# Short-term electricity load forecast using hybrid model based on neural network and evolutionary algorithm

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**Abstract.** Electricity load forecast needs to ensure minimum load wastage and requires intelligent decision-making systems to accurately predict future load demand. Learning capability, robustness and ability to solve non-linear problems make ANN widely acceptable. For accurate short-term load forecast (STLF), an ensemble soft computing approach namely ANN-PSOHm, composed of an artificial neural network (ANN) and particle swarm optimization (PSO) with homeostasis based mutation is proposed in this paper. To enhance the learning strength of ANN, PSO undergoes homeostasis mutation to bring greater diversity among solutions by exploring in wider search space.

To demonstrate the effectiveness of our proposed approach, three case studies on load data set of NEPOOL region (courtesy ISO New England) is performed to show the consequences of calendar effects (weekly, seasonal and yearly) on STLF. The experimental results show that ANN-PSOHm improves accuracy by 11.57% MAPE over ANN-PSO.

**Keywords:** Electricity Load Forecast Artificial Neural Network Particle Swarm Optimization Homeostasis Mutation

## 1 Introduction

The electricity load forecasting has become one of the major research areas in the field of forecasting. Accurate prediction helps in proper planning and operation of electric utilities and load scheduling [1]. Models like support vector machine [11], Bayesian [7], neural network [4], [15], [16], regression [3] are already available for a STLF. Among these, ANN has attracted the most and is capable of finding greater co-relation among forecasting variables. The overfitting problem, a chance of being trapped in local minima and no proper rule for selecting network architecture makes ANN undesirable. To overcome these difficulties, ANN has been integrated with other techniques to generate an accurate prediction [8]. Population-based methods have generated interest among researchers due to their evolution and combined them with the intelligence-based method to overcome the problem of STLF.

Unlike other population-based methods, particle swarm optimization (PSO) solve the stagnation problem due to its huge search space and diversity maintaining ability. It helps in finding an optimal solution in multi-dimensional search space by learning through self-experience and global experience [13]. PSO perform well with non-linear problems and converge faster in problems where analytical methods fail. But, results generated by PSO are not good, PSO still lacks its original problem of being trapped in a local minimum with regard to a multi-modal problem that has many sharp peaks [6]. To overcome this limitation of PSO, certain improvement can be made in PSO. It is more effective to improve existing heuristic with mutations, rather than iteratively executing an improved one starting from solutions generated randomly [5]. In [2], a new mutation feature has been combined with ant colony optimization (ACO) to increase the convergence rate and decrease computation time. In [20], PSO with Gaussian and adaptive mutation combined with SVM has been used for power load forecasting. Similarly, in [12], neural network based method has been implemented to find prediction intervals by combining PSO integrated with the mutation to generate diversity. Findings of this literature show that mutation brings diversity within the population-based algorithms and results in a higher convergence rate. Based on this, we have used newly proposed homeostasis mutation in our study. Homeostasis mutation help particles to adjust the condition that is optimal for their existence [18]. Homeostasis mutation has been integrated with differential evolution for software cost estimation. Results obtained show that homeostasis mutation help in generating more promising results.

From literature, it can be observed that appropriate learning algorithm and optimized network structure may enhance the learning capability of the neural network. To overcome the shortcomings of neural network, we propose a new approach to ANN by combining PSO with homeostasis mutation for solving the problem of the electricity load forecast.

The rest of this paper is organized as follows. Section 2 briefly describes the basics of artificial neural network, particle swarm optimization, and homeostasis mutation. Section 3 shows the implementation of our proposed approach on STLF and Section 4 demonstrates the performance of our proposed approach over traditional approaches. The last section provides a conclusion with some future remarks.

## 2 Background details

An artificial neural network is a computing system composed of several small processing elements called neurons. These neurons process information received from external inputs by its dynamic state response. ANN has great learning capability, which is inspired by the working of a human brain system [9]. ANN map relationship between input and output vector and output $F_j$ at node $j$ of a network is the weighted sum of its n input values $(X = x_1, x_2, x_3, .......x_k)$ given by Eq.-1.

$$F_j = \frac{1}{1 + e^{-ay_j}} \qquad j = 1, 2, 3, ....M \tag{1}$$

where, $a$ is a slope of the sigmoid function, $Y_j$ is the output of a single node $j$ and $M$ is number of output nodes in output layer.

