Data-Driven Beetle Antennae Search Algorithm for Electrical Power Modeling of a Combined Cycle Power Plant

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Abstract. Beetle Antennae Search (BAS) is a newly developed nature-inspired algorithm, which falls in the class of single-solution driven metaheuristic techniques. This algorithm mimics the searching behavior of the longhorn beetles for food or potential mate using their long antennae. This algorithm is potentially effective in achieving global best solutions promptly. An attempt is made in this paper to implement the data-driven BAS, which exploits the Cascade Feed-Forward Neural Network (CFNN) training for functional approximation. The proposed technique is utilized to model the electrical power output of a Combined Cycle Power Plant (CCPP). The power output of a power plant could be dependent on four input parameters, such as Ambient Temperature (AT), Exhaust Vacuum (V), Atmospheric Pressure (AP), and Relative Humidity (RH). These parameters affect the electrical power output, which is considered as the target variable. The CFNN based predictive model is shown to perform equivalently while compared with published machine learning based regression methods. The proposed data-driven BAS algorithm is effective in producing optimal electric power output for the CCPP.

Keywords: Beetle Antennae Search Algorithm· Artificial Neural Network· Data-Driven Modeling· Combined Cycle Power Plant· Surrogate Based Optimization

1 Introduction

Beetle Antennae Search (BAS) is a recently proposed technique, which is inspired by the odour sensing mechanism of beetles using their long antennae [1]. These longhorn beetles family is substantially large (26,000 species). Antennae works as a sensor with complex mechanism. Fundamental functions of such sensors are to follow the smell of the food or to sense the pheromone produced by the potential opposite gender for reproduction. The beetle moves its antennae in a particular direction to sense the smell of the food or mates. This movement is random in neighborhood area and directed according to the concentration of smell. Hence, the beetle turns to right or left depending upon high concentration of smell or odour data gathered by the antennae sensors. These phenomenon is depicted in Fig. 1. Based on this phenomenon, the BAS algorithm could be synopsized.

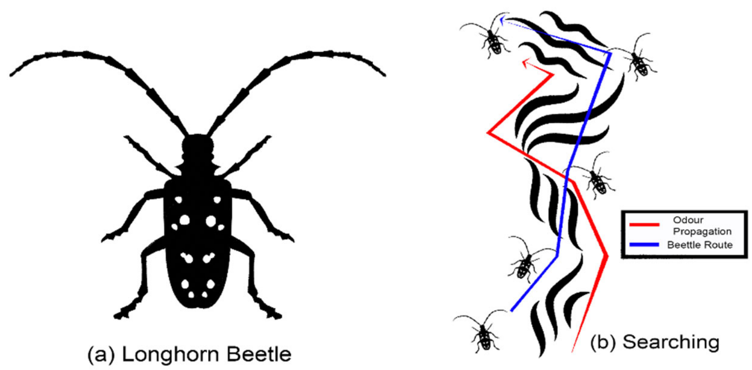

Fig. 1. Beetle Search procedure based on odour sensing mechanism using antennae

1.1 Data-Driven Optimization

Data-driven optimization has evolved as a novel category of optimization technique recently, which exploits small amount of empirical data to approximate objective functions and eliminate the need of practicing computationally complex mathematical expressions or expensive experimental runs. It facilitates the use of the traditional or existing optimization algorithms, such as, the exact methods, the evolutionary and bio-inspired algorithms as optimal solution searching modules. It uses different types of prediction or regression tool as surrogate models, such as Artificial Neural Network (ANN), Response Surface Method (RSM), Radial Basis Function (RBF), Kriging Model, Support Vector Machine (SVM), and Decision tree etc. Data-driven modeling is also categorized as the black-box modeling when there is little or no information available about the processes [2-3]. These techniques are capable of estimating functional relationships among process variables based on the sampled data obtained using Design of Experiment (DOE) techniques [4-5]. Accuracy of the solution approximation would be crucial while training the surrogate models. Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) could be used as performance measures. The lower the performance metric score, the better the accuracy of the model. Once the data-driven surrogate model is trained, an appropriate optimization algorithm, e.g. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Bat Inspired Algorithm (BA), and African Buffalo Optimization (ABO) etc. could be employed as the solution search technique which would be near optimum [6]. Surrogate models are substantially prompt and efficient therefore, these are computationally inexpensive.

