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Thermoexergetic analysis and multi-objective optimization of steam power plant performances

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***Abstract*— This study explores the performance of steam power plants through the use of Response Surface Methodology (RSM), which offers a more thorough multi-objective optimization compared to traditional methods that might analyze parameters independently. The thermodynamic simulations are conducted by the Engineering Equation Solver (EES) program for distinct parameters such as inlet temperature ($350 \leq T_3 \leq 600$°C), boiler pressure ($5000 \leq P_3 \leq 15000$kPa), and condenser pressure ($5 \leq T_1 \leq 15$ kPa). A centered composite design (CCD) with process parameters was used for statistical analysis. A second-order regression model was developed to correlate the process parameters with thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X), and specific fuel consumption (SFC). A better determination coefficient (R^2) was attained with the quadratic model, which showed 99.88%, 99.85%, 99.44%, and 99.80% for η_I, η_{II}, X, and SFC, respectively. Hence, numerical and graphical optimization was conducted operating the desirability function approach to get the suitable input variables to deliver the highest thermal and exergetic efficiencies with maximum vapor quality and minimal specific fuel consumption rate.**

***Index Terms*—Thermoexergetic analysis; Optimization; Steam turbine; Power plant; Performances; RSM**

I. INTRODUCTION

Steam Rankine power plants are crucial for global electricity generation, converting thermal energy into electricity. Performance analysis is essential for optimizing efficiency, sustainability, and economic viability, spanning fossil fuel, nuclear, and renewable sources. The efficiency of power generation units is often evaluated by comparing output to input, but this method is limited due to thermodynamic irreversibility [1]. Thermodynamic efficiency indicators, including heat energy conversion and cycle efficiency, are critical for assessing Steam Rankine Cycle (SRC) performance, seeking to minimize fuel consumption and environmental implications. Many parameters can affect the efficiency of the steam power plant performance, and one of the most crucial is the turbine inlet temperature. It is important to determine the optimal process parameters to improve thermal and exergetic efficiencies, vapor quality, and specific fuel consumption.

Various researchers have developed many enhancements and alterations of the SRC to improve efficiency and adapt to specific conditions innovations such as supercritical Rankine and combined cycles. Zhang et al. [2] studied the combined SRC and ORC in extreme cold areas. Also, they compared working fluids and found optimal matching schemes for varied situations and objects. Their study revealed that the combined system's net power increases with decreasing condenser outlet temperature. Zhu et al. [3] investigated the benefits and limitations of the Steam Injected Turbocompounding (SIT) idea in recuperating waste heat from the big marine two-stroke engine. They compared SIT and traditional SRC systems with various configurations. The results show that the dual-pressure steam production arrangement is better than the single-pressure scenario. Dokl et al. [4] explored the most efficient energy production configuration in actual circumstances, primarily focused on an SRC with water/steam and two ORCs employing organic fluid R245fa for thermal energy conversion. They stated that the lower cycles' temperature restrictions caused the working fluids' higher operating temperatures in the cascade design. Gonzalez et al. [5] compared the performance of Hygroscopic Cycle Technology (HCT) with the Rankine cycle (RC) in industrial-scale situations. The evaluation results illustrate that The HCT has a lower fuel exergy in absolute terms than the RC. Li et al. [6] Present a revolutionary partial cascade organic-steam Rankine cycle technology to boost the fluid evaporation temperature and thermal efficiency. The proposed system significantly increases the power fluid's average temperature during heating, achieving a maximum cycle efficiency of 45.3%. Maruf et al. [7] studies Bangladesh's power generating industry using energetic metrics to determine efficiency and sustainability. Efficiency is specified by energy and exergy, while exergy-based parameters determine sustainability. Their study revealed that the total energy efficiencies range between 34.55% and 36.10% and the overall exergy efficiencies vary between 35.07% and 36.59% throughout this timeframe. Liu et al. [8] presented a novel WHRS combining SRC and ORC to recycle waste heat from naval engines. The system transforms exhaust gas and jacket cooling water waste-heat into mechanical energy. The findings revealed that the enhanced thermal efficiency by 4.42% and minimized fuel consumption by 9322 tons per year. Qu et al. [9] focused on thermal cycle devices to recover waste heat from diesel engines to improving energy efficiency. SRC and

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ORC were designed and tested. Their study revealed that the proposed system can generate up to 1,079.1 KW at 100% load, with maximum thermal and exergy efficiency at 90%.

