

Prediction of energy generated from composite cycle power plant in smart cities

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ABSTRACT

In smart cities, it is significant to predict the energy generated from composite cycle power plants, in order to reduction the efforts and to extreme profit from the megawatt hours during the operation, which is consider from the important topics in mechanical engineering. The most significant component of a power plant with a composite cycle is the gas turbine, which generates the entire electrical energy via a fuel and distributes it to homes, schools and other institutions around the cities. In this paper artificial neural networks, regression machine learning with decision tree method is utilized to develop a model that can be able to predictive the estimate of electrical energy output of a composite cycle power plant. The basis load functioning of plant is impacted through four key characteristics, such as surroundings temperature, relative humidity, pressure of atmospheric, and generated steam pressure, which are utilized in the dataset as input variables. These variables have an impact on electrical energy output, which is the desired variable. The input and target variables are included in the dataset, obtained from an open online source. The decision tree algorithm produced the best results, with a mean absolute error of (0.009) and a root mean square error of (0.022).

Keywords: Composite cycle power plants, smart cities management, Intelligent control of outputs power plants, Energy Systems management, Machine learning techniques in Mechanical engineering

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1. Introduction

A smart city is a livable and efficient urban that is a hub provides excellent quality of life to its citizens through effective resource management, furthermore consider as a new concept have received great interest, so they took use the artificial intelligence techniques in the management of their facilities. Because of the difficulty and critical significance of energy systems, Energy power plant management considered is a one of that, in addition it is considered from the modern and significant application in mechanical engineering. Cities demands of energy are extensive and complicated [1]. As a result, should improve the modern cities by implement the smart technology management and effective manner, among all of these energy strategies [2]. The amount of power generated by power plants varies throughout the year due to a variety of factors, including environmental conditions. In order to depict the actual system accurate thermodynamic power plant analysis using mathematical models necessitates a large number of factors and assumptions [3][4]. Machine learning methodologies can be employed instead of mathematical modeling of the system's thermodynamics [5][6]. Artificial neural networks are one of these ways (ANNs), which it's became a part of our daily lives.

This techniques making the management of systems faster and provides a good options without delay [7]. For the model the environmental circumstances are analyzed as inputs, and the power generated as outputs, thanks to artificial neural networks' capacity to resolve nonlinear interactions. We are able to anticipate the plant's generated power using this strategy, based on the surrounding conditions [8]. composite cycle power plant (CCPP) consider is a one type of plants, As illustrate in figure 1., consisted of gas turbines (GT) as a first stage, steam turbines (ST) as a second stage and the final stage which is a heat recovery steam generators (HRSG) [8][9]. In a composite cycle power plant, the power generate by combining gas and steam turbine, which are built up in the same cycle [10]. up to 50 percent more electricity produced by a composite cycle power plant with the similar amount fuel than a conventional simple-cycle plant.

