Short-term load forecasting of the distribution system using cuckoo search algorithm

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ABSTRACT

For solving the different optimization problems, the cuckoo search is one of the best nature's inspired algorithms. It is an effective technique compare to other optimization methods. For this manuscript, we are using a back propagation neural network for the Xintai power plant consist of short-term electrical load forecasting. The limitation of back propagation is overcome by the cuckoo search algorithm. The function is used for cuckoo search is Gamma probability distribution and its result is compared with other possible cuckoo search methods. The mean average percentage error of Gamma cuckoo search is 0.123%, cuckoo search with Pareto based is 0.127% and Levy based cuckoo search is 0.407%. Other results of the cuckoo search are also found by a linear decreasing switching parameter with a mean average error is 0.344% and 0.389% of mean average error with the use of an exponentially increasing switching parameter. This improved cuckoo search algorithm brings good results in the predicted load which is very important for the Xintai power plant using short-term load forecasting.

1. INTRODUCTION

For a given problem, the optimal solution is obtained by a systematic procedure which is known as optimization [1]–[3]. It is used for the solution of maximum and minimum value of a problem and it is called cost function or objective function. There are two types of optimization problems, i.e., constrained and unconstrained problems. For the solution of all subsets, constrained problems are using and for all viable solutions, unconstrained functions are using [4]–[6]. Now a day, the optimization technique is adopted by different areas but not limited to specific systems. Like the transmission of electricity with a minimum loss, design of the system, operation of an electric circuit, generation of electricity and wireless communication routing. So, suitable optimization is required for the calculation of the computation time, converge rate and minimum or maximum value accurately [7], [8].

Nature's inspired algorithm is constructed by the researcher with the inspection of the behavior of animals. For the calculation of the distance between a bat and its surrounding, the researchers are using a bat-inspired algorithm [9]. This technique is also used for the calculation object in frequency tuning. Similarly, another nature's inspired algorithm is particle swarm optimization (PSO) where the fishes and birds are searching for their food considered as a potential solution in PSO [10]. In this technique, the animals are searching for food and they communicate the food to the rest of the group when the food source is found. Here, the food source is considered as the best solution for the processing of food among groups.
For the calculation of storm and prince, the differential evolution (DE) algorithm is using based on a population vector. This population vector consists of the size of the population which does not change during the searching process and uniform probability distribution. The different parameters are affecting the growth of the population i.e. mutation (new generation), crossover (increasing of diversity) and selection (finding of new solution). It is a robust and efficient process used for continuous space [11]. The behavior of foraging is used by Ant and Bee algorithm which is known as a chemical messenger. It is also known as pheromone [12]. For global optimization, the use of nature's inspired algorithm is simulated annealing (SA). This technique finds a good solution as compared to the limited time constraint of the global solution [13].

The other nature’s inspired algorithm is the cuckoo search (CS) algorithm which depends on the reproduction of the kids to increase the population [14]. But, this algorithm is good as compare to other algorithms because the other algorithms like DE, SA and PSO are derived from the CS algorithm has potential random walk and makes the balance between local and global search as compared to SA and GA [14]. The CS algorithm is better than the DE algorithm in terms of convergence speed and finding a good solution [15]. The computational efficiency of the CS algorithm is also good as compared to the PSO algorithm. The CS algorithm is also used in the smart grid for the minimization of loss of real power by control of fault and variation of voltage with allowable level [16]. So, with the consideration of time from one hour to one week, short term load forecasting (STLF) is using in industries. It is used for the planning and maintenance of power networks [17]. The factors which affect the STLF are considered for its work in [18].

The research gap from the above study is the old techniques are bringing poor results in STLF in past. So, in this manuscript, the research gap is fulfilled by the application of different distribution of cuckoo search algorithms in STLF which removes the disadvantages of old techniques. The other parts of this manuscript are arranged as follows: section 2 gives the simulation of STLF. Section 3 presents results and discussions of the work. At last, the conclusion of the work is represented by section 4.

2. STLF SIMULATION

It brings the results of the forecasted load in STLF. After that, the forecasted load will compare with the actual load. Then, we applied the mean absolute percentage error (MAPE) to calculate the error in the forecasted load as given in (1).

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{\text{Actual load} - \text{forecasted load}}{\text{Actual load}} \right) \times 100
\]

Where \( N \) is total number of the data set.

2.1. Collection of data

The historical data is collected from the Xintai power plant in the year 2016 from the date of 6.10 to 6.30. The data set is divided into three parts i.e. training, validation and testing as in [19]. Here sunny day is expressed by 0, cloudy day by 0.5 and rainy day by 1.

2.2. Pre-processing of data

The transfer function depends on the input value. If the input value is very large, then the output value does not contain the actual value. So it is avoided by set-up the normalized value within the range of [0, 1] using the minimap function in MATLAB 2015 software package. The processing data is also considered for the missing data.

2.3. Simulation result

The STLF using a feed-forward neural network (FFNN) [20–23] is shown in Figure 1. It contains 4 inputs, 25 hidden layers and one output layer with a transfer function. Here, the sigmoid function is used as a transfer function. Figure 1 explains the process of the data transformation from the input layer to the output layer through hidden layers. It also helps in the prediction of the forecasted load. The hourly based load is forecasted at the output of NN [24] uses Levenberg-Marquardt [25] back propagation for the training and forecasts.

