Short Term Load Forecasting using Metaheuristic Techniques

Saroj Kumar Panda\textsuperscript{1}, Papia Ray\textsuperscript{2} and Debani Prasad Mishra\textsuperscript{3}

\textsuperscript{1} VSSUT, Burla, India - 768018
\textsuperscript{2} VSSUT, Burla, India -768018
\textsuperscript{3} IIIT , Bhubaneswar, India -751003

E-mail: debani11@gmail.com

Abstract. The power systems are important by using short term load forecasting (STLF) because it predicts the load in 24 hours ahead or a week ahead. The artificial neural network (ANN) using short term load forecasting brings good result in the predicted load because of its accurateness, easiness in the processing of data, construction of the model as well as excellent performances. The optimization value of ANN is found by different methods which consist of some weights. This manuscript explains the work of ANN with back propagation (BP), genetic algorithm (GA) as well as particle swarm optimization (PSO) for the STLF. The detailed work of the GA and PSO based BP is presenting in this paper which helps for its utilization in the STLF and also able to find the good result in the predicted load. Finally, the result of GA and PSO are compared by simulation and after that, it concluded, the PSO-BP is a good method for STLF using ANN.

1. Introduction
The determination of load in any power industry is very important. Normally, the uses of methods in power industries are working with past data and weather conditions in forecasting. The aims of the methods are predicting the load in 24 hours ahead for the STLF. If the methods are used for the prediction of the load for long intervals like mid-term or long-term, they will bring maximum error in the predicted load because of the propagation error. The operation and cost of industry depend on the prediction of the exact load. So, the exact load determination is very important over the variation of load which causes deregulation of electricity.

The power system increases the efficiency with the use of STLF because of the daily work performance [1]. The exactness of load and fast operation power system depends on the factor influence the load and past load demand [2, 3]. The different types of methods are using for the STLF i.e. old and new methods. The old methods are bringing good results for STLF with their work [4, 5], like regression method [6], time series method [7], pattern recognition [8], kalman filter model [9] which are also known as traditional methods. These methods can also use for a long period [10]. But these methods are not suitable for the complex non-linear model which is creating a relation between factors (period, climate conditions or day time) affect the load and load demand. In other cases, the new methods are expert system [11], artificial neural network method [12, 13, 14], fuzzy logic based methods [15] as well as hybrid wavelet-kalman filter [16] which are giving accurate result in the predicted load.
But, ANN is good for the non-linear model which consists of load influencing factor and load demand because ANN is able to solve the problem of the non-linear problems and creates the relation between input and output through linear and non-linear function. The STLF based ANN model is constructed from back propagation, Hopfield and Boltzmann machine, feed forward or backward model which consists of weight, layer and some other arrangements [17]. The suitable training technique for ANN with STLF is BP. The work of BP is depending on input data, output data and controllable weight with a loss function. This is known as supervised learning and unsupervised learning does not require any preoperational training in the neural network.

The more works of ANN [18, 19] with BP [20, 21], GA [22-25] and PSO [26-28] have given its application in STLF. So that, the useful method for the prediction of the exact load in the power industry using STLF is PSO-BP because PSO solves any type of non-linear problems with the help of the BP technique and the reasons for using of ANN are flexibility, learning ability and able to generalized in complex problems. This manuscript is arranged in the following ways: Section 2 gives ANN with STLF. Section 3 represents metaheuristic methods and their improved algorithms. Section 4 gives load characteristics. Section 5 gives the simulation results of the work, Section-6 represents the conclusion of the work and Section-7 gives future scope.

2. ANN with STLF
The methods with ANN are using for solving the complicated network which consists of load influencing factors and load demand. So, it is used for STLF. This section gives detailed work of ANN for STLF.

2.1. ANN Model
Neurons are the main parts of ANN. It is shown in Figure 1 which is also known as feed forward neural network (FFNN). It consists of three layers i.e. input layer, hidden layer and output layer. The signal is propagated through these layers sequentially i.e. from the input layer to the hidden layer and hidden layer to the output layer. During this propagation of the signal, the error is found at the output layer. This error is calculated by comparison of the predicted load with respect to the real load. With the updating of the weight, the error is back propagated throughout the network. Here the input layer is consisting of past loads with some factors and the output layer consists of predicted loads with 24 hours ahead. The accurate training of a neural network depends on input variable, hidden nodes, scaling methods, transfer function and preparation. So, they should be select carefully.