The performance of optimization approaches in SRC power plant has garnered considerable attention in recent years. Several methods have been employed for the optimization of energy sources. Hernandez et al. [10] proposed a mathematical model for an SRC power plant to optimize design and operational parameters primarily for optimum system net power production and second law efficiency. This model was experimentally tested for a heat recovery-driven power plant, attaining sharp maxima at both levels with a 60% second law efficiency variation. Eftekhari et al. [11] developed a novel power tri-generation cycle that recovers energy from hot gases and waste energy from the steam cycle. The cycle is optimized using a multifunctional GA, with the goal functions being electricity cost and thermodynamic efficiency. Variables include fuel, compressor, turbine ratio, mass flow rate, pinch points, and maximum temperatures. Their study revealed that the thermal efficiency can be increased about twice and a half time by combining the steam and gas cycles. Elahifar et al. [12] investigate the exergy of a SRC, concentrating on improving the Rankine cycle and obtaining improved exergy efficiency. Intelligent algorithms like bees, fireflies, and teaching and learning were applied to improve the system's exergy efficiency. The findings revealed that these modifications might raise the plant's exergy efficiency by 0.58047%, 0.60368%, and 0.60369%. Naeimi et al. [13] conducted a multiobjective optimization of a combined cycle power plant using genetic algorithm. They regarded exergy efficiency, total exergy cost and exergoenvironmental effect as the goal functions. They stated that the heating improved by 11%, 12%, and 32%, respectively. Holik et al. [14] investigate waste-heat recovery system based on steam RC and ORC. A multiobjective optimization was used for a biogas power plant with two engines, resulting in a 42.1% electrical efficiency and 66.7% total energetic efficiency. They stated that the RC was shown to be more economical than the ORC employing toluene, with a 2.97%. Mahdavi et al. [15] focussed on optimizing a novel CCHP system consisting of a GT power plant using RSM coupled with the TOPSIS approach. The authors stated that maximum net power, minimum system emission, and maximum exergy efficiency are 61.73 MW, 52.87 g/MJ, and 44.22%, respectively.

Previous literature related to optimizing the performance characteristics of SRC power plants is limited. This study combines RSM with thermodynamic analysis to identify optimal operational parameters, including inlet temperature, boiler pressure, and condenser pressure. It also establishes quantitative relationships between these parameters and critical performance indicators like thermal efficiency, exergetic efficiency, vapor quality, and specific fuel consumption.

This study aims to address the gaps noted in existing literature on power plant optimization, and makes three substantial contributions: (i) this study uniquely combines RSM with thermodynamic principles to systematically identify and optimize operational parameters such as inlet temperature, boiler pressure, and condenser pressure, which are crucial for enhancing power plant efficiency, (ii) by establishing quantitative relationships between operational parameters and key performance indicators (thermal efficiency, exergetic efficiency, vapor quality, and specific fuel consumption) this research contributes a nuanced understanding of how these parameters interact, and (iii) the core novelty lies in the development of an empirical model and the execution of numerical simulations to identify the optimal design parameters that yield maximum thermal and energetic efficiencies, minimize specific fuel consumption, and maximize vapor quality under defined design constraints.

The structure of this paper is organized as follows: in Section II, offers an in-depth description of the system schemes and operational processes, elaborating on the mathematical model and thermodynamic analysis used. Section III focuses on methodology, detailing the application of RSM in developing mathematical models and analyzing how different variables influence response parameters. Section IV discusses the implications of the research findings and validates the mathematical models. Section V presents the results of numerical and graphical optimization using the desirability function approach. Finally, in section VI, Concludes with a summary of the main findings and outlines directions for future research.

II. STEAM POWER PLANT THERMODYNAMIC ANALYSIS

The schematic and T-s diagram of the SRC, which evaluates the thermodynamic efficiency in this research, are presented in Fig. 1. Both first- and second-law investigations of thermodynamics are used to analyze the system's thermal efficiency. The RC conducts the following four state-open system processes:

1-2 Irreversible pressure in pump
2-3 Addition constant heat transfer in boilers,
3-4 Irreversible growth in turbines
4-1 continuous heat loss in condenser

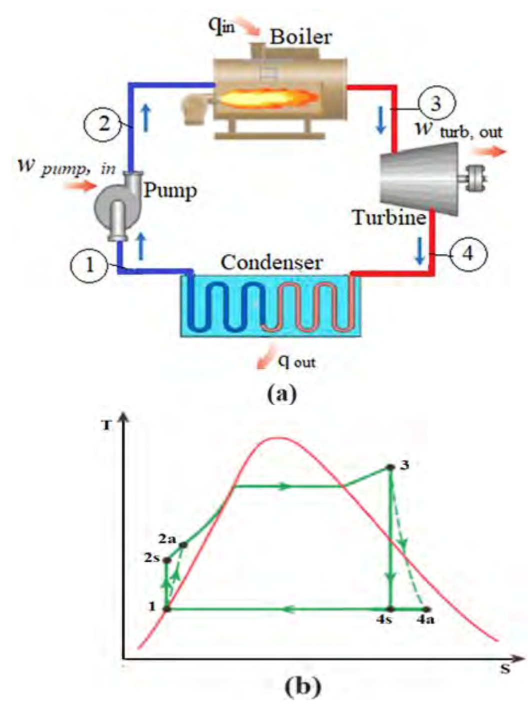

Fig.1.(a) Schematic cycle and (b) T-S diagram of a Rankine cycle

The pump isentropic efficiency is defined as:

$$\eta_{isP} = \frac{h_2 - h_1}{h_{2a} - h_1} \quad (1)$$

The turbine's isentropic efficiency is defined as:

$$\eta_{isT} = \frac{h_3 - h_{4a}}{h_3 - h_4} \quad (2)$$

From the energy balance in the combustion chamber:

$$\dot{m}_f \, LHV = \dot{m}_s (h_3 - h_{2a}) \quad (3)$$

With, LHV is the lower heating value of fuel, and $\dot{m}_s$ is the steam mass flow rate