1.2 Combined Cycle Power Plant (CCPP)

A Combined Cycle Power Plant (CCPP) consists of the gas turbines (GT), the steam turbines (ST) and the heat recovery steam generators (HRSG). In this system, gas and steam turbines are the generators of electric power in every cycle. This electric power is then transferred from one turbine to another [7]. Notable amount of hot exhaust is produced along with the electrical power by gas turbine in the CCPP. This waste heat is channelized further through a water-cooled heat exchanger to generate the steam. This steam could be further processed through a steam turbine and a generator to obtain the additional electric power. This system is one of the finest examples of the waste recycling systems. This type of power plants are being evolved more in number and becoming a topic of interest to the researchers recently. Ref. [8] has considered one such CCPP for their research and collected data from there. The CCPP layout is portrayed in Fig. 2.

Major process variables of a CCPP are, the ambient temperature (AT), atmospheric pressure (AP), and relative humidity (RH) for the gas turbine and the exhaust vacuum (V) for the steam turbine. These parameters are considered as input in the CCPP dataset. The dataset is available in the UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets/combined+cycle+power+plant). The produced electrical power from the CCPP is considered as output response. Possible ranges of the input and response variables are provided as, AT (1.81 - 37.11 °C), V (25.36 –81.56 cm Hg), AP (992.89–1033.30 mbar), RH (25.56 - 100.16 %), PE (420.26-49576 MW). The data file consists of 9568 sample data points spread over six years (2006-2011). Table 1 portrays the statistics of the data.

Table 1. Statistics of the input and output data

	AT	V	AP	RH	PE
Min	1.81	25.36	992.89	25.56	420.26
Max	37.11	81.56	1033.3	100.16	495.76
Mean	19.65123	54.3058	1013.259	73.30898	454.365
Std. Dev.	7.452473	12.70789	5.938784	14.60027	17.067

2 Research Methodology

In this study, the focus is put on the Multi-Layer Perceptron (MLP) network, which is used as the fitness evaluating function for BAS. The MLP networks are suitable for predictive modeling because of their natural ability of finding the correlations among the random inputs and outputs [9]. MLPs are classified in two categories, (1) Cascade Feed-Forward Neural Network (CFNN) and (2) Feed-Forward Neural Network (FFNN). Unlike CFNN, the FFNN does not have any direct connection between inputs and outputs.