![Figure 1. Structural design of ANN](image)

The equation (1) gives the calculation model of ANN.

\[ O_j = \varphi_j \sum_{i=1}^{n} (w_{ij} \cdot x_N) \]

Where, \( O_j \) = output of neuron, \( \varphi_j \) = transfer function, \( w_{ij} \) = weight of neuron, \( x_N \) = neuron’s input

2.2. Training
In this process, ANN creates a relation between input and output. In this time, the weight of ANN is used as the mean square error (MSE) decreases under the threshold value of a whole network. The training of ANN is processed by BP technique. For the non-linear problem, the metaheuristic technique during the training process follows the equation (2).

\[ W^{t+1} = -\eta \frac{\partial E}{\partial w} + \alpha w' \]  

(2)

With, \( W^{t+1} \) = weight of the later step, \( w' \) = change in weight for previous, \( \eta \) = learning rate, \( \alpha \) = momentum factor, \( w \) = weight in ANN. Figure 2 represents the ANN with STLF.

![Figure 2. ANN for STLF](image)

In this figure, the \( I_i \) as well as \( O_i \) used as input and output respectively to carry the value within the range [0, 1]. After scaling, the input and output equations are given in the equations (3) and (4).

\[ I_i^{(k)} = I_i^{(i)} / \text{MAX}(I_i^{(i)}) \]  

(3)

\[ O_i^{(i)} = O_i^{(i)} / \text{MAX}(O_i^{(i)}) \]  

(4)

Where \( I \) = input and output indicator vector.

The weights are adjusted in every time for the construction of the neural system and the adjustment is going on till the neural system will get good output. With the help of simulation, the neural network will produce a good result for the predicted load. For the changes of load, the fault (F) is calculated by the equation (5).

\[ F = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\text{Actual load} - \text{Forecasted load}}{\text{Actual load}} \right| \times 100 \]  

(5)

3. Metaheuristic Techniques

In this section, the different metaheuristic techniques are discussing the training of ANN using BP.

3.1. GA with BP

The reproduce capability of nature’s evolution process is known as GA which is stochastic in nature with global search capability [29]. Its work is started with initialization and chromosome selection. The binary and real encoded of chromosomes are based on the problem. The selection of cross over and mutation are two important factors in GA for finding a good result. This process is continuing for getting the new result and it will stop when the condition is met.

Different steps of GA are

3.1.1. Coding
The important parameter in the chromosome is a gene. The chromosomes are binary encoded in traditional GA. Exact coding is used in this manuscript instead of binary coded. The chromosome ‘p’ is present in the population. Where ‘p’ is population size.

3.1.2. Weight extraction

The chromosomes will fit by removing the weight. The characterized chromosome $x_1, x_2, \ldots, x_k, \ldots, x_L$ and $x_{k+1}, x_{k+2}, \ldots, x_{(k+1)d}$ present the $k^{th}$ gene ($k \geq 0$) in chromosome. The weight $W_k$ is given in the equations (6) and (7).

$$W_k = \begin{cases} \frac{x_{kd+2} \times 10^{d-2} + x_{kd+3} \times 10^{d-3} + \ldots + x_{k+1} \times 10^{d-2}}{10^{d-2}}, & \text{if } 0 \leq x_{kd+1} \leq 5 \\ \frac{x_{kd+2} \times 10^{d-2} + x_{kd+3} \times 10^{d-3} + \ldots + x_{k+1} \times 10^{d-2}}{10^{d-2}}, & \text{if } 5 \leq x_{kd+1} \leq 9 \end{cases}$$

(6) \hspace{1cm} (7)

3.1.3. Fitness function

It presents the quality of the result depends on the problem and for this manuscript, it is characterized by equation (8).

$$\text{Fitness} = \frac{1}{(1 + F)}$$

(8)

Where “F” = fault

By the above study, the GA with BP is carried out by the following steps

Step-1: The population value, chromosomes, mutation as well as crossover are initialized.

Step-2: The individual’s fitness value is calculated with the help of equation (8).

Step-3: Mutation as well as crossover will produce new generation with the calculation of fitness value.

Step-4: The best individual is selected by the roulette wheel.

Step-5: Check the condition, If the condition is met, go to Step-6; otherwise again start the Step-3 and Step-4.

