RESPONSE SURFACE MODELING FOR OPTIMIZING THE PERFORMANCE OF THERMAL TURBINE WHILE GENERATING ELECTRICAL ENERGY

Muhammad Ismail wasan[1], Muhammad Rafique Daudpoto[2], Mir Ghulam Haider Talpur[3], Naeem Ahmed Qureshi[4]

[1].PhD scholar department of Statistics University of Sindh Jamshoro

[2].Associte professor department of Statistics University of Sindh Jamshoro

[3].Professor Mathematics and Statistics department Institute of Business management, Karachi

[4]. Professor department of Statistics University of Sindh Jamshoro

Abstract:

Electrical energy is source of raising development of the world, the world has changed its shape time to time because of extent amount of electrical energy. Energy helps to achieve the goals such as health, high level of living standards, sustainable economy and a clean environment. Present study is concerned with the optimization of electrical generation for thermal turbine through response surface methodology. The data were collected from thermal power plant Jamshoro and unit one 200 MW mad by Japan was considered. The RSM has suggested the quadratic models for the data because both models were highly significant and have high predicted R-square vales greater than 90%. Analysis of variance decided that the suggest models are significant at specified level of significance (0.05) and the explanatory variables contributing significantly. There is main as well as interaction effect of explanatory variables. Verification of the models performed by different plots. If the thermal turbine run on the suggested parameters, then we can minimize the input source (fuel consumption) and maximize the output source (Electrical energy generation).

Keywords: Electrical energy, Response surface methodology, Thermal energy station, optimization

1.Introduction

Energy is not only essential for development; it is a powerful engine of social and economic opportunities (Owamah et al. 2020). No country develops considerably without providing the minimum power required for sustainable economy. Previous studies have shown that the economic growth of any country depends to a large extent, on its energy output (Owamah and Izinyon 2015; Izadyar et al. 2016). Sustainable utilization of energy resources is critical for socio-economic development and overall prosperity across the globe. In the last decade, enormous and unprecedented growth in energy consumption has been observed accompanied by technological advancement and the industrial revolution. Fossil fuels played a crucial part in meeting this ever-growing energy demand. However, the utilization of conventional fossil fuels results in severe environmental damages by releasing a large volume of greenhouse gases. According to the data published in World Energy Outlook, 2019. [world energy outlook 2019]**.**

Energy is one of the primary elements which are needed for social and economic development. Energy is a means to achieve the goals such as health, high level of living standards, sustainable economy and a clean environment [IAEA ,2005]**.** Energy resources of the countries are one of the main factors indicating their development and leadership position in the rivalry. Therefore, efficient use of energy becomes more of an issue for the countries. Energy efficiency is identified as the efficiency scaling the relation between energy inputs and outputs by means of comparison [Cui Q et al (2014)].

Energy is the primary element for the development of the country. Therefore, the availability of its extent amount is not easy task. Worldwide various methods are used for generating the electrical generation like hydro electrical plants, thermal, bio, nuclear and renewable energies.

The energy produced by power generation fleet during the fiscal year 2019-20 totaled 121,691 GWh and was contributed approximately 32% by hydroelectric plants, 57% by thermal plants which contains natural gas, local coal, imported coal, RFO and RLNG based technologies, 8% by nuclear plants, and 3% by renewable energy power plants which covers solar, wind and bagasse-based technologies. By the end of May, 2021, the total installed generation capacity in the country reached 34,501 MW of which 34% remains RE comprising of hydro-electric, solar, wind and bagasse-based technologies and 66% thermal plants which comprises of natural gas, local coal, imported coal, RFO and RLNG based technologies (IGCEP 2021).

By the year 2020, total number of electricity consumers have reached to 29,957,369 out of which 25,803,759 belong to domestic category, 3,245,508 belong to commercial category, 348,087 consumers fall under industries, there are 344,689 agriculture consumers, bulk supply consumers are 4,397, public lighting connections have been recorded as 10,932 and 199,970 consumers are categorized as general services consumers. During the year 2020, domestic consumption had a share of 47,643 GWh, commercial consumption used 6,260 GWh, industrial consumption was

21,489 GWh, agriculture consumption had a share of 9,642 GWh and 7,757 GWh has been consumed by other categories (IGCEP 2021).

According to the World Energy Outlook (2016) statistics, at least 51 million people in Pakistan or representing 27% of the population live without access to electricity.('WEO, 2016) According to IFC, the rate of energy for poor people is even higher with approximately 36% or 67 million out of 185 million without access to electricity (Umul Awan, , 2016) The National Electric Power Regulatory Authority, in its annual State of the Industry Report, concludes that approximately 20% of all villages, 32,889 out of 161,969, are not connected to the grid. Even those households that are statistically connected experience daily blackouts so that it is estimated that more than 144 million people across the country do not have reliable access to electricity. As a result, Pakistani households use a mix of technologies to power their homes and businesses.

