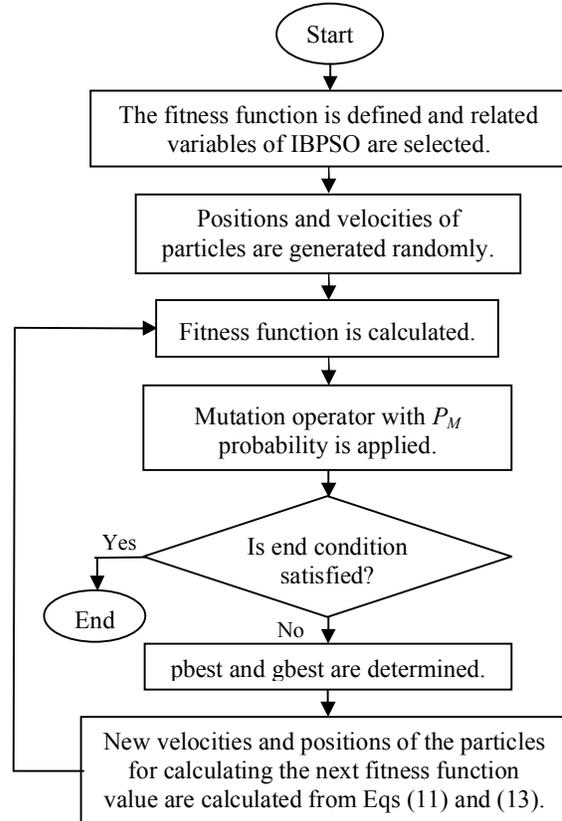


Fig. 1 Flowchart of the IBPSO algorithm

Table 1 Value of parameters for IBPSO algorithm

Parameter	Value
Problem dimension	153
Number of particles	10
Number of iterations	1500
C_1	1.5
C_2	1.8
C	1
ω_{max}	0.9
ω_{min}	0.4
v_{max}	4
v_{min}	-4

For considering uncertainty in STNEP problem, three different scenarios with equal occurrence probabilities have been

predicted for load growth. Also planning horizon is the year 2021 (10 years ahead) and network losses is calculated from the DC load flow from planning horizon year to 10 years after it (year 2031). Therefore, for feasibility of comparing the scenarios from their effective rate on network load viewpoint, rates of network load at planning horizon with related load growth coefficients for different scenarios are given in Table 2. Value of coefficients α and β , and C_{MWh} are considered 10^7 \$/US/MW, 40% and 33 (\$/US/MWh) respectively. The proposed method is applied to the case study system and the results (lines that must be added to the network during the planning horizon year) are given in Tables 3 and 4. The first and second configurations are obtained neglecting and considering the network losses, respectively. By comparing the Tables 3 and 4, ignoring the network losses, a configuration with lower voltage level lines is proposed for expansion of the network. But if the network losses is considered, a configuration with higher voltage level lines is proposed for expansion purpose.

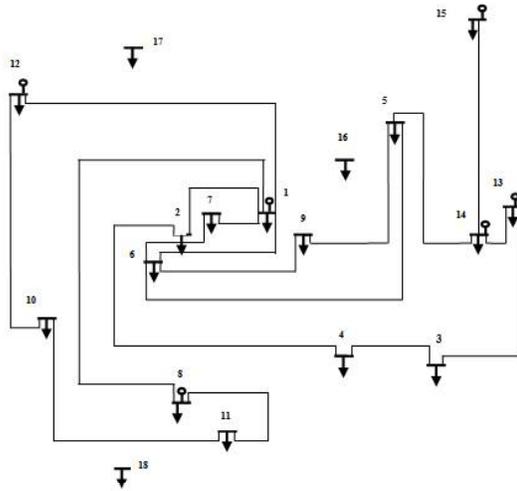


Fig. 2 Transmission network of the Azerbaijan regional electric company

Table 2 Proposed scenarios considering uncertainty in demand

Scenario Number	Scenario 1	Scenario 2	Scenario 3
Load Growth (%)	5	7	9
Load (MW)	3427	4139	4981

