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Transmission Network Expansion Planning Based on Hybridization Model of Probabilistic Neural Networks and Harmony Search Algorithm

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Abstract

Transmission network expansion planning (TNEP) is a basic part of power network planning that determines where, when and how many new transmission lines should be added to the network. So, the TNEP is an optimizing problem in which the expansion purposes are optimized. The Artificial Intelligence (AI) tools such as Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TS), Artificial neural networks (ANNs) and etc are various methods for solving the TNEP problem. Today, by using the hybridization models of AI tools, we can solve the TNEP problem for the large-scale systems, which shows effectiveness utilizing of this models. Therefore, in this paper by a new approach, the hybridization model Probabilistic Neural Networks (PNNs) and Harmony Search Algorithm (HSA) was used to solve the TNEP problem. Finally, by considering uncertainty role in the load based on scenario technique, this proposed model is tested on the Garver's 6-bus network.

Introduction

Transmission network expansion planning (TNEP) is an important component of power system planning. It determines the characteristic and performance of the future electric power network and influences power system operation directly. TNEP should be satisfied required adequacy of the lines for delivering safe and reliable electric power to load centers during the planning horizon [1-3]. Generally, transmission network expansion planning can 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 separated for several stages we will have dynamic planning [3-5]. Nowadays the growing trend of consumption of electrical energy, the need for optimum expansion planning of power networks is tangible more than ever. Especially network transmission as interface between production and resource centers, have fundamental role in the provision of reliable electricity. Upon this, the transmission network expansion planning systems should be in such manner that optimal operation of network transmission possible. What mandatory is to achieve the above objective is to survey the parameters which have effective role in this area. One of these parameters is transmission network losses that its reduction has been a priority for owners' transmission network. As for as, expansion cost and network losses in most cases are in conflict with each other, so upon the component losses in the objective function problem transmission network expansion planning, would be a Multi Criteria Decision Making (MCDM). Accordingly, the network planner can construct the lines with lower losses and higher cost or construct the lines with lower costs but higher losses [3], [6]. Another factor affecting on the transmission expansion planning problem is uncertainty that is simultaneous with the time from Garver's offering innovative famous ideas in 1970 and at the same time oil crisis planners were considered. Uncertainty means unknowns in the accurate diagnosis and determination a case or a quantity. Uncertainties in power systems is to non-feasibility in determining the exact parameters of the system that are feasible upon this fact that these parameters with the last case the system away altogether. Irrespective to the uncertainty in the parameters, the process of transmission network expansion planning is a technical – economic optimization problem. But if this uncertainty would be considered, transmission network expansion problem will be more complicated. Some of these uncertainties includes: (1) uncertainty in Load, (2) uncertainty in fuel availability, (3) uncertainty in factor prices and financial parameters and *etc* [7], [8]. Generally, TNEP problem is a complicated optimization problem in which various methods were used. In the reference [1], GA and in reference [3], Decimal Codification Genetic Algorithm (DCGA) used to solve the TNEP problem. Also, in the reference [9], GA and TS were used. In the reference [10], different hybridization models of AI were used such as the ANN with a Multi-Layer Perceptron (MLP) model, GA and TS. Therefore, in this paper by a new approach, the hybridization model Probabilistic Neural Networks (PNNs) and Harmony Search Algorithm (HSA) was used to solve the TNEP problem. According to this, different solving states are considered as the neural network input and suitable alternatives with the features which will be described in the next section, are considered as the neural network outputs. Therefore, the neural network is trained and the best n-solution set are made. Then, per every random input, the model uses one of the best n-solution set as an input for the HSA and the network expansion is based on this. Also, in this paper DC load flow is used. Finally, by considering uncertainty role in the load based on scenario technique, this proposed model is tested on the Garver's 6-bus network.