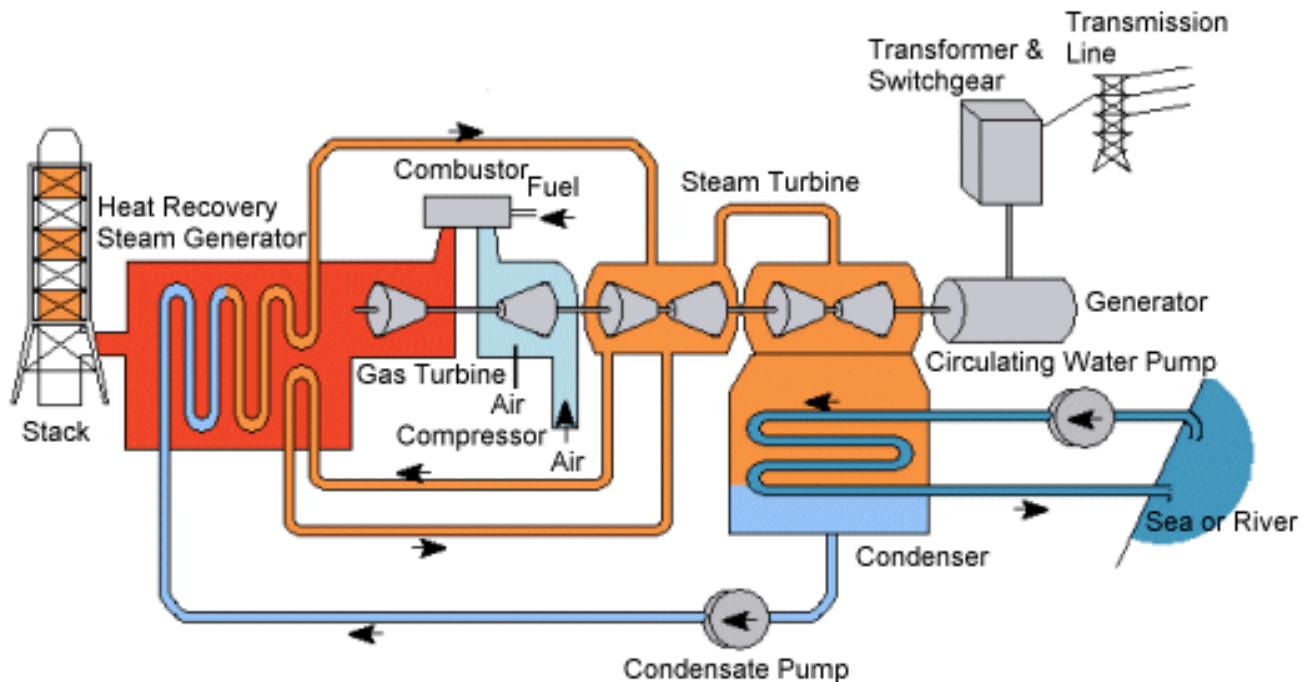


Figure 1. Diagram of a composite cycle power plant [9]

The heat waste via gas turbine guided toward the steam turbine in the composite cycle, which will generate extra power. The following is a description of the composite cycle power plant's mechanics [11]:

1. The blades of the turbine spin by burns the fuel at the gas turbine which will lead to driving the electricity generators.
2. The exhaust heat of a gas turbine is guided to the heat recovery steam generator (HRSG). The HRSG generated the steam from the heat of the gases expelled from the gas turbines and feeds it to the steam turbine.
3. The steam conceived by the heat recovery system in a steam turbine using to generate the extra electricity through operating a generator.

The load of a gas turbine is affected by the surrounding environment, particularly the surrounding temperature (ST), relative humidity (RH) and atmospheric pressure (AP). However, the load on a steam turbine is affected by the pressure of the exhaust steam (or vacuum, V) [12][13]. When compared to conventional power plants, The power plants with a composite cycle have a better efficiency of fuel conversion, which means they use less amount of fuel to produce the similar magnitude of electricity, resulting in lower energy prices and lesser emissions to the environment [11].

In this research, machine learning regression approach was examine in order to estimate a thermodynamic system's output, represented as a composite cycle power plant CCPP, which are consisting of a gas and steam turbine with two heating recovery systems. The dataset consists of 9568 information focuses obtained over the

course of 6 years from a composite cycle power plant (2006-2011), when the plant was operated at a maximum capacity. The Decision Tree method's performance was assessed, and it delivered the best results, with a mean absolute error of (0.009) and a root mean square error of (0.022).

2. Working of artificial neural networks in mechanical engineering of smart cities

A mechanical engineer's goal is to design systems that are intelligent and self-contained. Symbolic learning and machine learning are two methods for accomplishing this. Symbolic learning entails manipulating symbols, whereas machine learning entails manipulating facts. Machines that use symbolic learning provide output based on symbolic inputs. When the system is sophisticated, this becomes incompatible Database learning is called Machine Learning (ML)[14]. A large amount of data is fed into the machine. It is capable of recognizing patterns and making predictions. Statistical learning encompasses natural language processing and speech recognition. The human brain consider is the most intuitive way to think of artificial intelligence. The human brain is made up of a complicated network of neurons. Deep learning refers to the process of replicating the complex network of the human brain in order to solve complicated issues [15]. It entails the development of an Artificial Neural Network to address a challenging real-world issue. The ability to recognize and scan items is referred to as a Convolution Neural Network [16].

