The application of artificial intelligent tools to the transmission expansion problem

Article *in* Electric Power Systems Research · June 2002

DOI: 10.1016/S0378-7796(02)00037-8

2 authors:

Tawfiq Al-Saba
King Fahd University of Petroleum and Minerals

Ibrahim El-Amin
Institute of Electrical and Electronics Engineers

ELSEVIER

Electric Power Systems Research 62 (2002) 117–126

ELECTRIC POWER SYSTEMS RESEARCH

www.elsevier.com/locate/epsr

The application of artificial intelligent tools to the transmission expansion problem

Tawfiq Al-Saba [a,*], Ibrahim El-Amin [b]

[a] Saudi Aramco, Dhahran 31261, Saudi Arabia

[b] Electrical Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

Received 24 July 2001; accepted 22 January 2002

Abstract

The purpose of transmission expansion problem (TEP) is to determine the timing and type of new transmission facilities. The TEP has been formulated as an optimization problem. The objective was to minimize the transmission investment costs that handle the increased load and the additional generation requirements in terms of line additions and power losses. Several constraints were considered including the power flow on the network lines, the right-of-way's validity and its maximum line addition. The TEP was then solved using artificial intelligence (AI) tools such as the genetic algorithm, Tabu search and artificial neural networks (ANNs) with linear and quadratic programming models. The effectiveness of the AI methods in dealing with small and large-scale systems was tested through the applications of a six-bus system, the IEEE-24 bus network and a Saudi Arabian network. The hybridization of GA, TS and ANN has several features. Its results confirm that it is superior in dealing with a large-scale problem in which the size of the search spaces increases exponentially with the dimension of the network.

Keywords: Artificial intelligent tools; Transmission expansion problem; Artificial neural networks

1. Introduction

The purpose of transmission system planning is to determine the timing and type of new transmission facilities. The facilities are required in order to provide adequate transmission capacity to cope with future generating additions and power flow requirements. The transmission plans may require the introduction of higher voltage levels, the installation of new transmission elements and new substations. Transmission system planners tend to use many methods to address the expansion problem. Planners utilize automatic expansion models to determine an optimum expansion system by minimizing the mathematical objective function subject to a number of constraints [1–6].

Many researchers have investigated methods and algorithms in order to solve the transmission expansion problem (TEP). One of these is a static optimization model that determines the optimum network expansion without considering the timing of the expansion. It can be modeled using linear, integer or quadratic programming techniques, a decomposition approach or the gradient search method. In 1988, linear programming was used based on a maximum principle by Kim and others [7]. Also, Villarana et al. modeled the network in such a way as to use a DC power flow [8]. Integer programming has been applied though a static network synthesis method that uses an implicit enumeration search procedure [9]. Quadratic programming was applied by Al-Hamouz to a Jordanian power system [10]. The objective was to obtain the exact cost of power losses and capital investment in the new facilities. Levi and Calovic applied the decomposition approach based method in 1991 for a Yugoslavian power system [11]. Also, Romero and Monticelli developed a hierarchical decomposition approach in 1994 [12]. Hsu et al. applied the gradient search method using an oscillatory stability consideration index [13]. Unlike static transmission network expansion models, time-phased or dynamic optimization models take into account the timing of new installations through a given time horizon [14]. El-Metwally and Harb applied this model using an

* Corresponding author.
E-mail addresses: sabatt@aramco.com.sa (T. Al-Saba), imelamin@kfupm.edu.sa (I. El-Amin).

0378-7796/02/$ - see front matter
PII: S0378-7796(02)00037-8

admittance approach and the quadratic programming technique.

The TEP can be solved using artificial intelligence tools (AI). These tools include simulated annealing (SA), genetic algorithm (GA), artificial neural networks (ANN) and Tabu search (TS). Romero et al. applied SA in 1996 [15]. In 1997, Romero and others also applied SA using computer multi-processors [16]. GA was used in 1996 to determine an economically adopted elective transmission system in a deregulated open access environment though the application of a Chilean electric system [17]. Also, in 1998, Gallego et al. applied GA to the north-northeastern and southern electrical systems in Brazil [18]. ANN was used, in 1995, using neuron computing hybridized with GA [19]. In this method, the authors improved solutions compared to the individual use of these methods. Finally, TS uses memory structure to direct the search process using a neighborhood strategy. In 1998, Romero et al. proposed a hybrid method that incorporates the basic concepts of TS, SA, and GA [20].

2. Mathematical modeling of the transmission expansion problem

2.1. The objective function

The TEP can be formulated in the following terms:

$$\min v = \sum_{i=1}^{NB} \sum_{j=1}^{NB} c_{ij} n_{ij} + K \sum_{i=1}^{NL} I_i^2 R_i \tag{1}$$

where c_{ij} is the cost of the additional circuits in branch i–j; n_{ij} is the number of circuits added to the branch i–j; NB is the total number of buses in the system; K is the loss coefficient, $K = 8760 \times \text{NYE} \times C_{\text{kwh}}$; NYE is the estimated lifetime of the expansion network (years); C_{kWh}: is the cost of one kWh ($US/kWh); R_i is the resistance of the ith line; I_i is the flow on the ith line; and NL is the number of the existing lines.

