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Predicting Electrical Power Output in a Combined Cycle Power Plant - A Statistical Approach

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Abstract With the increasing demand for electrical energy worldwide and the proportionate inflation of natural resources, it is important to predict the electrical power output from baseload combined cycle power plants and the factors affecting the yield per hour. Finding reliable factors not only improves the performance of the power plant in terms of production or distribution but also ensures the proper utilization of natural resources (or fuels) with minimal effect on the environment and effective cost management. Though there are sophisticated machine learning models for predicting full load electrical power output, often these deployed models are unable to draw inferences. Thermodynamic models on the other hand are oftentimes too complex, are valid only under a set of assumptions, and are generally non-linear in nature adding to the computation time. Keeping these limitations in mind, the objectives of this study are to find potential predictor variables that affect the power output yield per hour and then use these inferences to construct a simple yet effective model to predict the electrical power output in combined cycle power plants. The dataset used for this study is from a combined cycle power plant over a span of six years (2006-2011), with the power plant operating in a full load. A combined cycle power plant is composed of gas turbines, steam turbines, and heat recovery steam generators. The gas and steam turbines generate the electricity which is combined in one cycle and is transferred from one turbine to another. The input features of the dataset considered for this study consist of average ambient variables: ambient temperature, ambient pressure, relative humidity, and exhaust vacuum which are used to predict the average hourly electrical power output.

Keywords Combined cycle power plant, Linear modelling, Regression, Power generation, Statistical inference, Prediction

1. Introduction

Steam turbines systems generate most of the electrical power generated worldwide. The prediction of the real power output of such baseload plants is important for the effective operation of the electric grid, especially in countries where the electric grid is still developing, and natural resources are in limited quantities.

Gas turbine power output mainly depends on the ambient parameters such as ambient temperature, atmospheric pressure, and relative humidity whereas steam turbine power output has a direct relationship with the vacuum at the exhaust. [1,2,3]. Gas turbine derivatives, such as combined cycle power plants (CCPP) are being established all over the world to fulfill the demand for electrical energy considering both economic and environmental concerns. It has been found that the three ambient predictor variables: ambient temperature (AT), ambient pressure (AP), and relative humidity (RH) affects while exhaust vacuum (V) affects the production of steam turbines.

Hence, the objective of this paper is to study the association of the average ambient variables with the hourly yield of electrical power output and find out reliable predictors for CCPP that would help inefficient production. This in turn would help in the proper utilization of resources in terms of maximum yield and minimum cost of production.

The main motivation for this study is that there exist thermodynamical studies to predict the output of a CCPP. However, detailed analysis of a system by using thermodynamical approaches [5,6] is a computationally intense effort, and sometimes the result of such analysis might be inaccurate due to the interaction of several assumptions being considered and the nonlinear nature of the governing equations. On the other hand, machine learning models have gained steam in recent years [7,8,9]. The inability to draw inferences from these wide-scale sophisticated state-of-the-art models remains a concern.

To overcome these obstacles, the analysis here is undertaken using a statistical approach of first drawing an inference from the data about the potential predictors, and

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then using the inferences a predictive model would be constructed for predicting the output of a thermodynamic system, which is a CCPP with two gas turbines, one steam turbine, and two heating systems in full load.

The remainder of the paper is organized as follows: section 2 highlights the statistical methods used in this study along with a description of the data source and general model assumptions. Section 3 presents a preliminary analysis of the potential predictors and a brief summary of the response variable. Section 4 throws light on the multicollinearity between the different predictor variables and explores the model selection and validation. Section 5 presents an overview of the goodness of fit test. Section 6 present a discussion of the statistical findings of the study, before ending with a concluding remark in section 7.

2. Statistical Methods

The primary objective of this study is to investigate the potential predictors, that is the average ambient variables, that affect the electrical power output in a CCPP; which would then be used to predict the electrical power output.

2.1. Material and Methods: Data Source

The dataset was obtained online in Microsoft excel format [10].

The dataset was collected over a period of six years (2006 - 2011) from a combined cycle power plant when the plant was set to operate on full load. A sample size n = 9568 was collected and shuffled five times; the data generated from each of these shuffles was provided in separate spreadsheets. For each shuffling 2-fold cross-validation (CV) [11] was carried out and the resulting ten measurements are used for statistical testing. For data analysis, only one of the spreadsheets is considered among the collection of five spreadsheets. The dataset consists of hourly average ambient variables per second taken from various sensors located around the plant. Variables in the data set include ambient temperature (AT) ranging from 1.81℃ to 37.11℃, ambient pressure (AP) ranges from $992.89 - 1033.30$ millibar, relative humidity (RH) in the range 25.56% to 100.16%, exhaust vacuum (V) range from $25.36 - 81.56$ cm Hg and net hourly electrical energy output (PE) $420.26 - 495.76$ MW.