Mathematical Model (Objective Function) of the TNEP Problem

As noted earlier, one of the expansion planning parameters in which made feasible optimize usage of transmission network are losses, that its reduction always is of priority of network owners' and the other one is uncertainties in load. On this basis, in this paper it is evaluated the role of losses in the network and while considering the uncertainty, it is considered the objective function related to equation (1) [3], [10]. Also, Load Not Supply (LNS) in normal state is considered as a penalty factor in objective function.

$$\text{Objective Function}: TEC = \sum_{(i,j)\in\Omega} CL_{ij} \times n_{ij} + \sum_{k=1}^{N_Y} ALC_k + \alpha \times \sum_{b\in B} r_b \tag{1}$$

Where:

$$ALC = Loss \times C_{Loss} \times K_{Loss} \times 8760 \tag{2}$$

$$Loss = \sum_{(i,j)\in\Omega} R_{ij} I_{ij}^2 \tag{3}$$

Where Ω is the set of all corridors, B the set of all buses, N_Y the expanded network adequacy (in year), TEC the total expansion cost of network, CL_{ij} the construction cost of each line in corridor *i-j*, ALC the annual losses cost of network, $Loss$ the total losses of network, r_b the load not supply in bus *b*, α the transfer coefficient of the load not supply to cost, R_{ij} the resistance of corridor *i–j*, I_{ij} the flow current of corridor *i–j*, C_{Loss} the cost of one kWh ($US/KWh) and K_{Loss} is the loss coefficient. The LNS component is the over load of the expanded network lines which hasn't achieve to the load center because of the power flow limitation and some of the load isn't supply. So, relational this component's cost to the consumed load value in the planning horizon, in affected by the considered scenario for the load growth. Of course, the value of LNS evaluation is very difficult and in this paper it is just considered as an approximate value for the coefficient α. Also, the constraints of the TNEP problem are according to the equations (4) to (9).

$$Sf + g - d = 0 \tag{4}$$

$$f_{ij} - \gamma_{ij}(n_{ij}^0 + n_{ij})(\theta_i - \theta_j) = 0 \ , \forall (i,j) \in \Omega \tag{5}$$

$$\left| f_{ij} \right| \le (n_{ij}^0 + n_{ij})\overline{f_{ij}} \ , \forall (i,j) \in \Omega \tag{6}$$

$$0 \le n_{ij} \le \overline{n_{ij}}, \ n_{ij} \ \textit{is integer variable} \ , \forall (i,j) \in \Omega \tag{7}$$

$$Y_{ij} = -(y_{ij}^0 + n_{ij}\tau_{ij}) \ , i \ne j \ , \forall (i,j) \in \Omega \tag{8}$$

$$Y_{ii} = y_{i0} + \sum_{j\in i}(y_{ij}^0 + n_{ij}\tau_{ij}) \ , i \ne j \ , \forall (i,j) \in \Omega \tag{9}$$

Where S is the branch-node incidence matrix, f the active power matrix in each corridor with elements f_{ij} , g the generation vector, d the demand vector, θ the phase angle of each bus, γ_{ij} the total admittance of circuits in corridor *i-j*, n_{ij}^0 the number of initial circuits in corridor *i-j*, n_{ij} the number of new circuits added to the corridor *i-j*, $\overline{n_{ij}}$ the maximum number of constructible circuits in corridor *i-j*, $\overline{f_{ij}}$ the maximum of transmissible active power through corridor *i-j*, y_{ij}^0 the initial admittance of corridor *i-j*, τ_{ij} the new circuit admittance of corridor *i-j*, y_{i0} the shunt admittance at bus *i* and Y is the bus admittance matrix of system. Equations (4) and (5) are DC load flow relationships and equation (6) points to the power flow limitations. Equation (7) requires transmission line expansion within the bounds of maximum line addition. Equations (8) and (9) simply update the network admittance matrix with expansion [11].

Probabilistic Neural Networks

One of the most powerful neural networks is a Radial Basis Function (RBF). This networks have more strategic benefits than perceptron neural networks [12]. Probabilistic Neural Networks (PNNs) are a kind of radial basis network suitable for classification problems. PNNs are feedforward networks which are built with three layers. The input Layer, hidden Layer and one output layer. In the hidden layer, an activation function is applied to the distance measure between the unknown input and the training example. PNNs estimate the probability density function for each class based on the training samples using similar probability density function which are calculated for each test vector. Vectors must be normalized prior to be input into the network for each dimension in the vector. The input layer is fully connected to the hidden layer which has a node for each classification. Each hidden node calculates the dot product of the input vector and the sum is sent to the output layer where the highest values win. Among the advantages offered by PNN are that they train faster (more than five times faster than backpropagation), they converge to a Bayesian classifier if enough training example examples are provided, they enable a fast incremental training and are robust to noisy example [13]. Also, for more description can refer to reference 13.