The first term of the objective function represents the capital costs of the new lines. The second term represents the costs of the system power loss. The system power flow and losses will change as a result of line additions.

Eq. (1) is a typical hard combinatorial problem. It is prone to combinatorial explosion as the number of decision variables increases. An extra complication relates to the fact that there are cases in which the planning does not simply mean the reinforcement of an existing network. The loss coefficient (K) depends on the number of years of operation and the kWh cost. The DC load flow is used in the problem formulation where the current (I) is approximately equal to the power flow, and voltage is assumed to be unity at all buses.

2.2. Transmission expansion constraints

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.

2.3. Limits in branch power flow

$$|P_{il}^{\max}| > P_{il} \tag{2}$$

where $P_{il}^{\max}$ is the maximum branch power flow between the buses i and l.

In a D.C. load flow model, each element of the branch power flow in constraint (2) can be described as follows:

$$P_{il} = (Z_{il}/x_{il})(\theta_i - \theta_l) \tag{3}$$

where Z_{il} is the total number of parallel links between the buses of i and l; x_{il} is the reactance of link of branch i to l; and θ_{I} is the voltage angles of the terminal buses of branch I.

In a matrix form, Eq. (3) becomes:

$$\text{B}\theta = P \tag{4}$$

where B is the susceptance matrix whose elements are $\text{B}_{il} = -(1/x_{il})$ for the off-diagonal terms, and $\text{B}_{ii} = \Sigma \text{B}_{il}$ for the diagonal terms; X_{il} is the total reactance of branch (i, l); $l \in O_i$ are the branches connected to bus i; and θ is the vector of nodal voltage angles.

2.3.1. Bus voltage angle

This constraint can be stated as the calculated phase angle at bus i. The calculated angle, θ_i^{cal}, should be less than the maximum phase angle $\theta_i^{\max}$.

$$|\theta_i^{\max}| \geq |\theta_i^{\text{cal}}| \tag{5}$$

2.3.2. Right-of-way

It is important to know the line location and the capacity of the required lines. This is because the planners have to meet the community standards of visual impact on the environment along with the economic considerations. So, the acquisition of right of way has to be considered by the planner and should be included as a constraint of the problem. Mathematically, this constraint defines the line location and the maximum number of lines that can be installed in a specified location. It is represented by:

$$0 \leq n_{ij} \leq n_{ij}^{\max} \tag{6}$$

where n_{ij} is the total number of circuits added in branch i–j, $n_{ij} = x_{ij}/\gamma_{ij}$; x_{ij} is the total reactance added in branch i–j; and γ_{ij} is the initial line reactance in the line i–j.

2.3.3. Power balance at the network buses

This constraint checks for the additional[u1] generation. Mathematically, this is represented by:

$$g = d + B\theta + r \tag{7}$$

where g is the generation vector in the existing power plants; d is the load demand vector in all network nodes; B is the susceptance matrix whose elements are the imaginary parts of the nodal admittance of existing ones ($B_{ij}^{existing}$) and the added lines to the existing network (B_{ij}^{added}); θ is the bus voltage angle phase vector; and r is the extra generation needed in case of high transmission losses or an unbalanced power system.

3. Proposed solution algorithms

This paper aims to obtain the optimal design using a fast automatic decision-maker. An intelligent tool starts from a random state and it proceeds to allocate the calculated cost recursively until the stage of the negotiation point is reached. These intelligent tools, GA, TS and ANN, are flexible to handle and easy to implement. This section will explain simulation procedures in order to handle the TEP. The hybridization methods of these techniques will also be explained.

3.1. Genetic algorithm approach

The GA used in this research is the simple GA [21–23], and a plural number of identical individuals are allowed to exist in the population. The genetic operation is carried out until the population converges to an individual. Through its application to the TEP problem, offspring (chromosome) length represents the number of the available rights-of-way in the network while the offspring itself represents the number of the newly added lines. Also, the cost of the new addition is represented in the fitness function.

3.2. Tabu search

TS has its antecedents in methods designed to cross boundaries of feasibility or local optimality normally treated as barriers, and systematically to impose and release constraints to permit exploration of otherwise forbidden regions [24,25]. The TS search used in this work is a simple algorithm with a neighborhood search method. Through its application to the TEP problem, the solution vector represents the number of new additions in each right-of-way. The cost of the new addition is represented in the objective function.

3.3. Hybridization algorithm

It is observed that the GA has the feature of combining the solution while the TS is a systematic exploration of memory function in search processes [26]. By taking advantage of these features to improve the performance in terms of obtaining the optimal solution, new mechanisms of solution search are used. Two forms of hybridization between GA and TS are considered.

