Hybrid Techniques for Short Term Load Forecasting

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ABSTRACT:
Short Term Load Forecasting (STLF) is the projection of system load demands for the next day or week. Because of its openness in modeling, simplicity of implementation, and improved performance, the ANN-based STLF model has gained traction. The neural model consists of weights whose optimal values are determined using various optimization approaches. This paper uses an Artificial Neural Network (ANN) trained using multiple hybrid techniques (HT) such as Back Propagation (BP), Cuckoo Search (CS) model, and Bat algorithm (BA) for load forecasting. Here, a thorough examination of the various strategies is taken to determine their scope and ability to produce results using different models in different settings. The simulation results show that the BA-BP model has less predicting error than other techniques. However, the Back Propagation model based on the Cuckoo Search method produces less inaccuracy, which is acceptable.

KEYWORDS: Short Term Load Forecasting, Hybrid Techniques, Artificial Neural Network, Back Propagation, Cuckoo Search, Bat Algorithm.

1. INTRODUCTION

Forecasting the load is a significant challenge in the power utility industry. To perform load forecasting, models are typically created based on memories of prior data of local weather and historical load demand data knowledge. Such forecasts are often geared at short-term forecastings, such as one-day forecasting, because forecasting over a longer interval, such as being less reliant on the midterm or long-term forecasting will be due to error propagation. The accuracy with which load data is predicted is essential for the operation and production cost of the electric utility. Given the ongoing changes in the power business due to deregulation, accurate load forecasting is critical.

STLF-based Energy Management System has always been important because it is part of the fundamental exercise for scheduling all normal operations, whether daily or weekly [1-3]. To obtain precise accuracy and forecasting rapidity, it is necessary to study the data of load demand distinctiveness and the load's element [4-6]. Typically, STLF techniques are classified into ancient techniques and current approaches. Various out-of-date load forecasting systems have had variable degrees of effectiveness [7-10]. Traditional practices which are scheme-dependent for load demand forecastings, such as regression [11], time series [12], pattern recognition [13], Kalman filters model [14], and others, have been in use for a long time, supporting the precision. These multi-model and utility-based methods are classic, and the systems in which they are used produce satisfactory outcomes [15]. The nonlinear relationships between the demand of load and factors like weather conditions, or time of day, influence it, which are all subject to model modifications and unable to calculate by these models. The sophisticated load forecasting algorithms like Expert System [16], Artificial neural network-based method [17], Fuzzy logic-based method [18], and Hybrid Wavelets-Kalman filter [19] provide unrestricted results in STLF.

The following is the structure of this paper: The ANN model for STLF is shown in Section 2. The hybrid techniques are explained in Section 3. Section 4 describes the performance evaluation. The simulation results are defined in Section 5. The conclusion of the work is presented in Section 6.

2. ANN

Due to its simple, improved generalized characteristic and adaptive nature, ANN is popularly applied for load forecast in the power system (PS). Some of the types of ANN are described in the section below.

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2.1. Feed-forward neural network (FFNN)

In Fig. 1, the Input, hidden, and output layers of FFNN are explained. In FFNN, Multilayer perceptron (MLP) and back-propagation learning methods are used. At least three layers of nodes are present in MLP, a class of FFNN. Each node is a neuron in which a nonlinear activation function is applied except for the input nodes; multiple layers, non-linear activation function, etc., are the properties of FFNN. To minimize the error generated by this technique, fine-tuning the weight and biases of the network in FFNN are required.

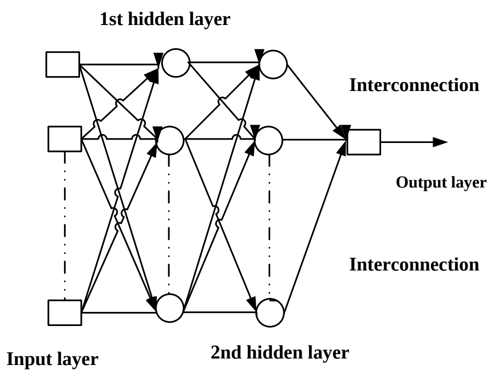

Fig. 1. The neural network structure of Feedforward.