2.2. Material and Methods: Statistical Analysis

The data analysis is conducted using the statistical software R version 3.5.2 (2018-12-20) and the study focuses mainly on multiple linear regression. A significance value (α) = 0.05 is considered in this study. The input features are continuous variables, which are summarized using the five summary statistics (mean, median, minimum, maximum, and standard deviation). The original dataset is divided into 90:10 training - testing sets.

Each of the predictor variables is explored individually and the preliminary investigation is conducted on the training dataset. No missing values were found in the dataset.

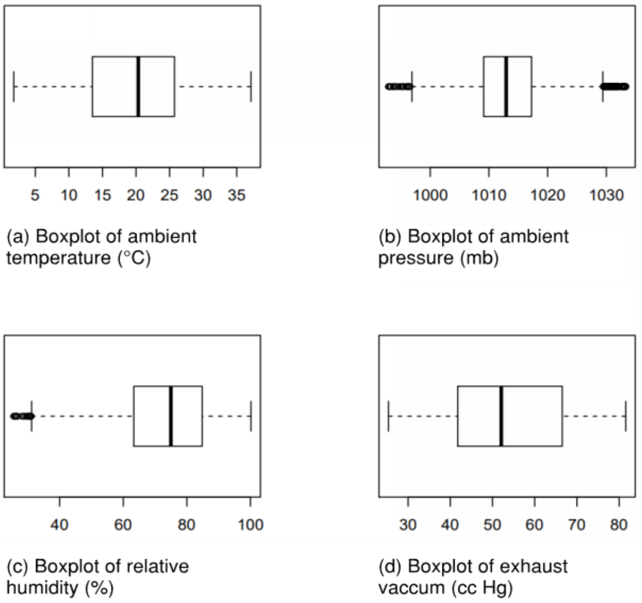
The automatic model selection method has been used on the training set to arrive at the final model. The final model is validated using model diagnostics and the goodness of fit tests. The model assumptions including homoskedasticity, normality, and independence of error terms, as well as linearity of the association between the outcome and the ambient variables, are checked before finalizing the estimated fitted regression function. The finalized model is then used on the test set to find the predicted values and compared to the observed value at a 95% prediction interval.

3. Preliminary Data Analysis

Preliminary data analysis help in detecting skewness, presence of outliers or can also suggest if transformations are necessary to fit a better model. Preliminary data analysis also gives an idea about the association of the potential predictors with the outcome.

3.1. Analysis of the Potential Predictors

Figure 1 illustrates the distribution while Table 1 presents the summary statistics of the individual ambient variables: ambient temperature (AT), ambient pressure (AP), relative humidity (RH), and exhaust vacuum (V). Figure 1 (a), (b), and (d) shows that ambient temperature (AT), ambient pressure (AP), and exhaust vacuum (V) appear to be approximately symmetrical while Figure 1 (c) shows relative humidity (RH) to be a little skewed (left or negatively skewed). Some outliers can also be detected in ambient pressure (AP) and relative humidity (RH) (Figure 1 (b) and (c)).



(a) Boxplot of ambient temperature (°C)

(b) Boxplot of ambient pressure (mb)

(c) Boxplot of relative humidity (%)

(d) Boxplot of exhaust vaccum (cc Hg)

Figure 1. Analysis of predictors using box and whisker plots

3.2. Analysis of the Electrical Power Output

Preliminary data analysis on the electrical power output

(PE) shows that the response variable is positively skewed as the whiskers to the right are longer than the ones on the left. The presence of outlying values is not observed in Figure 2. The summary statistics of PE have been presented in Table 1.

3.3. Effect of Ambient Temperature (AT) on the Electrical Power Output (PE)

Figure 3 illustrates the scatter plot for the ambient temperature (AT) and electrical power output (PE) with the fitted regression line. The resultant predictive model can be written as (1), where Y_i represents the electrical power output (PE) and X_{1i} is the ambient temperature (AT). The model states that for every 1℃ rise in ambient temperature (AT), the electrical power output (PE) drops by 2.171 MW per hour.

$$Y_i = 497.03 - 2.171X_{1i} \tag{1}$$

Table 1. Basic statistics for dataset variables

	AT	V	AP	RH	PE
Min	1.81	999.8	25.56	25.36	420.2
1st quartile	13.51	1009.1	63.32	41.74	439.75
Mean	19.65	54.3	1013.25	73.30	454.36
3rd quartile	25.72	1017.2	84.83	66.54	468.43
Max	37.11	1033.3	100.16	81.56	495.76
Standard deviation	7.45	5.93	14.6	12.708	17.06
Variance	55.53	35.26	213.16	161.49	291.28