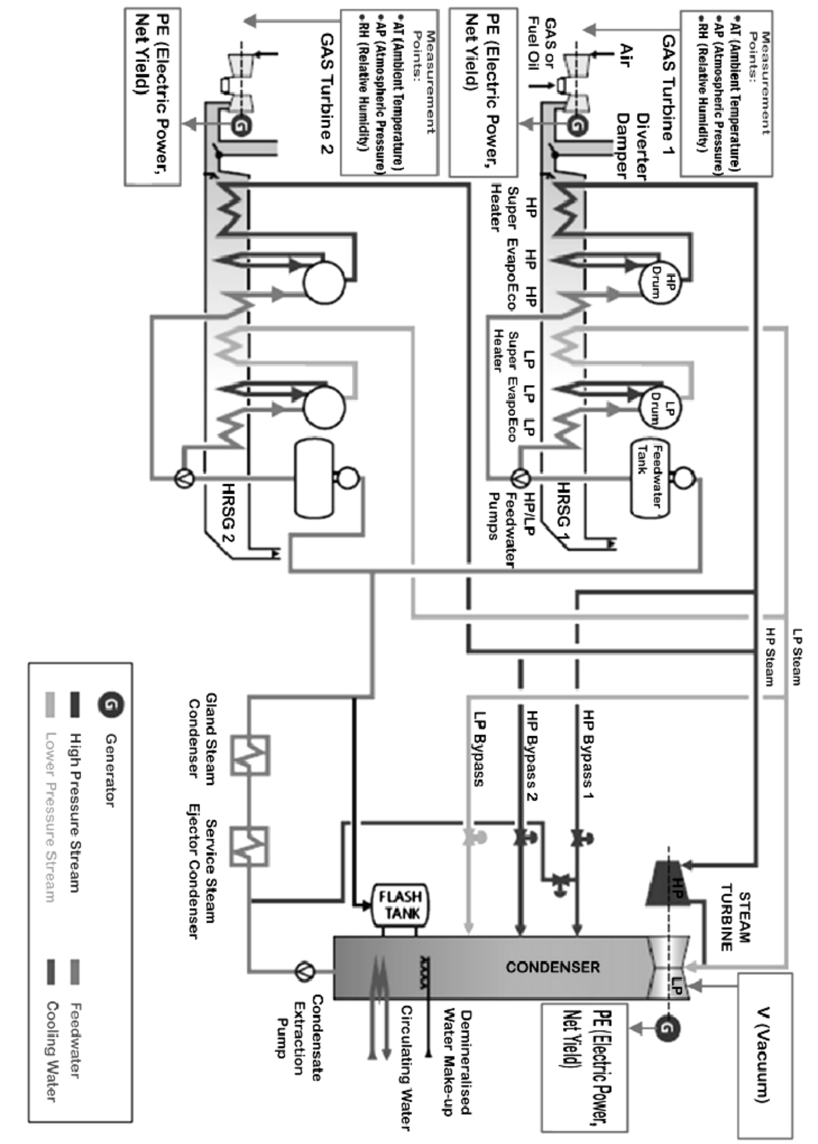

Fig. 2. CCPP Layout [8]

2.1 Cascade Feed-Forward Neural Network (CFNN)

The MLP variant used in this study, is known as CFNN. The CFNN architecture is shown in Fig. 3.

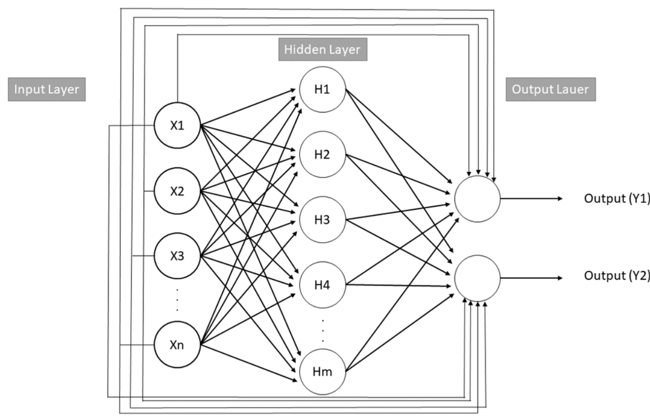

Fig. 3. CFNN schematic diagram

It has some direct connections among the inputs and the outputs. It has *n* input neurons, *m* hidden layers neurons, and output neurons. The output equation is shown as,

$$y_i = \sum_{k=1}^{n} Z_i^k \times w_j^k x_k + Z_i^{oa}\left(\sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{1}$$

Where Z_i^{oa} is denoted as activation function for i^{th} output y_i, $w_{ji}{}^{oa}$ is the weight from jth hidden layer neuron to i^{th} output node, Z_k^{ha} is the activation function for j^{th} hidden layer neuron, $w_{jk}{}^{ha}$ is the weight from the k^{th} input to the j^{th} hidden layer neuron, and x_k is the k^{th} input signal. Z_i^k is the activation function and w_j^k is the weight from the inputs to outputs. Further, if some bias is added to the input layer, the equation (1) becomes,

$$y_i = \sum_{k=1}^{n} Z_i^k \times w_j^k x_k + Z_i^{oa}\left(\beta_i + \sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\beta_j + \sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{2}$$

Where β_i is the weight from the bias to the i^{th} output layer neuron and β_j is the weight from the bias to the j^{th} hidden layer neuron. Z_i^k is the activation function and w_j^k is the weight from the inputs to outputs. The network weight in CFNN is approximated based on the neurons in the input layer.

