Estimation Load Forecasting Based on the Intelligent Systems

Hanan A.R. Akkar **Wissam H. Ali**
Department of Electrical Engineering, University of Technology, Baghdad, IRAQ
hnn_aaa@yahoo.com wisamas1976@yahoo.com
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Abstract:
The daily peak load forecasting for the next day is the basic operation of generation scheduling. The approach of using ANN methodology alone is limited which has generated interest to explore hybrid system. In this paper a search of genetic programming to a short term load forecasting is presented. A genetic architecture with the fitness normalization has been used to find as optimum data peak load of Baghdad city. The optimize data applied to the ANN to be trained and tested to estimate the daily peak load of Baghdad city. Different cases for load forecasting are considered with the aid of MATLAB 7 package to get the estimation of the next day. So an improvement method of genetic optimization is proposed to get a better solution for the load estimation rather than artificial neural network.

Keyword: Short term Load Forecasting, Artificial Intelligent AI, Neural network, Genetic

1. Introduction
The main objective of power system forecasting is to enable in any time on adaptation between demand and generation. This adaptation must consider load and generation characteristic and possible paths in transmission and distribution network to supply energy to consumer [1].

Two functions are very important in load estimation. The first is short term load forecasting such that predicating from hour to days. The second is long term forecasting where the load will be estimated month to year[2].

The research approach of short term load forecasting (STLF) can be divided into two categories: statistical and artificial intelligent methods. In statistical method (multiple linear regression, stochastic time series, general exponential smoothing state space and etc…) equation can be obtained showing the relationship between load and relative forecasting after training the historical data. While artificial intelligent methods try to imitate human being way of thinking and reasoning to get knowledge from the past experience and forecast the future load [3]. In this paper combinations of intelligent system have been used (ANN and GA).

Using more than on AI methods would increase the ability of these methods.

The most popular ANN architecture for load forecasting is back propagation. This network uses continuously values function and supervised learning. The ANN used in this work to predicate the daily peak load va1ue.

GA operates on populations of string, with the string coded to represent some underlying parameters set. Reproduction, crossover and mutation are applied successive string population to create a new string population [4]. . In this work GA approach is used to find the optimum value from the input vectors.

2. Load Estimation
Short-term forecasting being one of the most proposed design based on perceptron network Multi-layer perceptron (MLP) [5]. The attraction of MLP has been explained by the ability of the network to learn complex relationships between input and output pattern which would be difficult to model with conventional algorithm's methods. The main objective of short term load estimation is to expect hourly load, one day or even one week beforehand, so it necessary for the future operational planning of power system [6].

In this models, input to the network with optimize are globally present and past load values and outputs are future load 'value. The networks are generally present and past load values and outputs are future load values. The network trained using realload data from the past.

Generally the load of an electric utility is composed of different consumption units. A large part of electricity is consumed by industrial activities. Another part is of course used by private people informs of heating, lighting, cocking, laundry... etc [7]. Also many services offered by society demand electricity as an example street lighting real way traffic...etc. As far as electrical power system is concerned there has been a need to find out the future load in advance. Load estimation has been the central integral process, throughout planning and operation of electric utilities.

Economic and reliable operation of an electric utility power system depends to a significant extent on the accuracy of the load forecast. The daily peak load is ·an indication of many factors that have a direct influence on its value, the determination at these factors is very important since they give the system operator a good idea about the expected value of the peak load from day to day. The operator can perform unit commitment programs, economic load dispatch, and energy generation [2].

3. Genetic algorithm for load estimation optimization

Genetic algorithm is surpassing their more traditional cousins in the quest for robustness, so GA must differ in some very fundamental way [8].

In compare with artificial networks, these networks as brief models of the Intelligent-system: It is highly interconnected neural computing elements that have the ability to response-to the input to adapt to the environment.

The genetic algorithm have high robustness than artificial neural network by finding the solution of optimization problems it can be describe in brief as follows [10].