The work generated from the turbine is defined using this equation:

$$W_t = \dot{m}_s (h_3 - h_{4a}) \quad (4)$$

The work required to run the pump is expressed as:

$$W_P = \dot{m}_s (h_{2a} - h_1) \quad (5)$$

The working of the cycle is given by:

$$W_{net} = W_t - W_P \quad (6)$$

The heat supplied is also expressed by:

$$q_{in} = \dot{m}_s (h_3 - h_{2a}) \quad (7)$$

Thermal and exergetic efficiencies of the steam turbine are evaluated using Eqs:

$$\eta_I = \frac{W_{net}}{q_{in}} \quad (8)$$

$$\eta_{II} = \frac{\eta_I}{\left(1 - \frac{T_1}{T_3}\right)} \quad (9)$$

The specific fuel consumption (SFC) is determined by:

$$SFC = \frac{3600 \dot{m}_f}{W_{net}} \quad (10)$$

Where $\dot{m}_f$ is the fuel mass flow rate

The vapor quality may be determined by splitting the mass of the vapor (mV) by the mass of the entire mixture (m_T):

$$X = \frac{m_V}{m_T} \quad (11)$$

With

$$m_T = m_L + m_V \quad (12)$$

Where m_L is the mass of the liquid

The above-mentioned equations (Eqs. (1)–(12)) were solved using thermodynamic Engineering Equation Software (EES). The outcomes of each of the variables employed in this research have been provided in Table 1. Careful selection of particular important parameters is necessary to increase the thermal performance of a steam power plant for highest thermal and exergetic efficiencies with maximum vapor quality and minimal specific fuel consumption rate.

TABLE I
OPERATING PARAMETERS

Operating parameters	Value Unit	Unit
Steam mass flow rate ($\dot{m}$s) [21]	15	kg/s
Boiler pressure (P_3) [17], [20]	5000-15000	kPa
Condenser pressure (P_4) [16]	5-15	kPa
Turbine inlet temperature (T_3) [17], [18]	350-600	°C
Lower heating value (LHV) (CH4) [22], [23]	47622	kJ/kg
Isentropic efficiency of pump (η_{isP}) [18], [19]	80	%
Isentropic efficiency of turbine (η_{isT}) [18], [19]	85	%

III. Response surface methodology

Response surface methodology (RSM) is a set of mathematical and statistical approaches that are helpful for the modeling and analysis of situations in which various variables affect the response to demand, and the objective is to maximize this response [24]. Accordingly, the RSM is used to characterize and identify, with remarkable precision, the effect of the relationships among multiple distinct variables on the response when they are altered concurrently. RSM tries to construct a research approach for assessing responses and determining the ideal settings. Central composite designs (CCD) are regarded as effective RSM designs as they effectively examine the influence of experimental conditions on the outcome with fewer test runs. Model performance was evaluated using ANOVA. This strategy modifies the input variables to determine the reasons for variations in the output response. The numerical simulation results were evaluated using the response surface regression process using the following second-order polynomial solution [25]:

$$y = b_0 + \sum_{i=1}^{3} b_i x_i + \sum_{i=1}^{3} b_{ii} x_i^2 + \sum_{i<j}^{3} b_{ij} x_i x_j \quad (13)$$

Where y is the response, and x_i and x_j are the encoded variables. When adjusted centered approximations (coded levels) are employed for displaying variable levels, b_0, b_i, b_{ii}, and b_{ij} are the average values of results, linear, polynomial, and relationship constant coefficients, respectively. Every variable permitted calculating the variation in the average output per unit rise in x when any additional variables were kept constant. In creating the regression model, the test data were coded based on Eq. (14):

$$x_i = \frac{X_i - X_i^*}{\Delta X_i} \quad (14)$$

Where x_i is the i^{th} individual parameter of the empty encoded value, the uncoded value of the i^{th} independent parameter is indicated by X_i; similarly, at the middle point, the uncoded value of the i^{th} individual parameter is designated by x_{ij}, and the variation in the step value has been described as ΔX_i [26].

Matrix notation is shown in the following equations:

$$y = X\beta + \varepsilon \quad (15)$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1k} \\ 1 & X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{nk} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_k \end{bmatrix} \quad (16)$$

Multivariate regression analysis using the empirical model in Eq. (16) was performed to give the full quadratic model in Eq. (13) that was utilized in modeling the development process of the models presented in equations 15 to 18.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{11} {X_1}^2 + \beta_{22} {X_2}^2 + \beta_{33} {X_3}^2 + X_1 X_2 + \beta_{13} X_1 X_2 + \beta_{23} X_2 X_3 + \varepsilon \quad (17)$$

In the current study, mathematical models have been established by utilizing CCD and regression approach in RSM for three variables with three levels of each characteristic. The design expert 13 software was utilized for analysis and optimization using RSM. Simulations were carried out and the influence of these design parameters on thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X) and specific fuel consumption (SFC). The numerical simulation parameters and their coded levels for CCD are listed in Table II.

TABLE II
VARIABLES AND LEVELS OF THE DESIGN MODEL

Symbol	Factors	Unit	Level		
			-1	0	+1
A: T_3	Turbine inlet temperature	°C	350	475	600
B: P_3	Boiler pressure	kPa	5000	10000	15000
C: P_4	Condenser pressure	kPa	5	10	15

The examination of statistical data was executed in three parts. In the first step, ANOVA was employed to assess the influence of factors and their relationships with the response variables. The next stage is focused on nonlinear regression to create computational models displaying the fluctuation of outputs. The final one is employed for the optimization of outcomes.