PSO is population-based search algorithm, every particle moves in a multi-dimensional search space with velocity and this velocity dynamically get adjusted according to its own moving experience and its companions moving experience which continually falls towards the optimal solution [14], [19]. While implementing PSO, the position of each particle is randomly initialized and their velocity and position are updated by Eq. 2 and Eq. 3.

$$V_{new} = w * V_{old} + c_1 * r_1() * (P_{best} - P) + c_2 * r_2() * (P_{gbest} - P) \tag{2}$$

$$P_{new} = \delta * V_{new} + P_{old} \tag{3}$$

where, $V$ is velocity of the particle, $P$ is position of the particle, $P_{best}$ is particle's own best position, $G_{best}$ is global best position, $w$ is inertial weight, $r_1$ & $r_2$ is random value between 0 and 1, $c_1$ & $c_2$ is Constants, $\delta$ is retardation factor and $P_{old}$ is particle's previous position.

Homeostasis is a self-regulating process by which stability is maintained inside biological bodies by adjusting to the conditions that are optimal for their own survival by multiplying different parameter values depending on the nature of the problem and available counterbalancing resources [18] [17]. If homeostasis process is successful, then the life of the biological body continues else death occurs. With this concept, a new mutant vector is generated to maintain diversity within the population. Homeostasis mutation vector is defined by Eq. 4.

$$\gamma_{i,G} = \alpha_{best,G} + \delta_1.(\alpha_{r_i^1,G} * H_v - \alpha_{r_i^2,G} * H_v) \tag{4}$$

where, $\alpha_{best}$ is best vector of current population, $\alpha_{r_i^1,G}$ & $\alpha_{r_i^2,G}$ are random individuals generated from the entire search space, $H_v$ is Homeostasis value that lies between 0.01 to 0.1 and $\delta_1$ is random value between 0 and 1.

## 3 Short-term electricity load forecast

Load forecasting plays a very significant role in decisions of purchasing and generating electric load. Therefore, it is highly recommended to develop simple, feasible, fast and precise load forecasters. ANN is one of these forecasters, but sometimes it fails due to the problem of over-fitting and over-training. To overcome this problem, evolutionary based algorithms are combined to optimize network parameters such as PSO. Although PSO is a simple search algorithm, it suffers from partial optimism. One of the solutions to this problem is to bring diversity within the population by mutation. Figure 1 presents a flowchart of our load forecasting approach. The steps involved during load forecast are as follows:

- **Data splitting :** Split load data set into training and testing set and then normalize them. The training set is used to train the neural network and testing set generates the final performance of the proposed approach.