Harmony Search Algorithm

In research of Transmission expansion planning, for solved problem is used many Algorithm[9]. Harmony Search Algorithm (HSA) was recently developed in an analogy with music improvisation process where music players improvise the pitches of their instruments to obtain better harmony. The steps in the procedure of harmony search are shown in Figure 1. They are as follows [14]:

- Step 1: Initialize the problem and algorithm parameters.
- Step 2: Initialize the harmony memory.
- Step 3: Improvise a new harmony.
- Step 4: Update the harmony memory.
- Step 5: Check the stopping criterion.

These steps are described in the next five subsections.

A- Initialize the problem and algorithm parameters

In Step 1, the optimization problem is specified as follows:

$$minimize:\{f(x) \mid x \in X\} \tag{10}$$

$$Subject\ To: g(x) \geq 0 - and - h(x) = 0$$

Where $f(x)$ is the objective function and $g(x)$ is the inequality constraint function, $h(x)$ is the equality constraint function. x is the set of each decision variable, x_i, and X is the set of the possible range of values for each decision variable, that is $x_{iL} \leq x_i \leq x_{iU}$, where x_{iL} and x_{iU} are the lower and upper bounds for each decision variable. The HS algorithm parameters are also specified in this step. These are the harmony memory size (HMS), or the number of solution vectors in the harmony memory, harmony memory considering rate (HMCR), pitch adjusting rate (PAR), number of decision variables (N) and the number of improvisations (NI), or stopping criterion. The harmony memory (HM) is a memory location where all the solution vectors (sets of decision variables) are stored. This HM is similar to the genetic pool in the GA. Here, HMCR and PAR are parameters that are used to improve the solution vector. Both are defined in Step 3.