TABLE III
SIMULATION RESULTS FOR η_I, η_{II}, x and SFC

Run N°	Design parameters			Response parameters			
	A: T_3 (°C)	B: P_3 (kPa)	C: P_4 (kPa)	η_I (%)	η_{II} (%)	X (%)	SFC (kg/kWh)
1	475	10000	10	34	59.25	78.16	0.2224
2	600	5000	15	32.43	51.85	89.68	0.2331
3	600	15000	5	38.15	58.72	78.32	0.1982
4	600	15000	15	35.91	57.41	81.66	0.2105
5	475	5000	10	31.77	55.37	83.34	0.2379
6	475	10000	10	34	59.25	78.16	0.2224
7	350	10000	10	32.43	66.4	70.58	0.2331
8	350	5000	5	31.97	62.81	75.44	0.2365
9	350	15000	15	32.13	67.61	64.61	0.2353
10	600	5000	5	34.99	53.87	85.67	0.216
11	475	10000	5	35.48	60.02	76.23	0.2131
12	475	15000	10	35.11	61.18	74.65	0.2153
13	350	5000	15	29.29	61.63	78.51	0.2581
14	350	15000	5	34.4	67.59	62.71	0.2197
15	475	10000	10	34	59.25	78.16	0.2224
16	475	10000	10	34	59.25	78.16	0.2224
17	600	10000	10	35.61	56.09	83.38	0.2123
18	475	10000	15	33.07	58.74	79.37	0.2286
19	475	10000	10	34	59.25	78.16	0.2224

IV. RESULTS AND DISCUSSIONS

In the present section, the obtained results related to effects of design parameters, statistical analysis and mathematical modelling of thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X) and specific fuel consumption (SFC) as well as the response surface analysis, are presented. A series of experiments according to the numerical simulation plan and CCD design for response parameters are presented in Table III.

A. *Statistical analysis*

In In this work, ANOVA is applied to verify the prediction's correctness. MS, Df, SS, F-value, and P-value are characteristics to verify the usefulness of the equation. The F-value calculation measures the data's variation around the standard deviation. Furthermore, the P-values verify the hypothesis according to the statistics. The variables have better accuracy at F-values greater than one based on the variance estimation. To continue with the ANOVA, the technique of least squares is utilized. The findings of this study in the form of an ANOVA are reported. The evaluation was done at an acceptance rate of 95 %. An ANOVA analysis table is typically used to explain the regression equation test and examine the most critical variables.

Tables IV, V, VI, and VII indicate that thermal efficiency (ηI), exergetic efficiency (η_{II}), vapor quality (X), and specific fuel consumption (SFC) simulations are meaningful with Prob>F values lower than 0.0001. The percentage of the impact of any given model variable was computed. The model F-value for thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X) and specific fuel consumption (SFC) are 851.6, 691.29, 468.71 and 573.36, respectively, which implies that the models is significant. It can also be seen from Table IV that the effect of input parameters on thermal efficiency (η_I) are statistically significant and the variation of η_I with condenser pressure (P_4) is minimal; however, the effect of turbine inlet temperature (T_3) on η_I is of statistical importance followed by boiler pressure (P_3). The proportion of the factor's impact provides an improved basis for the explanation of the findings, which demonstrates that the impact made by the turbine inlet temperature (T_3) is 41.82% and that the boiler pressure (P_3) was found to be the second-greatest contributor with a contribution of 34.18% followed by condenser pressure (P_4) with a contribution of 21.37%. Next to them, quadratic impact B_2 and C_2 with the contributions of 1.39% and 0.24%, respectively. ANOVA table for exergetic efficiency (η_{II}) is presented in Table V. It can be apparently seen that the turbine inlet temperature (T_3) has a considerable effect on exergetic efficiency (η_{II}) by 72.10% contribution. Following the boiler pressure (Cont. ≈ 22.68%) and condenser pressure (Cont. ≈ 1.03%) which are also significant. The findings of ANOVA for vapor quality (X) are shown in Table VI. It can be observed that the T_3 is the most outstanding impact parameter compared to the other two variables and that the P_3 was discovered to be the second greatest influence after P_4. The ANOVA show that the interaction between T_3 and P_3 is statistically significant. The proportion of the factor's impact provides an improved basis for explaining the data, which reveals that the percentage attributable to the T_1 is 59.21%. In comparison, the P_3 provides only 34.03% and P_4 with an impact of 3.16%. Finality from analysis of the influence of Table VII, it can be apparently seen that all design parameters (T_3, P_3, and P_4) have statistically significant on SFC with the same contribution (41.93%, 35.48% and 22.58%). The interactions (AC and BC) were found to be less significant rate with the same contribution (0.24% and 0.32%), while the quadratic effect (B^2) is statistically significant on SFC

TABLE IV

ANOVA RESULTS OF THERMAL EFFICIENCY (η_I)