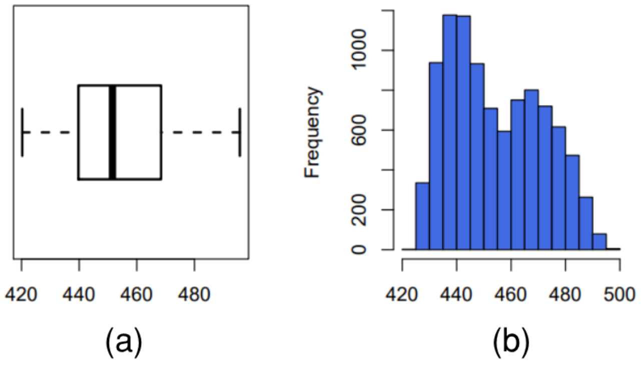


Figure 2. Distribution of electrical power output through (a) box and whisker plot, (b) histogram

3.4. Effect of Ambient Pressure (AP) on the Electrical Power Output (PE)

Figure 4 illustrates the scatter plot for the ambient pressure (AP) and electrical power output (PE) with the fitted regression line. The resultant predictive model can be shown as (2), where Y_i represents the electrical power output (PE) and X_{2i} is the ambient pressure (AP).

$$Y_i = -1055.26 + 1.49X_{2i} \tag{2}$$

The model states that for every 1 mb (or millibar) rise in ambient pressure (AP), the electrical power output (PE) increases by 1.49 MW per hour.

3.5. Effect of Relative Humidity (RH) on the Electrical Power Output (PE)

The scatter plot of relative humidity (RH) and electrical power output (PE) is illustrated in Figure 5 with the fitted regression model. Thus, the resultant predictive model is represented by (3), where Y_i represents the electrical power output (PE) and X_{3i} is the relative humidity (RH). It can thus be inferred that for every one percent rise in relative humidity (RH) increases the electrical power output by 0.456 MW per hour.

$$Y_i = 420.96 + 0.456X_{3i} \tag{3}$$

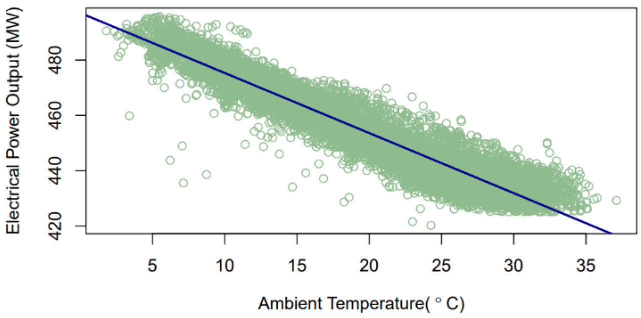


Figure 3. Prediction of PE (MW) with reference to AT (℃)

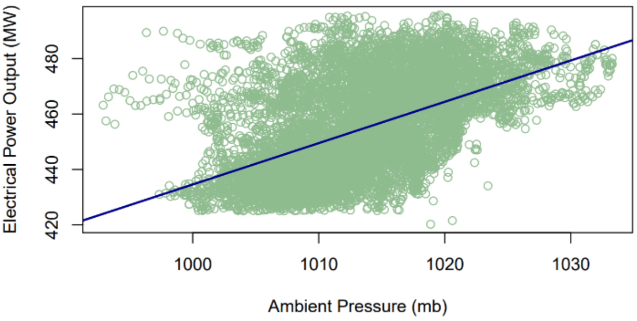


Figure 4. Prediction of PE (MW) with reference to AP (mb)

3.6. Effect of Exhaust Vacuum (V) on the Electrical Power Output (PE)

Figure 6 illustrates the scatter diagram of exhaust vacuum (V) and electrical power output (PE) produced after fitting the linear regression model. The resultant predictive model can be represented by (4), where Y_i represents the electrical power output (PE) and X_{4i} is the exhaust vacuum (V). The predictive model can thus infer that for every 1 cm Hg rise in exhaust vacuum, the electrical power output decreases by 1.168 MW per hour.

$$Y_i = 517.802 - 1.168X_{4i} \tag{4}$$

Table 2 shows the summary statistics for each the fitted regression model (1), (2), (3), and (4) along with the model fit statistics: coefficient of determination (R^2), F statistics, adjusted R^2 (R_a^2), and MSE is in Table 2.