3.3.1. Hybridization of TS and GA (Model-1)

In this method, TS will be applied with the same searching strategy as in Section 3.2, but the best *n-solution set* will be stored. Then GA will be applied to start from the best *n-solution set* as an initial population. This is illustrated in Fig. 1.

3.3.2. Hybridization (Model-2)

Since the neighborhood method was applied in the TS algorithm, the proposed method here will be to apply GA operators in place of the neighborhood method. The proposed algorithm will be as follows. The first step starts from the random solution set then obtains the objective function and applies the stopping criteria. The second step is to apply the Tabu list acceptance test. The last is to apply the GA operators to generate a new solution set. Fig. 2 illustrates this hybridization procedure.

3.4. Artificial neural network model (ANN)

An ANN with a multi-layer perceptron model using a back-propagation algorithm is the proposed algorithm for TEP applications [27,28]. The output neurons represent the solution state at each iteration while the state represents the number of lines that should be added in each right-of-way in the network. Also, the costs of these additions are represented in the objective function.

3.5. Hybridization methods With ANN

Two hybridization methods are used. The first one is the hybridization algorithm between the ANN and GA while the other one is the ANN hybridized with TS and GA.

3.5.1. ANN hybridized With GA

Since the ANN performs the local search, it will converge to the feasible solutions in the neighborhood of the initial state. If the initial state is set in the neighborhood of the optimal solution, the solution may be obtained. This is generally difficult if there is no information relating to the optimal solution. On the other hand, the GA forms a population based on a multi-point parallel search while escaping from local

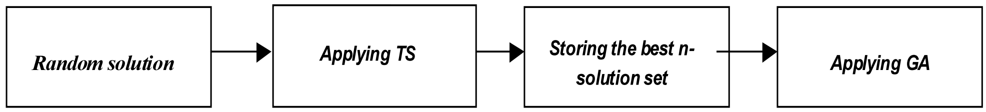

Fig. 1. Hybridization algorithm (Model-1).

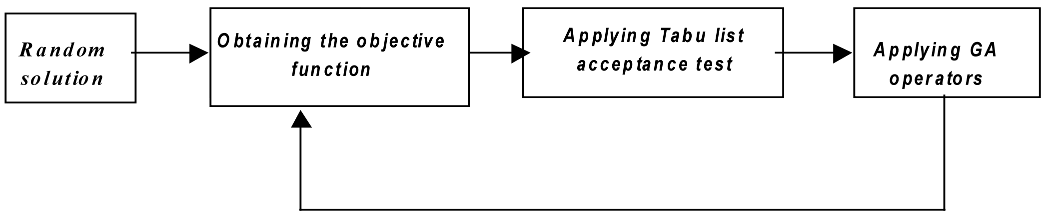

Fig. 2. Hybridization algorithm (Model-2).

minimum points. If the ANN and GA were hybridized, better results might be obtained. The ANN will be applied with the same searching strategy as in the last section but the best n-solution set will be stored. Then GA will be applied with the same strategy as in Section 3.3 by considering the best n-solution set as an initial population. By implementing this method, it can be expected that the disadvantages of ANN and GA will be resolved, as illustrated in Fig. 3.

3.5.2. Hybridizing algorithm using TS, GA and ANN

Both TS and ANN perform a local search, which leads them to state that the optimal solution is in the neighborhood of the starting solution set. This means that neither can guarantee obtaining the optimal solution. However, the GA has the best performance since it can escape from the local to a global search. Fig. 4 shows a hybridization scheme using ANN, GA, and TS algorithms.

4. Systems applications

The algorithms described earlier will be used to solve the TEP of several power networks. The power networks include the Graver six-bus system, the IEEE-24 system and a Saudi Arabian utility's system.

4.1. Graver six-bus Network

The Graver model (a six-bus system), as shown in Fig. 5, was studied [8]. Buses 1 and 3 have both generation and load supplied: 2, 4, and 5 are pure loads, and 6 is a new generation bus that needs to be connected to the network. The dotted lines represent possible line additions, and the solid lines are the existing lines.

During the expansion analysis, it was assumed that four new possible rights-of-way: 2–6, 3–5, 4–6 and 5–6 are available. This means that the total possible rights-of-way are nine, with a limit of four parallel paths in each right-of-way. In the case of including the power losses to the objective function, the loss coefficient, K, was chosen as 1000. The PU base in the DC-load flow analysis is 100 MVA while the cost base is 10^5. The estimated lifetime of the network lines was assumed to be 25 years and the cost of one kWh was assumed to be 0.005 monetary units.

4.1.1. Application of linear and quadratic programming methods

At $K = 0$, the LP obtained an optimal solution that had a cost of 200 monetary units, which is similar to the one provided by Graver with full generation scheduling (generator outputs 1, 3 and 6 are 50, 165 and 545 MW, respectively). The additional circuits, as shown in Fig. 6, are as follows:

1) four circuits between bus 2 and 6 ($n_{26} = 4$ circuits);
2) one circuit between bus 3 and 5 ($n_{35} = 1$ circuit);
3) two circuits between bus 4 and 6 ($n_{46} = 2$ circuits).