3. Related works

Several earlier researches have used machine learning approaches to predict the electric energy for the composite cycle power plants. The simple linear regression and multiple linear regression are two forms of linear regression and REP Tree were among the fifteen regression methods evaluated and compared. The comparison is based on a Root Mean-Squared Error and the mean absolute error. With a mean absolute error of (2.818) and a Root Mean Squared Error of (3.787), the best technique was the Bagging method with REP Tree algorithm[13]. Furthermore, a study compared machine learning algorithms to forecast the energy of composite power plant. To construct local and general forms the traditional K-Means clustering, multivariate regression, additive regression, k-NN, feedforward ANN were all used. KNN is the best option for a fine-tuned dataset, While In speed and memory tests, the ANN performed was well [17]. To predicate the total energy of a composite cycle power plant, seven machine language algorithms were applied. Linear Regression, RANSAC regressions and K-NN produced the best results [18]. Another research utilized only ANN with a random subset and various hidden layers to improve net power prediction[8]. The composite cycle power plant's steam turbine has been the subject of very few studies (CCPP) [4][13][10][17]. Three gas turbine, three HRSGs, and one steam turbine were used to anticipate the overall power production of a cogeneration power plant [3]. A linearization model technique was used to investigate the gas turbine control strategy in a composite cycle power plant [10]. With inputs such as pressure of atmospheric, relative humidity, surrounding temperature and the steam turbine vacuum exhaust, two artificial neural networks were utilized to represent a composite cycle power plant. The generated steam pressure is not a predictable parameter because it is a result of surrounding conditions [4]. To forecast the to forecast the outputs of full load electrical of a composite cycle power plant operated in a basis load, researchers examined various machine learning algorithms [13][17].

4. Methodology

4.1 System overview

In this research, regression machine learning with decision tree method is used to develop a model that can be able to predictive the estimate of electrical generated from a composite cycle power plant. The general structure of the proposed model explained in Figure 2.

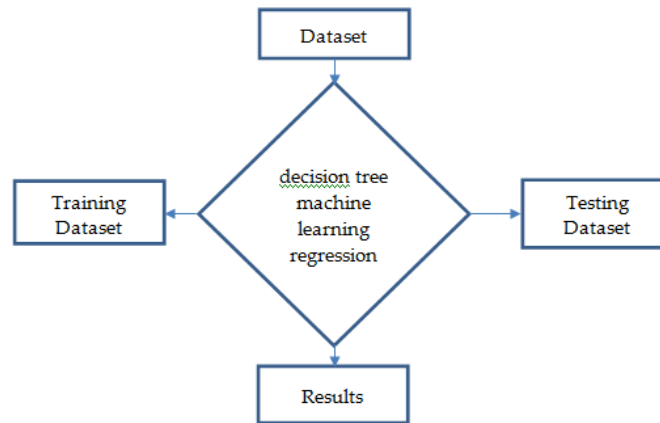


Figure 2. General structure of the proposed model

as appear in Figure 2., The data set was split into two groups, which are training data set and testing data set. (60%) of the data is utilized as training data, while (40%) is utilized as test data.

4.2 Decision trees

Decision trees a very compelling approach to decide unique conditions which can be spread out choices and search the conceivable and most fitting yield. Both can be handled using decision trees characterization and relapse issues, understanding and approving the model utilizing factual structures is extensively straightforward. As opposed to the in addition to sides, Decision trees can without much of a stretch overfit the information. Accordingly, pruning, eliminating areas of the tree that makes the least contribution expectation is expected to keep in such conditions .During the assessment, the Decision tree strategy has gotten a mean absolute error of (0.009) and a root mean square error of (0.022).

4.3 Dataset description

Dataset is provide from online site [19]. The dataset consist of 9568 information focuses obtained over the course of 6 years from a composite cycle power plant (2006-2011), when the plant was operated at a maximum capacity. Elements comprise of hourly normal encompassing factors to predict the net hourly electrical energy generated of the plant (EP):

- Surrounding Temperature (ST)
- Relative Humidity (RH)
- Atmospheric Pressure (AP)
- Exhaust Vacuum (V)

Characteristics compromised of hourly in Table 1. Figure 3., depicts the interrelationships between the factors (ST, RH, AP, and V) and energy output (EP), and the linear correlation between inputs and output for every chart.

Table 1. Characteristics of variables

Characteristic	Symbol	Unit	Species	Lowest Value	Highest Value
Surrounding temperature	ST	°C	Input	1.80	37.50
Relative Humidity	RH%	—	Input	25.50	100.20
Exhaust Vacuum	V	cm Hg	Input	25	82
Atmospheric Pressure	AP	mbar	Input	992	1033.25
Net energy output hourly electrical	EP	MW	Output	420.20	496.50