Fig. 1 explains the processing of the input data from the input layer to the output through the hidden layers for the forecasting of the load.

3. HYBRID TECHNIQUES

This paper's several hybrid-based BP techniques utilized to train the ANN network are detailed below.

3.1. Cuckoo Search Based Back Propagation

X. S. Yang and S. Deb propose CS as a recent nature-based metaheuristic approach based on the parasitic behavior of different cuckoo species in 2009. Lévy flights improved this process in comparison to isotropic arbitrary walks. Lévy flight, which is not exponentially bounded, is defined as an arbitrary walk with a probability distribution, also referred to as a heavy-tailed probability distribution. Many studies have revealed that the flying characteristics of insects and birds are similar to those of Lévy flight. To explore its surrounding landscape, fruit flies, or Drosophila melanogaster, the straight flight paths are interrupted by sudden right angular turns or bends using the Lévy flight type of irregular-scale free search pattern, according to a discovery by Reynolds and Frye. The three immaculate principles used are listed here for clarity's sake.

1- At a time, the cuckoo can only lay one egg, and in the chosen nest, the egg is laid in an arbitrary.

2- The superseding generation advances to the nests with superior eggs.

3- The host bird recognized the probability "P_a" of a cuckoo's egg. Depending on its preference, the cuckoo's egg may either be discarded by the host bird or the unattended nest leave and build a new nest for itself. According to these criteria, new nests replace the "P_a" fraction of the "n" host nests.

The CS algorithm calculation depends on the following as in (1) and (2).

$$y_i^{(t+1)} = y_i^t + \alpha \oplus Levy(\lambda) \quad (1)$$

$$Levy \Theta u = t^{-\lambda}, (1 < \lambda \le 3) \quad (2)$$

Where $= i, j$ and k are counter variables and the Lévy flight is achieved for a cuckoo "i" with "$y(t+1)$" is a new solution. Step size is α, and L is the problem's characteristic scale.

3.2. Bat Algorithm Based Back Propagation

A primary section heading is enumerated by a Roman numeral followed by a period and is centered above the text. A primary heading should be in capital letters.

A secondary section heading is enumerated by a capital letter followed by a period and is flush left above the section. The first letter of each important word is capitalized and the heading is italicized.

A tertiary section heading is enumerated by an Arabic numeral followed by a parenthesis. It is indented and is followed by a colon. The first letter of each important word is capitalized and the heading is italicized.

A quaternary section heading is rarely necessary, but is perfectly acceptable if required. It is enumerated by a lowercase letter followed by a parenthesis. It is indented and is followed by a colon. Only the first letter of the heading is capitalized and the heading is italicized.

Xin She Yang modeled BP, a new metaheuristic method utilized in optimization issues, in 2010 [20]. The echolocation abilities like sound waves of varied frequencies, loudness, and pulse rates of microbats, inspired the BA. Microbats use sound echolocation skills to avoid obstacles and find prey during flight. Ultrasonic sound waves generate echoes in echolocation, like the created outgoing waves to produce concise representations of its surroundings, the bat's brain and auditory system process the rebounding echoes. As a result of these occurrences, the bat can recognize and classify its prey even in complete darkness. The bat's pulse rate increases as it gets closer to its prey, and the volume of the sound waves it produces decreases. With its unique pulse rate and loudness level in BA, the particle considerations of microbat possess. For the implementation of the BA algorithm, the following rules are used:

1- Bats use the echolocation method to determine the distance between themselves and other objects. They can also identify the difference between food and prey and other obstacles.

2- "X_i" is the arbitrary position and during flight, "V_i" denotes the velocity of bats, respectively. To emit sound waves with a set minimum frequency "F_{min}," a bat is chosen for wavelength variable "λ," and a level of volume level A_0". Depending on the distance between their targets and themselves, the emission rate of these "R" radiated waves is assumed in the [0, 1] range of value.

3- From an "A_0" with a higher positive value to an "A_{min}" set with a lower value, the loudness of the sound wave is considered to decline.