First the algorithm generator and one population of chromosome from a population according to their fitness function after that a crossover probability. Make the crossover the parent to find a new offspring (child).

If crossover is performed offspring is deferent from their parents, then mutate new offspring at each locus or the point in chromosome take the result to place new offspring in the new population. Using the new generating children for more than runs of the algorithm, finally if the end condition is satisfied. Then end and return to best solution in current population [10, 11]. The system load is the sum of all the consumers' load at the same time. The objective of system STLF is to forecast the future system load. Good understanding of the system characteristics helps to design reasonable forecasting models and select appropriate models in different situations [8].

Regression is one of most widely used statistical techniques. For load forecasting regression methods "'are usually employed to model the relationship of load consumption and other factors such as weather, day type and customer class [12].

A multi-variable regression can be written as

$$k(t) = b_0 + \sum_{j=1}^{m} b_j t^j + g(t) \qquad \ldots(1)$$

Where K(t) is the peak load at time t , b_0 and b_j are the regression coefficient which have relationship with K(t) at time t and g(t) is the gradual load. Form the above equation the calculation of gradual autocorrelation function RF at different time t can be finding as [13]:

$$RF = \frac{\sum_{t=j+1}^{n} w_j w_t}{\sum_{t=1}^{n} w_j^2} \qquad \ldots(2)$$

So know RF is gradual autocorrelation at time t and w is the estimated residual [14].

This function is the method of optimization the input data to forecast the peak load. In this paper a proposed optimization method is presented using the genetic algorithm by replacing the RF function with one of the fitness function for GA to present a high performance of optimization input data. Fig. (1) shows the proposed hybrid system.

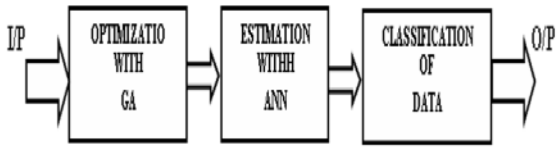

Figure 1: The hybrid system process

4. Model description

In this paper two models have been proposed to estimate the next day peak load. The input parameters to the structure contains the forecasted maximum temperature in the three different areas (north, middle, south), for the day being conducted. There corded maximum ‘temperature of the previous day in the three areas, and the recorded maximum temperature and peak load in the past ten days with the same load pattern like the forecasted day the total number of neurons are (46) neuron in the input layer for the two models. Load shape values, can be affected by weather or seasonal variations or even weekly, monthly, and annual cycle. The input-vectors sorted according to the four seasons: The distribution of months over the' seasons decided depending upon the relation between the peak load demand and weather conditions.

(1) Winter season from 1st Mar. to 30th Feb.
(2) Spring season from 1st May to 30th Sep.
(3) Summer season from 1st May to 30th Sep.
(4) Autumn season from 1st Oct. to 30th Nov.

The existence of bad data in historical load curve affects the precision of load forecasting result.

4.1 First Model

First model uses artificial neural network. The network construction consist of input layer, which represents one hidden layer with (60) neuron and output layer with (1) neuron which represents peak load to forecast the next day peak load for the four seasons. Neural network deals with numbers between (0-1) , therefore the data are normalized using the equation:

$$Z_{nor} = \frac{z - z_{min}}{z_{max} - z_{min}} \qquad \ldots(3)$$

Where Z_{nor}=normalized value,
Z_{min}=minimum value and
Z_{max}=maximum value

4.2 The Second Model (GA-ANN)

The second model uses the technique of combining Genetic Algorithm and Artificial Neural Network. GA approach *is* employed to find the optimum values of the state vector z(input data). Fitness function is normalized with range between (0-1).The fitness function adopted is:

$$f = \frac{1}{1+k\sum_{j=1}^{m}|z(i,j)|} \quad \text{……….}\ (4)$$

Where z(i, j) is the input matrix , k is a scaling vector. After applying data to

GA they apply to ANN. The construction of ANN changes due to that, input layer, one hidden layer (24;-24, 28, 25) neurons for winter, spring, summer and autumn respectively and(1) neuron in the output layer to forecast the next day peak load for the four seasons.