Source	SS	Df	MS	F-value	P-value	Cont. (%)
Model	67.96	9	7.55	851.6	< 0.0001	–
A-T_3	28.46	1	28.46	3209.84	< 0.0001	41.82
B-P_3	23.26	1	23.26	2622.97	< 0.0001	34.18
C-P_4	14.79	1	14.79	1667.71	< 0.0001	21.37
AB	0.2346	1	0.2346	26.46	0.0006	0.34
AC	0.0028	1	0.0028	0.3172	0.587	0.004
BC	0.0666	1	0.0666	7.51	0.0228	0.097
A^2	0.0002	1	0.0002	0.0212	0.8874	0.0002
B^2	0.9457	1	0.9457	106.66	< 0.0001	1.39
C^2	0.1663	1	0.1663	18.76	0.0019	0.244
Residual	0.0798	9	0.0089	–	–	–
Lack of Fit	0.0798	5	0.016	–	–	–
Pure error	0	4	0	–	–	–
Corr. Total	68.04	18	–	–	–	–

TABLE V

ANOVA RESULTS OF EXERGETIC EFFICIENCY (η_{II})

Source	SS	Df	MS	F-value	P-value	Cont. (%)
Model	320.39	9	35.60	691.29	< 0.0001	–
A-T_3	231.36	1	231.36	4492.83	< 0.0001	72.10
B-P_3	72.79	1	72.79	1413.56	< 0.0001	22.68
C-P_4	3.33	1	3.33	64.65	< 0.0001	1.037
AB	0.0153	1	0.0153	0.2974	0.5988	0.0047
AC	0.5886	1	0.5886	11.43	0.0081	0.183
BC	0.456	1	0.4560	8.86	0.0156	0.142
A^2	10.03	1	10.03	194.72	< 0.0001	3.126
B^2	3.04	1	3.04	58.98	< 0.0001	0.947
C^2	0.007	1	0.0070	0.1362	0.7206	0.002
Residual	0.4635	9	0.0515	–	–	–
Lack of Fit	0.4635	5	0.0927	–	–	–
Pure error	1E-08	4	1E-08	–	–	–
Corr. Total	320.85	18	–	–	–	–

TABLE VI

ANOVA RESULTS OF VAPOR QUALITY (X)

Source	SS	Df	MS	F-value	P-value	Cont. (%)
Model	753.29	9	83.7	468.71	< 0.0001	–
A-T_3	447.03	1	447.03	2503.31	< 0.0001	59.21
B-P_3	256.95	1	256.95	1438.89	< 0.0001	34.03
C-P_4	23.9	1	23.9	133.84	< 0.0001	3.16
AB	15.85	1	15.85	88.75	< 0.0001	2.09
AC	0.708	1	0.708	3.97	0.0776	0.09
BC	0.4232	1	0.4232	2.37	0.1581	0.05
A^2	4.77	1	4.77	26.7	0.0006	0.63
B^2	1.32	1	1.32	7.37	0.0238	0.17
C^2	0.6859	1	0.6859	3.84	0.0817	0.09
Residual	1.61	9	0.1786	–	–	–
Lack of Fit	1.61	5	0.3214	–	–	–
Pure error	0	4	0	–	–	–
Corr. Total	754.9	18	–	–	–	–

TABLE VII

ANOVA RESULTS OF SPECIFIC FUEL CONSUMPTION (SFC)

Source	SS	Df	MS	F-value	P-value	Cont. (%)
Model	0.0031	9	0.0003	573.36	< 0.0001	–
A-T_3	0.0013	1	0.0013	2113.78	< 0.0001	41.93
B-P_3	0.0011	1	0.0011	1755	< 0.0001	35.48
C-P_4	0.0007	1	0.0007	1123.75	< 0.0001	22.58
AB	8E-08	1	8E-08	0.1334	0.7234	0.002
AC	7.6E-06	1	7.61E-06	12.68	0.0061	0.24
BC	1E-05	1	1E-05	24.31	0.0008	0.32
A^2	7.2E-07	1	7.2E-07	1.2	0.3016	0.022
B^2	0.0001	1	0.0001	88.73	< 0.0001	3.22
C^2	4.8E-06	1	4.88E-06	8.14	0.062	0.154
Residual	5.4E-06	9	6.00E-07	–	–	–
Lack of Fit	5.4E-06	5	1.08E-06	–	–	–
Pure error	0	4	0	–	–	–
Corr. Total	0.0031	18	–	–	–	–

B. Development of mathematical models

A mathematical model was established for the thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X) and specific fuel consumption (SFC). The insignificant terms were excluded, except the main effects. Thus, reduced and improved η_I, η_{II}, X and SFC prediction models were generated. Therefore, the formulas of the estimated equations as a function of coded variables η_I, η_{II}, X, and SFC are provided as follows.

The thermal efficiency (η_I) model is given below in Eq. (18). Its coefficient of determination (R^2) is 99.88%.

$$\eta_I = 34 + 1.7A + 1.5B - 1.2C + 0.2AB + 0.1BC - 0.6B^2 + 0.24C^2 \quad (18)$$

The exergetic efficiency (η_{II}) model is given below in Eq. (19). Its coefficient of determination (R^2) is 99.85%.

$$\eta_{II} = 59 - 1.7A + 1.5B - 0.6C - 0.3AC + 0.3BC + 0.6A^2 - 0.2B^2 \quad (19)$$

The vapor quality (X) model is given below in Eq. (20). Its coefficient of determination (R^2) is 99.44%.

$$X = 78.27 + 6.69A - 5.07B + 1.55C + 1.41AB - 1.21A^2 \quad (20)$$

The specific fuel consumption (SFC) model is given below in Eq. (21). Its coefficient of determination (R^2) is 99.80%.