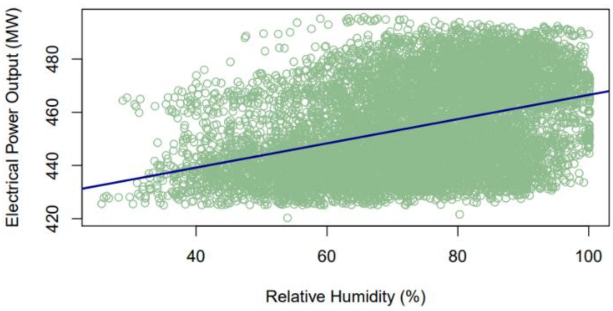


Figure 5. Prediction of PE (MW) with reference to RH (%)

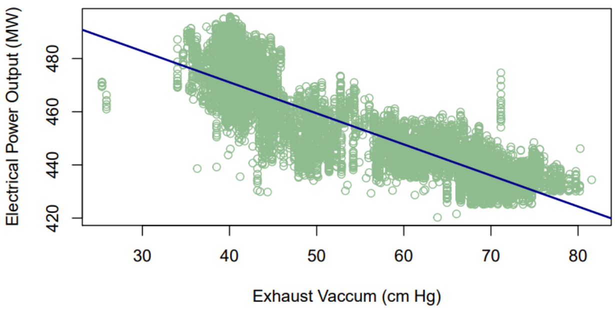


Figure 6. Prediction of PE (MW) with reference to V (cm Hg)

Table 2. Summary statistics of four separate models: outcome and each of the predictors

	Dependent variables:			
	Electrical power output (PE)			
	Model 1 *lm(PE~AT)*	Model 2 *lm(PE~AP)*	Model 3 *lm(PE~RH)*	Model 4 *lm(PE~V)*
AT	-2.170*** (0.007)			
AP		1.490*** (0.025)		
RH			0.456*** (0.011)	
V				-1.170*** (0.007)
Constant	497.000*** (0.156)	-1055.0*** (25.5)	421.0*** (0.823)	518.0*** (0.378)
Observations	8,611	8,611	8,611	8,611
R^2	0.899	0.269	0.152	0.757
Adjusted R^2	0.899	0.269	0.152	0.757
Residual std. error (df=8609)	5.43	14.6	15.7	8.42
F statistics (df=1;8609)	84,098***	3,516***	1,714***	29,722***
Note:	*p<0.01; **p<0.05; ***p<0.01			

4. Multicollinearity, Model Selection and Validation

In a typical scenario, multicollinearity [12] makes data analysis complicated. The association between predictors is often observed by considering the coefficient of correlation or Pearson correlation (*r*). Values of *r* closer to ±1 indicate that the predictors are highly correlated. Figure 7 and Table 3 show the correlation matrix or pairwise Pearson's correlation coefficients. The *r* values between the electrical power output (PE) and all the ambient variables are greater than ±5, except relative humidity (RH). The *r* value between ambient temperature (AT) and exhaust vacuum (V) seems to be high (0.84). Once the model has been finalized, the effect of multicollinearity on the final model fit can be analyzed using the variation inflation factor (VIF) [13]. In case the values of VIF exceed 10, it is often regarded as the presence of multicollinearity and measures need to be taken.

Table 3. Correlation matrix for the dataset

	AT	**AP**	**RH**	**V**	**PE**
AT	1.00	-0.508	-0.543	0.844	-0.948
AP	-0.508	1.00	0.100	-0.414	0.518
RH	-0.543	0.100	1.00	-0.312	0.390
V	0.844	-0.414	-0.312	1.00	-0.870
PE	-0.948	0.518	0.390	-0.870	1.00