Step-6: The best individual is obtained and it is used as a weight of ANN for performing the STLF using BP.

3.2. PSO with BP

Eberhart and Kennedy proposed PSO [30]. The group of birds and fishes behaviour is calculated by this method. The self velocity and neighbour’s velocity is determining the behaviour of the individual. In this way, the particle will locate in a good position. Suppose the D-dimensional numerical consist of $x_i, L, x_{id}, L, x_{id}$ represents every particle in PSO containing m particles and this particle carry the approximate solution of the problem. The particle is updated by the position and velocity with the equations of (9) and (10).

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

(9)

$$v_i^{t+1} = \omega v_i^t + c_1 r_{1i} (p_{yi} - x_i^t) + c_2 r_{2i} (p_{yi} - x_i^t)$$

(10)
Where, \( w \) = constraint of weight, \( c_1 \) = coefficient of cognitive, \( c_2 \) = coefficient of social, \( r_{1j}, r_{2j} \) = arbitrary value chooses among 0 as well as 1.

Different steps of PSO-BP are

Step-1: All parameters should be assigned like weight matrix \( w_0 \) and its range, learning rate \( \eta \), initial weight factor \( w \), particle size, local best position \( P_{\text{best}} \), global best position \( g_{\text{best}} \), \( c_1 \), \( c_2 \) and \( i = 1 \). Stopping criteria should be written at starting.

Step-2: Define fitness value by equation (8) and it represents the best particles in the group.

Step-3: \( P_{\text{besti}} \) represents the extreme value of particle which is selected global best \( g_{\text{besti}} \) of the particle.

Step-4: Particle is updated by position and velocity with equations of (9) and (10).

Step-5: \( i+1 \) is set followed by \( i \)

Step-6: If the choosing condition came, then iteration will stop as well as global position \( g_{\text{best}} \) is the optimal solution otherwise again start from Steps-2.

4. Load Characteristics

The electric load is characterized by following the equation (11).

\[
T_l = T_u + T_w + T_s + T_r
\]  

(11)

Where, \( T_l \) = total load, \( T_u \) = usual load, \( T_w \) = weather load, \( T_s \) = seasonal load and \( T_r \) = random load.

The future loads are influenced by factors which are used as input for the processing of the forecast. The load changes from time to time. So, it should be controlled by a controller \( L(i) \), with \( i = 1 \) to 24. In this manuscript, we are considering 0, 0.5 and 1 for a sunny day, cloudy day and rainy day respectively.

5. Case Study

The data has taken from the Xintai power plant which is situated at China for the calculation of good results in STLF.

5.1. Sample dataset

The data sets of training, validation and testing divide the data has taken from 10\(^{\text{th}}\) to 30\(^{\text{th}}\) June 2006 are given in Table 1 and the complete data set is given in Table 2.

| Table 1. Classifications of dataset |
|-------------------------------------|
| Types of Data | Time Zone (June, 2006) |
| Training | 10\(^{\text{th}}\) to 21\(^{\text{st}}\) |
| Validation | 22\(^{\text{nd}}\) to 28\(^{\text{th}}\) |
| Testing | 30\(^{\text{th}}\) |