While Rana and Patel (2018) investigated the determination of best location for small hydro energy project using multi-criteria techniques, Ghimire and Reddy (2013) applied Swarm optimization to evaluating the optimal reservoir operation for hydro energy generation. In spite of these, in relation to hydro energy generation optimization, researchers are still aspiring to new and more effective optimization techniques given the issues of high dimensionality in the majority of existing models. Furthermore, to the best of our knowledge, literature contains scanty or no information on the optimization of the performance characteristics of hydro energy plants to enhance electricity generation using the Response Surface Methodology (RSM).

Yan et al. (2013) studied a novel Solid oxide fuel Cell –Gas Turbine –Organic Rankine Cycle (SOFC-GT-ORC) system with liquefied natural gas as heat sink through thermodynamic analysis. A net electrical efficiency of 67.38% was reported. Liu et al. (2018) and Yan et al (2018). used a model of a coal-fired power plant in the simulation software GSE to improve ramp rates by the utilization of process-inherent thermal storages, e.g., by regulating the extraction steam of high-pressure pre heaters and adjusting the condensate mass flow. Bhattacharya, (2021) the central composite design is the foremost usually utilized fractional factorial plan utilized within the response surface model. In this plan, the middle focuses are increased with a bunch of pivotal focuses known as star points. With this plan, rapidly first-order and second-order terms can be assessed. In this book chapter, diverse sorts of central composite design and their importance in different exploratory plan were visibly clarified. By the by, a calculation based on alpha ()

assurance and hub focuses were visibly depicted. This book chapter moreover amalgamates as of late incepted central composite design models in different test situations. At last, one case thinks about was moreover examined to get it the genuine interior of the central composite design. Manuel Pais-Chanfrau et al. (2021) response surface methodology could be a device for the plan of tests, broadly utilized nowadays to optimize mechanical procedures, comprising agro-industrial ones. Meanwhile its presence within the final century's fifties, hundreds of articles, chapters of books, and books verify to this. In this effort, a common diagram of this tool's common practical features is prepared. This measurable instrument's convenience and notoriety utilized within the optimization of agro-industrial forms and in creating them more effective and maintainable, is portrayed through numerous illustrations.

2. MATERIAL AND METHODS

2.1 Study area

Present study is based on the data provided from Thermal energy station Jamshoro is located in district Jamshoro (Sindh) 5- Km North west of the town Jamshoro on Indus High-way at the right bank of River, about 18 Km from center of Hyderabad. This energy station comprises the of four units having total installed capacity of 850 MW.

2.2 Data collection

The electrical energy generation of thermal turbine (unit two -200 MW made by China) was recorded on different input variables like (Turbine installed load, Furnace oil (fuel) consumption, temperature, pressure and steam flow. Every observation was considered after 24 hours. The total 200 observations were taken into account in this study as well as data of explanatory variables also taken.

2.3 Statistical analysis

Data collected, tabulated and analyzed by different ways in the present work. Descriptive and inferential statistics are used. The best statistical model is developed and suggested by the help of different criteria. The Statistical software for Social Sciences (SPSS: 23), MS Excel and Design expert -13.0 are used for the purpose of analysis.

2.4 Detection of multicollinearity

The absence of multicollinearity among the independent variables is a strong assumption while running cause and effect relationship such as regression analysis and RSM. Perfect multicollinearity is uncommon and is typically detectable before to running a regression. But if it is found after the regression has been performed, one of the parameters should be eliminated. Variance Inflation Factor (VIF) is used for the detection of multicollinearity between the variables. It is well documented in the literature that if the VIF value is greater than 10 is an indication for the presence of multicollinearity (Evern & Howell, 2005, O'Brien, 2007).

2.5 Model fit summary and significance

After removing the variable(s) causing multicollinearity, the next step is to re-estimate the model and look for VIF values and report the results for the fitted model's summary statistics. These statistics show that how many models are fitted by the response surface methodology and similarly at the same time the best model is suggested by the RSM which might be linear, quadratic, cubic, or of any other polynomial regression models. The mathematical equation for the quadratic model (also known as second degree polynomial regression model) is shown as under (Zarringhalami et al, 2021)

$$Y= \beta_{0} + \Sigma^{K}_{J=1} \beta_j x_j + \Sigma^{K}_{J=1} \beta_{jj} x^2 + \Sigma\Sigma^{k}_{i<j} \beta_{ij} X_i X_j$$

Where β_0 is defined as the constant stands for the number of independent variables. For the present study the value of j goes from 1 to 5. ANOVA table is very important to break the variation into different component such as variation due to factors at levels, their squares and interactions as well. The table also reports significance of the parameters and for fitted model as well. Parameters having p value of less than or equal to 0.05 are considered as significant.