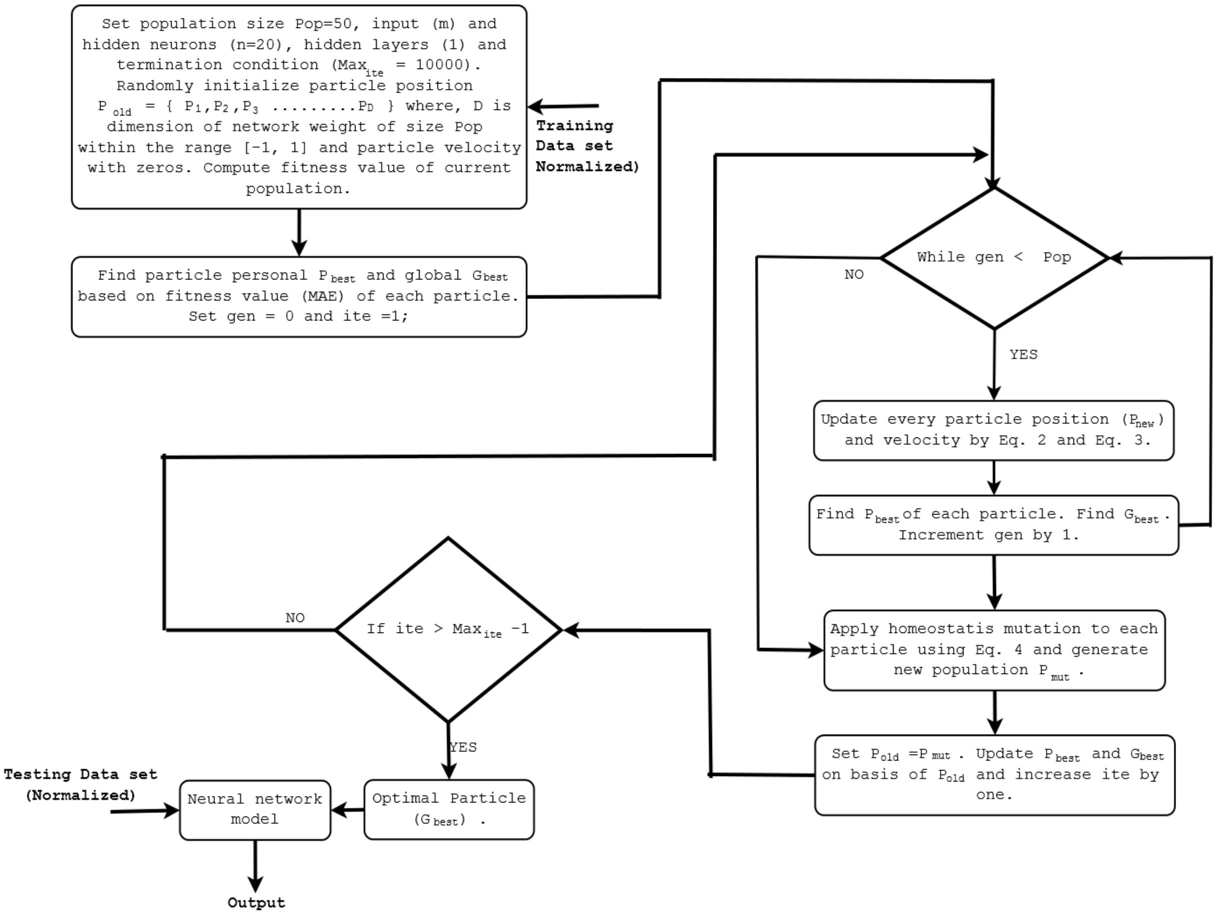



**Fig. 1.** The sequence of building ANN-PSOHm load forecast model.

- **Initialization :** Choose a multi-layer feed forward neural network with one hidden layer, 20 hidden neurons. Set maximum numbers of generation as 10000. Input neurons are the same as input variables chosen for network learning. Initialize random weights of neural network which represents particle position. Initialize particle velocity with zeros.
- **Velocity and position update :** Updated velocity and position of the particles by exchanging their findings with each other. These are updated by Eq. 5 and Eq. 6 respectively.
- **Mutation operator :** Homeostasis mutation is performed to generate diversity within the population which is integrated with PSO.
- **Update $P_{best}$ and $G_{best}$:** $P_{best}$ is the personal best value of each particle and $G_{best}$ is the best value within the swarm. Update $P_{best}$ and $G_{best}$ on the basis of fitness value of generated child particles,.
- **Training termination :** Training stops when maximum generation is reached.
- **Test and evaluation :** An optimal solution ($G_{best}$) is chosen for model testing. The forecasted load is again scaled back with the same factor with which training data is normalized to get its actual load value.

## 4 Experiments and result analysis

This section presents forecasting evaluation metrics and results of our proposed approach to verify the effectiveness of our proposed approach. Implementation is performed on MATLAB R2017a software on a Windows 8.1, 64-bit machine with Intel(R) Core(TM) i5 CPU 760 @ 2.80GHz with 1 processor.

New England Pool region load data set is used [10] to predict load demand. Following input parameters are considered in our case study for load prediction: dry bulb temperature, dew point temperature, hour of the day, day of the week, holiday/weekend indicator, previous 24-hr average load, 24-hr lagged load, and 168-hr (previous week) lagged load. Further, load data set is grouped in four different categories depending on England seasons namely autumn (September to November), winter (December to February), Spring (March to May) and Summer (June to August). Load data from the year 2004 - 2007 is chosen as training samples and data for the year 2008 and 2009 as testing samples.