At $K = 1000$, the QP obtained the optimal solution with a total investment cost of 291 monetary units. The power loss cost before the expansion of the transmission system was 1353.6 monetary units. The new additions lead to a minimization of this cost to 382.54 monetary units. The new added lines are listed as below and are shown in Fig. 7:

1) three circuits between bus 4 and bus 6;
2) four circuits between bus 2 and bus 6;
3) one circuit between bus 5 and bus 6;
4) one circuit between bus 3 and bus 5.

4.1.2. Application of Tabu search, genetic algorithm and their hybrid methods

During the application of the six-bus system, the TS operator's value settings were listed as follows: the Tabu list size was set to be seven and the movement set was four. The vector size of each solution state in the movement set was equal to the number of the rights-

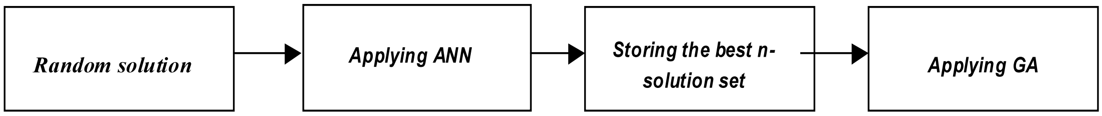

Fig. 3. Hybridization algorithm between GA and ANN.

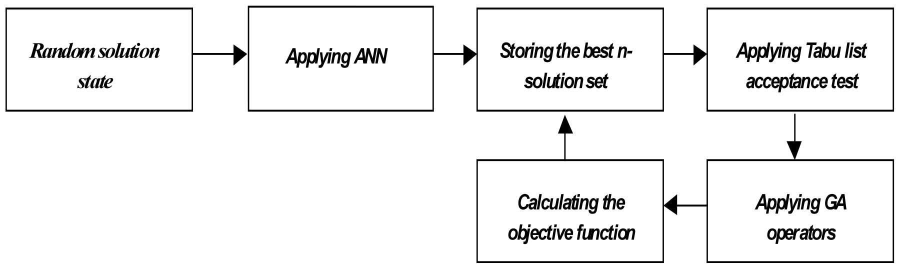

Fig. 4. Hybridization method using ANN, TS and GA.

of-way, which were nine. The neighbor principle was applied by generating a new random movement so that a new state becomes a neighbor to an old state. A random number was generated and inserted in a random right-of-way. Also, for any random selected new state a random right-of-way was selected. This algorithm was then repeated until the limit of 1000 iterations was reached.

During the use of the GA, the best values of its parameters were found to be as follows: population size was assumed to be 15 and the chromosome length is 9. The crossover and mutation probabilities were set to be 0.82 and 0.07, respectively. The GA was iterated until the maximum generation value of 1200 was reached.

The performance of the GA and TS was the same because both converged to the optimal solution for both cases (at $K = 0$ and 1000). They provided 200 monetary units when the cost of power losses was excluded and 291 under the consideration of power loss cost.

The hybridization of GA and TS was applied to the TEP of the six-bus system. It was expected that these methods would increase the ability of obtaining the optimal solution. This is because the tracking algorithm of the two methods is a combination of GA and TS as explained in section Section 3.3. They obtained the same optimal solution for both cases.

4.1.3. ANN and its hybrid algorithms

The parameters of the ANN were set as follows: the neurons of the input layer were set to one while the hidden layer was set to three neurons. The number of output layer neurons was set to be the same as the number of the available rights-of-way, which were nine. The training set had a size of 50 states with a training error set to 0.08 and below. They were iterated until the limit of 2000 was reached. The ANN algorithm was not able to reach the optimum solution. It converged to a reasonable solution with a cost of 231 monetary units at K = 0. Also, at K = 1000, it reached 261 monetary units of the new added lines cost with a power loss cost of 448.83 monetary units calculated for 25 years.

Also the two hybrid algorithms were used to solve the TEP of the six-bus system.

4.1.4. Summary of performance

In summary, all AI and classical models (linear and quadratic programming methods) except the ANN can search for and obtain the optimal solution. The ANN recorded a higher cost in the case of excluding the cost of power losses ($K = 0$) and the lowest saved cost of the power losses when $K = 1000$. This is because the initial states of ANN are not set in the neighborhood of the optimal solution. This means that convergence is very difficult while there is no information about the optimal solution. Although TS and GA cannot guarantee the optimal solution, they converge to the optimal one. Table 1 summarizes the performance of all the methods applied to the six-bus system.