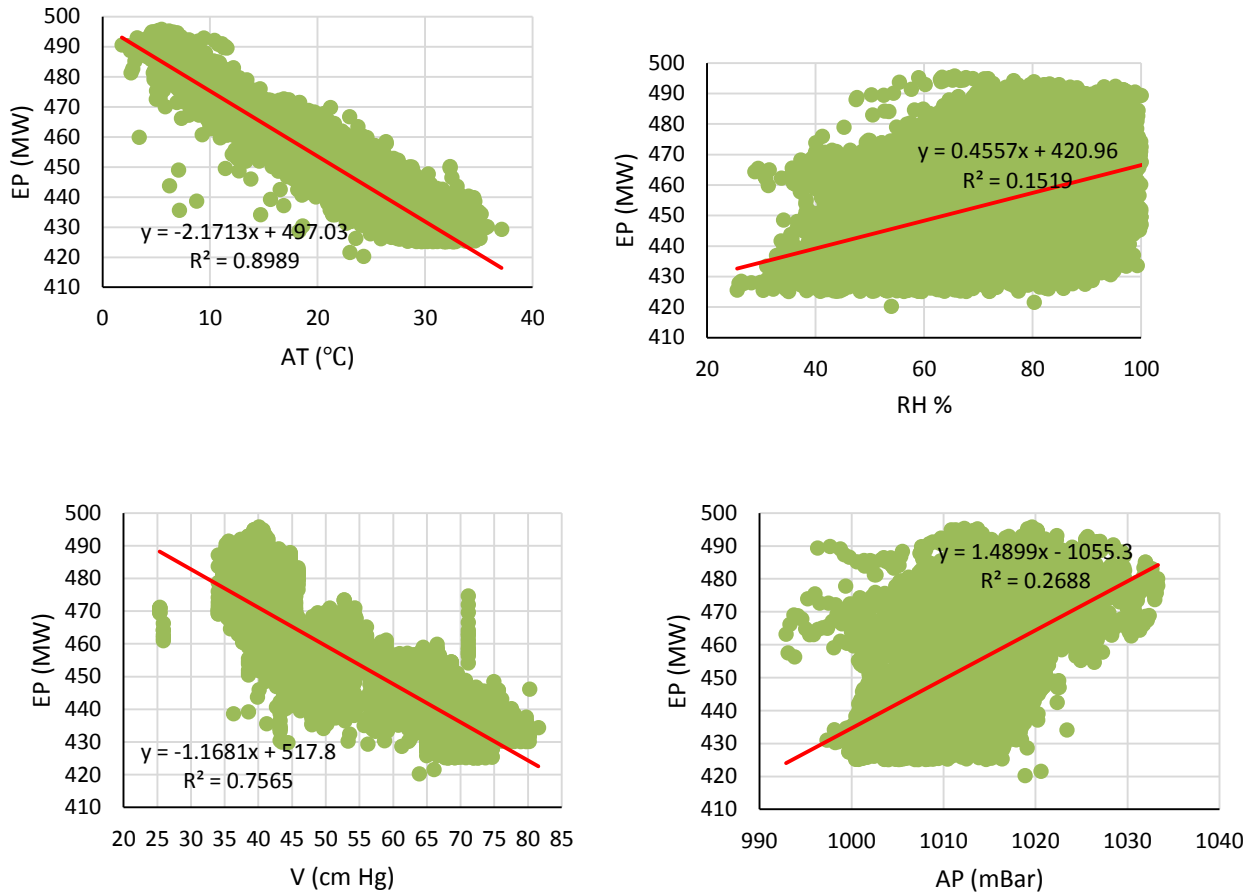


Figure 3. Linear Correlation between inputs and output EP

4.4 Experimental Results

Machine learning methods utilized in this research to guess the generated energy in a composite cycle power plant, which can be employed in smart cities, wherein the performances were evaluated of used algorithm. Table 2. shows the performance of used algorithm by presenting the Mean Absolute Error, Mean Squared Error and Root Mean Squared Error.

Table 2. performance evaluation

Mean Absolute Error	Mean Squared Error	Root Mean Squared Error
0.00910	0.00049	0.02225

5. Conclusions

This research proposed an alternate solution model to predicting by electrical power outputs for a composite cycle power plant (CCPP) operated with basis load at full load. Machine learning strategy were selected for precise prediction instead of using thermodynamic methods, which require some hypotheses and a large number of nonlinear equations in the real system application. Furthermore, the system analysis utilizing thermodynamical methodologies takes an excessive amount of computational time and effort, and the results can be unsatisfying and due to various assumptions and nonlinear equations, it is making it unreliable. machine learning regression approach was examine in order to estimate a thermodynamic system's output, represented in a composite cycle power plant which are consisted of gas and steam turbine with two heating recovery systems, was presented as an alternate analysis in order to solve this problem. One machine learning

strategy to predicting the energy generated from a consolidated cycle power plant was implemented, which can be employed in smart cities, represented by decision tree method. The Decision Tree method's performance was assessed, and it delivered the best results, with a mean absolute error of (0.009) and a root mean square error of (0.022).

For the future work, other comparison algorithms, such as Decision stump, Support Vector Machines (SVM) and K star could be utilized.

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