The calculation of the BA algorithm depends on the following as in (3)-4.

$$F_i = F_{\min} + (F_{\max} - F_{\min})\beta \tag{3}$$

$$V_i^{k+1} = V_i^k + (X_i^k - X^*)F_i \tag{4}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{5}$$

Where, V_i, X_i and F_i are velocity, position and frequency of microbat. F_{min} and F_{max} are minimum and maximum values of frequencies.

4. PERFORMANCE EVALUATION

The mean absolute percentage error (MAPE) is used to evaluate the performances of BP, CS-BP and BA-BP as in (6).

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|f_i - l_i|}{l_i}X100 \tag{6}$$

The forecasted load is fi and the recorded load is li for i^{th} time-step N.

5. CASE STUDY

In this work, the efficiency of the suggested STLF approaches is evaluated using Xingtai Power Plant's data from the area of China.

5.1. Sample Dataset

The historical dataset comprises hourly load demands and weather-related data from June 10th to June 30th, 2006. Table 1 explains the training period, validation period, and Period of testing data. Table 2 shows the total load demand statistics for the Xingtai Power Plant throughout the period specified.

Table 1. Classifications of the dataset.

Data types	Duration
Period of training	10th - 21st
Period of validation	22nd - 28th
Period of testing	30th

Table 2. Total datasheet.

Dates	Demand (MW)	Climate
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 1379 1390 1389 1408 1345 965 796	0.2415 0.1027 0
6.13	750 733 703 697 718 716 820 937 976 1048 1115 1165 1153 1006 957 949 959 1023 1052 1066 1074 1055 937 843	0.2421 0.1423 0
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
6.15	970 930 901 898 882 968 1129 1238 1272 1344 1400 1412 1427 1337 1285 1333 1362 1395 1432 1388 1379 1371 1283 1134	0.2523 0.3124 0
6.16	1044 998 959 952 975 1075 1276 1316 1381 1448 1498 1559 1549 1456 1407 1437 1506 1509 1518 1445 1453 1440 1338 1194	0.2103 0.2126 0
6.17	1066 1028 983 981 1000 1080 1305 1398 1438 1534 1559 1583 1583 1515 1498 1512 1547 1589 1611 1623 1589 1587 1493 1315	0.2156 0.2470 0
6.18	1223 1154 1122 1087 1099 1199 1386 1466 1515 1594 1620 1678 1619 1565 1512 1537 1591 1628 1649 1613 1647 1650 1568 1391	0.2380 0.2416 0
6.19	1250 1194 1175 1122 1085 1215 1395 1453 1513 1612 1672 1723 1698 1657 1608 1600 1567 1627 1608 1513 1486 1477 1420 1304	0.2351 0.3215 0
6.20	1169 1136 1070 1060 1057 1137 1330 1408 1470 1541 1595 1640 1566 1550 1533 1564 1580 1572 1585 1567 1509 1493 1406 1244	0.2419 0.2780 0
6.21	1144 1096 1039 983 938 1016 1222 1358 1443 1539 1570 1571 1518 1443 1408 1470 1511 1532 1517 1519 1440 1380 1290 1129	0.2411 0.2801 0
6.22	1039 985 977 934 944 1037 1227 1332 1461 1548 1597 1625 1571 1453 1429 1477 1526 1528 1514 1478 1411 1377 1307 1138	0.2512 0.2456 0
6.23	1056 991 982 949 938 1033 1243 1322 1430 1536 1587 1622	0.2123 0.1476 0