| Table 2. Total datasheet |
|--------------------------|
| Date of year 2006 | LOAD (MW) | WEATHER |
|-------------------|------------|--------|
| 6.10              | 897 878 826 830 824 854 1037 1094 1176 1272 1300 1317 1281 1304 1286 1287 1286 1178 1034 | 0.2385 0.2125 0 |
| 6.11              | 930 892 890 846 832 890 1059 1136 1181 1273 1331 1359 1321 1250 1223 1259 1299 1336 1364 1343 1354 1383 1271 1131 | 0.2152 0.2101 0 |
| 6.12              | 1025 982 944 921 916 987 1142 1246 1277 1359 1408 1441 1460 1380 1342 1322 1378 | 0.2415 0.1027 0 |
| 6.13 | 1379 1390 1389 1408 1345 965 796 |
|      | 750 733 703 697 718 716 820 937 976 1048 |
|      | 1115 1165 1153 1006 957 949 959 1023 1052 0.2421 0.1423 0 |
|      | 1066 1074 1055 937 843 |
| 6.14 | 776 788 750 754 766 785 956 1052 1139 1240 |
|      | 1273 1335 1321 1254 1241 1274 1333 1345 1349 1346 1351 1338 1237 1096 0.2154 0.1212 0 |
|      | 970 930 901 898 882 968 1129 1238 1272 |
| 6.15 | 1344 1400 1412 1427 1337 1285 1333 1362 1395 1432 1388 1379 1371 1283 1134 0.2523 0.3124 0 |
|      | 1044 998 959 952 975 1075 1276 1316 1381 |
| 6.16 | 1448 1498 1559 1549 1456 1407 1437 1506 1509 1518 1445 1453 1440 1338 1194 0.2103 0.2126 0 |
|      | 1066 1028 983 981 1000 1080 1305 1398 |
| 6.17 | 1438 1534 1559 1583 1583 1515 1498 1512 1547 1589 1611 1623 1589 1587 1493 1315 0.2156 0.2470 0 |
|      | 1223 1154 1122 1087 1099 1199 1386 1466 |
| 6.18 | 1515 1594 1620 1678 1619 1565 1512 1537 1591 1628 1649 1613 1647 1650 1568 1391 0.2380 0.2416 0 |
|      | 1250 1194 1175 1122 1085 1215 1395 1453 |
| 6.19 | 1513 1612 1672 1723 1698 1657 1608 1600 1567 1627 1608 1513 1486 1477 1420 1304 0.2351 0.3215 0 |
|      | 1169 1136 1070 1060 1057 1137 1330 1408 |
| 6.20 | 1470 1541 1595 1640 1566 1550 1533 1564 1580 1572 1585 1567 1509 1493 1406 1244 |
|      | 1144 1096 1039 983 938 1016 1222 1358 |
| 6.21 | 1443 1539 1570 1571 1518 1443 1408 1470 1511 1532 1517 1519 1440 1380 1290 1129 0.2411 0.2801 0 |
|      | 1039 985 977 934 944 1037 1227 1332 1461 |
| 6.22 | 1548 1597 1625 1571 1453 1429 1477 1526 0.2512 0.2456 0 |
|      | 1528 1514 1478 1411 1377 1307 1138 1056 991 982 949 938 1033 1243 1322 1430 |
| 6.23 | 1536 1587 1622 1544 1447 1408 1451 1540 1567 1565 1548 1501 1480 1374 1224 |
|      | 1102 1039 990 951 947 1037 1249 1353 1419 |
| 6.24 | 1543 1608 1591 1549 1423 1392 1432 1504 547 1580 1486 1400 1373 1251 1095 996 948 925 881 908 984 1227 1317 1410 0.2416 0.2134 0 |
|      | 1513 1578 1566 1525 1449 1369 1430 1471 0.2751 0.2347 0 |
|      | 1442 1384 1287 1261 1311 1224 1077 994 938 939 901 912 991 1182 1310 1356 |
| 6.25 | 1488 1513 1533 1490 1435 1384 1444 1497 1581 1576 1551 1474 1448 1379 1252 |
|      | 1135 1079 1033 999 988 1091 1290 1392 0.2415 0.2556 0 |
| 6.26 | 1445 1557 1608 1599 1557 1465 1401 1434 1501 1579 1561 1585 1537 1520 1441 1326 0.2315 0.2647 0 |
|      | 1196 1104 993 821 760 728 729 800 838 934 973 1047 1069 1018 1079 1092 1116 0.2372 0.2502 1 |
|      | 1083 1096 1060 1112 1036 954 |
| 6.27 | 861 828 800 798 787 799 845 912 982 1090 1122 1181 1174 1122 1092 1151 1199 1204 0.2134 0.2199 0 |
| 6.28 | 0.2421 0.1423 0 |
| 6.29 | 0.2154 0.1212 0 |
|      | 0.2523 0.3124 0 |
|      | 0.2103 0.2126 0 |
|      | 0.2156 0.2470 0 |
|      | 0.2419 0.2780 0 |
|      | 0.2411 0.2801 0 |
|      | 0.2512 0.2456 0 |
|      | 0.2123 0.1476 0 |
|      | 0.2416 0.2134 0 |
|      | 0.2751 0.2347 0 |
|      | 0.2415 0.2556 0 |
|      | 0.2315 0.2647 0 |
|      | 0.2372 0.2502 1 |
|      | 0.2134 0.2199 0 |
5.2. Simulation Result

With the help of simulation results, the real loads, predicted loads as well as fault in percentage between them are calculated in Table 3 and the MATLAB software package helps to bring this simulation result. Except that, Table 3 gives the examination of every real load with respect to the predicted load. So that, we can easily find a suitable technique for the STLF using ANN and Table 4 gives the error of different schemes which helps to find the exact method for the power industry.

