Electrical Energy Output prediction using Cuckoo Search supported Artificial Neural Network

Sankhadeep Chatterjee[1], Nilanjan Dey[2], Amira S. Ashour[3], Cornelia Victoria Anghel Drugarin[4]

[1]Department of Computer Science and Engineering, University of Calcutta, Kolkata, INDIA Email – chatterjeesankhadeep.cu@gmail.com

[2]Department of Information Technology, Techno India College of Technology, Kolkata, INDIA Email – neelanjandey@gmail.com

[3]Department of Electronics & Electrical Communications Engineering, Faculty of Engg., Tanta Univ., EGYPT. College of CIT, Taif University, KSA. Email - amirasashour@yahoo.com

[4]Department of Electrical and Informatics Engineering, "Eftimie Murgu" University of Resita, Romania, Email – c.anghel@uem.ro

Abstract.
Increasing demand of electricity in presence of ever demanding improvement in environmental issues attracted researchers in designing efficient, accurate and robust models to predict energy output of combined steam and gas turbine mechanisms. The applicability of such systems highly depends on their sustainability. Thus, in the process of making the combined mechanisms more trustworthy, it is inevitable to predict their energy output while put against certain constrains pushing the system to the limits. The acceptability of the aforesaid turbine systems is judged in terms of their profitability. Nevertheless, the prediction of output energy plays a vital role in that. In machine learning, NN based models have been proven to be a trustworthy in dealing with critical prediction tasks. Though as a matter of fact, it has also been found that NNs do not perform well while traditional learning algorithms are used to train it due to their premature convergence to local optima while finding the optimum weight vectors of NNs. Motivated by this, the present work proposes a Cuckoo Search (CS) supported NN (NN-CS) and a Particle Swarm Optimization (PSO) supported NN (NN-PSO) to efficiently predict the output of electrical energy output of combined cycle gas turbines. Five features such as ambient temperature, relative humidity and ambient pressure in gas turbines and exhaust vacuum from steam turbine have been utilized in the current study. The performance of NN has been improved significantly while CS is used for training. The proposed model has been compared with well-known Multilayer perceptron Feed-

forward Neural Network (MLP-FFN) & NN-PSO in terms of root mean squared error. Proposed NN-CS achieved an average of 2.58% RMSE.

Keywords : Artificial Neural Network, Particle Swarm Optimization, Cuckoo Search, MLP-FFN, Combined cycle, Electrical energy, Gas Turbines

1 Introduction

Greater demand of electricity all over the world, especially in developing countries is a major concern. The ever increasing demand is indirectly effecting price levels of minerals and materials used to produce electricity and thereby increasing the price of electricity itself. One way to tackle this problem is to engage more advanced and efficient energy producing mechanism [1]. Recent trends pointed out Gas Turbines (GT) as a potential solution and it is currently being used in several power plants around the globe. Although, it is important to ensure that such systems are reliable and sustainable. Only then it is possible to cope with the current challenges of power demand effectively. Reliability and sustainability of a GT highly depends on the accurate prediction of output energy while subjected to profit. Thus, it becomes imperative to predict the power generation of GT based systems accurately and effectively. Traditional attempts include [2], which proposes a simulation method for performance analysis of different GTs. The stage-stacking method was utilized for compressor while stage-by-stage model was adopted for turbine. The simulation based method was quite accurate in real life scenario. The effects of different ambient conditions such as ambient temperature, ambient pressure etc. are well studied [3 - 8]. ANN has been successfully employed in determining performance of industrial GTs as well. Muhammad et al. [22] proposed a recurrent neural network based approach to predict the performance of GTs in a very short time. Though, application of machine learning and especially neural network in prediction of output energy prediction is still at its primitive level. Few research works considered ANN based method for this task [9]. The ANN based method proposed, has utilized a primitive MLP-FFN trained with back-propagation strategy and achieved reasonable accuracy.This lack of presence of ANN based methods in prediction of output energy of GTs has motivated the authors to apply more accurate and efficient NN based models for the same. Chen et al. [19] revealed that ANN trained with traditional learning algorithms can prematurely converge into local optima during optimization. The problem can be overcome by employing meta-heuristics algorithms in the training phase of ANN. Such nature inspired meta-heuristic algorithms [20] are the Artificial bee colony (ABC), Ant colony optimization (ACO), Bacterial foraging optimization algorithm (BFOA), Cuckoo search (CS), Particle swarm optimization (PSO) and Firefly algorithms (FA). Meta-heuristic trained NNs performed well in predicting real life problems to a greater extent [10, 11]. Consequently, an extension to the preceding literatures is suggested in the current work to realize accurate and trustworthy model for electrical energy output prediction of GTs. A model based on NN trained with Cuckoo Search (CS) optimization algorithm [12] is proposed, where the CS is a very efficient meta-heuristic optimization technique that recently developed [13].In addition most of the previous works on the same have proposed Machine learning based systems, although no comparison of different models is reported. The current study employs three different models for the prediction of electrical energy output of GTs. First, a MLP-FFN trained with scaled conjugate gradient descent algorithm [21] has been employed, next NN trained with Particle Swarm Optimization (NN-PSO) is employed and finally the Cuckoo Search based NN model (NN-CS) is used. The models are compared in terms of Root Mean Squared Error (RMSE).