5. Results Evaluation

To test the performance of the network the Relative Percentage Error (RPE) is used to defined as follows:

$$RPE = \left|\frac{actual_i - forecasted_i}{actual_i}\right| \times 100 \ldots(5)$$

Where actual is the actual load of the same I and forecast is the forecasted load of that sample. Test would require the use of data at all the year, but must not be carried with same data used in the training set.

6. Comparison & Irison of ANN Results With GA-ANN

The final accuracy of the forecasted process depends on the model selection and the accuracy of estimated parameters. The simulation results are presented in tables (1),(2), (3) and (4) for winter, spring, summer and autumn respectively.

Table 1: winter testing result for two model.

NO. of tested patterns	*Actual load Value (MW)*	*Estimated loads value of ANN (MW)*	*Estimated load value of ANN &GA (MW)*
1	1821	1859	1812
2	1829	1803	1847
3	1848	1928	1817
4	1850	1956	1779
5	1871	2094	1893
6	1979	1788	1991
7	2041	1922	2043
8	1940	1987	1899
9	1950	1865	1907
10	1960	1828	1895
11	1965	1877	1954
12	1976	1955	1997
13	2008	2026	2007
14	1990	1759	2020
15	1980	1984	1921
16	1979	2044	1979
17	1885	1829	1928
18	1870	1807	1938
19	1963	1964	1963
20	1746	1752	1850

Table 2: spring testing result for two model

NO. of tested patterns	*Actual load Value (MW)*	*Estimated loads Value of ANN (MW)*	*Estimated load Value of ANN & GA (MW)*
1	*1432*	*1614*	*1426*
2	*1437*	*1423*	*1439*
3	*1436*	*1456*	*1538*
4	*1428*	*1423*	*1432*
5	*1431*	*1431*	*1439*
6	*1434*	*1520*	*1433*
7	*1438*	*1441*	*1435*
8	*1445*	*1347*	*1447*
9	*1440*	*1385*	*1438*
10	*1470*	*1381*	*1458*
11	*1432*	*1355*	*1450*
12	*1415*	*1467*	*1402*
13	*1408*	*1396*	*1435*
14	*1397*	*1507*	*1420*
15	*1407*	*1544*	*1420*
16	*1400*	*1538*	*1430*
17	*1410*	*1560*	*1433*
18	*1444*	*1426*	*1444*
19	*1439*	*1523*	*1447*
20	*1450*	*1518*	*1447*

Table 3: Summer testing result for two model

NO. of tested Patterns	*Actual loads Value (MW)*	*Estimated loads Value of ANN (MW)*	*Estimated loads Value of ANN & GA (MA)*
1	1540	1352	1540
2	1555	1493	1486
3	1755	1768	1721
4	1818	2010	1809
5	1861	1849	1861
6	1880	1897	1905
7	1932	1960	1990
8	1942	1962	1892
9	1970	2099	1899
10	2017	2025	2022
11	2056	2162	2068
12	2095	2181	2092
13	2135	2167	2147
14	1979	1980	2061
15	1950	1930	1952
16	1850	1887	1904
17	1830	1879	1831
18	1772	1842	1734
19	1768	1745	1748
20	1709	1679	1637

Table 4: autumn testing result for two model.

NO. of tested Patterns	*Actual load Value (MW)*	*Estimated load Value of ANN (MW)*	*Estimated load Value of ANN & GA (MW)*
1	1580	1537	1565
2	1560	1571	1572
3	1549	1582	1502
4	1543	1491	1543
5	1537	1463	1476
6	1521	1551	1531
7	1519	1602	1519
8	1506	1580	1512
9	1482	1523	1467
10	1456	1537	1456
11	1435	1436	1516
12	1323	1360	1323
13	1335	1355	1338
14	1388	1499	1360
15	1474	1418	1474
16	1605	1687	1605
17	1692	1682	1717
18	1725	1763	1760
19	1809	1790	1792
20	1812	1849	1812

Table (5): summarizes the difference between the two models in the number of iteration for the simulation process.

