Prediction of Hourly Generated Electric Power Using Artificial Neural Network for Combined Cycle Power Plant

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Abstract—**Energy is one the important subjects in the world because of its cost and achievable. In order to reduce energy costs, some kinds of plants may have founded and are managed related to demands and environmental conditions. Artificial neural network is one of the famous artificial intelligent in literature to solve nonlinear problems from medical to constructions. Artificial neural network uses nodes to weights to achieve the output. In this study, obtainable power per hour from combined gas and steam turbine power plant tries to be predicted. Data include 9685 features and 4 variables. Artificial neural network results have been evaluated with mean square error and two fold cross validation. Mean square error and two-fold cross validation are statistical evaluation methods to evaluate the results. Dataset divided 2 sections to test and train. Two datasets are trained and tested using two fold cross validation and generated R^2 value to evaluate the fitting performance. R^2 is famous comparing method to figure out the fitting ability. The obtained mean square error after two fold cross validation and R^2 value are 3.176 and 0.96675, respectively.**

Index Terms—**artificial neural network, power plant, predicting, generated power, two fold cross validation**

I. Introduction

Energy is one of the important subjects that must be managed targeting maximum efficiency. There are many ways to generate energy methods such as oil, hydro or renewable sources. For energy generating method, management is so important not to waste time and energy more over pollution. In this study, Combined Cycle Power Plant (CCPP) is targeted. CCPP is combined gas and steam turbine and heat recovery steam generator. System performance is related to ambient temperature, exhaust vacuum, relative humidity and ambient pressure. Environmental conditions affect the generated power. Weather temperature in winter season goes to below zero, on the contrary, in summers reach the forty degrees. Changed weather and related conditions make difficult to manage the power plant [1]-[3]. It is not easy to solve the all variables for undetermined situations and more over relations among the variables are not linear. In order to find out any expectable and valid predicted output between inputs variables and output, artificial intelligence was used. Artificial intelligences are widely used to solve many kinds of nonlinear problems even if dataset includes huge data or multi inputs [4], [5]. In this study, Artificial Neural Network (ANN) is used to predict CCPP hourly generated power.

Artificial neural network is one of the common and famous ways to solve nonlinear problems in literature from medical to construction [6]-[8]. ANN was reported first 1956 [9]. An ANN has lots of paralleled interconnected computational unit which are connected as a hierarchical structure. The elementary of this unit is called as neuron which has computational ability. ANN has learning ability via neurons and weights among the neuron connections.

Performance of ANN was evaluated using two fold cross validation and statistical methods, R^2, MSE. Two-fold cross validation is a method to improve reliability of results via crossing the test and train dataset [10], [11]. Error between predicted and real output value was evaluated using Mean Square Error (MSE). MSE is a widely used method to present error power.

In this study, ANN was arranged as two layers, 20 nodes of first layer, 1000 epochs, logsig transfer characteristic and Levenberg-Marquart method to increase the execution speed. ANN performance was evaluated two fold cross validation, R^2 statistical value and Mean Square Error (MSE). In this study, R^2 value is a way to show fitting ability between obtained test results and real data values. Deviation of the error spreads from -51.3 to 17.94. On the contrary, the target value varies from 420.26 to 495.76 Mega watts per hour. Mean Square Error 3.176 and predicting capacity was calculated as 96%. Mean Square Error is 17.39.

II. Proposed Method

ANN is famous an impressive model among the artificial intelligences. ANN is based on simulation of neural activity. Nodes and connections among the nodes are form of the structure. Proposed method based on ANN and evaluated using MSE and two fold cross validation

Data structure: Data structure has been taken from University of California data base (UCI). UCI has wide repository for machine learning to achieve qualified

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research studies. Combined cycle power plant data structure has been created through the 6 years and uploaded to UCI by Pınar Tüfekci and Heysem Kaya [12].

Combined cycle power plant dataset has 4 attributes except output and 9568 number of instance. The attributes are temperature, ambient pressure, relative humidity, exhaust vacuum and hourly electrical energy output. Hourly electrical energy output is output and created from real application from 2006 to 2011. Table I contains maximum and minimum values of the features.

TABLE I. STATISTICAL FEATURES OF THE DATASET

Attributes	Unit	Max	Min	Average
Temperature	℃	1.81	37.11	19.651
Ambient pressure	mBar	992.89	1033.3	1013.2
Relative Humidity	%	25.56	100.16	54.305
Exhaust Vacuum	cmHg	25.36	81.36	73.308
Generated Energy	MW	420.26	495.76	454.36

From the Table I, temperature, ambient pressure and relative humidity are environmental conditions. Exhaust vacuum is sign for stack performance and burned gas.