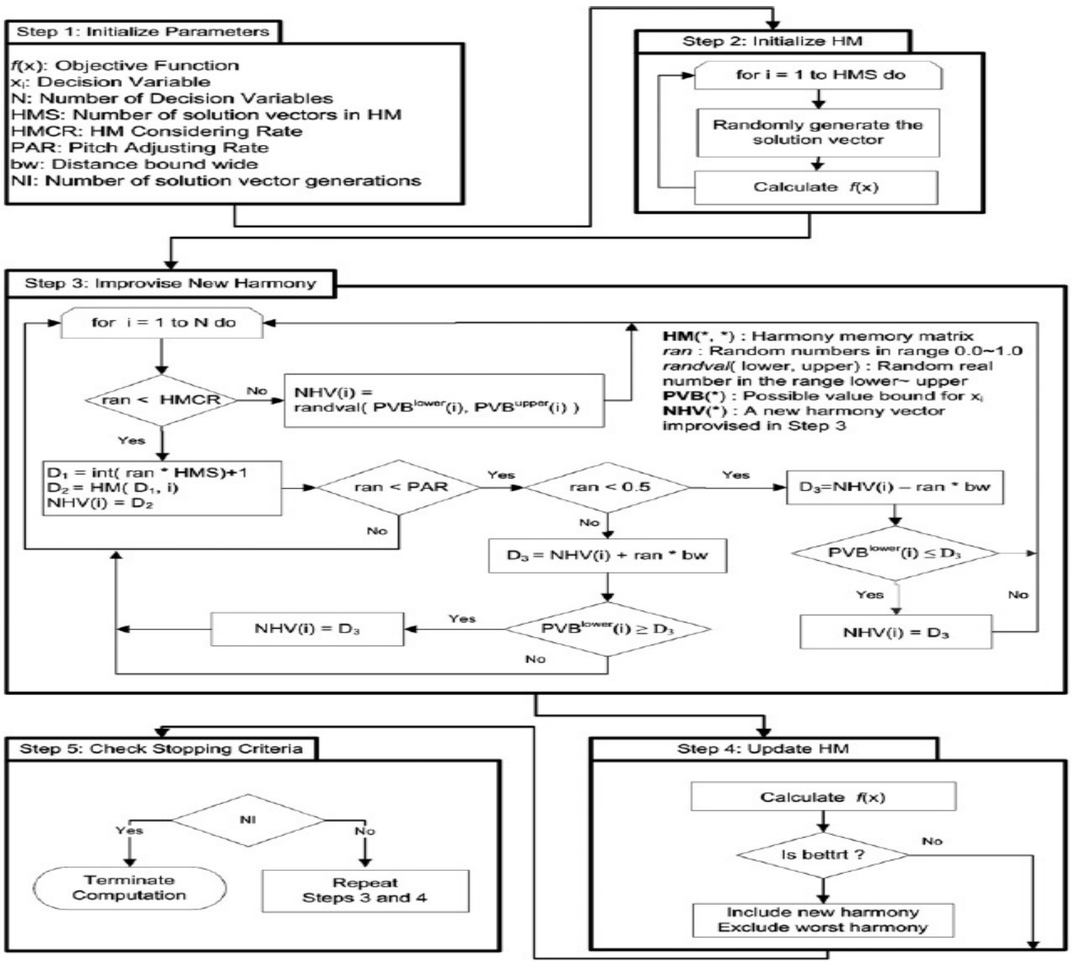

Figure 1: Optimization procedure of the harmony search algorithm

B- Initialize the harmony memory

In Step 2, the HM matrix is filled with as many randomly generated solution vectors as the HMS.

$$\mathrm{HM} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_{N-1}^2 & x_N^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{\mathrm{HMS}-1} & x_2^{\mathrm{HMS}-1} & \cdots & x_{N-1}^{\mathrm{HMS}-1} & x_N^{\mathrm{HMS}-1} \\ x_1^{\mathrm{HMS}} & x_2^{\mathrm{HMS}} & \cdots & x_{N-1}^{\mathrm{HMS}} & x_N^{\mathrm{HMS}} \end{bmatrix} \qquad (11)$$

C- Improvise a new harmony

A new harmony vector, $x^{'} = (x_1^{'}, x_2^{'}, ... x_N^{'})$, is generated based on three rules: (1) memory consideration, (2) pitch adjustment and (3) random selection. Generating a new harmony is called 'improvisation'. In the memory consideration, the value of the first decision variable (x_1^1) for the new vector is chosen from any value in the specified HM range $(x_1^1 - x_1^{HMS})$ Values of the other decision variables $(x_2^{'}, x_3^{'}, ... x_N^{'})$ are chosen in the same manner The HMCR, which varies between 0 and 1, is the rate of choosing one value from the historical values stored in the HM, while (1-HMCR) is the rate of randomly selecting one value from the possible range of values.

$$x_i^{'} \Leftarrow \begin{cases} x_i^{'} \in \{x_i^1, x_i^2, ..., x_i^{HMS}\} & \text{, with probability } HMCR \\ x_i^{'} \in X_i & \text{, with probability (1-}HMCR\text{)} \end{cases} \tag{12}$$

For example, a HMCR of 0.85 indicates that the HS algorithm will choose the decision variable value from historically stored values in the HM with the 85% probability or from the entire possible range with the (100–85) =15% probability. Every component obtained by the memory consideration is examined to determine whether it should be pitch-adjusted. This operation uses the PAR parameter, which is the rate of pitch adjustment as follows:

$$\text{Pitch adjusting decision for } x_i^{'} \Leftarrow \begin{cases} Yes\text{, with probability } PAR \\ No\text{, with probability } (1-PAR) \end{cases} \tag{13}$$

D- Update harmony memory

The value of (1-PAR) sets the rate of doing nothing. If the pitch adjustment decision For $x_i^{'}$ is Yes, $x_i^{'}$ is replaced as follows:

$$x_i^{'} \Leftarrow x_i^{'} \pm rand\ () * bw \tag{14}$$

Where bw is an arbitrary distance bandwidth, *rand* () is a random number between 0 and 1. In Step 3, HM consideration, pitch adjustment or random selection is applied to each variable of the new harmony vector in turn. If the new harmony vector, $x^{'} = (x_1^{'}, x_2^{'}, ... x_N^{'})$ is better than the worst harmony in the HM, judged in terms of the objective function value, the new harmony is included in the HM and the existing worst harmony is excluded from the HM.