03 RESULTS AND DISCUSSION

Table. No:01: Summary statistics of unit two thermal power station Jamshoro 200 MW

Name	Minimum	Maximum	Mean	Std. Dev.
Electrical generation	2677.624	4313.176	3676.30994	481.699239
Load	140.00	180.00	160.00	17.01
Fuel	810.00	1109.00	959.50	127.15
Temperature	510.00	540.00	525.00	12.76
Pressure	104.00	133.00	118.50	12.33
Flow	122.00	381.00	251.50	110.14

The summary statistics in the table 01 show the minimum, maximum, mean, and standard deviation of six variables electrical generation, load, fuel, temperature, pressure and flow. The minimum electrical generation was recorded as 2677.24 MW while the maximum value was recorded at 4313.76 MW. The mean of the electrical generation was found to be 3676.30994 MW with 481.699239 MW standard deviation. Similarly, the minimum of load, Fuel consumption, temperature, pressure and steam flow was reported to be 140 MW, 810 metric ton, 510 C^0,104 kg/cm^2, 122 metric ton respectively. The maximum and average values of said variables are mention in above table. So far as the dispersion in the variables under study is concerned, the amount of variability was observed in load (17.01), fuel consumption (127.15), temperature (12.76), pressure (12.33), and steam flow (110.14), respectively.

The shape of distribution and outliers of the data for different variables are detected by box and whisker plot.

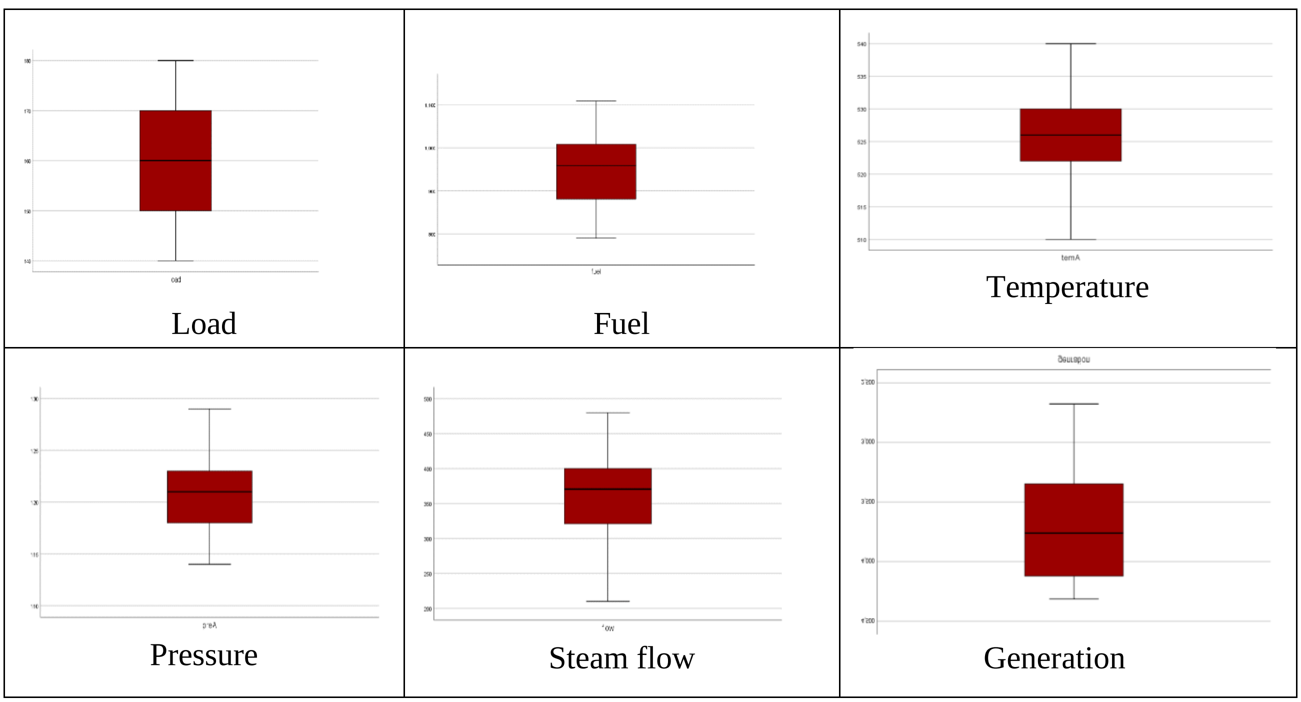


Figure. No :1: Box and whisker plots for unit two TPS Jamshoro

Figure 4.2.1 is indicating that there is no outlier in the data set that effect the results of the suggested model.