The rest of the article is arranged as following; Section 2 introduces the Cuckoo search algorithm along with the Neural Network which has been trained with it. Next in Section 3 describes experimental methods and flow of the experiments in detail. Finally, Section 4 discusses the experimental results.

2 Cuckoo Search based Neural Network

2.1 Neural network training using Cuckoo Search

Typically, the CS algorithm establishes its effectiveness for improved convergence towards global optimization compared to other global search algorithm. Therefore, it is involved in the current study to support the ANN [14 - 17] for optimal weight selection. These optimal NN weights are used in prediction of the electrical energy output of GTs. The working flowof CS algorithm based optimization of the weight is given in Figure 1. In the proposed system, the following assumptions are considered; Each Cuckoo nest is represented by the weightvector w.For the CS algorithm, the number of populations is set to 20, whereas other algorithm parameters are $\boldsymbol{\alpha}$ = 0.25, $\boldsymbol{P_a}$ = 0.01 and $\boldsymbol{\lambda}$ = 1.3. The parameters are set by running the algorithm 50 times with different configurations and the best configuring is taken. The range of the weight w has taken within the interval [-1.0, 1.0].The fitness of each nest is determined, where the fitness function is the Root Mean Squared Error (RMSE) of the NN.All cuckoos move towards the nest using the Lévy flight scheme after every iteration.The fitness of the solution should be linked to the objective function and start iterating to generate a new nest by Levy flight while keeping the current best.A new nest is produced along with the best nest of the previous iteration.Once the CS algorithm reaches its maximum iteration, it stops and gives the global optimum solution for the weightvector w, which are the optimized of values using the CS algorithm. In our current the maximum iteration was set to 300.These optimal weights $w$are used in predicting the electrical energy output of GTs.The block diagram of the CS procedure is illustrated in Figure 1. This procedure is used in the proposed system for prediction of the electrical energy output of GTs as in the following section.The training phase of Neural Network using PSO is similar as the NN-CS model. The training phase follows a similar flow as described in Figure 2.

3 Experimental Method

The proposed system for the prediction of the electrical energy output of GTs using the NN-CS is depicted in Figure 2 which illustrated that the CS algorithm is employed to optimize the input weight vectors of the NN by minimizing the RMSE of the NN. Prediction of the electrical energy output of GTs using CCPP dataset is performed, which is supported by the CS algorithm for optimal weight selection. Finally, test phase is performed followed by performance metrics calculations. The Cuckoo Search and PSO fitness function by considering the RMSE is calculated as the difference between the predicted values by the NN and the actual discovered values. The RMSE of a prediction model with respect to the computed variable v_{c_k} is determined as the square root of the mean-squared error is given by:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(v_{d_k} - v_{c_k})^2}{n}} \quad (1)$$

Where,v_{d_k} denotes the originally observed value of k^{th} data instance and v_{c_k} denotes the predicted value by the prediction model.The experimental setup for NN-PSO based model can found in [10]. The dataset used in current study is composed of 9568 data points collected when the combined cycle plant is set to work with full load over 674 different days. The dataset spans a variety of ambient conditions over 6 years of operation. The dataset is freely available in [23].