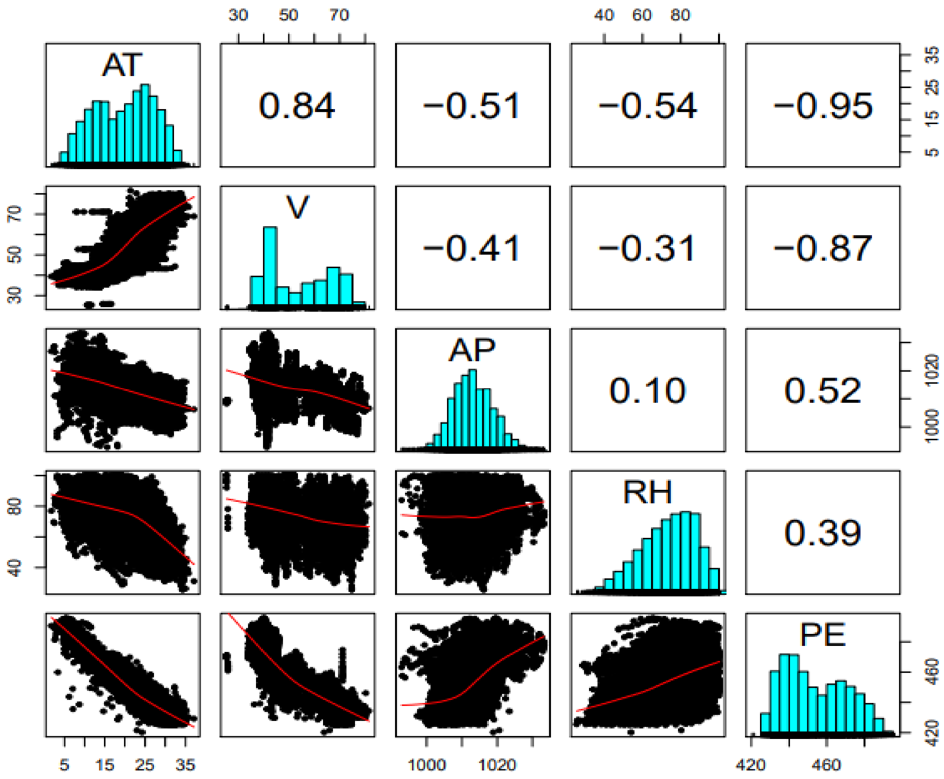


Figure 7. Pairwise Pearson's correlations coefficients for the ambient variables

4.1. Model Selection: Automatic Variable Selection Method

The automatic variable selection method is a starting point to eliminate the redundant variables from the model. The "regsubsets" function from the "leap" package in R is used. The best model is selected based on Mallow's Cp, BIC, and R_a^2 [15,16]. The automatic variable selection method selects the model which has the least value for Mallow's Cp and BIC, while the model with the largest value of R_a^2 is considered best. For this particular data set, the best model includes all four ambient variables. Refer to Table 4 for a summary of the automatic selection method.

Thus, the final model can be expressed as (5).

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \epsilon_i \qquad (5)$$

where,

Y_i is the electrical power output

X_{1i} is the ambient temperature

X_{2i} is the exhaust vacuum

X_{3i} is the ambient pressure

X_{4i} is the relative humidity

ϵ_i is the error term; $\epsilon_i \sim N(0, \sigma^2)$

$i = 1,2,3 \ldots, 8611$

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \sigma^2$ are the unknown parameters to be estimated which is discussed in section 6. However, the model assumptions must be checked and validated before diving into the model parameter estimates. Thus, the remainder of this section is dedicated to model validation and diagnostics.

4.2. Model Validation

4.2.1. Added Variable Plots (Residual Plots)

The added variable, also known as partial residual plots, are useful to detect the significance of a particular variable in the presence of the other covariates. It can also be useful in detecting outliers or in case any transformations are required in the model predictors [15]. Figure 8 represents the partial residual plot suggesting that no transformations are required in the current model. However, the presence of outliers is detected.

4.2.2. Outliers and Influential Points

To detect outliers in this study, a studentized residual plot and cook's distance are considered. For a more rigorous treatment of Cooks distance, including a modification of the classical form in the context of regression models, readers are encouraged to refer [14]. As per standards, 99% of the data points should be within the range of ±3 [15] which is confirmed by Figure 9 (a). Fifteen outliers are detected in the study as evident from Figure 9 (b). To check if these outliers are influential to the model fit, a linear model is considered excluding these data points. It is found that the final model is robust to these data points since no significant changes in model statistics are observed (Table 5), hence these fifteen observations are included in the final model.

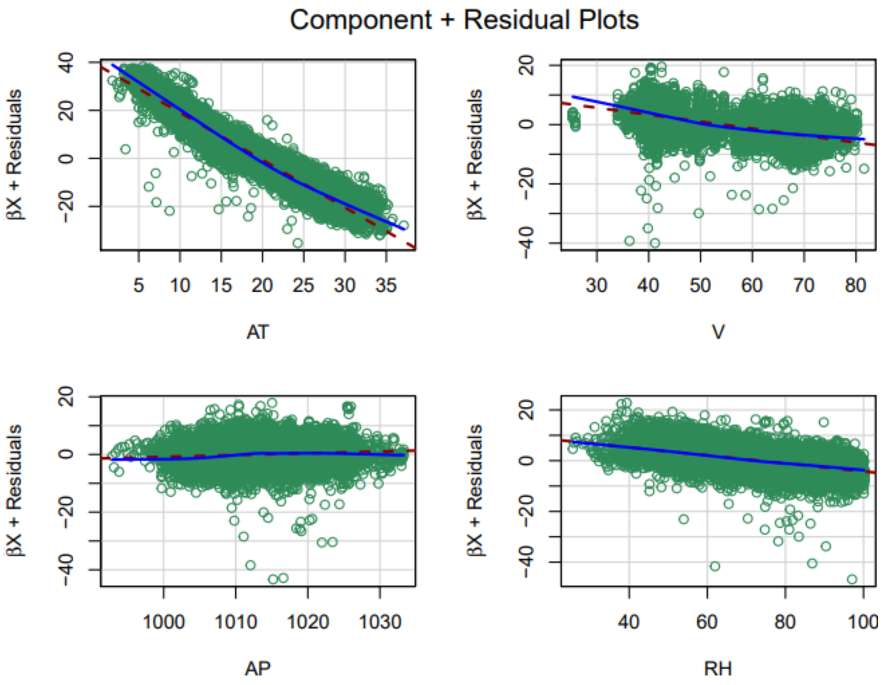


Figure 8. Added variable plots (showing component and residual plots)

Table 4. Automatic selection method statistics

	Dependent variable: PE		
Predictors	C_p	R^2_a	*BIC*
AT	3988.8	0.899	-21913
AT +RH	1040.1	0.921	-24253
AT+V+RH	46.1	0.928	-25188
AT+V+AP+RH	5.0	0.929	-25221

4.3. Model Diagnostics

Figure 10 shows that all the model assumptions are satisfied. Figure 10 (a) shows that the model follows homoskedasticity or equal variance. Figures 10 (b) and (c) confirm that the error terms follow normality. The independence of error terms is also quite evident in the sequence plot (Figure 10 (d)). However, since the dataset was shuffled, assessing the independence might not be technically possible.