Table. No: 02: Multicollinearity Analysis after removing some factors

		Collinearity Statistics	
Model	**Std. Error**	**VIF**	**Tolerance**
Load	1.661	7.737	.129
Fuel	.211	4.793	.209
Temperature	1.714	1.245	.803
Pressure	1.537	1.080	.926
Steam Flow	.224	3.689	.271

Table. No: 2: shows the most of the VIF values for all independent variables are less than 10 which reject the presence of the multicollinearity between the variables and tolerance values are also less than 1 it is clear evidence of unavailability of multicollinearity.

Table. No:03: Best fitted models by RSM

Source	Sequential p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Linear	**< 0.0001**	**0.8032**	**0.9219**	**0.9153**	**Suggested**
2FI	0.3994	0.8162	0.9235	0.9191	
Quadratic	0.1413	0.8801	0.9323	0.8983	
Cubic	0.8841	0.6932	0.9076	-1.1872	**Aliased**

The table 03 provides, the Linear model has the lowest sequential p-value (< 0.0001) and the highest adjusted R-squared (0.9219) and predicted R-squared (0.9153) values. This indicates that the Linear model fits the data the best out of the four models. The Quadratic model has the second lowest sequential p-value (0.1413) and the second highest adjusted R-squared (0.9323) and predicted R-squared (0.8983) values. This indicates that the Quadratic model also fits the data well, but not as well as the Linear model. The Cubic model has the third lowest sequential p-value (0.8841) and the third highest adjusted R-squared (0.9076) and predicted R-squared (-1.1872) values. This indicates that the Cubic model does not fit the data as well as the Linear or Quadratic models. The 2FI model has the highest sequential p-value (0.3994) and the lowest adjusted R-squared (0.9235) and predicted R-squared (0.9191) values. This indicates that the 2FI model does not fit the data as well as the other three models. Overall, the Fit Summary table suggests that the Linear model is the best model for fitting the data. The Linear model is statistically significant and explains a large portion of the variation in the data, while the other models are either not statistically significant or do not explain as much of the variation in the data.

Table. No:04: Sequential Model Sum of Squares

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	6.282E+08	1	6.282E+08			
Linear vs Mean	**1.471E+07**	**5**	**2.943E+06**	**111.96**	**< 0.0001**	**Suggested**
2FI vs Linear	2.802E+05	10	28023.12	1.09	0.3994	
Quadratic vs 2FI	2.082E+05	5	41633.85	1.83	0.1413	
Cubic vs Quadratic	2.425E+05	15	16167.77	0.5201	0.8841	Aliased
Residual	3.730E+05	12	31086.25			
Total	6.440E+08	48	1.342E+07			

The Sequential Model Sum of Squares table 04 shows the reduction in the error sum of squares (SSE) when one or more predictor variables are added to the model. It is also equal to the increase in the regression sum of squares (SSR) when one or more predictor variables are added to the model. The Sequential Model Sum of Squares table in the image you provided shows that the linear model explains the most variation in the response variable, followed by the quadratic model, the cubic model, and the 2FI model. The other models (mean and 2FI vs Linear) do not explain much variation in the response variable. The table also shows that the linear model is significantly better than the mean model (F-value of 111.96, p-value < 0.0001). This means that adding the linear predictor variable to the model significantly reduces the error sum of squares. The quadratic model is also significantly better than the linear model (F-value of 2.943E+06, p-value < 0.0001). This means that adding the quadratic predictor variable to the model significantly reduces the error sum of squares, given that the linear predictor variable is already in the model. However, the cubic model is not significantly better than the quadratic model (F-value of 16167.77, p-value = 0.8841). This means that adding the cubic predictor variable to the model does not significantly reduce the error sum of squares, given that the quadratic predictor variable is already in the model. Overall, the Sequential Model Sum of Squares table shows that the linear model is the best model for explaining the variation in the response variable. The quadratic model is also a good model, but it does not explain significantly more variation than the linear model. The cubic model is not a good model, as it does not explain significantly more variation than the quadratic model. Select the highest order polynomial where the additional terms are significant and the model is not aliased.