Combined cycle power plant: In electric power generation a combined cycle is an assembly of heat engines that work in tandem from the same source of heat, converts it into mechanical energy and usually drives electrical generator [13]. First starting is related to gas turbine generator and after first cycle, working fluid of the first engine has enough entropy to suck the waste energy. Combining two or more thermodynamic cycles results in improved overall efficiency, reducing fuel costs. In stationary power plants, a widely used combination is a gas turbine, a steam power plant and steam turbine. In this study, CCPP based on Gas Turbines (GT), Steam Turbines (ST) and heat recovery steam generators. In order to improve the efficiency, gas turbine and steam turbine were merged [14], [15]. Fig. 1 shows the all combined cycle power plant.

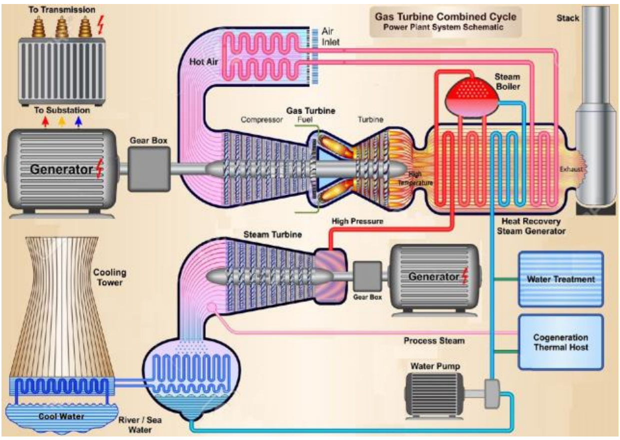

Figure 1. Schematic of a combined cycle power plant.

First step to generate electricity starts with gas turbine. Exhaust of the gas turbine leads to boil the water. Boiled water is distributed two ways to makes hot the inlet air and goes to steam boiler to go to steam turbine.

General concept is to obtain maximum regeneration and system force to achieve maximum heat recovery to improve the efficiency. Efficiency at first cycle may occur lower than 40% but after heat recovery processing executed, efficiency can be improved more than 50%. One of the maximum energy efficiency was reported as over 60% by Siemens in 2011 [16]. After installation and beginning of the energy producing, improving system efficiency has much importance to hold at high point. CCPP has nonlinear characteristics and CCPP data was tried to solve using heuristic and numerical methods to achieve acceptable solution [17]-[20].

III. ARTIFICIAL NEURAL NETWORK

ANN is the oldest and one the common artificial intelligence in literature. ANN is famous an impressive model among the artificial intelligences. ANN is inspired from neural activity. ANN emulates the neural neuron characteristics. ANN has learning ability comes from neurons [21], [22]. Nodes and connections among the nodes are form of the ANN structure. A generalized ANN structure includes an input layer, hidden layer and an output layer. Output layer has only one node connected to previous nodes. Every node has its own transfer function. Connections among the nodes have weighted multiplier to affect the following node input. A Multi Layer Perception (MLP) ANN structure is shown in Fig. 2.

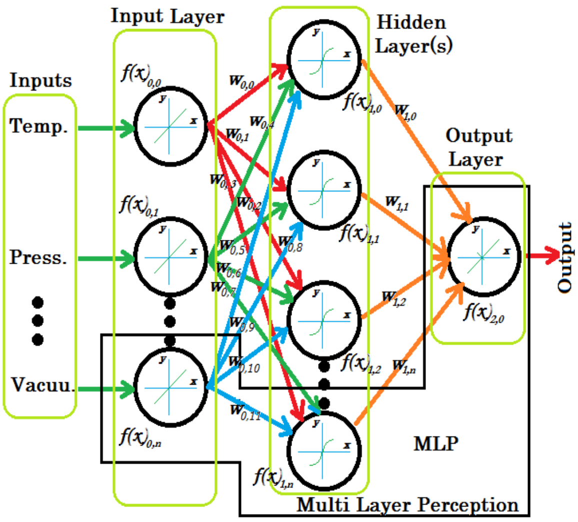

Figure 2. MLP-ANN structure.

ANN learns by examples like human through the learning process. An ANN structure consists of an input layer with three neurons, a hidden layer with three neurons, and an output layer. ANN can generate a valid solution for any kind of nonlinear problems. This problem can be related to pattern recognition, predictions or data classification and so on. For an ANN, three nodes from three layers is called Multi Layer Perception (MLP) [23]. This is miniature of an ANN. The back propagation is widely used to adjust connection weights and bias values using training. Each MLP layer is formed by a number of predefined neurons.