### Table 3. Fault calculation between real as well as predicted loads

| Period (hour) | Real load (MW) | BP | GA-BP | PSO-BP |
|---------------|----------------|-----|-------|--------|
|               | Predicted load | Fault (%) | Predicted load | Fault (%) | Predicted load | Fault (%) |
| 1             | 943            | 920  | 2.43  | 928    | 1.59  | 930    | 1.37  |
| 2             | 914            | 880  | 3.86  | 885    | 3.17  | 910    | 0.43  |
| 3             | 907            | 875  | 3.52  | 900    | 0.77  | 895    | 1.32  |
| 4             | 875            | 860  | 1.71  | 870    | 0.57  | 875    | 0     |
Table 4. Calculation of fault \((F)\) for different techniques

| Proposed techniques | \(F\) |
|---------------------|------|
| BP                  | 2.01 |
| GA-BP               | 1.52 |
| PSO-BP              | 1.40 |

The forecasted load is calculated by BP, GA-BP and PSO-BP and it is compared with the actual load. But the ANN is trained by BP. The discussing of the actual load as well as forecasted load is compared with appropriate techniques in Figure 3 and it also gives the analysis of applied methods in deeply. So, we calculated the predicted loads for each technique as given in Table 3.

From Table 4, it is cleared that, the average percentage of PSO-BP is 1.40 as compared to GA-BP. So, PSO-BP is very important as compare to GA-BP for the prediction of the load.

6. Conclusion

The main aim of this job is the application of various techniques in STLF. The determination of the exact load is important for the operation and cost of electricity. But the accurate load calculation is critical for which we are using ANN. The work of PSO-BP is considered as a hybrid training method in STLF which brought good results as compared to BP and GA-BP. GA-BP is also good but when a new generation is creating, it loses its behaviour. The updating velocity and position of a particle bring good results in the predicted load of PSO-BP as compare to GA-BP.

7. Future Scope
It can use in more potential areas like telecommunication, signal processing, data mining and combinational optimization etc. and some other extended areas like charge estimation, power scheduling, transportation asset allocation and military applications.

Conflict of Interest: There is no conflict between the authors for this research work.