Table 3 First configuration for all scenarios: neglecting the network losses

Corridor	Voltage Level (kV)	Number of Circuits
1-5	230	2
1-17	230	1
2-5	230	1
3-11	230	2
4-9	230	1
4-14	230	1
8-9	230	2
8-11	230	1

Table 4 Second configuration for all scenarios: considering the network losses

Corridor	Voltage Level (kV)	Number of Circuits
1-5	400	2
1-8	400	2
2-5	400	2
2-6	230	2
2-7	230	2
3-13	400	2
4-5	400	1
5-6	400	1
5-7	400	2
5-9	400	2
6-13	400	2
7-8	400	2
8-11	400	1
8-18	400	2
9-13	400	2
10-11	230	2
11-13	400	2
12-18	230	2
13-14	400	2
13-15	400	2
15-16	230	1

In addition, for better analyzing of

proposed configurations, their expansion costs for different scenarios from load growth point of view are given in Tables 5 and 6. Comparison between Tables 5 and 6 shows that if network losses is neglected for solution of STNEP problem, a configuration with lower expansion cost (expansion cost of lines and substations) and higher network losses is obtained. However, considering the network losses, a plan with higher expansion cost and lower network losses is proposed for network expansion. Moreover, Tables 5 and 6 show that uncertainty in demand has no effect on expansion cost of lines while it effects on losses cost and expansion cost of substations. The reason is that expansion cost of substations from voltage level point of view and losses cost depend on loading of lines and substations. Thus, different load growths can affect on these costs. Finally, it can be said that proposed configurations by IBPSO for different scenarios are same and any loss of load is not exist. This fact reveals that proposed method has high efficiency for solution of STNEP problem. Total expansion cost (sum of expansion and losses costs) of expanded network with the two proposed configurations for different scenarios is shown in Figs 3-5.

Table 5 The costs for first configuration

Scenario Number	Scenario 1	Scenario 2	Scenario 3
Expansion Cost of Lines (M\$US)	43.4	43.4	43.4
Expansion Cost of Substations (M\$US)	0	0	0
Losses Cost (million \$US)	434.25	1259.25	3293.5
Loss of Load Cost (M\$US)	0	0	0
Total Expansion Cost of Network (M\$US)	477.65	1302.65	3336.9

Table 6 The costs for second configuration

Scenario Number	Scenario 1	Scenario 2	Scenario 3
Expansion Cost of Lines (M\$US)	214	214	214
Expansion Cost of Substations (M\$US)	15.9	17	18.5
Losses Cost (million \$US)	45	125	321.2
Loss of Load Cost (M\$US)	0	0	0
Total Expansion Cost of Network (M\$US)	274.9	356	553.7

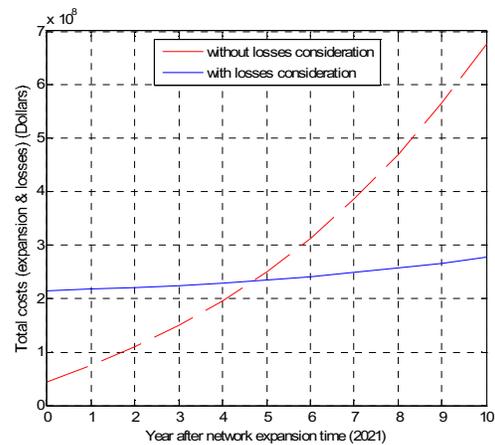


Fig. 3 Sum of expansion costs and annual losses cost of the network for two proposed configurations under scenario 1

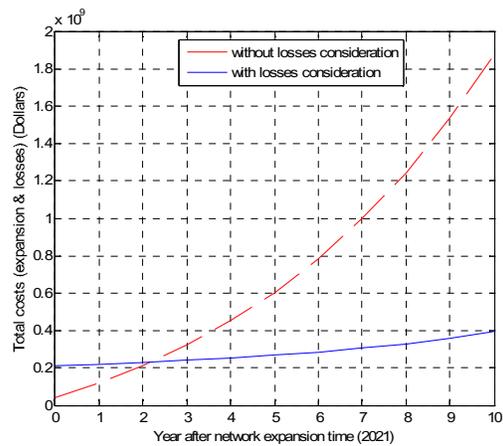


Fig. 4 Sum of expansion costs and annual losses cost of the network for two proposed configurations under scenario 2