Items	*NO. of Epoch of ANN*	*NO. of Epoch of ANN & GA*
Winter	3500	6
Spring	810	4
Summer	25000	51
Autumn	21000	7

The GAs approach presented in this optimum values of the state vector which minimizes the ' absolute summation of the forecasted vector in order to emphasize the best string and speed up convergence 'of iteration procedure.

Fig.(2), Fig.(3), Fig.(4) 'and Fig.(5) winter, spring, summer and autumn respectively show" the Relative Percentage Error (RPE) for the two models.

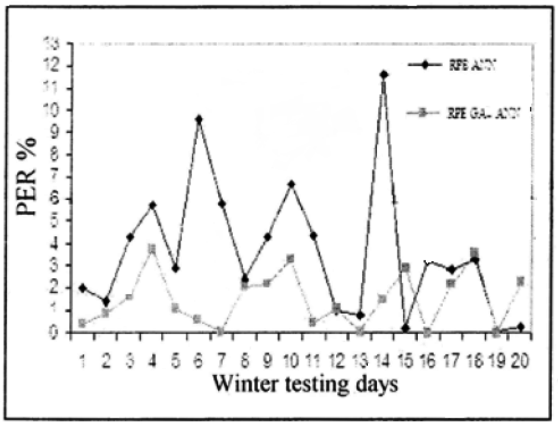

Figure 2: RPE for winter season.

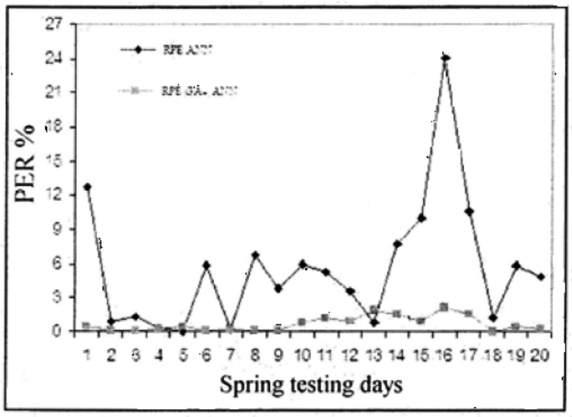

Fig 3 RPE for spring season

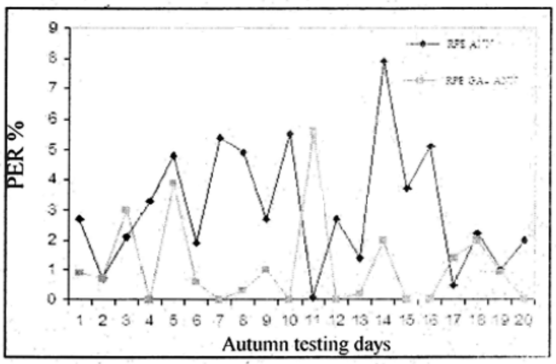

Fig 4 RPE for Autumn season

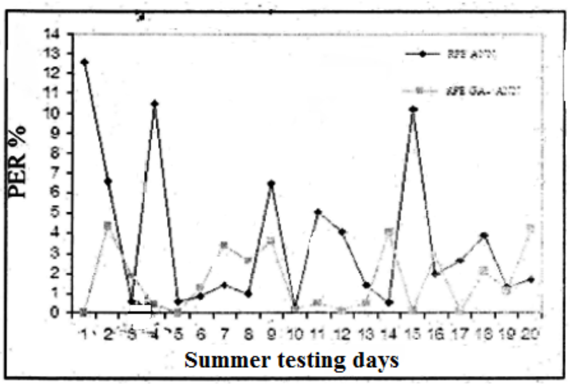

Fig 5 RPE for summer season

Table (6): Summarizes the difference between two model proposed in over all percentage error for the whole year