Table.No:05: Coefficient in term of coded variables

Factor	Coefficient Estimate	Df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	3617.60	1	23.40	3570.38	3664.82	
A-load	651.83	1	27.80	595.72	707.94	1.0000
B-fuel	84.91	1	27.80	28.80	141.03	1.0000
C-temperature	11.61	1	27.80	-44.50	67.72	1.0000
D-pressure	-0.5029	1	27.80	-56.61	55.61	1.0000
E-flow	22.85	1	27.80	-33.26	78.96	1.0000

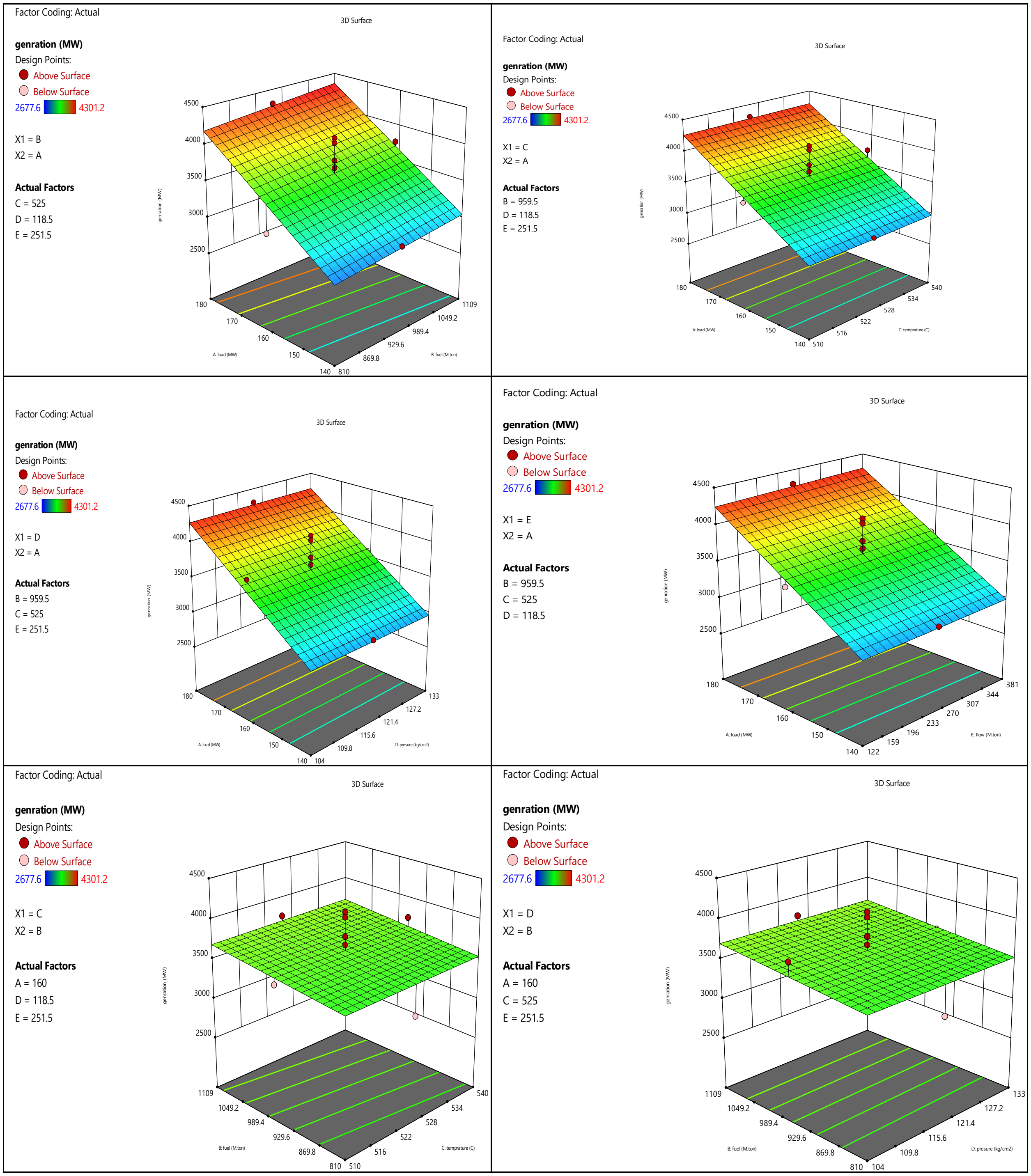
The coefficients in the table 05 of coded var factors represent the estimated change in the response variable for a one-unit increase in the coded factor, holding all other factors constant. The sign of the coefficient indicates the direction of the relationship between the factor and the response variable. The size of the coefficient can be interpreted as the marginal effect of the factor on the response variable, in coded units. A-load: The coefficient for A-load is 651.83. This means that, on average, we expect the response variable to increase by 651.83 units for every one-unit increase in the original A-load variable, holding all other variables constant. B-fuel: The coefficient for B-fuel is 84.91. This means that, on average, we expect the response variable to increase by 84.91 units for every one-unit increase in the original B-fuel variable, holding all other variables constant. C-temperature: The coefficient for C-temperature is 11.61. This means that, on average, we expect the response variable to increase by 11.61 units for every one-unit increase in the original C-temperature variable, holding all other variables constant. D-Pressure: the coefficient for the factor pressure is -0.5029. This means that, on average, we expect the response variable to decrease by 0.5029 coded units for every one-unit increase in the coded temperature factor, holding all other factors constant. E-Steam flow: The coefficient for E-Flow is 22.85. This means that, on average, we expect the response variable to increase by 22.85units for every one-unit increase in the original E-Flow variable, holding all other variables constant.