2.2 Performance Measure

The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are utilized as the performance evaluation metrics for the trained CFNN model. The MAE and RMSE are the improved metrics, which accurately measure the regression errors [10]. If the model produces the output response *y* and the target response is *t* and *i* is the index of experimental run for the machining processes. The MAE and RMSE are calculated using,

$$RMSE = \frac{1}{N}\sqrt{\sum_i (y_i - t_i)^2} \quad (3)$$

$$MAE = \frac{1}{N}\sum_i |y_i - t_i| \quad (4)$$

2.3 BAS Algorithm

According to ref. [11], the BAS algorithm is demonstrated as,

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Algorithm 1: BAS algorithm for global minimum searching

Input: Establish an objective function $f(xt)$, where
Variable $x^t = [x_1, \ldots, x_i]^T$, initialize the
Parameters x^0, d^0, δ^0.
Output: x_{bst}, f_{bst}.

While *(t < T_{max}) or (stopping condition)* **do**
Generate the direction vector unit $\vec{b}$ according to Eq. (5);
Search in variable space with two kinds of antennae according to Eq. (6) or (7)
Update the state variable x_t according to Eq. (8)
if $f(x_t) < f_{bst}$ **then**
$f_{bst} = f(x_t)$, $x_{bst} = x_t$.
Update sensing diameter *d* and step size δ using Eq. (9) and (10)
Return x_{bst}, f_{bst}.

The BAS algorithm is a single solution based metaheuristic technique which is similar to the Simulated Annealing (SA) algorithm. The BAS starts with a randomly generated beetle with the position vector x^t at t^{th} time instant ($t = 1, 2, \ldots, n$) and the position is evaluated using some fitness function *f* which determines the smell or odour concentration [12]. The beetle would decide to move further based on the smell concentration by generating the next promising position for it to move. This next position would be obtained in the neighborhood of the previous position by following some rules. These rules are derived from the behavior of the beetle, which includes exploring and exploiting behavior. The directional move is determined by,

$$\vec{b} = \frac{rnd(k,1)}{\|rnd(k,1)\|} \tag{5}$$

Where, *rnd* is considered as a random function, and *k* signifies the input dimensions of the beetle position. The exploring is performed on right (x_r) and left (x_l) sides as the beetle moves similarly using its antennae. The moves could be presented using,

$$x_r = x^t + d^t \times \vec{b} \tag{6}$$
$$x_l = x^t - d^t \times \vec{b} \tag{7}$$

Where *d* is the sensing length of the antennae, which implies the exploiting skill. Value of *d* must enfold the solution space which is large enough. This phenomenon could further guide the algorithm to escape from being stuck at the local optima and improve the convergence speed. Secondly, to formulate the behavior of detecting, following iterative model is generated,

$$x^t = x^{t-1} + \delta^t \vec{b} sign\big(f(x_r) - f(x_l)\big) \tag{8}$$

Where δ is the step size of the exploring mechanism, which follows a decreasing function of *t*. *sign* represents a sign function. Update rules are defined using the antennae length *d* and step size δ, as,

$$d^t = 0.95d^{t-1} + 0.01 \tag{9}$$

$$\delta^t = 0.95\delta^{t-1} \tag{10}$$

The proposed data-driven BAS framework is depicted in Fig. 4. It shows that the CFNN model is used as a surrogate model to the BAS algorithm, which can evaluate the candidate solutions effectively. The CCPP module of this framework, is used for collecting data.