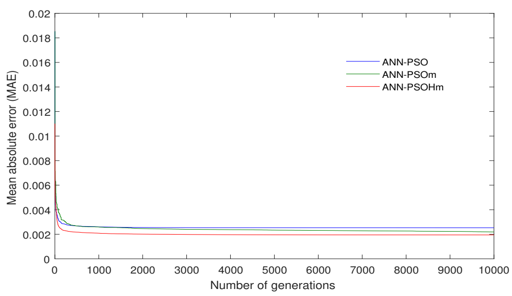
Statistical metrics used to evaluate the performance of our proposed approach is shown in Table 1. MAE generate total absolute forecasting error but data transformation, change in scale and noise data affect these metrics. RMSE is more stable and less sensitive to noise. NMSE estimates the overall deviations between predicted and measured values. MAPE describe forecasting error which indicates accuracy as a percentage. Daily peak MAPE is a mean value of percentage error change in every 24 hours.

**Table 1.** Evaluation metrics

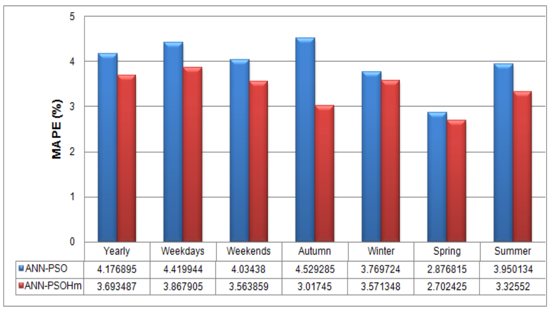
| S.No. | Metric | Error metrics equation |
|---|---|---|
| 1 | Mean absolute error | $MAE = \frac{1}{N}\sum_{j=1}^{N} \lvert y_j - y'_j \rvert$ |
| 2 | Root of mean squared error | $RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{n}(y_j - y'_j)^2}$ |
| 3 | Normalized mean squared error | $NMSE = \frac{1}{\Delta^2 N}\sum_{j=1}^{N}(y_j - y'_j)^2,\ \Delta^2 = \frac{1}{N-1}\sum_{j=1}^{N}(y_j - \bar{y})^2$ |
| 4 | Mean absolute percentage error | $MAPE = \frac{1}{N}\sum_{j=1}^{N}\frac{\lvert y_j - y'_j \rvert}{y_j} * 100$ |
| 5 | Daily peak mean absolute percent error | $Daily\ Peak\ MAPE = \frac{1}{N} * \frac{\lvert max(TL_m) - max(FL_m) \rvert}{max(TL_m)} * 100$ |

***Note:*** *$y_j$ = actual value of day $j$, $y'_j$ = predicted value of day $j$, $\bar{y}$ = mean of actual value, $\bar{y'}$ = mean of Predicted value, $FL_m$ = forecast load value for every 24 hours, $TL_m$ = target load for every 24 hours, $N$ = number of elements in training data.*

**Result Analysis-** To investigate the performance of our proposed approach, we have compared our approach with Linear regression, back propagation neural network (BPNN), generalized regression neural network (GRNN)), ANN-PSO and ANN-PSOm (ANN-PSO with Gaussian mutation).




(a)




(b)

**Fig. 2.** 2(a) Convergence rate shown by ANN-PSO, ANN-PSOm and ANN-PSOHm with increasing number of generations and 2(b) Graph showing comparison between ANN-PSO and ANN-PSOHm using MAPE as an error metric.

After successful implementation of forecasting approaches, rigorous analysis has been done to show the effectiveness of our proposed approach. Figure-2(a) shows the learning ability of neural network with PSO, PSOm, and PSOHm. This figure demonstrates that PSO with homeostasis mutation based ANN approach network has a faster convergence rate along with minimized error compared to the one without a mutation and with traditional mutation (Gaussian mutation). Homeostasis mutation operator creates greater diversity among the population than that of Gaussian mutation, which helps in increased exploration and exploitation capability of PSO.

Table-2 shows the comparative analysis of error metrics produced by the proposed approach (ANN-PSOHm) along with other traditional approaches for yearly, weekly and seasonal calendars. The analysis shows that ANN-PSOHm performs better with the least value of 3.69% MAPE and 548.46(MWh) MAE while BPNN generates higher error percentage. ANN-PSOHm lowers the MAE of ANN-PSOm by 0.1979% and ANN-PSO by 0.4838% because of higher diversity maintaining ability for the yearly forecast.