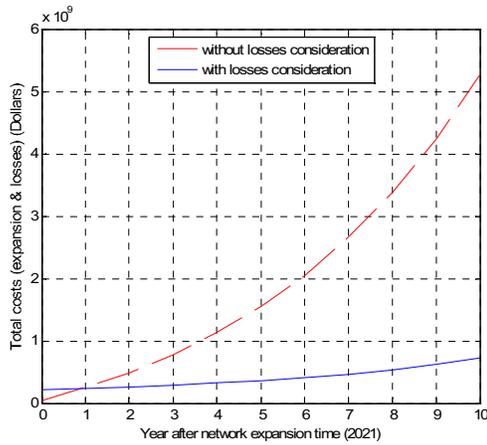


Fig. 5 Sum of expansion costs and annual losses cost of the network for two proposed configurations under scenario 3

It can be seen that, for all scenarios, the total expansion cost of network with the second configuration is more than that of the first one until, about a few years after planning horizon, but afterward, the total expansion cost of network with first configuration becomes more than another one. For load growth of 5%, second one has investment return in comparison with first one about 5 years after expansion time. With rising load growth, investment return takes places earlier (for load growths of 7% and 9% this time is about 2 years and 1 year respectively). Accordingly, it can be concluded that the network losses has important role in transmission expansion planning even for low load growths.

Moreover, fitness function values of both methods for different iterations are illustrated in Fig. 6 to compare the convergence speed and precision of the IBPSO algorithm. It should be mentioned that the convergence curves only for the second configuration (considering network losses) under scenario 3, as instant, have been shown. These convergence curves show that improved BPSO by making some

particles jump out local optima and search in other area of the solution space is caused that the fitness function is optimized more than BPSO one. Thus, it can be concluded that solution of desired STNEP by IBPSO is more precise and finally better than BPSO method.

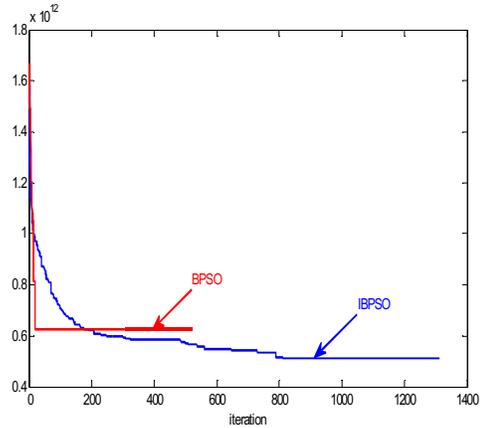


Fig. 6 Convergence curves of IBPSO and BPSO for second configuration under scenario 3.

5. CONCLUSIONS

In this paper, static transmission expansion planning considering network losses, voltage level, and uncertainty in demand is studied using IBPSO algorithm. The results analysis reveals that considering the network losses in transmission expansion planning under different load growths is caused that total expansion costs and losses cost of network is decreased for long-term and mid-term. In addition, it can be said that although cost of lines with higher voltage levels are more than lines with lower voltage levels, constructing this type of lines in transmission network is caused that investment cost is considerably saved and therefore the total expansion cost is calculated more exactly. Consequently, even in networks with low load growth, network losses plays important role in

transmission expansion planning and subsequent determination of network arrangement and configuration. Finally, by comparing the results of the proposed method with BPSO, it could be concluded that although convergence speed of binary particle swarm optimization (BPSO) is more than proposed approach, however, improved BPSO, introducing the mutation operator makes some particles jump out local optima. Search in other areas of the solution space and leads in increase of the precision of algorithm for finding the more optimal solutions.

Appendix:

Costs for different types of 400/230 kV transformers are listed in Table 7.

Table7. Costs of transformers for different rating outputs

Rating output (MVA)	125	160	200	315
Cost (M\$)	18	22	26	32

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