References

[1] Papalexopoulos A D, Hao S and Peng T M 1994 An Implementation of a Neural Network Based Load Forecasting Model for the EMS Trans. on Power Syst. 9(4) (IEEE) pp 1956-1962.
[2] Chen H A 1996 Practical On-line Predicting System for Short-Term Load East China Electric Power 24(3).
[3] Chen H 1997 An Implementation of Power System Short-Term Load Forecasting Power Syst. Automation China.
[4] Slutsker I, Nodheki H, Mokhtari S, Burns K, Szymanski D and Clapp P 1998 Market Participants Gain Energy Trading Tools Computer Application in Power 11(2) (IEEE) pp 47-52.
[5] Moghram I and Rahman S 1989 Analysis and Evaluation of Five Short-Term Load Forecasting Techniques Trans. on Power Syst. 4(4) (IEEE) pp 1484-1491.
[6] Papalexopoulos A D and Hesterberg T C 1990 A Regression-Based Approach to Short-Term System Load Forecasting Trans. on Power Syst. 5(4) (IEEE) pp 1535-1547.
[7] Hagan M T and Behr S M 1987 The Time Series Approach to Short-Term Load Forecasting Trans. on Power Syst. 2(3) (IEEE) pp 785-791.
[8] Dhdashti A S, Tudor J R and Smith M C 1982 Forecasting of Hourly Load By Pattern Recognition: A Deterministic Approach Trans. Proc. Apparatus and Syst. 101(9) (IEEE) pp 3290-3294.
[9] Toyada J, Chen M and Inoue Y 1970 An Application of State Estimation to Short-Term Load Forecasting I and II Trans. on Power Syst.89 (IEEE) pp 1678-1688.
[10] Chen H and Liu J A 1998 Weighted multi-model Short-term Load Forecasting System Proc. Int. Conf. on Power Syst. Technology NY. 1 (IEEE) pp 557-561.
[11] Rahman S and Bhatnagar R. 1998 An Expert System Based Algorithm for Short-Term Load Forecast Trans. on Power Syst. 3(2) (IEEE) pp 392-399.
[12] Lu C N, Wu H T and Vemuri S 1993 Neural Network Based Short Term Load Forecasting Trans. on Power Syst. 8(1) (IEEE) pp 337-342.
[13] Dash P K, Satpathy H P, Liew A C and Rahman S 1997 A Real-time Short-Term Load Forecasting System Using Functional Link Network Trans. on Power Syst. 12(2) (IEEE) pp 675-680.
[14] Vermaak J 1998 Recurrent Neural Networks for Short-Term Load Forecasting Trans. on Power Syst. 13(1) (IEEE) pp 126-132.
[15] Papadakis S E 1998 A Novel Approach to Short-Term Load Forecasting Using Fuzzy Neural Network Trans. on Power Syst. 13(2) (IEEE) pp 480-492.
[16] Zheng T, Girgis A A and Makram E B 2000 A Hybrid Wavelet- Kalman Filter Method for Load Forecasting Electric Power Syst. Research 54(1) pp 11-17.
[17] Yang, Tzer H, and Huang C M 1998 A new short-term load forecasting approach using self-organizing fuzzy ARMAX models Trans. on Power Syst. (IEEE) pp 217-225.
[18] Ray P, Mishra D P and Lenka R K 2016 Short Term Load Forecasting by Artificial Neural Network Int. Conf. on Next Generation Intelligent Syst. (ICNGIS) (IEEE) pp 1-6.
[19] Mishra D P and Ray P 2018 Fault detection, location and classification of a transmission line Neural Computing and Applications 30(5) pp 1377-1424.
[20] Sun W and Zou Y 2007 Short term load forecasting based on bp neural network trained by PSO In Proc. of the Sixth Int. Conf. on Machine Learning and Cybernetics pp 2863–2868.

IOP Conf. Series: Materials Science and Engineering 1033 (2021) 012016 doi:10.1088/1757-899X/1033/1/012016
[21] El-Desouky A A and El-Kateb M M 2000 Hybrid adaptive techniques for electric-load forecast using ANN and ARIMA Proc. Generation Transmission and Distribution 147 (IEEE) pp 213–217.

[22] Ray P, Panda S K and Mishra D 2017 Short-term load forecasting using genetic algorithm In 4th Int. Conf. on Computational Intelligence in Data Mining (ICCIDM) (Springer) pp 863–872.

[23] Panda S K, Ray P and Mishra D 2019 Effectiveness of GA in Short-term load forecasting using genetic In 18th Int. Conf. on Information Technology (ICIT) (IEEE) pp 27–32.

[24] Wang X and Elbuluk M 1996 Neural network control of induction machines using genetic algorithm training Industry Applications Conf. 31st IAS Annual Meeting 3 (IEEE) pp 1733–1740.

[25] Lu W Z, Fan H Y and Lo S M 2003 Application of evolutionary neural network method in predicting pollutant levels in downtown area of Hong Kong Neurocomputing 51 pp 387–400.

[26] Panda S K, Ray P and Mishra D 2019 Effectiveness of PSO on short-term load forecasting In 1st Int. Conf. on Application of Robotics in Industry Using Advanced Mechanisms (ARIAM) (Springer) pp 122–129.

[27] Kennedy J 1997 The particle swarm: social adaptation of knowledge In Proc. of the Int. Conf. on Evolutionary Computation Indianapolis Indiana USA pp 303–308.

[28] Panda S K, Ray P and Mishra D P 2019 Short Term Load Forecasting Using Empirical Mode Decomposition (EMD), Particle Swarm Optimization (PSO) and Adaptive Network-Based Fuzzy Interference Systems (ANFIS) 10th Int. Conf. on Innovations in Bio-Inspired Computing and Applications (IBICA) (Springer) pp. 161-168.

[29] Pham D T and Karaboga D 2000 Intelligent Optimization Techniques Genetic Algorithm Tabu Search Simulated Annealing and Neural Network (Springer-Verlag).

[30] Hassnain S and Khan A 2007 Short term Load Forecasting Using Particle Swarm Optimization Based ANN Approach Int. Joint Conf. on Neural Network 1 (IEEE) pp 1476-1481.