E- Check stopping criterion

If the stopping criterion (maximum number of improvisations) is satisfied, computation is terminated. Otherwise, Steps 3 and 4 are repeated.

Case Study

TNEP model and the proposed method for solving it, was implemented in MATLAB software and the TNEP algorithm was applied to the Garver's 6-bus network shown in Figure 2. Also, characteristic of the transmission lines is presented in Table 1 [15]. Total number of the possible corridors for TNEP, are considered nine corridors, out of which three corridors are new. The new corridors are shown by dotted in Figure 2. On the other hand, in order to consider uncertainty in load, two scenarios 10% (first scenario) and 12% (second scenario) have been predicted based on the scenario technique and by the same probability of occurrence for the load growth [10]. The α coefficient, is assumed 10 m$US/MW. Also, the other considered parameters are according to the reference 10. Planning horizon is 10 years and the network losses from year of planning horizon in the time of operation to 10 years after it is determined [3]. Also in this paper, three expansion alternatives are suggested which are given in Table 2. The suggested alternatives with regard to the suggested prices by producers and the competitive power market mechanism, buying the maximum power from plant, flatness of the Locational Marginal Prices (LMPs) in the network and the congestion reduction and actually are experimentally achieved by planner. So, without complicating the TNEP model, we can evaluated plans for different criteria such as congestion, price profile and *etc*. So, the TNEP can be solved easily for the large-scale systems. Also, for generating the alternatives, different methods can be used such as forward and backward expansion algorithms. Using each of these algorithms will generate an alternative. The basic engineering concepts suggest using a lot of alternatives, so in this paper three different hybridization are considered.

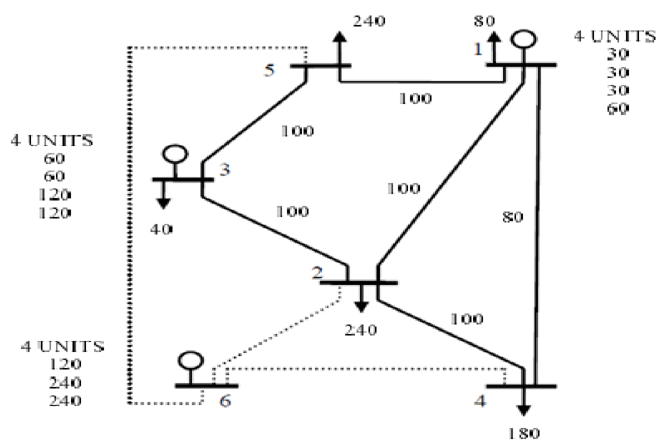

Figure 2: Garver's 6-bus network

Table 1: Lines Data (X in P.U on 100 MVA BASE)

Line N.O	From	To	Capacity (MW)	Reactance (Ohm)	Investment cost (m$)
1	1	2	100	0.4	2
2	1	4	80	0.6	6
3	1	5	100	0.2	2
4	2	3	100	0.2	1.5
5	2	4	100	0.4	4
6	3	5	100	0.2	2.5
7	2	6	100	0.3	3
8	4	6	100	0.3	3
9	5	6	78	0.3	6.1

Table 2: Proposed Alternatives for Network Expansion

Alternatives N.O	Rights-of-Way
Alternative1	{2-6, 3-5, 4-6, 5-6}
Alternative2	{2-6, 3-2, 4-6, 5-6}
Alternative3	{2-6,1-2, 4-6, 5-6}

It should be noted that in practical power expansion, after determining the optimized plan, this plan is evaluated based on the stability and short circuit level limitations and if selected plan was determined unsuitable due to technical, the planner should use the other alternatives. PNNs, are also used for classifying the TNEP solutions. In this paper, the expansion solutions are four hybridization of the total possible corridors which totally 126 states were achieved. These states have been used for training and testing the PNN. So, for training the PNN, 80 different states were chosen out of the expansion solutions. The PNN output is one of the three suggested alternatives. Thus, best n-solution set is produced. Then for every randomized input, the model selects one of the best n-solution set as an input for the HSA and base on this, the network expansion is done. Figure 3, shows the hybridization algorithm between HSA and PNN. Since the number of layers and neurons are definite in a PNNs, the only control parameter is core width [13]. So for determining it, the network error is evaluated based on the different core width values. It should be noted that the small core width will increase the accuracy and sensitivity of the network and the large core width will improve the network generality. So, there should be a compromise between the network accuracy its generality. So, value of this variable is selected 0.9. Also, in this paper the HSA algorithm parameters were set as follows: HMS = 8, HMCR = 0.85, PAR = 0.5 and bw=0.01.