The neurons in the input layer can be explained as a buffer which distributes the input signals x_i to next neurons in the hidden layer without humiliating the signal. Each neuron j in the hidden layer sums the input signals x_i after weighting them with the strengths of the respective connections $w_{i,j}$ from the input layer, and computes its output y_j as a function f of the sum (Eq. (1)):

$$y_i = f(\sum w_{i,j} y_i) \tag{1}$$

where, f is the activation function which is needed to transform the weighted sum of all signals influence a neuron. Although there are many activation function for ANN application due to different dataset groups, logsig is very common activation function for ANN applications. All activation functions have different transfer curve that may be threshold, linear tangent etc. In the end, the output neuron in the output layer can be calculated similarly. Dataset after divided as two parts; the training parameters and structure of the MLP was set as 40% training, 30% validation and 30% testing. In this study, the experimental studies were performed on MATLAB(™) 6.5 environment.

IV. Evaluation Method

Performance measurement methods Performance measurement is a way to compare and present for any implementation. Every measurement method has its own characteristic and implementation method. Mean square error and R^2 are famous methods of success measurement for any implementation. N-fold cross validation is a method to check system reliability. In this study, n-fold was arranged as two fold cross validation.

System performance is characterized using MSE and R^2. Training and testing are 50% of whole data. Next step is same execution of the rest data to obtain two-fold cross validation. Fig. 3 shows one cycle of the execution of two fold cross validation.

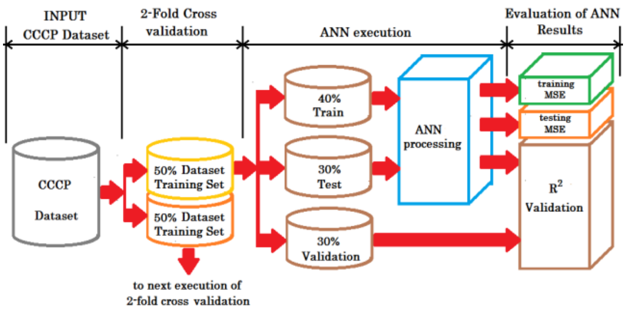

Figure 3. Evaluation method for ANN results.

Mean square error: Mean square error is one of the simplest ways to evaluate any success. Mean and depends on mean of difference among observations and real values [24], [25]. Equation (2) shows MSE calculation. MSE measures the average of the squares of the "errors", between target and observed value.

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \tag{2}$$

MSE is widely used to show success and reliability in literature [26], [27].

Two-Fold cross validation: Two fold cross validation is way to improve reliability of the results. According to number of the samples, n-fold cross validation vary from 2 to 10. For low data structure 10 fold cross validation may be applied [28], [29]. For huge structures, two fold cross validation could be adequate. N-fold cross validation name comes from data divided *n*. For 10-fold cross validation, data is divided by ten and 9 pieces of divided data will be used for train and the rest piece of data is for test. This execution will be processed for ten times and every route one pieces of data is changed to one of the train pieces. Fig. 4 shows a ten-fold cross validation to understand. In this study, because of the number of data two-fold cross validation arranged.

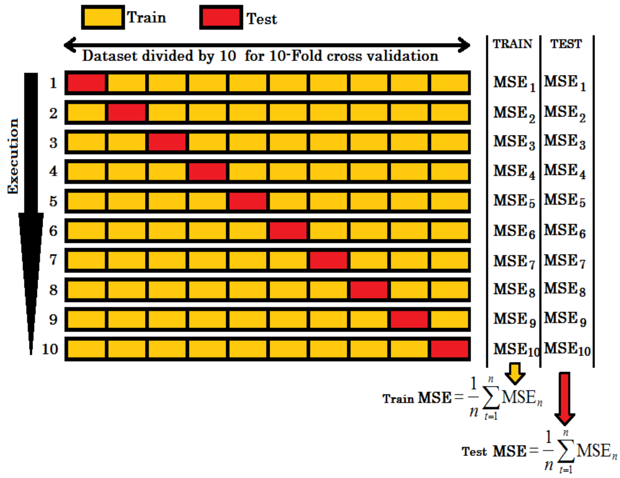

Figure 4. Execution of 10-fold cross validation.

N-fold cross validation is a way to present reliability of the application and has common using among the artificial intelligence applications [30], [31]. In this study, CCPP data structure was accepted as huge thus two fold cross validation was used.