Table 2 also shows the result of the load forecast predicted over weekdays and weekends. Result reveals that ANN-PSOHm produced the best forecasting results with 0.2165% MAPE variation over

**Table 2.** Comparison of error metrics for year 2008 to 2009

| Calendar | | Algorithm | RMSE (MWh) | NMSE | MAE (MWh) | MAPE (%) | Daily Peak MAPE (%) |
|---|---|---|---|---|---|---|---|
| Yearly | 2008-2009 | Linear Regression | 876.1726 | 0.096165 | 645.5463 | 4.347394 | 3.979897 |
| | | GRNN | 1186.348 | 0.176303 | 840.4085 | 5.614846 | 4.497605 |
| | | BPNN | 1129.586 | 0.159836 | 852.0643 | 5.917566 | 4.978817 |
| | | ANN-PSO | 850.1101 | 0.090529 | 623.4493 | 4.176895 | 3.850884 |
| | | ANN-PSOm | 793.091 | 0.078792 | 580.3469 | 3.891394 | 3.683529 |
| | | ***ANN-PSOHm*** | ***746.1335*** | ***0.069738*** | ***548.4582*** | ***3.693487*** | ***3.616976*** |
| Weekly | Weekdays | Linear Regression | 900.5164 | 0.097886 | 664.8451 | 4.377995 | 3.753069 |
| | | GRNN | 1186.511 | 0.169934 | 819.543 | 5.362099 | 4.392156 |
| | | BPNN | 1216.229 | 0.178553 | 903.3511 | 5.880937 | 5.397314 |
| | | ANN-PSO | 912.4786 | 0.100504 | 665.1454 | 4.419944 | 3.675826 |
| | | ANN-PSOm | 861.6829 | 0.089626 | 618.0008 | 4.080443 | 3.743331 |
| | | ***ANN-PSOHm*** | ***785.8354*** | ***0.074542*** | ***576.6551*** | ***3.867905*** | ***3.35671*** |
| | Weekends | Linear Regression | 743.238 | 0.095049 | 561.3386 | 4.020267 | 4.877239 |
| | | GRNN | 1031.779 | 0.183175 | 757.3971 | 5.337287 | 4.598976 |
| | | BPNN | 915.8744 | 0.144333 | 702.525 | 5.21507 | 4.449637 |
| | | ANN-PSO | 765.5896 | 0.100852 | 566.2481 | 4.03438 | 4.161539 |
| | | ANN-PSOm | 753.5384 | 0.097702 | 555.2023 | 3.957178 | 4.112578 |
| | | ***ANN-PSOHm*** | ***687.7966*** | ***0.081398*** | ***502.7183*** | ***3.563859*** | ***3.998135*** |
| Season | Autumn | Linear Regression | 772.3644 | 0.099265 | 575.005 | 4.106392 | 3.958938 |
| | | GRNN | 1085.279 | 0.19599 | 760.4547 | 5.399025 | 4.028724 |
| | | BPNN | 1009.285 | 0.169504 | 758.4348 | 5.378196 | 5.167414 |
| | | ANN-PSO | 820.0898 | 0.111911 | 625.9252 | 4.529285 | 4.356279 |
| | | ANN-PSOm | 753.6649 | 0.094517 | 568.1676 | 4.057046 | 4.061379 |
| | | ***ANN-PSOHm*** | ***587.1167*** | ***0.057359*** | ***424.1457*** | ***3.017453*** | ***3.514169*** |
| | Winter | Linear Regression | 749.0536 | 0.100129 | 574.0396 | 3.825044 | 3.207751 |
| | | GRNN | 1184.201 | 0.250256 | 894.4198 | 5.801034 | 4.174389 |
| | | BPNN | 865.4497 | 0.133665 | 682.3763 | 4.463057 | 5.139326 |
| | | ANN-PSO | 735.6062 | 0.096566 | 566.1826 | 3.769724 | 2.753557 |
| | | ANN-PSOm | 715.8424 | 0.091447 | 551.4715 | 3.669858 | ***2.617679*** |
| | | ***ANN-PSOHm*** | ***694.8657*** | ***0.086166*** | ***537.4397*** | ***3.571348*** | ***2.65845*** |
| | Spring | Linear Regression | 587.7354 | 0.069575 | 438.0351 | 3.188387 | 2.684402 |
| | | GRNN | 777.7608 | 0.121838 | 565.8317 | 4.101719 | 3.716093 |
| | | BPNN | 751.2703 | 0.11368 | 574.2589 | 4.173754 | 4.042743 |
| | | ANN-PSO | 525.9699 | 0.05572 | 393.9254 | 2.876815 | 2.48476 |
| | | ANN-PSOm | 495.574 | 0.049466 | 373.4645 | 2.705296 | 2.681057 |
| | | ***ANN-PSOHm*** | ***482.9654*** | ***0.046981*** | ***367.3192*** | ***2.702425*** | ***2.355562*** |
| | Summer | Linear Regression | 891.4899 | 0.067415 | 700.9039 | 4.668146 | 3.78347 |
| | | GRNN | 1571.863 | 0.20958 | 1149.011 | 7.183112 | 6.020333 |
| | | BPNN | 1458.383 | 0.180411 | 1075.106 | 6.53912 | 6.223644 |
| | | ANN-PSO | 758.27 | 0.048772 | 595.4153 | 3.950134 | 3.003364 |
| | | ANN-PSOmm | 640.0093 | 0.034745 | 501.8638 | 3.319555 | 2.930752 |
| | | ***ANN-PSOHm*** | ***633.3212*** | ***0.034023*** | ***496.0001*** | ***3.32552*** | ***2.664822*** |

