A PREDICTIVE MODEL FOR TURBINE ENERGY YIELD ESTIMATION IN A COMBINED CYCLE POWER PLANT

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Keywords: PREDICTIVE MODELLING, TURBINE ENERGY YIELD, GAS TURBINES, LINEAR REGRESSION

Abstract

Gas turbines are a key player in the energy generation sector and thus form a key component in energy systems as a critical infrastructure. The determination of key parameters in optimization and efficiency of the gas turbines are of utmost importance to increase their power conversion efficiency. This paper presents a simple power estimation model for a gas turbine considering all its parameters. 7412 multivariate data records from the UCI Machine Learning Repository were used in the development of a linear prediction model for estimating the turbine energy yield for a combined cycle power plant. Simulation results show that the inlet temperature of the turbine is the most critical parameter that predicts its energy yield capacity, while ambient atmospheric conditions of temperature, humidity and pressure do not predict its energy yield capacity.

1 Introduction

Gas turbines are one of the most widely adopted machines for power generation [1], and numerous studies have been carried out to further optimize the performance of gas turbines as well as understand its operational limitations [2]. Energy systems behavior was identified as a key area of interest for research as certain parameters such as ambient temperature and humidity are deemed key to the optimal operation of the gas turbine as discussed in [3], where the researchers highlighted that gas turbine efficiency drops by 0.06% per ^{o} C rise in ambient temperature (AT) above 15 ^{o} C. Turbine inlet temperatures (TIT) were also identified to play a key role in improving output power and efficiency. This study thus presents a predictive model that ties all identified gas turbine variables/parameters together to identify the net correlation between them all and the turbine's energy yield capacity.

2. Methodology

A multi-variate regression method will be used for developing the predictive model of this study. It can be defined based on the simple regression model in (1), which relates one predictor to another

$$y_i = b_o + \sum_{j=1}^{p} b_j x_{ij} + e_i \quad (1)$$

where, $i \in \{1, \dots \dots .., n\}$, $y_i \in \mathbb{R}$ is the real-value response for the i-th observation, $b_o \in \mathbb{R}$, is the regression intercept, $b_j \in \mathbb{R}$, is the j-th predictor's regression slope, $x_{ij} \in \mathbb{R}$, is the j-th predictor for the i-th observation and the Gaussian error term is defined using equation (2):

$$e_i \sim N(0, \sigma^2) \quad (2)$$

A dataset from the UCI repository [4] was used in developing the predictive model for this research. It contained 7412 multivariate data with measurements relating to ambient temperature (AT), ambient pressure (AP), ambient humidity (AH), air filter difference pressure (AFDP), gas turbine exhaust pressure (GTEP), Turbine inlet temperature (TIT), turbine after temperature (TAT), compressor discharge pressure (CDP) and turbine energy yield (TEY), carbon monoxide (CO) and Nitrogen Oxide (NO) respectively. Python programming language and its associated libraries such as NumPy and Pandas was used within the Jupyter environment to develop a predictive. Due to large values present in the dataset, the data had to be scaled using a Standard_Scaler object derived in equation (3) created from the sklearn library.

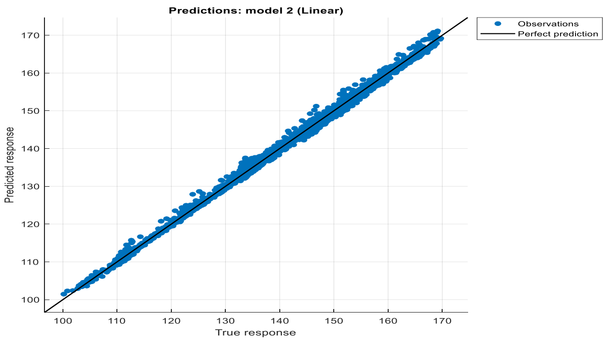
$$Z = \frac{(X-U)}{S} \quad (3)$$

where, Z is a feature's standard score, U is the training feature's mean, S is the standard deviation, while X is an observation. This ensures all the data points are scaled to a range between 0 and 1. The MATLAB software platform was used to illustrate the prediction results and the residual error.

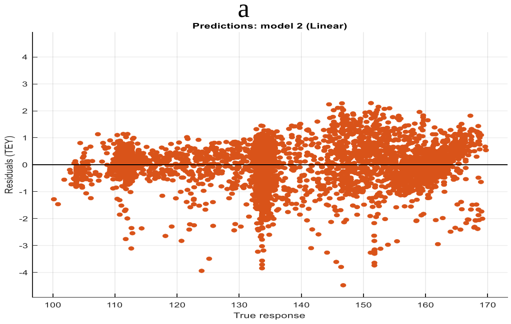
3 Results

The dataset was split into training and test sets, with 70% of the data used for training, while 30 % of the data was used for testing, five (5) folds validation was also selected to improve the accuracy of the model prediction. The predicted response plot is shown in Fig.1a, while Fig.1b shows the Gaussian error with the error randomly dispersed around zero. Table 1 describes the model performance for the training set and the test set, respectively. The multivariate regressor model which was used to predict the turbine energy yield variable is described in (4):

$$Y = 135.75 - 2.53 X_1 - 0.42X_2 - 0.06X_3 - 0.38 X_4 + 1.99 X_5 + 9.66 X_6 - 5.08 X_7 + 1.51 X_8 \quad (4)$$



a



b

Fig. 1 (a) Predicted versus Actual plot of Model, (b) Gaussian Error Residual Plot

TABLE 1: Model Performance

	RMSE	R-Squared	MSE	MAE
Model (Train)	0.74165	1.00	0.4112	0.5765
Model (Test)	0.72641	1.00	0.49	0.51

The predictive capacity of the model is shown in Fig.1a. shows a near accurate prediction between the independent and dependent variables. The R-squared value described in Table.1. of 1.00 in the training and testing phases indicate the overall high level of correlation between the parameters of the turbine and its energy yield output. However, the root mean square error (RMSE) values depicts the presence of large residuals. The findings of this study for the impact of ambient temperature to turbine energy yield correlates with observations in literature [5], while the impact of humidity disagrees with observations made in [6], where humidity had an inverse relationship with energy yield. The most positively correlated parameter is the turbine inlet temperature with a b_p of 9.66, which shows that the energy yield of a turbine is highly dependent on the turbine inlet temperature (TIT) as also observed in comparative studies in [7].

4 Conclusion

Multiple Linear regression offers a simplistic and reliable method for estimating the relationship between predictors in a multi-variate dataset, as the result of this study shows that the model predicts over 95% of the relationship between the dependent and independent variables. To improve the energy yield of a turbine based on the predictions of this model, the design must ensure that the turbine inlet temperature, gas turbine exhaust pressure and compressor discharge pressure variables are high enough to ensure improved efficiency in performance. Parameters such as ambient pressure, temperature and humidity, air filter difference pressure and turbine after temperature are to be kept low, as they are negatively correlated with the energy yield. Further studies could also explore the role of emissions in Turbine energy yield estimation as those variables were excluded in this study**.**

6 References

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