	1544 1447 1408 1451 1540 1567 1565 1548 1501 1480 1374 1224	
6.24	1102 1039 990 951 947 1037 1249 1353 1419 1543 1608 1591 1549 1423 1392 1432 1504 547 1580 1486 1400 1373 1251 1095	0.2416 0.2134 0
6.25	996 948 925 881 908 984 1227 1317 1410 1513 1578 1566 1525 1449 1369 1430 1471 1442 1384 1287 1261 1311 1224 1077	0.2751 0.2347 0
6.26	994 938 939 901 912 991 1182 1310 1356 1488 1513 1533 1490 1435 1384 1444 1497 1581 1576 1551 1474 1448 1379 1252	0.2415 0.2556 0
6.27	1135 1079 1033 999 988 1091 1290 1392 1445 1557 1608 1599 1557 1465 1401 1434 1501 1579 1561 1585 1537 1520 1441 1326	0.2315 0.2647 0
6.28	1196 1104 993 821 760 728 729 800 838 934 973 1047 1069 1018 1013 1079 1092 1116 1083 1096 1060 1112 1036 954	0.2372 0.2502 1
6.29	861 828 800 798 787 799 845 912 982 1090 1122 1181 1174 1122 1092 1151 1199 1204 1207 1167 1177 1238 1168 1033	0.2134 0.2199 0
6.30	943 914 907 875 873 872 931 976 1062 1144 1213 1263 1231 1196 1150 1190 1212 1231 1223 1228 1245 1317 1214 1081	0.2385 0.2125 0

Before processing the input data, i.e., during the pre-processing step, the dataset is normalized to exist within the range [0, 1], as shown in Table 2. A bright day is given a value of 0, a cloudy day is assigned a value of 0.5, and a wet day is given a value of 1.

5.2. Simulation Results

The MATLAB 15a software suite was used to run the simulation. The direct adaptive method for faster learning is the neural network trained using resilient BP. The various parametric values are chosen for the multiple approaches, explained in the appendix. As in Tables (3-5) and Figs. (2-10) compare actual demand numbers and anticipated demand values using the methodologies above with their errors, respectively.

Table 3. Comparison of hybrid techniques.

Time (hr.)	Actual load	BP	CS-BP	BA-BP
1	943	942	943	943
2	914	911	914	914
3	907	903	907	907
4	875	870	875	875
5	873	870	873	873
6	872	871	872	872
7	931	920	931	931
8	976	930	976	976
9	1062	1060	1062	1062
10	1144	1104	1144	1144
11	1213	1210	1213	1213
12	1263	1260	1263	1263
13	1231	1200	1231	1231
14	1196	1100	1196	1196
15	1150	1130	1150	1150
16	1190	1100	1191	1192
17	1212	1210	1213	1213
18	1231	1230	1232	1234
19	1223	1202	1224	1223
20	1228	1212	1226	1228
21	1245	1220	1247	1245
22	1317	1310	1318	1317
23	1214	1210	1219	1214
24	**1081**	**1080**	**1081**	**1081**

Table 3 compares actual demand numbers and anticipated demand values using the methodologies above for STLF.

Table 4. Comparison of errors.

BP	CS-BP	BA-BP
010	0	0
0.32	0	0
0.44	0	0
0.57	0	0
0.34	0	0
0.11	0	0
1.18	0	0
4.71	0	0
0.18	0	0
3.49	0	0
0.24	0	0
0.23	0	0
2.51	0	0
8.72	0	0
1.73	0	0
7.56	0.08	0.16
0.16	0.08	0.08
0.08	0.08	0.24
1.71	0.08	0
7.07	0.16	0
2.00	0.16	0
0.53	0.07	0
0.32	0.41	0
0.09	**0**	**0**

Table 4 explains the comparison between the errors using the methodologies above.

Table 5. Comparison of different values of errors.

Methods	Error in Maximum	Error in Minimum	Mean error
BP	20	15	1.84
CS-BP	5	3	0.04
BA-BP	**4**	**1**	**0.02**

Table 5 explains the comparison between the errors using the methodologies above.

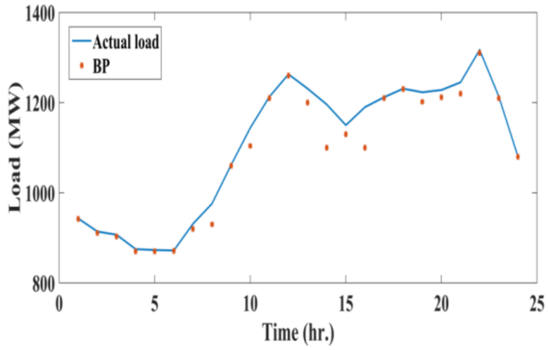

Fig. 2. Predicted load of BP with the actual load.