Item	*Percentage error of ANN*	*Percentage error of ANN & GA*
Winter	3.63	1.5
Spring	5.59	0.7
Summer	3.69	1.7
Autumn	3.0	1.1
Average error	3.97	1.2

Fig (6), ,Fig (7), Fig.(8) and Fig. (9) shows the training curve using the first model for winter, spring, summer and autumn respectively. Fig(l0) Fig(11),Fig(l2)and Fig.(13) show the training curve using the second model for winter, spring, summer and autumn respectively.

Conclusions

In the first an improvement method in the first an improvement method of genetic optirf1ization is proposes to get a better solution for the load estimation rather than artificial neural network. Load forecasting is an important component of power system energy management system;1 But the global method not introduced a solution for many problems in. future load demand from this research it can be seen that optimizing the input data with GA will reduce the estimation error from 70% to 87% than sin ANN. The integration of two intelligent allows the computer system to solve problems and to find solutions. Noting that one of the techniques alone could not get the use of two techniques to get her allow limitations be covered always using each one's better characteristic. Combing ANN with GA would reduce the PER for the forecasted daily peak load and greatly reduce the number of iteration of the artificial neural network epoch as shown in the result and minimize the SSE.

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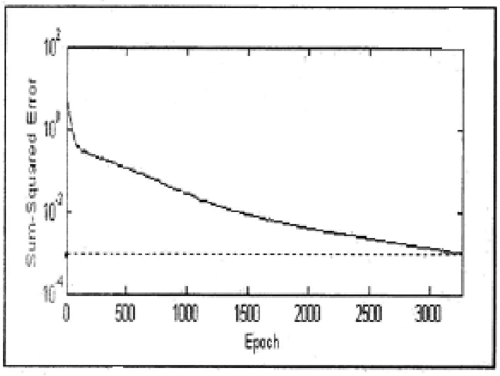

Fig.(6) Training curve for winter season for the first model.

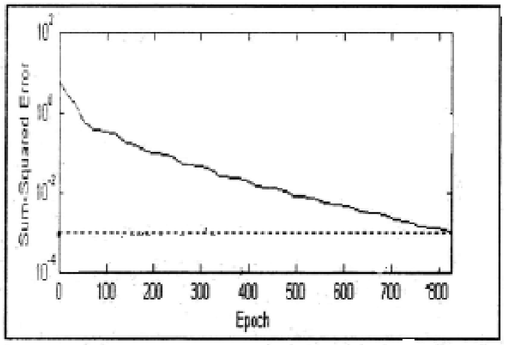

Fig.(7) Training curve for spring season for the first model.

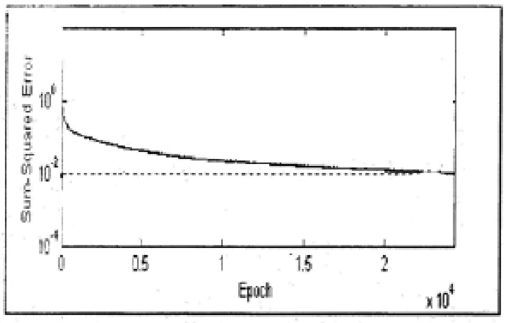

Fig.(8) Training curve for summer season for the first model.

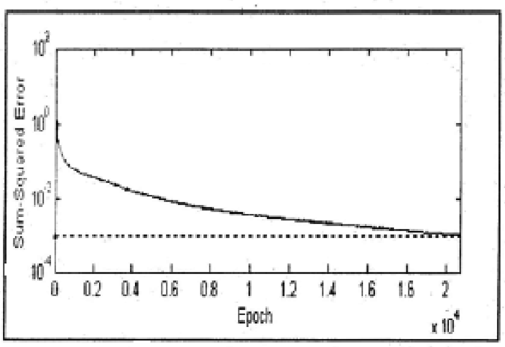

Fig.(9) Training curve for autumn season for the first model.