Final equation in terms of coded factors

Electrical generation = 3617.60 + 651.83*Load + 84.91*Fuel + 11.61*Temperature - 0.5029*Pressure + 22.85* Steam flow

Final equation in terms of actual factors

Electrical generation = 2588.70115 + 32.59147* Load + 0.567991* Fuel + 0.774118* Temperature - 0.034686* Pressure + 0.176448 * Steam flow


Factor Coding: Actual
3D Surface
genration (MW)
Design Points:
Above Surface
Below Surface
2677.6
4301.2
X1 = B
X2 = A
Actual Factors
C = 525
D = 118.5
E = 251.5
Factor Coding: Actual
3D Surface
genration (MW)
Design Points:
Above Surface
Below Surface
2677.6
4301.2
X1 = C
X2 = A
Actual Factors
B = 959.5
D = 118.5
E = 251.5
Factor Coding: Actual
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X1 = D
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Actual Factors
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D = 118.5
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C = 525
E = 251.5

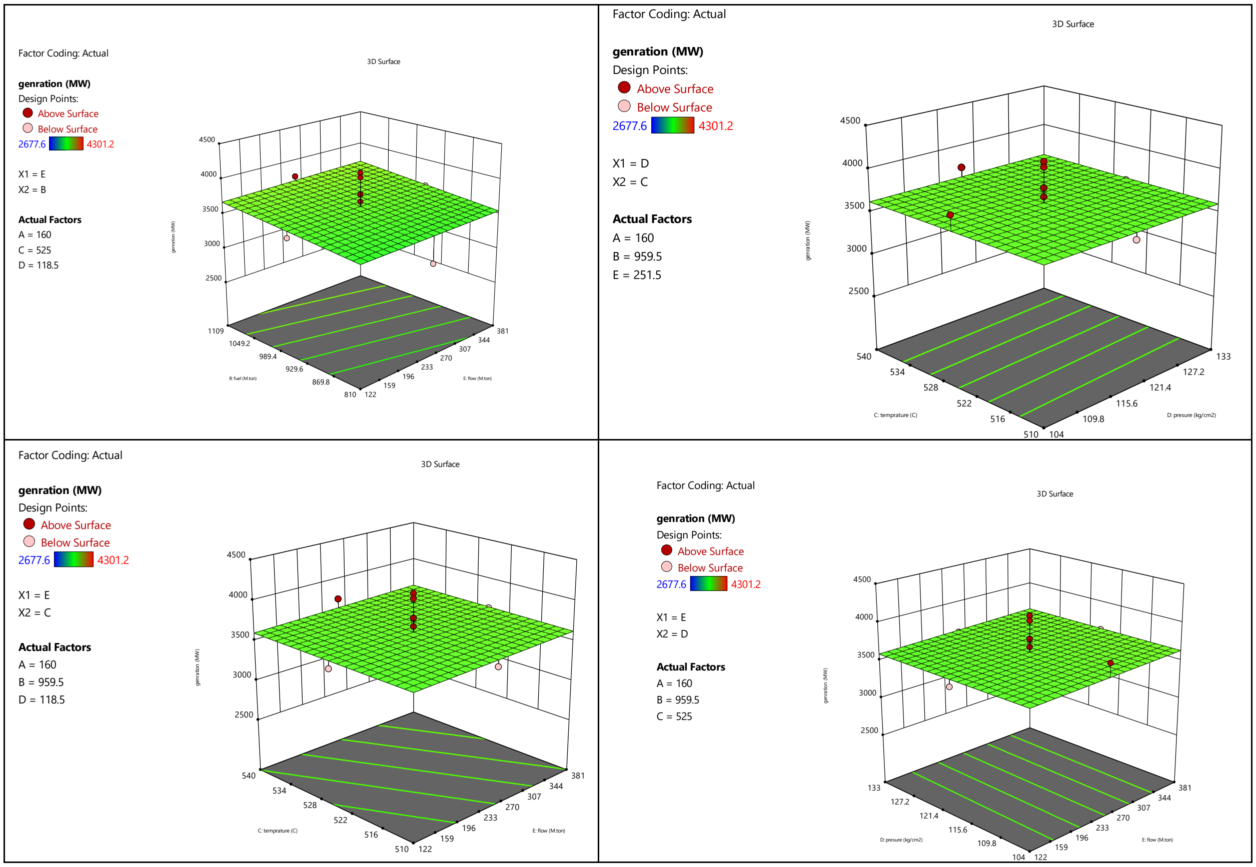

Figure.No:02: Response surface 3Dcurves unit one TPS Jamshoro 200 MW

3.2 THE SIGNIFICANCE OF MODEL

ANOVA of the quadratic model is required to test the significance and adequacy of the model. The significance and the fitness of the model was verified by using analysis of variance (ANOVA) in the design expert software.