Since the model is finalized and the assumptions are validated, multicollinearity is assessed using the VIF. Table 6 shows the VIF values exhibited by the final model, which are significantly less than 10. Thus, it can be assumed that multicollinearity is not significant in the finalized model (5).

Table 5. Comparison of model summary with and without outliers

	Dependent variables:	
	Electrical power output (PE)	
	Final model with outliers	Final model without outliers
AT	-1.980*** (0.015)	-1.990*** (0.015)
V	-0.234*** (0.007)	-0.231*** (0.007)
AP	0.062*** (0.009)	0.063*** (0.009)
RH	-0.158*** (0.004)	-0.159*** (0.004)
Constant	455.000*** (9.750)	454.000*** (9.444)
Observations	8611	8596
R^2	0.929	0.933
Adjusted R^2	0.929	0.933
Residual std. error	4.560 (df=8606)	4,410 (df=8591)
F statistics (df=1;8609)	31,138.000*** (df = 4; 8606)	33,383.000*** (df = 4; 8591)
Note:	*p<0.01; **p<0.05; ***p<0.01	

Table 6. Variation inflation factor (VIF) values from the final model

AT	**V**	**AP**	**RH**
5.98	3.940	1.450	1.710

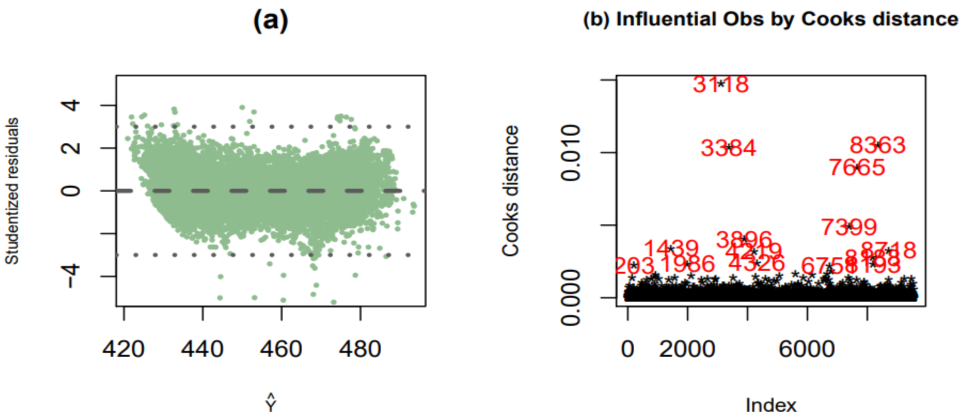


Figure 9. Detecting outliers using studentized residuals and Cook's distance

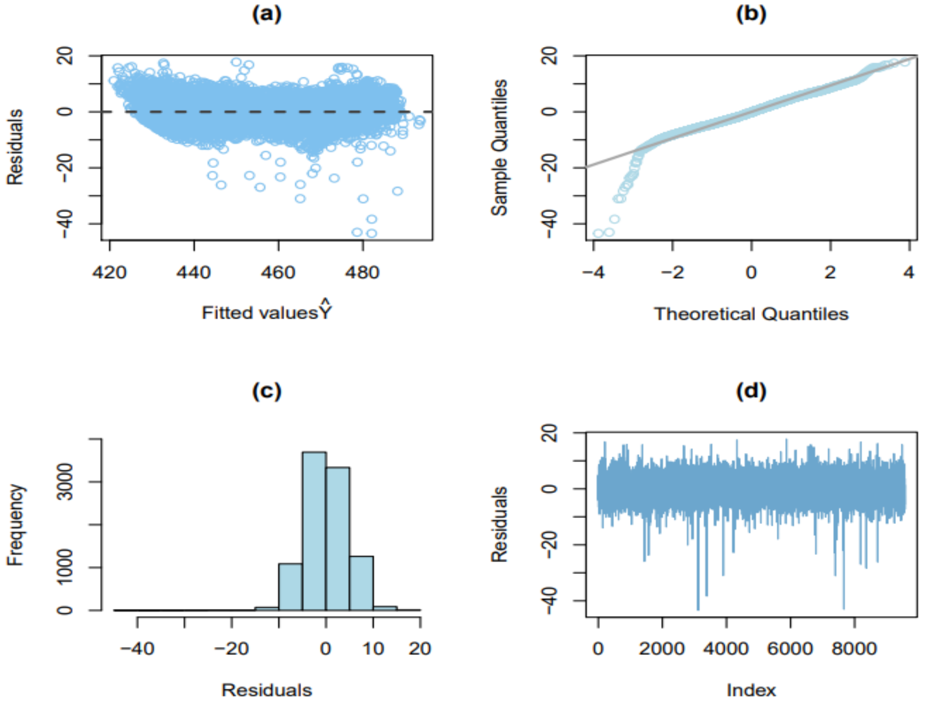


Figure 10. Residual's diagnostics showing a. fitted values, b. theoretical quantiles, c. residuals, and d. index

5. Goodness of Fit Test and Results

For each of the ambient variables, we test if there exists a linear association with power output (PE) using a two-tailed t-test individually. Since more than one t-test is conducted, Bonferroni's multiple comparisons is considered [15]. The t-test considers the following hypothesis:

* **Null hypothesis:** $H_0 : \beta_i = 0$

* **Alternative hypothesis:** $H_1 : \beta_i \neq 0$.

The decision is taken considering $t *= \frac{b_i - \beta_i}{SE(b_1)}$

where,

-t* is the test-statistics for the t-test

-b_i is the observed slope coefficient

- β_i is the expected slope coefficient of the fitted regression model

- $SE(b_i)$ is the sampling variability of b_i

The t* is tested against $t_{(1-\frac{\alpha}{2},df)}$,

where,

-α is the level of significance = 0.05

-*df* is the degrees of freedom, i.e., df = number of observations minus number of estimate parameters = (n − 2)

If $t_{(1-\frac{\alpha}{2},df)}$, H_0 is rejected else the decision is taken in the favour of H_0. The decision rule also considers the p-value and the R^2. If, p-value ≤ α, the decision is to reject H_0 else we fail to reject H_0 [15].

While considering the coefficient of determination (R^2), if the value is closer to 1, the association is considered strong as the percentage or proportion of explained variation in electrical power output (PE) is significantly higher than the unexplained variation. However, if R^2 is closer to 0, the model will be not be considered as a good fit as it would indicate that there exists no or a weak association between the ambient variables and electrical power output (PE) as the percentage of unexplained variation is significantly low).