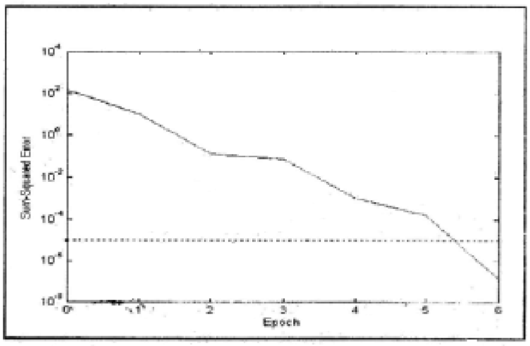

Fig.(10) Training curve for winter season for the second model.

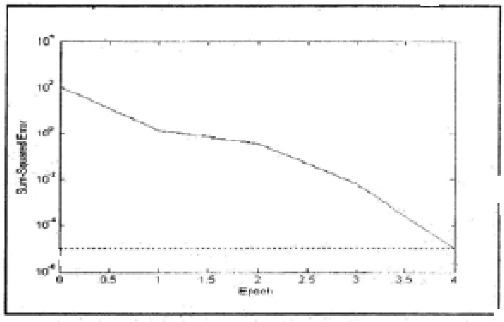

Fig.(11) Training curve for spring season for the second model.

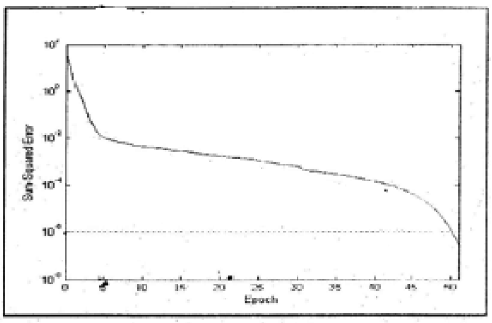

Fig.(12) Training curve for summer season for the second model.

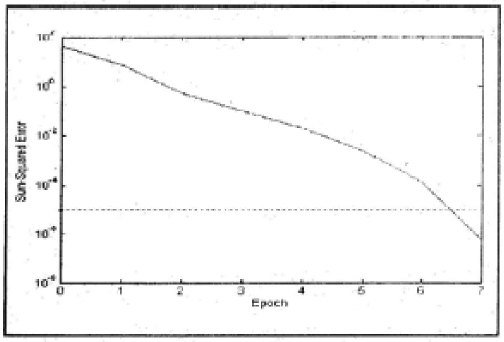

Fig.(13) Training curve for autumn season for the second model.

تخمين احمال القدره بالاعتماد على الأنظمة الذكية

حنان عبد الرضا عكار **وسام حسن علي**
قسم الهندسة الكهربائية – الجامعة التكنولوجية – بغداد - العراق

الخلاصه :

التنبؤ اليومي لأحمال الذروة لليوم التالي هو التشغيل الأساسي لجدولة التوليد. إن نهج استخدام منهجية ANN وحده محدود مما أدى إلى اهتمام باستكشاف النظام المختلط. في هذه البحث ، يتم عرض البرمجة للتنبؤ بالحمل قصير المدى بالاعتماد على النظريه الجينيه Genetic programming. تم استخدام بنية وراثية مع تطبيع التماثل لإيجاد الحمل الأمثل لذروة البيانات في مدينة بغداد. تحسين البيانات المطبقة على شبكة (ANN) لتدريبها واختبارها لتقدير حمل الذروة اليومي لمدينة بغداد. يتم النظر في حالات مختلفات للتنبؤ بالأحمال بمساعدة حزمة MATLAB 7 للحصول على تقدير اليوم التالي. لذا يقترح طريقة تحسين التحسين الوراثي للحصول على حل أفضل لتقدير الحمل بدلاً من الشبكة العصبية الاصطناعية.