ANN-PSOm and 0.552% variation over ANN-PSO during weekdays. It shows that ANN-PSOHm achieved the most accurate prediction value with a variation of 0.1144% MAPE over ANN-PSOm and 0.1634% over ANN-PSO on weekends.

Results obtained in all four seasons show that ANN-PSOHm achieved the most predictive values. In the autumn season, the load forecast of ANN-PSOHm overcomes all approaches by generating the optimal results, with 3.0174% MAPE and 424.1457 (MWh) MAPE. In winter, ANN-PSOHm offered the least error than any other state-of-art algorithm, with a MAPE value of 3.5713% and MAE value of 537.4397 (MWh). Apart from the optimal solution produced by ANN-PSOHm, results also present that the error has been reduced by the MAPE value of 0.0985% and 0.1984% for ANN-PSOm and ANN-PSO respectively. For the spring season, ANN-PSOHm produced the ideal forecasting results than any other mentioned approach, with MAPE value of 2.7024% and MAE value of 367.3192 (MWh). The optimal solution produced by ANN-PSOHm shows that the error of ANN-PSOm and ANN-PSO has been reduced by MAPE value of 0.0028% and 0.1744%. For the summer season, ANN-PSOHm provides greater improvement in forecasting accuracy than any other mentioned approach, with a MAPE value of 3.3255% and MAE value of 496.0001 (MWh).

**Remark-** Summary of all three case study has been presented in Figure 2 (b). This figure shows the comparison of MAPE generated by ANN-PSO and ANN-PSOHm for all calendar effects. Graph reveal that ANN-PSOHm performed better in all the three case studies and is independent of calendar effects. There is 11.57% improvement of MAPE in ANN-PSOHm over ANN-PSO on yearly basis, 12.48% and 11.66% improvement of MAPE in ANN-PSOHm over ANN-PSO on weekdays and weekends respectively. The improvement of 33.37%, 5.26%, 6.06% and 15.81% MAPE in autumn, winter, spring and summer for ANN-PSOHm over ANN-PSO has been seen in the study.

## 5 Conclusion

Forecasting is a prediction or estimation of future events. In this paper, an ensemble soft computing approach composed of ANN and PSO with homeostasis based mutation is presented for forecasting the electricity load. Results are drawn from numerous experiments based on weekly, seasonal and yearly. It can be stated that homeostasis mutation provides great diversity among the population and accurate results than that of the algorithms without mutation and with Gaussian mutation when applied to short-term load forecast application. Homeostasis mutation supplies a great combination of exploration and exploitation within a population, resulting in a higher convergence rate and wider search space. Further, this approach can be used in other applications such as wind forecasting and stock market prediction.

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