4.2. IEEE 24-bus system

The IEEE 24-bus test system, as shown in Fig. 8 [29], was studied. The dotted lines represent possible line additions while the solid lines are the existing lines. The buses are numbered from 1 to 25. The new bus, 25, is connected to buses 5 and 24. During the analysis of this system, it was assumed that the loads are increased by 10% and at a future period a new generation plant is to be built to satisfy the increased load. Also, a maximum of *4 extra lines* was allowed in each of the *36 possible rights-of-way*, these being of equal importance with all transmission lines. Moreover, in the case of including the power losses in the objective function, the loss coefficient, *K, was chosen to be 10 000*. The estimated life time of the network lines was *assumed to be 25 years*

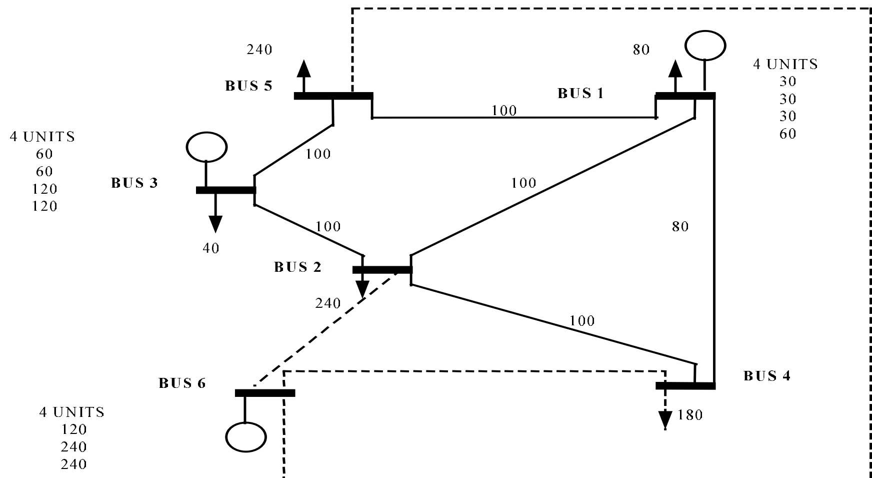

Fig. 5. Initial six-bus system.

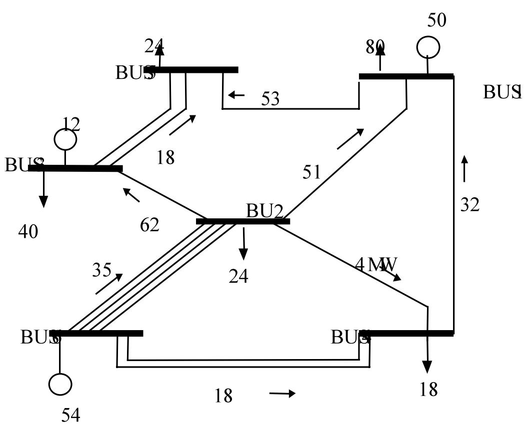

Fig. 6. Optimal solution at $K = 0$.

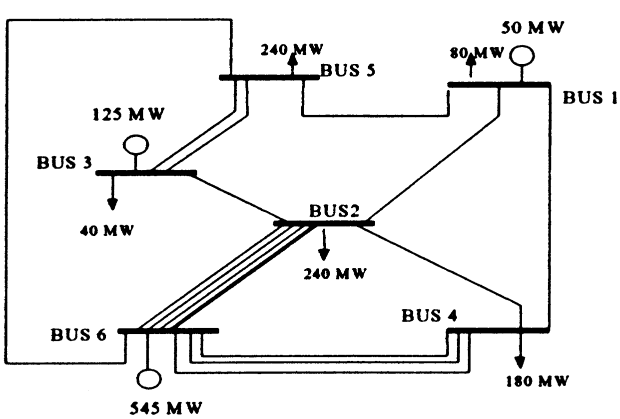

Fig. 7. Optimal solution at $K = 1000$.

while the cost of one kWh was assumed to be 1.12 US cents/kWh).

Table 2 shows the summary performance of all solution methods. It appears that the combination of ANN, GA and TS has the best performance in terms of obtaining the optimal solution for the two cases ($K = 0$ and $K = 10\,000$) while ANN is the poorest performance. LP and QP did not produce the optimal solution because it might stick with the local minimal value. Although their starting conditions have been changed, little improvement can be observed. However, GA has converged to a better solution when compared to TS but the hybridization between both algorithms leads to improved the results. Also, the performance of the hybridization model between GA and ANN does not lead to the optimal solution but its results are better than the results obtained from these algorithms when they were applied individually.

4.3. Saudi Arabian utility

This section presents the results of the work undertaken to address the TEP for one of the Saudi Arabian networks [30]. The study deals with expansion from the year 1999 to the year 2010. The 380 KV-transmission line portion of the network was studied through the application of hybridization methods between TS, GA and ANN. The existing initial plan, as developed by the Saudi Utility, is shown in Fig. 9 [30]. As per the utility plan, it is clear that there will be three buses to be added to the network configuration for the year 2000.

This system was studied under the assumption with that *4 extra* lines are allowed in each of the *14 possible rights-of-way,* these being of equal importance of all transmission lines. Also, the power losses were calculated in the objective function for four cases, when the cost of each kWh was assumed to be \$0.0133, \$0.0266, \$0.0399, and \$0.0533. Thus the loss coefficients K are approximately 10 000, 20 000, 30 000 and 40 000, respectively. The PU base in the DC-load flow analysis is 100 MVA and the base cost of the added lines is \$2666.66.