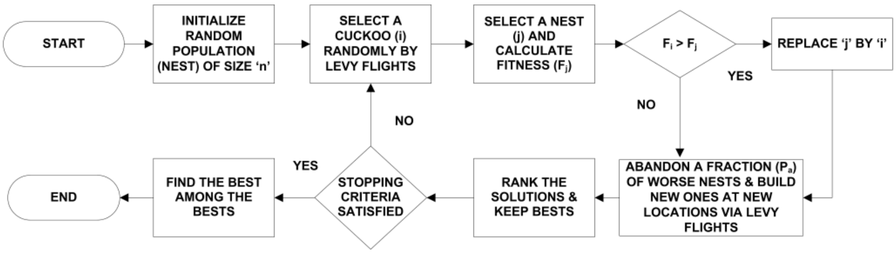

Fig. 1. Flowchart of Cuckoo Search algorithm

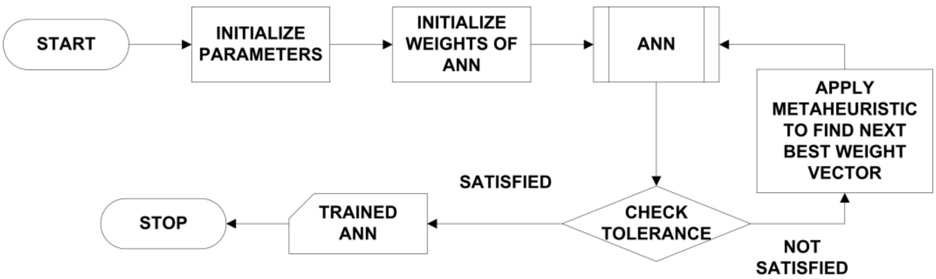

Fig. 2. Flow chart of training phase of ANN using different Metaheuristics

4 Results & Discussion

The current article proposes a NN-CS model for predicting electrical energy output of a GT from a combined cycle power plant. The experiments are carried out by following the experimental setup described in the previous section. The testing of the models is based on a 5×2 cross validation scheme [18]. In this scheme the dataset is randomly shuffled to produce five instances each of which is employed in a 2-fold cross validation scheme. The experimental results for each of the tests are tabulated in Table 1. The table basically tabulates RMSE for each of the experiments for the models considered in the current study. The average RMSE of MLP-FFN is 3.92% while NN-PSO improved the result and achieved average RMSE of 2.94%. The proposed NN-CS based model outperformed the others with an average RMSE of 2.58%. The superiority of NN-CS is further established in Figure 3. The figure depicts the RMSE of all the experiments for each of the proposed models in the current study. The figure depicts the RMSE of MLP-FFN model for all the experiments in smooth line, the same for NN-PSO based model is depicted in a semi dashed and NN-CS in dashed line.

Table 1. Comparison of Experimental Results for MLP-FFN, NN-PSO & NN-CS

	MLP-FFN (%)	NN-PSO(%)	NN-CS (%)
Experiment 1	3.58	2.88	2.25
Experiment 2	4.15	2.95	2.84
Experiment 3	3.95	3.22	2.59
Experiment 4	3.65	2.84	2.68
Experiment 5	4.25	3.15	2.14
Experiment 6	4.36	3.06	2.89
Experiment 7	3.68	2.88	2.65
Experiment 8	3.89	2.78	2.49
Experiment 9	3.82	2.68	2.61
Experiment 10	3.91	2.96	2.68
Average	**3.92**	**2.94**	**2.58**

The plot reveals that NN-PSO performed well in every experiment compared to the MLP-FFN model. In all of the experiments the RMSE for NN-PSO is significantly less than the MLP-FFN model. Although, NN-CS based model reduced the RMSE further in almost all the experiments and established its ingenuity.