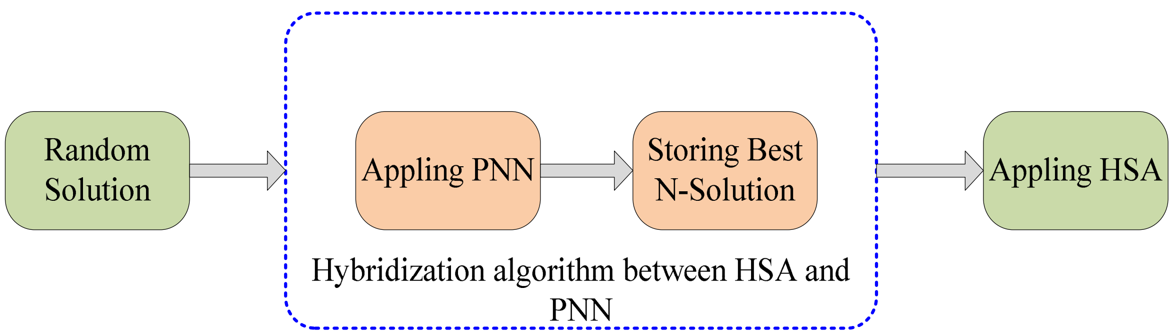

Figure 3: Hybridization algorithm between HSA and PNN

On the other hand, its assumed that each corridor maximum four lines can be existing. Optimal plan of the Garver's 6-bus network and the resulted costs of the suggested alternatives based on first scenario are presented in Table 3. Figure 4 show the comparison objectives values for the first and second scenario. As it is observed, the investment cost and the suggested first alternative losses cost is more suitable than the second and third alternatives and so the plan is more economical. The saved cost by considering the losses component, is calculated by the difference in losses cost, before and after the expansion. Before the expansion, the losses cost for the test network is 135.36 million $. So, for example for the first alternative according the first scenario, the saved cost is (135.36-34.2) = 101.16 million $.

Table 3: Optimal plan and objectives values for the first scenario

Alternative N.O	Rights-of-Way	Lines N.O	Cost (million $)			
			Investment	Active Losses	Load not Supply	Saved Cost
Alternative1	2-6	4	29.1	34.2	0	101.16
	3-5	2				
	4-6	2				
	5-6	1				
Alternative2	2-6	4	28.6	36.9	0	98.46
	3-2	1				
	4-6	3				
	5-6	1				
Alternative3	1-2	2	28.1	38.4	0	96.96
	2-6	4				
	4-6	2				
	5-6	1				