Fig, 2 explains the predicted loads of BP with the actual load.

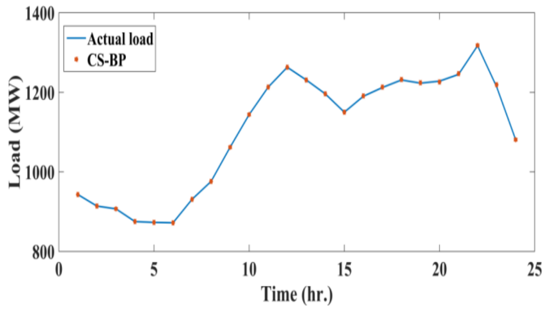

Fig. 3. Predicted load of CS-BP with the actual load.

Fig. 3 explains the predicted load of CS-BP with the actual load.

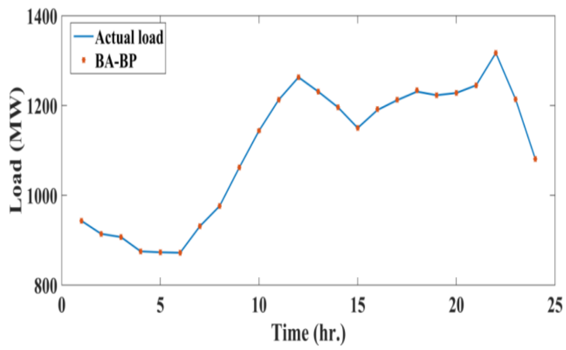

Fig. 4. Predicted load BA-BP with the actual load.

Fig. 4 explains the predicted load BA-BP with the actual load

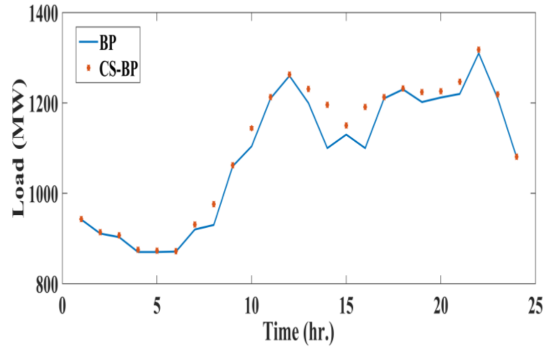

Fig. 5. Comparison between the predicted loads of BP and CS-BP.

Fig. 5 explains the comparison between the forecasted load of BP with CS-BP.

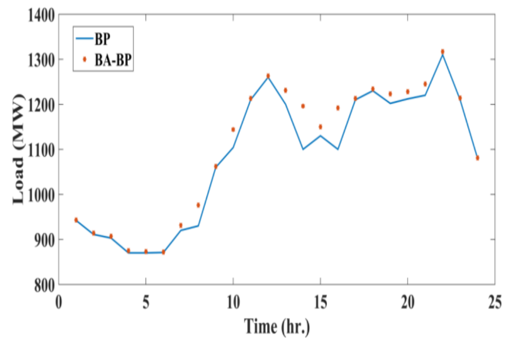

Fig. 6. Comparison between the predicted loads of BP and BA-BP.

Fig. 6 explains the comparison between the forecasted load of BP with BA-BP.

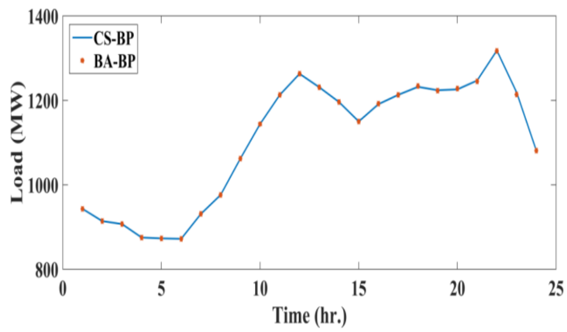

Fig. 7. Comparison between the predicted loads of CS-BP and BA-BP.