The prediction of output electrical energy by the NN-CS model is depicted in Fig 5. The plot reveals that the output predicted by NN-CS based model is highly closed to the expected output in the testing phase. This plot further establishes the claim of ingenuity of NN-CS based model. A similar plot is depicted for NN-PSO model in Fig 4. A comparison of both figures reveals that the predicted output energy of NN-CS model is more dense and closer to the perfect fit line (dashed) while in case of NN-PSO several predicted values have significant deviation from the expected output. This establishes the superiority of NN-CS model over NN-PSO in predicting output electrical energy of GTs.

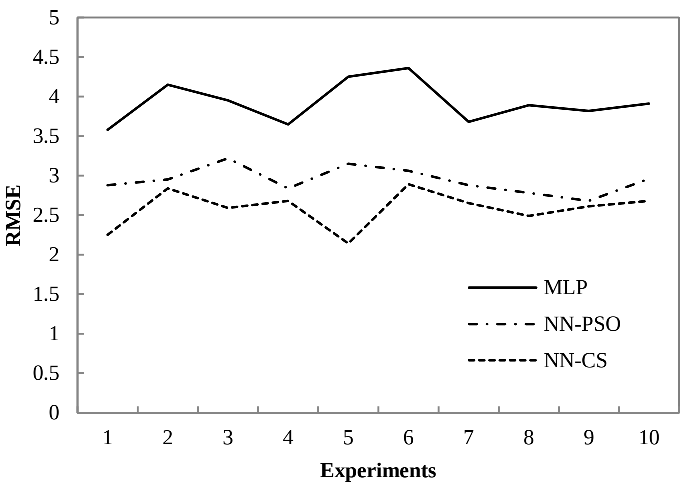

Fig. 2.RMSE of different experiments for different models

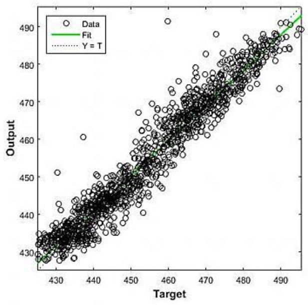

Fig. 3. Prediction electrical energy output by NN-PSO based model

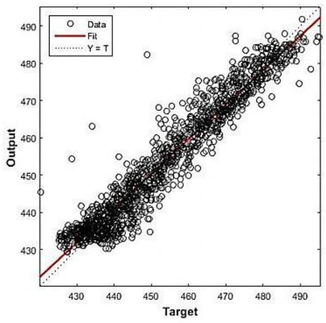

Fig. 4. Prediction electrical energy output by NN-CS based model

Conclusion

In the present work a Cuckoo search based Neural Network model has been proposed along with a well-known NN-PSO based model to predict the electrical energy output of a GT depending on different ambient features. Accurate prediction of electrical output energy is inevitable for the success of GTs. The current work has studied three different models and tested them on a dataset collected from a combined cycle power plant in different times of six years of span. The features considered in the current study are ambient temperature, relative humidity and ambient pressure in gas turbines and exhaust vacuum from steam turbine. Proposed models are compared with each other in terms of RMSE. Experimental results have suggested that MLP-FFN is poor at predicting output energy; NN-PSO reduced the RMSE to some extent. Average RMSE achieved by the NN-PSO model was 2.94% while NN-CS based prediction model achieved an average of 2.58% RMSE. The study has revealed that the NN-CS based model is far more superior to traditional machine learning algorithms which have been applied to solve this task recently. Nevertheless, other meta-heuristics based Neural Networks are still needed to be tested to see if more accurate results can be obtained.

References

1. singingriver.com/wp-content/uploads/2014/10/smepa_insert_august08.pdf

2. Lee, Jong Jun, and Tong Seop Kim. "Development of a gas turbine performance analysis program and its application." Energy 36.8 (2011): 5274-5285.

3. W. Yang, M. Su, Influence of moist combustion gas on performance of a sub-critical turbine, Energy Conversion and Management, vol. 46, is. 5, pp. 821-832, Mar. 2005.