$$SFC = 0.2 - 0.1A - 0.01B + 0.1C - 0.01AC - 0.01BC + 0.004B^2 \quad (21)$$

The mean likelihood curves of the errors on η_I, η_{II}, X and SFC are presented in Figs.2 (a), (b), (c) and (d) correspondingly. Fig.2 demonstrates that the errors fall near a straight line, confirming that the factors indicated in the regression model are relevant [24]. Thus, normalcy looks adequate, and the calculation coefficients are reasonably significant, suggesting that the simulation outcomes correspond with the values estimated by the equation [27]. Figs.3 (a), (b), (c), and (d) show the predicted values of η_I, η_{II}, X, and SFC based on formulas of the fit equations and the simulation values. The numerical simulation results are definitely in accord with the projected values.

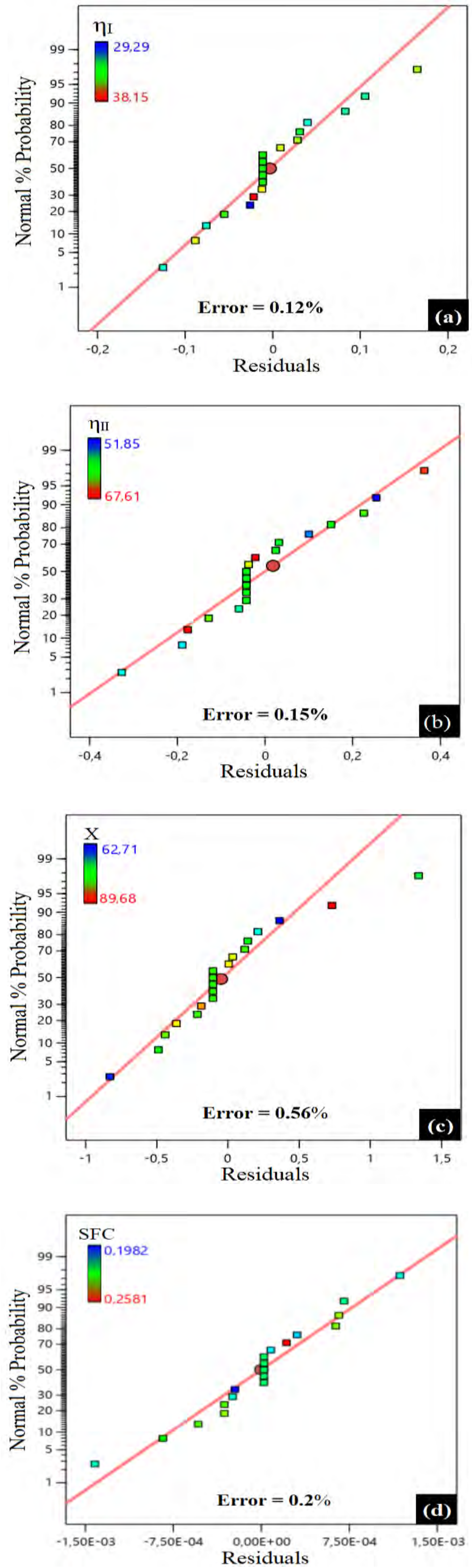

Fig. 2. Normal probability plot of residuals for η_I(a), η_{II}(b), X(c) and SFC(d)

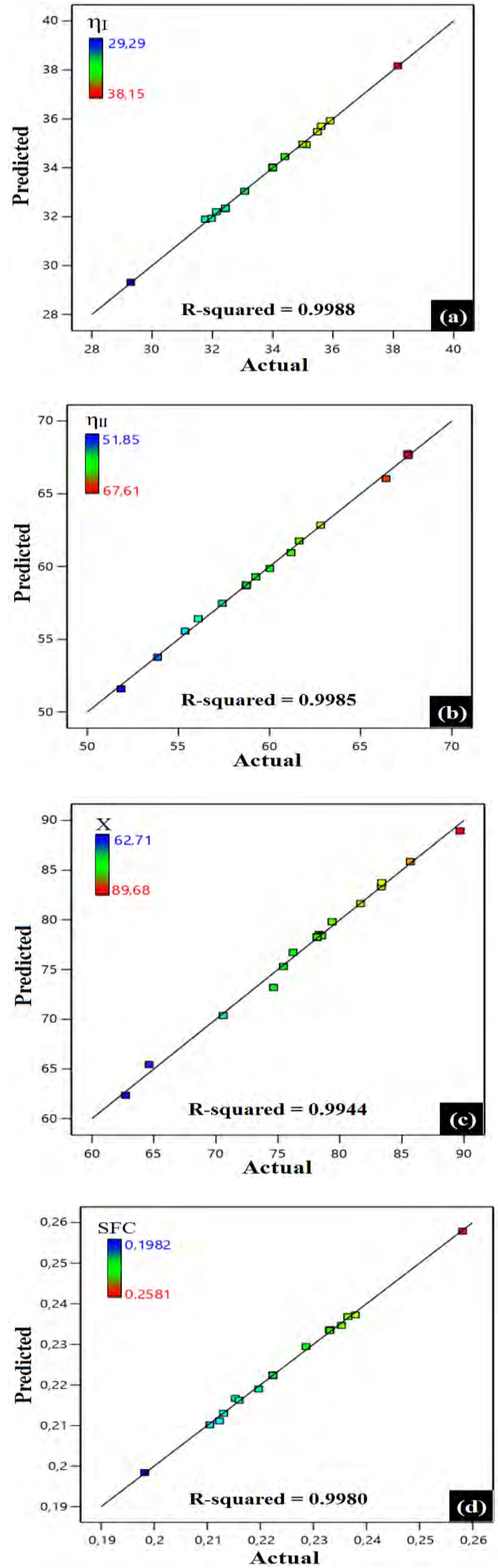

Fig. 3. Simulation vs. predicted values of η_I(a), η_{II}(b), X(c) and SFC(d)