5.1. Effect of Ambient Temperature (AT) on the Electrical Power Output (PE)

The t-test rejects $H_0: \beta_{AT} = 0$ thus, concluding that there exists evidence of a linear association between ambient temperature (AT) and electrical power output (PE). The R^2 explains that model (1) can explain 89.9% of the unexplained variation in electrical power output (PE), indicating that the model is a good fit.

5.2. Effect of Ambient Pressure (AP) on the Electrical Power Output (PE)

The t-test rejects $H_0: \beta_{AP} = 0$ and concludes that there exists evidence of a linear association between ambient pressure (AP) and electrical power output (PE). The R^2 for model (2) is only 26.9%, which indicates that ambient pressure (AP) is not strongly associated with electrical power output (PE).

5.3. Effect of Relative Humidity (RH) on the Electrical Power Output (PE)

The t-test $H_0: \beta_{RH} = 0$ rejects the H_0. Though there exists sufficient evidence of a linear association between relative humidity (RH) and electrical power output (PE), the value of R^2 is relatively small. Only 15.2% of the unexplained variation can be explained by the fitted model (3) while the other 84.4% remains as unexplained variation in PE.

5.4. Effect of Exhaust Vacuum (V) on the Electrical Power Output (PE)

The t-test reject the $H_0: \beta_V = 0$ suggesting that a linear association exists between exhaust vacuum (V) and electrical power output (PE). The percentage of explained variation is high for model (4). Around 75.7% of the unexplained variation in electrical power output (PE) is explained (4) while only 24.3% remains as the unexplained variation.

5.5. Discussion of Results from the T-Test

The results from the t-test show that a linear association exists between PE and all the average ambient variables (AT, AP, RH, and V). To find the most effective predictor variable, the R^2 or R_a^2 can be referred to, which indicates the percentage or proportion of explained variation in electrical power output (PE) to the total variation in electrical power output (PE).

Referring to the R^2 and R_a^2 (Table 2) value, variables that can predict the maximum percentage of unexplained variation are the ambient temperature (AT), followed by exhaust vacuum (V) while the variable that explains the least of the unexplained variation in PE is relative humidity (RH).

To confirm that ambient variables can significantly predict the electrical power output (PE), the predicted values are compared to the actual observed values from the test set (Table 7). At 95% prediction interval, it is found that the model performs well in estimating the average power electrical output using ambient variables.