R^2 value: R^2, statistical value, is a way to present similarity of two successive pictures that how they cover each other. Fig. 5 shows the geometrical meaning of R^2.

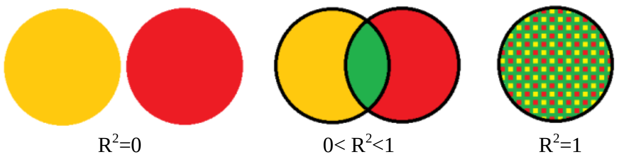

Figure 5. Meaning of R2.

If two attempts or input and output patterns are same R^2 equals to 1. Meaning of 0 is maximum dissimilarity; on the contrary 1 is parameter of maximum similarity. Equation (3) shows R^2 value and R^2 is common statistical method to measure of the success [32], [33].

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{3}$$

In this study, R^2 used to measure validation of ANN for CCPP dataset.

V. Result and Discussion

In this study, CCPP dataset evaluated with ANN to achieve hourly maximum power generating. ANN outputs were evaluated using R^2 and MSE. In order to create a cross check and improve the ANN reliability, two-fold cross validation was applied. First, dataset was divided 2 parts as 50% and one part designed as train and the rest part is arranged for test. After ANN evaluation, train and test parts are changed each other's and applied to ANN again. Table II shows the results after two fold cross validation and was executed ANN.

TABLE II. STATISTICAL FEATURES OF THE DATASET

	Step 1	Step 2	Two-Fold
Train	0.97316	0.97509	0.974125
Test	0.96893	0.96458	0.966755
Validation	0.96516	0.96921	0. 967185
All	0.97082	0.97188	0.97135

From the Table II, obtained R^2 values are close to 1 that sign of the success. It is important that not easy to understand if ANN learned or memorized. Good training and low test and low validation value point out memorizing. On the contrary balanced and regular acceptable results for test and validation sign the learning capability. Fig. 6 shows R^2 evaluation of ANN results. From the Fig. 6, *x* and y axis includes same values. In case of same values for predicted and observed data, R^2 turns a linear line as *y*=*x* function.

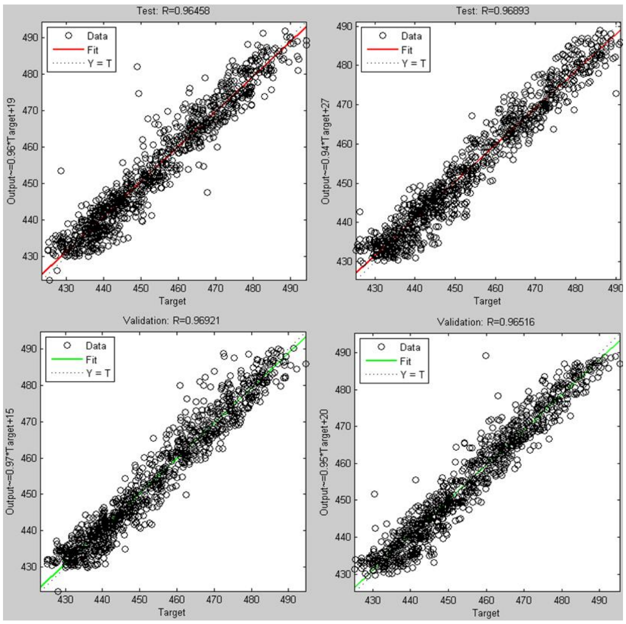

Figure 6. Evaluation of ANN results after two fold cross validation using R^2.

Clustering on the *y*=*x* line point out the success rate. Fig. 6 shows test and validation of ANN results. The obtained values for the R^2 show the success as much close to 1. R^2 testing method was both two-fold cross validation segments.

VI. CONCLUSION

ANN is famous an impressive model among the artificial intelligences. CCPP is a method to generate energy in real life and based on energy recovery idea to improve efficiency during the producing. Environmental conditions effect power station work and change the cost and amount of energy.

In this study, artificial intelligence, ANN, was used to manage CCPP plant and try to obtain predictable energy level according to environmental conditions. Real CCPP data has importance to test the ANN performance. Result of ANN signs the plant capability during the managing. ANN performance tested using MSE and R^2 and reliability was improved with two-fold cross validation. The success was obtained 96.7% after two fold cross validations and 3.176 MSE. R^2 shows that how real and obtained results cover each other and close to 1 according to success.

ANN finds the valid results according to real inputs. ANN covers untested values related to learned abilities and generates an output to manage the system.

This study encourages us to use ANN for predicting CCPP energy capability and shows that artificial intelligence could be a trustable method to manage CCPP plant.

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