Table 1
Summary results of six-bus system by applying all proposed methods

$K = 0$

Model	Investment cost
TS	200
GA	200
ANN	231
GA–TS (1)	200
GA–GA (2)	200
ANN–GA	200
ANN–TS–GA	200
Linear model	200

$K = 1000$

Model	Investment cost	Losses cost after the new line additions[a] (calculated for 25 years)	Cost saved by minimizing the power losses[b] (calculated for 25 years)
TS	291	382.54	971.06
GA	291	382.54	971.06
ANN	261	448.83	904.77
GA-TS (1)	291	382.54	971.06
GA-TS (2)	291	382.54	971.06
ANN–GA	291	382.54	971.06
ANN–TS–GA	291	382.54	971.06
Quadratic model	291	382.54	971.06

[b] This cost is calculated as difference between the cost of ohmic power losses before the new line additions (1353.6 monetary units) based on a 25-year line lifetime and the cost calculated after the expansion as in ([a]) for the same period.

4.3.1. Discussion of the utility result

The concern in this TEP is how to handle the expected load increase in the network in 2010. As a result, three additional buses are proposed, one of which is a new generation in Ras Az Zawr while the other two are new load demand locations. The TEP of the network was

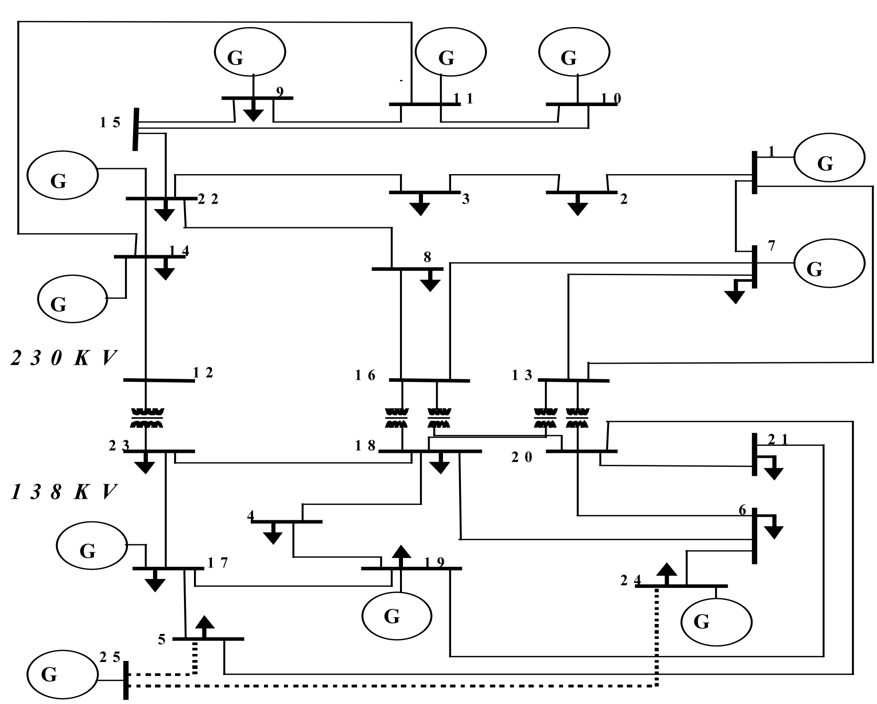

Fig. 8. IEEE 24-bus test system.

Table 2
Summary performance of AI applied to 24-bus IEEE

$K = 0$

Model	Best cost value ($million)
LP	170.200
TS	148.146
GA	147.997
TS and GA (1)	146.152
TS and GA (2)	143.560
ANN	202.277
ANN and GA	144.912
ANN, GA and TS	143.560

$K = 10\,000$

Model	Investment cost $million	Ohmic losses cost after expansion ($million[a]) (calculated for 25 years)	Saved cost by minimizing ohmic power losses during expansion[b] (calculated for 25 years)
QP	181.458	197.757	112.213
TS	180.664	155.264	154.709
GA	162.430	171.947	138.016
TS and GA (1)	174.701	155.392	154.581
TS and GA (2)	171.634	157.845	152.128
ANN	224.178	161.995	147.979
ANN and GA	173.352	155.248	154.725
ANN, GA and TS	168.784	152.320	157.653

[b] This cost is calculated as the difference between the cost of ohmic power losses before the expansion of the transmission system in the network ($million 309 973) based on a 25-year line life-time and the cost calculated after the expansion as in ([a]) for the same period.

solved by the utility and the development plan cost proposed by the *Saudi Utility to fit this expansion is $million 904.63*. The author does not have access to the methodology and the *algorithm used by the utility.*

4.3.2. Proposed algorithm application

The proposed hybrid method that combines the ANN, TS and GA was used to solve the TEP of the network. The parameter settings are in Table 3. The results are summarized in Table 4. If power cost losses are excluded in the planning calculations, the total cost reaches $million 386.138 with the new additions.