Table 7. Validating model prediction

Observed PE	Predicted PE	Predicted range
467	468	$459 \leq \hat{Y} \leq 476$
445	442	$433 \leq \hat{Y} \leq 451$
450	448	$439 \leq \hat{Y} \leq 457$
485	490	$481 \leq \hat{Y} \leq 498$
476	474	$465 \leq \hat{Y} \leq 483$
426	425	$416 \leq \hat{Y} \leq 434$

6. Discussion

The model estimates from (5) can be summarized as below:

$$\hat{Y}_i = 454.6093 - 1.9775X_{1i} - 0.2339X_{2i} + 0.0621X_{3i} - 0.1581X_{4i} \qquad (6)$$

where,

Y_i is the electrical power output
X_{1i} is the ambient temperature
X_{2i} is the exhaust vacuum
X_{3i} is the ambient pressure
X_{4i} is the relative humidity
$\hat{\epsilon}_i$ is the error term; $\hat{\epsilon}_i \sim N(0, \hat{\sigma}^2)$
$i = 1,2,3 \ldots, 8611$

The study shows that the average ambient variables: ambient temperature (AT), ambient pressure (AP), relative humidity (RH), and exhaust vacuum (V) can predict the electrical power output (PE) per hour in a combined cycle power plant (CCPP) having both gas and steam turbines. The average ambient variables were explored individually, and the two-tailed t-test was conducted on each of the fitted linear regression models and a linear association was found in each case.

The final model (6) was able to explain about 92.9% of the unexplained variation in the electrical power output (PE), indicated by both R^2 and R_a^2 (Table 8). Further, model validation and residual analysis confirmed the model assumptions. The estimated mean squared error (MSE) or $\hat{\sigma}^2$ from the final model is 20.8.

Table 8 shows the estimated regression coefficient, the standard error, t value, p-value associated with each of the predictors, R^2, R_a^2, MSE and F-statistics of the final model. Table 9 shows the ANOVA table for the final model Exploring the test statistics, it is found that the strongest association among all average ambient variables and power output is best explained by the linear association of ambient temperature and exhaust vacuum, which is evident by the fact that about 90% and 76% of the unexplained variation in the output power per hour (Table 2) and also by the magnitude of the $\hat{\beta}s$ corresponding to ambient temperature and exhaust vacuum.

Table 8. Statistics table for the regression model

	Estimate	**Std. Error**	**T value**	**Pr(>|t|)**
(Intercept)	454.6093	9.7485	46.63	0.0000
AT	-1.9775	0.0153	-129.34	0.0000
AP	0.0621	0.0095	6.56	0.0000
RH	-0.1581	0.0042	-37.92	0.0000
V	-0.2339	0.0073	-32.12	0.0000
Observations	8,611			
R^2	0.929			
Adjusted R^2	0.929			
Residual std. error	4.560 (df = 8606)			
F statistics	31,138.000∗∗∗ (df = 4; 8606)			

Table 9. ANOVA table for the regression model

	Df	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
AT	1	2258512	2258512	108568	0.0000
AP	1	6078	6078	292	0.0000
RH	1	27381	27381	1316	0.0000
V	1	42789	42789	2057	0.0000
Residuals	8606	179029	20.8		

The study showed that except for ambient pressure all the other predictors exhibit a negative association with the response variable electrical power. Given the well-behaved residuals and high percentage of explained variation of 92.9% (R^2 = R_a^2 = 0.929) (Table 8), it can be concluded that the model performs well.

At 95% prediction interval, the electrical power output from the predicted model was compared with the observed values and it confirmed that ambient variables can be used to predict the electrical power output in a CCPP operated by both gas and steam turbines (Table 7). The presence of outliers was detected in the model and it was found that the model is robust to outliers (Table 5).

7. Conclusions

This paper presents a statistical model for a prediction of the electrical power output of a baseload operated CCPP when it was full load. Instead of thermodynamical modeling which involves a substantial number of assumptions and nonlinear system equations, or black-box machine learning models with multiple neural networks with unknown weights and biases, a statistical approach was used which can not only predict but draw useful inferences. Substantiated with large sample size and absence of missing values, this study's strength lies in less sampling variability thus ensuring better prediction, which is evident by the model's robustness to the outliers.

The two main purposes of this study were to discover the predictors which potentially have a linear association with full load electrical power output, and if these potential predictors could accurately predict the full load power output. Both of these objectives were achieved using multiple linear regression models.

Future work may be undertaken to refine the input to this predictive model by first predicting the next day's ambient variables more precisely and investigating the prediction of electrical power output for different types of power plants. Further, given that the ambient temperature was essentially found to be the most influential variable, more studies can be conducted on the effect of temperature on different types of power plants and how the temperature variance throughout the day affects the power output. Another interesting approach can involve testing the association of electrical power output with the relative humidity and ambient pressure since this study was not able to capture a strong association of the power output with these two ambient variables.

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