C. 3D Response surface

The 3D surface graphs derived for the most pertinent variables associated with the thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X), and specific fuel consumption (SFC) of the Rankine steam turbine power plant concerning the process parameters are presented. Figs. 4–9 depicts the variance of adaptable variables with the design parameters, namely turbine inlet temperature (T_3), boiler pressure (P_3), and condenser pressure (P_4). Fig.4 shows the variation in thermal efficiency (η_I) with T_3 and boiler pressure (P_3). It is seen that T_3 has the highest impact on thermal efficiency compared to boiler pressure. The maximum thermal efficiency (η_I) value obtained was 37% at a P_3 of 15000 kPa and a T_3 of 600°C when the condenser pressure was kept at 10 kPa. Fig.5 shows the variation in thermal efficiency with P_4 and P_3. The thermal efficiency is considerably high for a higher boiler pressure value and a lower condenser pressure value. The maximum thermal efficiency (η_I) value obtained was 36.5% at a boiler pressure of 15000 kPa and condenser pressure of 5 kPa when T_3 was fixed at 500°C.

Fig.6 shows the variation in exergetic efficiency (η_{II}) with T_3 and P_3. It is seen that T_3 has a more substantial influence on η_{II}, and its variation is very high compared to others. Also, the η_{II} increases by decreasing the T_3 at higher P_3. The maximum η_{II} value obtained was 68% at a P_3 of 15000 kPa and a T_3 of 350°C when the P_4 was kept at 10 kPa. Fig.7 illustrates the estimated η_{II} response for the corresponding T_3 and P_4. It is confirmed that T_3 has the most significant effect on η_{II}. The maximum η_{II} value obtained was 67% at a T_3 of 350°C and P_4 of 5 kPa when the P_3 was fixed at 10000 kPa. The effects of the T_3 and P_3 on vapor quality (X) are presented in Fig.8. It is seen that T_3 has the highest impact on X. It is confirmed that the X increases by increasing T_3 and decreasing P_3 values. The maximum X value obtained was 87% at a P_3 of 5000 kPa and a T_3 of 600°C when the P_4 was fixed at 10 kPa. Fig. 9 depicts the 3D response behavior of SFC with the T_3 and P_3. This figure shows that the SFC is considerably minimum, with higher T_3 and P_3 values. The minimum SFC value obtained was 0.209 at a P_3 of 15000 kPa and a T_3 of 600°C when the $P_4$was fixed at 14 kPa

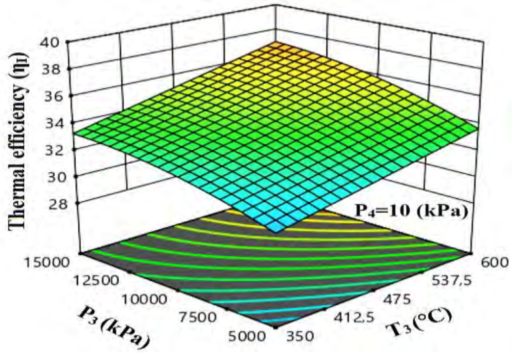

Fig. 4. Effect of T_3 and P_4 on thermal efficiency (η_I)

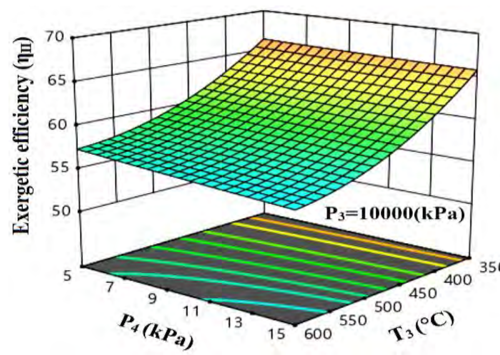

Fig. 7. Effect of T_3 and P_4 on exergetic efficiency (η_{II})

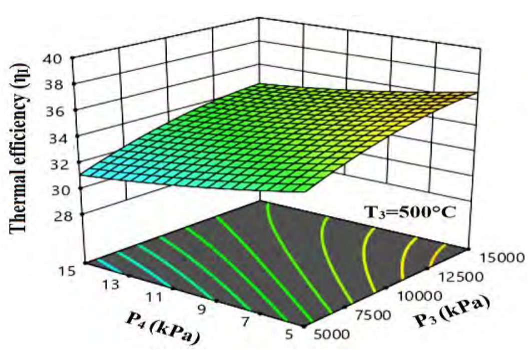

Fig. 5. Effect of P_3 and P_4 on thermal efficiency (η_I)