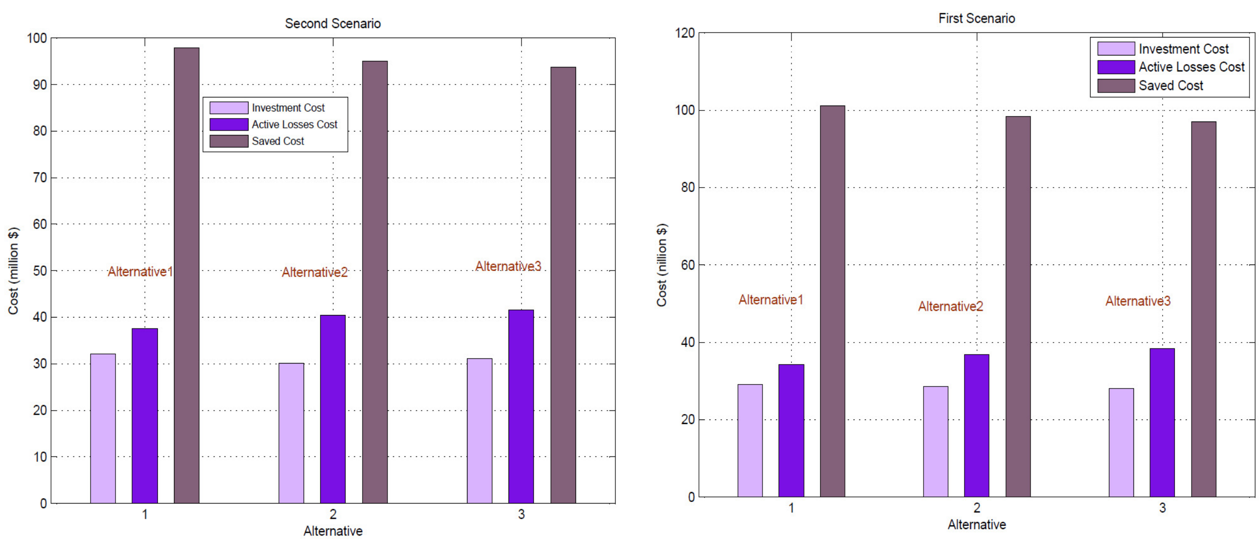

Figure 4: Comparison the objectives values for the first and second scenario

In order to compare the results of this study, the extracted costs in first alternative based on first scenario are compared with the similar results in the reference 10 in Table 4. Also, Figure 5 show the comparison objectives values with the similar results in the reference 10. In the mentioned reference, different AI models are used for TNEP. So, in Table 4 the Hybridization model used in reference 10 which includes MLP neural network and GA is used to be compared with the presented model in this paper. It should be noted that in the mentioned reference, the LNS in not calculated. As it is observed, the suggested first alternative based on first scenario, has more optimized losses and expansion cost than the similar case in reference 10. So a more optimized plan is achieved which shows the effectiveness of the optimized plan.

Table 4: Comparison of the objectives values with the similar results in the reference 10

Cost (million $)	Algorithms	
	HSA-PNN Alternative1 (based on first scenario)	GA-ANN Reference 10
Investment	29.1	29.1
Active Losses	34.2	38.254
Saved Cost	101.16	97.11
Load not Supply	0	Not Calculated

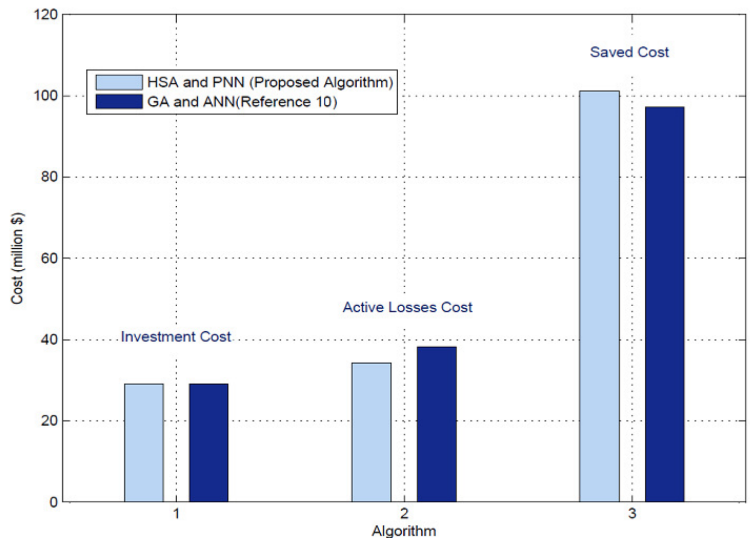

Figure 5: Comparison the objectives values with the similar results in the reference 10

Conclusion

In this paper, the transmission network expansion planning problem was formulized integrated in order to optimize the expansion cost, active losses cost and load not supply component and by a new method, a hybridization model of the artificial intelligence tools was used to solve it. This model includes a hybridization of the probabilistic neural networks and harmony search algorithm. Also, the suggested alternatives by considering uncertainty role in the load based on scenario technique, are evaluated based on the expansion criteria. So, based on results, it was observed that the expansion plans are economical and have effectiveness.

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