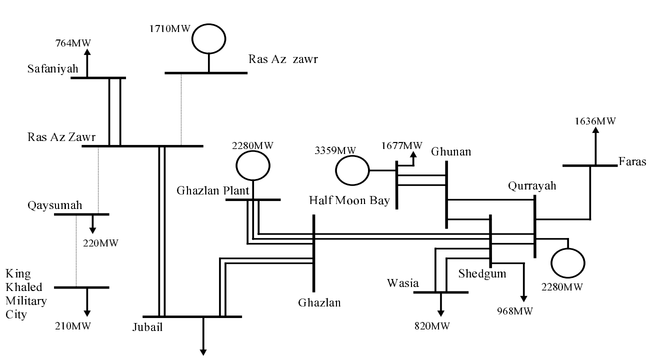

Fig. 9. Initial network plan.

On the other hand, this method was also applied to four cases that include the power losses. Assuming the cost of a kWh to be $0.0133, $K = 10\,000$, the configuration of the new network is $million 550.722. These additions will minimize the cost of the losses from $million 1455.6 to $million 877.44. At $K = 20\,000$, the investment cost reaches $million 744.08. This saves $million 1404.16 by minimizing the power loss cost over 25 years compared to the losses before expansion.

Table 3
Proposed method parameters

Model	The parameter	Setting value
ANN	Neurons of the input layer	1
	Neurons of the hidden layer	3
	Neurons of the output layer	14
	The training set at each iteration	50
	Training error	0.08
	Total number of iteration	1000
TS	TS list size	9
	Vector size	14
GA	Population size	20
	Crossover probability	0.82
	Mutation probability	0.09
	Chromosome length	14
	Total generation	1000

Table 4
Summary performance of ANN, GA and TS

Cost of $/kWh	Corresponding K	Investment cost $Million
Not-considered	0	386.138
0.0133	10 000	550.722
0.0266	20 000	744.000
0.0399	30 000	859.173
0.0533	40 000	1429.45

Cost of SR/kWh	Ohmic losses cost before the new line additions $million ([a]) (Calculated for 25 years)	Ohmic losses cost after expansion $million ([b]) (Calculated for 25 years)	Saved cost by minimizing ohmic power losses during expansion ([c]) (Calculated for 25 years)
0.0133	1455.6	877.44	577.653
0.0266	2911.2	1507.04	1404.16
0.0399	4366.9	2118.77	2248.16
0.0533	5822.7	2168.05	3654.61

[c] This cost is calculated as the difference between the cost of ohmic power losses before the new line additions ([a]) and the cost calculated after the expansion as in ([b]).

When one kWh is sold at $0.04, the network will incur losses amounting to $million 4366.93 over 25 years. As a result of expansion, the investment cost of the new lines is $million 859.173 and the cost of the losses over 25 years will be minimized to $million 2118.77. Finally, at $K = 40\,000$, the investment cost reaches $million 1429.453. Knowing that the cost of the ohmic power losses before the addition is $million 5822.667, the new scenario leads to a saving of $million 3654.528 compared to the cost of the power losses after the expansion which is $million 2168.05. Table 4 shows the results in detail.

5. Conclusion

The power system TEP has been formulated as an optimization problem. The objective was to minimize the transmission investment costs that handle the increased load and the additional generation requirements in terms of line additions and power losses. Several constraints were considered including the power flow on the network lines, the right-of-way's validity and its maximum line addition, and the maximum angle change across the buses. The TEP was then solved using AI tools such as the GA, TS and ANNs with linear and quadratic programming models. Based on the quality of the final solution and computational speed, these methods have proved to be suitable for solving difficult optimization problems.

The effectiveness of the AI methods in dealing with small and large-scale systems was tested through the applications of a six-bus system, the IEEE-24 bus network and a Saudi Arabian network. For the six-bus system, all the proposed models were applied and the optimum design obtained and compared to the linear and quadratic programming approaches. For the IEEE-25-bus system, the hybridization of TS, GA and ANN proved to be more effective than other approaches. The TEP of the Saudi Arabian network from 2000 to 2010 was also solved using the best-tested method (hybridization of all AI). It provided a future network configuration for four different cases.

The hybridization of GA, TS and ANN has the following features:

1) Its results confirm that it is superior in dealing with a large-scale problem in which the size of the search spaces increases exponentially with the dimension of the network.
2) It considers the investment cost in terms minimal of line additions and ohmic power losses under technical and economical constraints.

Acknowledgements

The author acknowledge the support of King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia.

References

[1] T. Gonen, Electric Power Transmission System Engineering Analysis and Design, Wiley, USA, 1988.
[2] M. llic, F. Galiana, L. Fink, A. Bose, P. Mallet, H. Othman, Transmission capacity in power network, Electrical Power and Energy Systems 20 (2) (1998) 99–110.
[3] Transmission System, Electrical Power System-I, Saudi ARAMCO Engineering Encyclopedia, pp. 47–60.