Fig. 7 explains the comparison between the forecasted load of CS-BP with BA-BP.

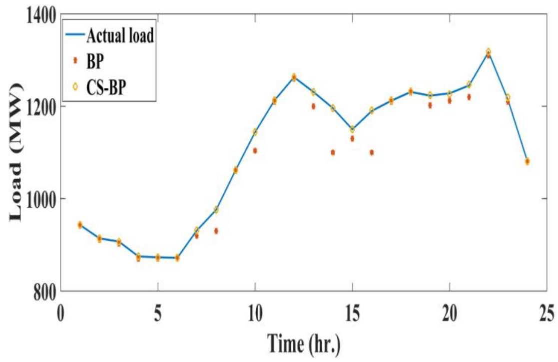

Fig. 8. Comparison between the actual load and predicted loads of BP, CS-BP.

Fig. 8 explains the Comparison between the actual and predicted loads of BP and CS-BP.

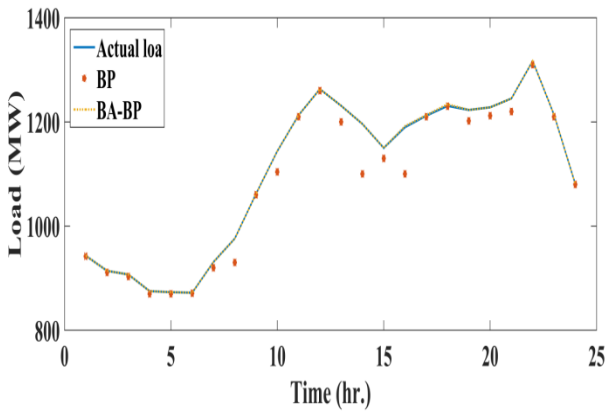

Fig. 9. Predicted loads of BP and BA-BP with the actual load.

Fig. 9 explains the Predicted loads of BP and BA-BP with the actual load.

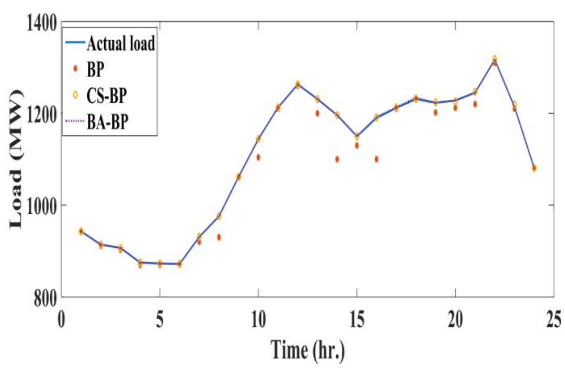

Fig. 10. Predicted loads of BP, CS-BP, and BA-BP with the actual load.

Fig. 10 explains the predicted loads of BP, CS-BP, and BA-BP with the actual load

6. CONCLUSION

The examination of the computational-intellectual in nature of various STLF methods is the main focus of this research. For an electrical utility's operation and production costs, the precision of a load forecasting technique has a significant effect. As a result, ANN is applied here for precise load demand forecasting, which is critical. The training for hybridized approaches, such as the algorithms like CS-BP and BA-BP, were discovered to outperform the traditional BP method. On the other hand, the CS method is far more resistant to parameter fluctuation than the conventional BP and finds the global optima more competently and with more excellent success rates. Because it does not require a virtual bat's velocity and factors of inertia weight, compared to other optimization methods, BA is faster, allowing it to get the best result among other procedures.

APPENDIX

Table A1. Parameters of CS-BP.

Parameter	Values
Values of n in nests	10
Values of α	0.1
Values of P_a	0.15

Table A2. Parameters of BA-BP.

Parameter	Values
Bats value	15
External archive size	80
Maximum value of F	3
Minimum value of F	2
Maximum value of W	0.2
Minimum value of W	0.1
Values of α	0.3
Iterations value	10000

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