Figure 2 shows the flow chart of a hybrid Levenberg-Marquardt. It is good as compared to Levenberg-Marquardt BP. Because BP [26–29] able to finds the minimum but it will not able to find the global minima in test function or loss. Figure 2 explains that, the feasibility solution of the forecasted load [30–32]. It helps in the removal of the disturbance signal present in the data set for the smooth train of FFNN.
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Table 2. MAPE with probability CS algorithm

| CS algorithms | MAPE (%) |
|---------------|----------|
| LevyCS        | 0.407    |
| CauchyCS      | 0.168    |
| GaussCS       | 0.264    |
| GammaCS       | 0.123    |
| ParetoCS      | 0.127    |

Table 3 explains the results of the different distribution of the cuckoo search. It also helps to know that, the proposed distribution is good for STLF. The predicted loads are very important for STLF which controls the price of electricity. Table 4 explains the MAPE results of the different distribution of cuckoo search. It also helps to know that, the proposed distribution is good for STLF which also gives less error in forecasted load. It indicates the load stability of different methods.

Table 3. Load forecasting with switching parameter CS algorithm

| Actual load (MW) | CSCo | CSLD | CSLI | CSPI | CSEI |
|------------------|------|------|------|------|------|
| 943              | 909  | 911  | 910  | 911  | 912  |
| 914              | 908  | 912  | 910  | 912  | 913  |
| 907              | 895  | 905  | 900  | 905  | 906  |
| 875              | 849  | 870  | 850  | 872  | 873  |
| 873              | 855  | 870  | 860  | 870  | 871  |
| 872              | 855  | 870  | 860  | 869  | 870  |
| 931              | 915  | 930  | 920  | 929  | 930  |
| 976              | 961  | 970  | 960  | 970  | 973  |
| 1062             | 1051 | 1060 | 1050 | 1060 | 1061 |
| 1144             | 1132 | 1140 | 1130 | 1142 | 1143 |
| 1213             | 1211 | 1212 | 1210 | 1211 | 1212 |
| 1263             | 1262 | 1262 | 1260 | 1259 | 1260 |
| 1231             | 1226 | 1230 | 1225 | 1230 | 1231 |
| 1196             | 1193 | 1195 | 1190 | 1192 | 1195 |
| 1150             | 1141 | 1149 | 1140 | 1130 | 1149 |
| 1190             | 1181 | 1189 | 1180 | 1183 | 1185 |
| 1212             | 1206 | 1210 | 1205 | 1209 | 1210 |
| 1231             | 1228 | 1230 | 1225 | 1228 | 1229 |
| 1223             | 1216 | 1220 | 1215 | 1211 | 1213 |
| 1228             | 1222 | 1227 | 1220 | 1228 | 1226 |
| 1245             | 1231 | 1240 | 1230 | 1234 | 1235 |
| 1317             | 1307 | 1310 | 1305 | 1308 | 1309 |
| 1214             | 1206 | 1210 | 1205 | 1205 | 1208 |
| 1081             | 1072 | 1080 | 1070 | 1074 | 1075 |

Table 4. MAPE with switching parameter CS algorithm

| CS algorithms | MAPE (%) |
|---------------|----------|
| CSCo          | 0.895    |
| CSLD          | 0.344    |
| CSLI          | 0.957    |
| CSPI          | 0.574    |
| CSEI          | 0.389    |
Table 5. MAPE with different algorithms

| Algorithms                                      | MAPE (%) |
|------------------------------------------------|----------|
| Back propagation neural network (BPNN)          | 3.42     |
| Genetic algorithm back propagation neural network (GA-BPNN) | 3.86     |
| Particle swarm optimization Elman neural network (PSO-ENN) | 1.17     |

Figure 3 (a) gives the forecasted load of the LevyCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 3 (b) gives the forecasted load of the CauchyCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation.

Figure 4 (a) gives the forecasted load of the GaussCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 4 (b) gives the forecasted load of the GammaCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation.

Figure 5 (a) gives the forecasted load of the Pareto distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 5 (b) gives the forecasted load of the different distribution of cuckoo search. These methods are bringing good accuracy and maintain load stability. These are robust methods which include all variable affect the load in a short interval of time and give less error in output with the use of MAPE calculation.

Figure 6 (a) gives the forecasted load of the CSCo distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 6 (b) gives the forecasted load of the CSLD distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation.
Figure 5. Comparison between actual and predicted loads: (a) using ParetoCS method and (b) using different methods

Figure 6. Comparison between actual and predicted loads: (a) using CSCo method and (b) using CSLD method

Figure 7 (a) gives the forecasted load of the CSLI distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variables affecting the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 7 (b) gives the forecasted load of the CSPI distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variables affecting the load in a short interval of time and gives less error in output with the use of MAPE calculation.

Figure 8 (a) gives the forecasted load of the CSEI distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variables affecting the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 8 (b) gives the forecasted load of the different distribution of cuckoo search. These methods are bringing good accuracy and maintain load stability. These are robust methods which include all variables affecting the load in a short interval of time and give less error in output with the use of MAPE calculation.
4. CONCLUSION

The optimization theory and its importance in the engineering problem are described in this manuscript. The different nature's inspired algorithms like PSO, DE and SA are discussed with their work. Here we got good results in efficient random work of the CS algorithm and maintained the balance between the local and global random walk as compared to other algorithms. It is also reviewed the work of NN for the STLF. The CS for improved BP is also discussed. The probability distribution and dynamic switching parameters are also discussed for the improvement of CS. For the electric load forecasting, 4-25-1 FFNN is used. The Gamma probability rings good results as compared to other methods and its error is 0.123%. The average error of Pareto and Levy based CS is 0.127% and 0.407%. The average error of decreasing switching parameter is 0.344% in CS and it is good as compared to exponentially increasing parameters i.e. 0.389%

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