3 Computational Results and Analysis

To validate the proposed data-driven BAS algorithm, the CCPP dataset is used from the UCI Machine Learning Repository, which is portrayed in subsection 1.2. This data is divided in 70:30 for the training, and testing. Thereafter, 100 data points are randomly picked for the validation purpose. Levenberg-Marquardt backpropagation is used for the network training. Parameters for the CFNN are set as, learning rate = 0.1, error goal = 1e-7, and number of epochs = 1000. The convergence property of the data-driven BAS algorithm is demonstrated in Fig. 5 for 500 generations. The parameters of the BAS algorithm are set as $d^0 = 0.001$, and $\delta^0 = 0.8$. It could be observed that the proposed algorithm achieves global optimal solution promptly. The best solution obtained is f_{bst} [PE= 498.2971] with the optimal parameters set = [AT=7.9415, V=42.92045, AP=1003.937, RH=51.678] $^{t=253}$. This solution shows better electric power output than the best result portrayed in the dataset [AT=5.48, V=40.07, AP=1019.63, RH=65.62, PE=495.76].

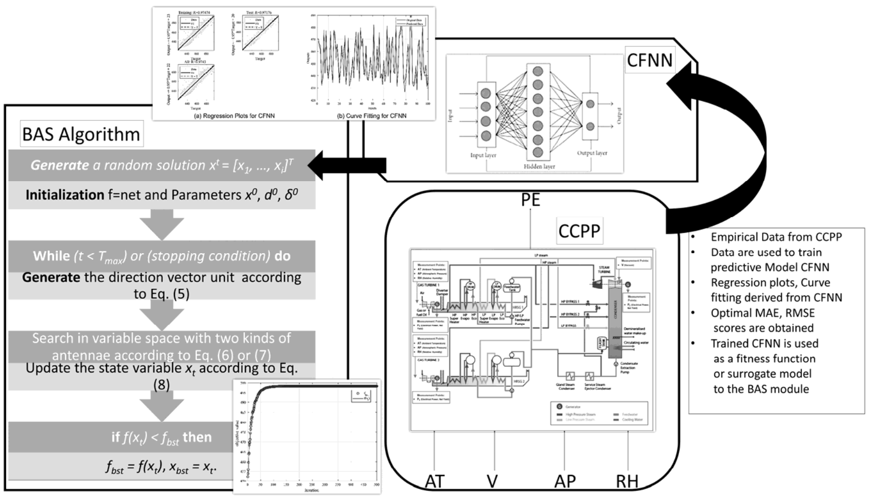


Fig. 4. CFNN Assisted Data-Driven BAS framework

Based on the data considered in ref. [6], input variables are divided in 4 subsets and the CFNN based predictive model is tested on these. The obtained MAE and RMSE scores are compared with seven different regression models published previously. Results are depicted in Table 2. It could be observed that the CFNN model is clearly better than the published six models out of seven except the one. The CFNN scores are very close to the best published results with low variance scores overall.

Table 2. Comparison among the CFNN prediction model and published methods [6]

	AT		AT-V		AT-V-AP		AT-V-AP-RH		Mean		Variance	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
CFNN	3.92	5.08	3.24	4.25	2.98	4.01	2.92	3.89	3.27	4.31	0.21	0.29
LMS	4.28	5.43	3.91	4.97	3.62	4.58	3.62	4.57	3.86	4.89	0.10	0.17
SMO	4.28	5.43	3.91	4.97	3.62	4.58	3.62	4.56	3.86	4.89	0.10	0.17
K*	4.26	5.38	3.63	4.63	3.36	4.33	2.88	3.86	3.53	4.55	0.33	0.41
BREP	4.07	5.21	3.03	4.03	2.95	3.93	2.82	3.79	3.22	4.24	0.33	0.43
M5R	3.98	5.08	3.42	4.42	3.26	4.22	3.17	4.13	3.46	4.46	0.13	0.19
M5P	3.98	5.09	3.36	4.36	3.23	4.18	3.14	4.09	3.43	4.43	0.14	0.21
REP	4.09	5.23	3.26	4.34	3.21	4.29	3.13	4.21	3.42	4.52	0.20	0.23