4. F. R.P. Arrieta, E. E. S. Lora. "Influence of ambient temperature on combined-cycle power-plant performance", Applied Energy, vol. 80, pp. 261–72, Mar. 2005

5. H. H. Erdem, S. H. Sevilgen, "Case study: Effect of ambient temperature on the electricity production and fuel consumption of a simple cycle gas turbine in Turkey", Applied Thermal Engineering, vol. 26, is. 2-3, pp. 320-326, Feb. 2006

6. R. Lugo-Leyte, J.M. Zamora-Mata, M. Toledo-Velázquez, M. Salazar- Pereyra, A. Torres-Aldaco, "Methodology to determine the appropriate amount of excess air for the operation of a gas turbine in a wet environment Original Research Article",Energy, vol. 35, is. 2, pp. 550- 555, Feb. 2010

7. F. Basrawi, T. Yamada, K. Nakanishi, S. Naing , "Effect of ambient temperature on the performance of micro gas turbine with cogeneration system in cold region", Applied Thermal Engineering,vol. 31, is. 6-7, pp. 1058-1067, May 2011

8. A. De Sa, S. Al Zubaidy, "Gas turbine performance at varying ambient temperature",Applied Thermal Engineering, vol. 31, is. 14-15, pp. 2735-2739, Oct. 2011

9. Fast, M., M. Assadi, and S. De. "Development and multi-utility of an ANN model for an industrial gas turbine." Applied Energy 86.1 (2009): 9-17.

10. Chatterjee, Sankhadeep, et al. (2016) Particle swarm optimization trained neural network for structural failure prediction of multistoried RC buildings. Neural Computing and Applications: 1-12.

11. Chatterjee, Sankhadeep, et al. (2016) Forest Type Classification: A Hybrid NN-GA Model Based Approach. Information Systems Design and Intelligent Applications. Springer India. 227-236.

12. Yang, X.S., and Deb, S., Cuckoo search via Lévy flights. In: Proceedings of World Congress on Nature & Biologically Inspired Computing, India, pp 210--214. (2009)

13. Walton, S., Hassan, O., Morgan, K., and Brown, M.: Modified cuckoo search: A new gradient free optimisation algorithm. J. Chaos, Solitons& Fractals, vol. 44 (9), pp. 710--718. (2011)

14. Maren AJ, Harston CT, Pap RM (2014) Handbook of neural computing applications. Academic Press, San Diego

15. Baughman DR, Liu YA (2014) Neural networks in bioprocessing and chemical engineering. Academic press, San Diego

16. Rojas R (2013) Neural networks: a systematic introduction. Springer Science & Business Media, Berlin

17. Dash RN, Subudhi B, Das S. (2010) A comparison between MLP NN and RBF NN techniques for the detection of stator inter-turn fault of an induction motor. In: 2010 International conference on industrial electronics, control and robotics (IECR), pp 251–256

18. T. G. Dietterich, "Approximate Statistical Tests for Comparing Supervised Classification Learning Algorithms", Neural Computation, vol. 10, pp. 1895-1923, 1998.

19. Jeng-Fung Chen, Quang Hung Do and Ho-Nien Hsieh, Training Artificial Neural Networks by a Hybrid PSO-CS Algorithm, Algorithms 2015, 8, 292-308.

20. SatyasaiJagannath Nanda, Ganapati Panda, A survey on nature inspired metaheuristic algorithms for partitional clustering, Swarm and Evolutionary Computation, Volume 16, June 2014, Pages 1–18.

21. Møller, Martin Fodslette. "A scaled conjugate gradient algorithm for fast supervised learning." Neural networks 6, no. 4 (1993): 525-533.

22. Muhammad, M., Mohammadreza, T. B., &Karim, Z. A. (2015, December). Methodology for short-term performance prognostic of gas turbine using recurrent neural network. In Industrial Engineering and Engineering Management (IEEM), 2015 IEEE International Conference on (pp. 787-791). IEEE.

23. Tüfekci, P. (2014). Prediction of full load electrical power output of a base load operated combined cycle power plant using machine learning methods. International Journal of Electrical Power & Energy Systems, 60, 126-140.