Table.No:06: ANOVA TABLE for best fitted models

Source	Sum of Squares	Df	Mean Square	F-value	p-value	
Model	1.471E+07	5	2.943E+06	111.96	< 0.0001	Significant
A-load	1.445E+07	1	1.445E+07	549.60	< 0.0001	
B-fuel	2.452E+05	1	2.452E+05	9.33	0.0039	
C-temprature	4584.32	1	4584.32	0.1744	0.6783	
D-presure	8.60	1	8.60	0.0003	0.9857	
E-flow	17752.16	1	17752.16	0.6754	0.4158	
Residual	1.104E+06	42	26284.57			
Lack of Fit	9.122E+05	37	24654.12	0.6429	0.8032	not significant
Pure Error	1.917E+05	5	38349.91			
Cor Total	1.582E+07	47				

The ANOVA table 06 for the linear model shows that the model is statistically significant (F-value of 111.96, p-value < 0.0001). This means that the model is good at explaining the variation in the response variable. The table also shows that the following factors are statistically significant A-load (F-value of 549.60, p-value < 0.0001) B-fuel (F-value of 9.33, p-value = 0.0039) E-flow (F-value of 0.6754, p-value = 0.4158) This means that these factors have a significant impact on the response variable. The other factors (C-temperature and D-pressure) are not statistically significant. This means that they do not have a significant impact on the response variable. The Lack of Fit test is not statistically significant (F-value of 0.6429, p-value = 0.8032). This means that the linear model fits the data well. Overall, the ANOVA table shows that the linear model is a good fit for the data and that the factors A-load, B-fuel, and E-flow have a significant impact on the response variable.

3.3 Validity of the fitted model

Table. No:07: Validity of the fitted model

Std. Dev.	162.13		**R^2**	0.9302
Mean	3617.60		**Adjusted R^2**	0.9219
C.V. %	4.48		**Predicted R^2**	0.9153
			Adeq Precision	26.9264

The fit statistics in the Table. No:07 are as follows standard deviation (162.13), coefficient of variation (4.48%) R-squared (0.9302), Adjusted R-squared (0.9219), R-squared (0.9153) and Adeg Precision (26.9264) Standard deviation measures the amount of variation in the data. A lower standard deviation indicates that the data is more tightly clustered around the mean. In this case, the standard deviation is 162.13, which indicates that there is a moderate amount of variation in the data. Coefficient of variation indicates the less amount of variation in the data. R-squared is a measure of how well the model fits the data. It ranges from 0 to 1, with higher values indicating a better fit. In this case, the R-squared is 0.9302, which indicates that the model fits the data very well. Adjusted R-squared is a modified version of R-squared that takes into account the number of predictor variables in the model. It is generally considered to be a more reliable measure of model fit than R-squared. In this case, the adjusted R-squared is 0.9219, which indicates that the model fits the data very well, even taking into account the number of predictor variables. Predicted R-squared is a measure of how well the model will generalize to new data. It is calculated by crossvalidating the model, which means that the model is trained on a subset of the data and then tested on the remaining subset of the data. This process is repeated multiple times, and the average predicted R-squared is calculated. In this case, the predicted R-squared is 0.9153, which indicates that the model is expected to generalize well to new data. Adeg Precision is a measure of how well the model predicts the direction of the response variable. It ranges from 0 to 1, with higher values indicating better predictions. In this case, the Adeg Precision is 26.9264, which indicates that the model does a good job of predicting the direction of the response variable.

4.1.4 VERIFICATION OF THE MODEL ADEQUACY

There are many numerical and graphical ways of verification of the best fitted models. The obtained model's verification is tested by graphically. The four graphs are given below for this purpose. The adequacy of the suggested (linear) model was ascertained through the figures the QQ-plot of the residuals with reference to normal distribution, residual vs. predicted, predicted vs. actual, and Box and Cox plot.