[4] R. Billinton, J. Oteng-Adjei, Utilization of interrupted energy assessment rates in generation and transmission system planning, IEEE Transaction on Power Systems 6 (3) (1991) 1245–1253.
[5] M.E. El-Hawary, G.S. Christensen, Optimal Operation of Electric Power System, Academic Press, New York, USA, 1979.
[6] W.L. Weeks, Transmission and Distribution of Electrical Energy, Harper and Row Publishers, New York, USA, 1981.
[7] K.J. Kim, Y.M. Park, K.Y. Lee, Optimal long term transmission expansion planning based on maximum principle, IEEE Transaction on Power Systems 3 (1988) 4.
[8] R. Villosana, L.L. Garver, S.J. Solon, Transmission network planning using linear programming, IEEE Transaction on Power Apparatus and System PAS-104 (2) (1985) 349–356.
[9] R. Romero, A. Monticelli, A zero–one implicit enumeration method for optimizing investments in transmission expansion planning, IEEE Transactions on Power Systems 9 (3) (1994) 1385–1391.
[10] Z.M. Al-Hamouz, Transmission Network Planning Using Quadratic Programming, Master's Thesis, Jordan University of Sciences and Technology, 1989.
[11] V.A. Levi, M.S. Calovic, A new decomposition based method for optimal expansion planning of large transmission networks, IEEE Transaction on Power System 6 (1991) 3.
[12] R. Romero, A. Monticelli, A hierarchical decomposition approach for transmission network expansion planning, IEEE Transaction on Power Systems 9 (1) (1994) 373–380.
[13] Y.-Y. Hsu, P.-H. Huang, C.-J. Lin, C.-T. Huang, Oscillatory stability considerations in transmission expansion planning, IEEE Transaction on Power System 4 (3) (1989) 1110–1114.
[14] M.M. El-Metwally, A.M. Harb, Transmission planning using admittance approach and quadratic programming, Electrical Machines and Power Systems 21 (1993) 61–83.
[15] R. Romero, R.A. Gallego, A. Monticelli, Transmission system expansion planning by simulated annealing, IEEE Transaction on Power System 11 (1) (1996) 364–369.
[16] R. Romero, R.A. Gallego, A. Monticelli, Parallel simulated annealing applied to long term transmission network expansion planning, IEEE Transaction on Power Systems 12 (1997) 1.
[17] H. Radnick, R. Palam, E. Cura, C. Silva, Economically adapted transmission systems in open access schemes—application of genetic algorithms, IEEE Transaction on Power Systems 11 (3) (1996) 1427–1440.
[18] R. Romero, R.A. Gallego, A. Monticelli, Transmission system expansion planning by an extended genetic algorithm, IEEE Transaction on Power Systems 145 (3) (1998) 329–335.
[19] K. Yoshimoto, K. Yasuda, R. Yokoyama, Transmission expansion planning using neuro-computing hybridized with genetic algorithm, IEEE Transaction on Neural Network 1 (1995) 126–131.
[20] R. Romero, R.A. Gallego, A. Monticelli, Comparative studies on non-convex optimization methods for transmission network expansion planning, IEEE Transaction on Power Systems 13 (3) (1998) 822–828.
[21] D.E. Goldberg, Genetic Algorithm in Search, Optimization and Machine Learning, Addison Wesley, Reading, MA, 1989.
[22] Z. Michalewicz, Genetic Algorithm+Data Structures = Evolution Programs, Springer-Verlag, Berlin, Heidelberg, New York, USA, 1992.
[23] L. Davis, Handbook of Genetic Algorithms, Van Nostrand, New York, 1991.
[24] R.L. Daniels, J.B. Mazzola, A Tabu search heuristic for the flexible-resource flow shop scheduling program, Annals of Operation and Research 41 (1993) 207–230.
[25] M. Dell Amico, M. Trubian, Applying tabu search to the jop-shop scheduling problem, Annals of Operation and Research 41 (1993) 253–278.
[26] M. Laguna, T. Feo, H. Elrod, Genetic algorithm and tabu search: hybrids for optimization, Operations Research 42 (4) (1994) 677–687.
[27] T.T. Al-Saba, I.M. El-Amin, Artificial neural network as applied to long-term demand forecasting, Artificial Intelligence in Engineering 13 (2) (1999) 189–197.
[28] D. Highlay, T. Hilmns, Load forecasting by ANN, Computer Application in Power IEEE 6 (3) (1994) 10–15.
[29] A.O. Ekwu, B.J. Cory, Transmission system expansion planning by interactive method, IEEE Transaction on Power Apparatus and System. PAS-103 (7) (1984) 1583–1591.
[30] SCECO-East and Central Reference Scenario at 2000 and 2010 at Peak Load Developed at June 1995. File # LF6-3-LDVG and LF6-5-LDVG.