Fig. 6 portrays the CFNN regression plots (with R-Values) and the scatter plot of the CFNN predictive model. The prediction result for electrical power output of a CCPP is substantially accurate. Due to this accuracy and high R-values obtained during CFF training, cross-validation is not performed. This is demonstrated based on the actual PE values and estimated PE values (for the 100 data points obtained randomly from the dataset). It is observed from Table 2, that the CFNN obtains (MAE=2.919 and RMSE=3.895) scores for the subset of all four parameters and very close to the BREP scores (MAE=2.818 and RMSE=3.787). Therefore, this could be concluded that the CFNN based predictive model is an efficient tool for electric power prediction in the CCPP. This could be further used as a tool to forecast the accurate power output for the next hours or days for the CCPP. Thereafter, the BAS algorithm is depicted as an efficient data-driven optimization tool, which could select the right set of the process parameters and optimal level of the electric power output. This approach could be employed to increase the efficiency of CCPP. This further proves that the BAS is capable of achieving the near-optimal solution even when the specific objective function is not available and the process is solely dependent on the empirical process data.

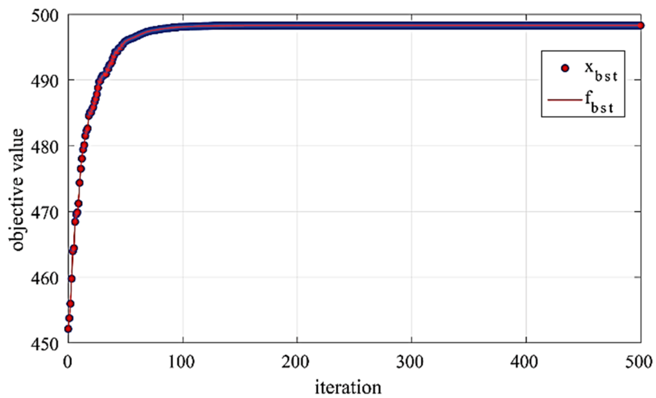
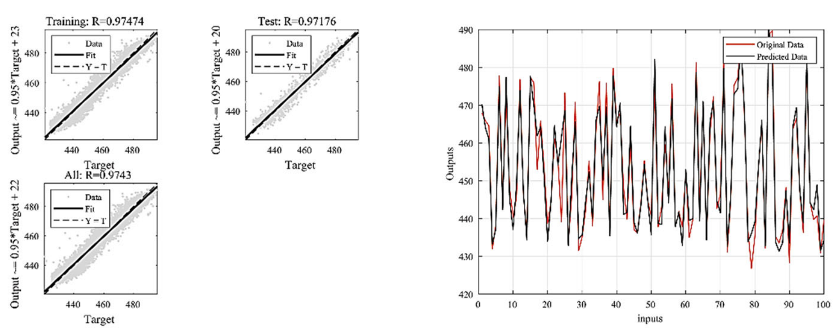


Fig. 5. Convergence plot for data-driven BAS Algorithm



(a) Regression Plots for CFNN

(b) Curve Fitting for CFNN

Fig. 6. Regression plots and curve fitting plots (Scatter plot) of four parameter subset by CFNN

4 Conclusions

This article proposes a novel data-driven CFNN assisted BAS algorithm for optimal power output of the CCPP. The BAS is a latest metaheuristic algorithm in the category of the single solution based metaheuristics, which mimics the searching behavior of the longhorn beetles. The CFNN network is used as the predictive model for output approximation for the CCPP. The proposed technique is successfully tested on the CCPP dataset published in the UCI Machine Learning Repository. The conclusions are, the CFNN model is competitive and can produce outputs with very low MAE and RMSE scores, the BAS algorithm is substantially efficient and capable of producing optimal parameter sets and output of the CCPP, and The CFNN assisted BAS produces next hour/day/month prediction accurately and enhances the efficiency of the CCPP. This technique could be further extended for various engineering process modelling and could be compared with the other standing metaheuristics in future.

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