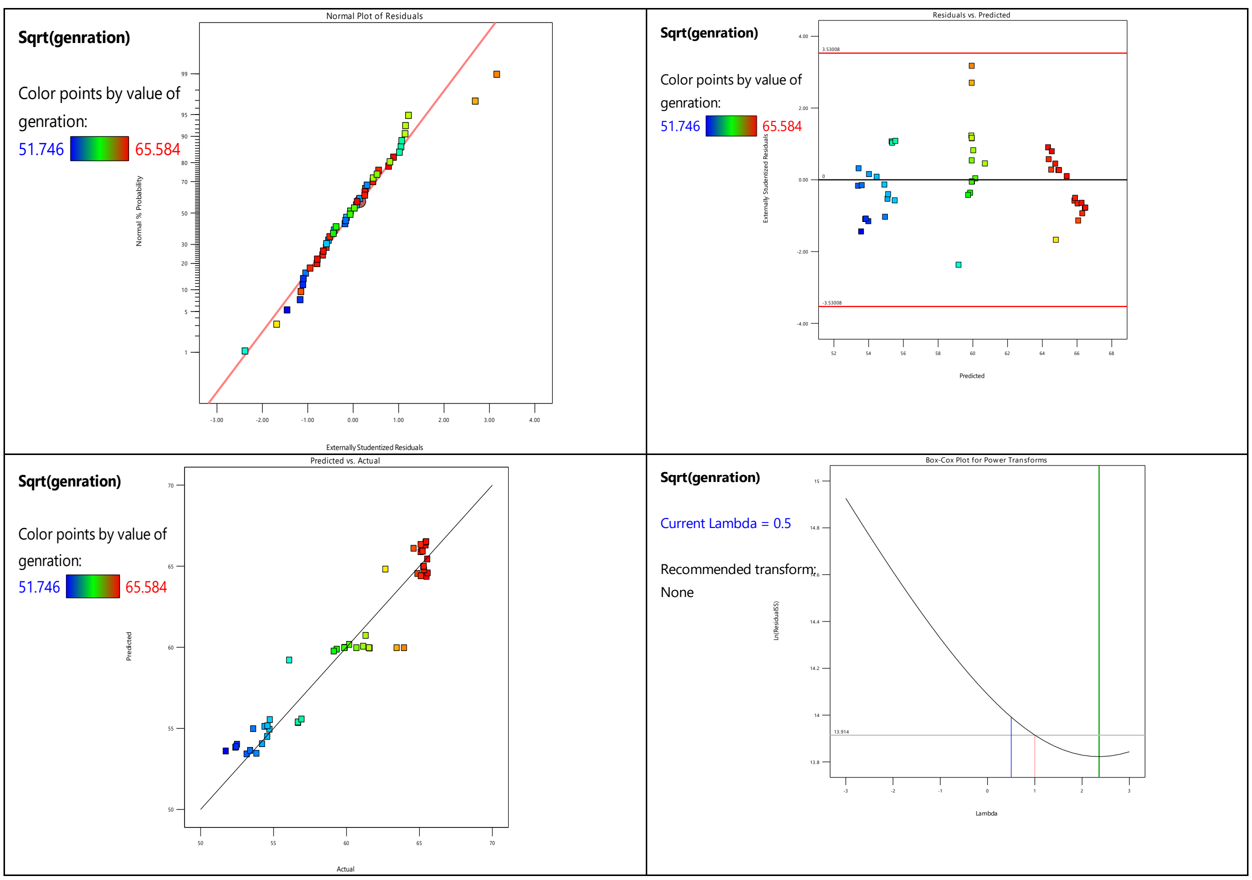

Figure.No:4.2.4: verification plots unit two TPS Jamshoro 200MW

The normal plot of the generation is approximately linear, which suggests that the residuals are normally distributed. However, there are a few outliers in the plot, which indicates that there are some data points that are not well-represented by the normal distribution. These outliers could be due to measurement errors or other factors. It is important to be aware of these outliers when interpreting the results of any statistical test. The residual vs predicted graph you sent shows that the residuals are generally evenly distributed around the zero line, with no clear patterns. This is a good sign, as it suggests that the model is not overfitting the data and that the residuals are normally distributed. However, there are a few outliers in the plot, which are indicated by the data points that are far away from the zero line. The predicted vs. actual plot shows that the points are generally close to the diagonal line, which is a good sign. However, there are a few outliers, particularly at the higher values of generation. Overall, the Box-Cox plot suggests that the optimal lambda value for the Box-Cox transformation is 0.5 and that the Box-Cox transformation is likely to have a significant impact on the normality of the dataset. All of these plots were in favor of normality among the internally studentized residuals which was also reported by (Muhamad et al., 2020).

Conclusion

Present study has provided the optimal solution for the thermal turbine in getting maximum electrical generation by using several explanatory variables. The response surface modeling suggested the linear model for achieving the maximum electrical generation for thermal turbine. The suggested model was validated and verified by different statistical methods.it is concluded that if administration of thermal power station follows the suggested pattern (model) then at minimum fuel consumption can receive optimal amount of electrical generation.

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