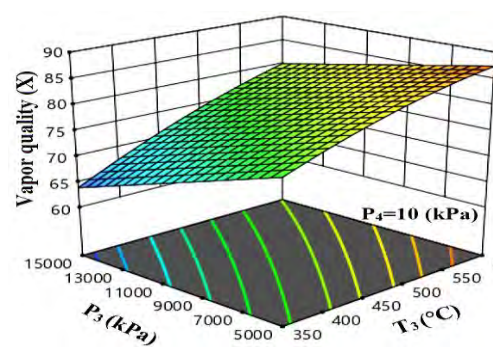

Fig. 8. Effect of T_3 and P_3 on vapor quality (x)

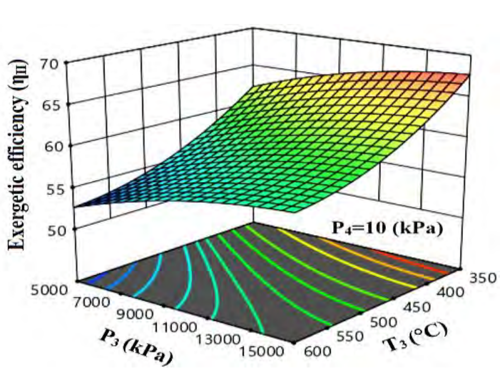

Fig. 6. Effect of T_3 and P_3 on exergetic efficiency (η_{II})

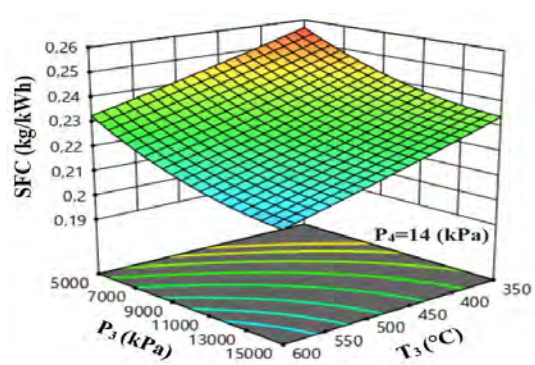

Fig. 9. Effect of T_3 and P_3 on specific fuel consumption (SFC)

D. Validation of the mathematical models

To verify the precision of the regression models for thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X), and specific fuel consumption (SFC), three sets of simulation data were randomly chosen from the defined simulation ranges and analyzed to compare with the predictions made by the models. The details of the process parameters and the validation results for these models are outlined in Table VIII. The predicted and simulated values were juxtaposed, and the percentage discrepancy was determined. The range of percentage errors between the simulated and predicted values for the response variables (η_I, η_{II}, X, and SFC) are as follows: ηI ranges from 0.18% to 1.3%, ηII from 1.21% to 2.06%, X from 0.73% to 1.68%, and SFC from 1.02% to 1.35%. It can be concluded that the developed regression models perform adequately well.

TABLE VIII

VALIDATION OF THE REGRESSION MODELS

Run N°	Designing parameters			For regression models		
	T_3 (°C)	P_3 (kPa)	P_4 (kPa)	Pred.	Simu.	Error (%)
η_I (%)						
1	350	5000	5	32.03	31.97	0.18
2	475	10000	10	34.45	34	1.3
3	600	15000	15	36.28	35.91	1.02
η_{II} (%)						
1	350	5000	5	61.54	62.81	2.06
2	475	10000	10	58.29	59.25	1.64
3	600	15000	15	56.72	57.41	1.21
X (%)						
1	350	5000	5	74.78	75.44	0.88
2	475	10000	10	77.59	78.16	0.73
3	600	15000	15	80.31	81.66	1.68
SFC (kg/kWh)						
1	350	5000	5	0.2396	0.2365	1.29
2	475	10000	10	0.2247	0.2224	1.02
3	600	15000	15	0.2134	0.2105	1.35

V. MULTI-OBJECTIVE OPTIMIZATION

The desirability technique has become one of the more extensively utilized procedures in industries for optimizing various response systems. The desirability function approach is used in this study due to its efficacy in optimizing multiple performance indicators of a steam power plant, which include thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X), and specific fuel consumption (SFC). These indicators often present conflicting objectives, making it challenging to optimize them simultaneously using traditional methods. Moreover, the desirability function method provides the flexibility to assign varying weights and priorities to each metric, tailored to the specific goals of the optimization process. This approach is particularly useful in complex systems where multiple outcomes must be balanced to achieve the best overall operational performance. In the DF method, each answer, y_i, was transformed into an individual desire function, d_i. The scale of d_i runs from 0 to 1 to the potential magnitudes of y_i, while $d_i=0$ denotes the reaction is entirely unsatisfactory, and $d_i=1$ represents the fully desired response. Single-sided conversion equations are presented in Eq. (22), and Eq. (23) were employed in the investigation. If y_i is to be maximized as opposed, d_i is described as Eq. (22); if y_i is to be reduced as opposed, d_i is given as Eq. (23).

$$d_i = \begin{cases} 0 & \text{if} \quad y_i \leq y_{i\,min} \\ \left(\dfrac{y_i - y_{i\,min}}{y_{i\,max} - y_{i\,min}}\right)^w & \text{if } y_{i\,min} \leq y_i \leq y_{i\,max} \\ 1 & \text{if} \quad y_i \geq y_{i\,max} \end{cases} \tag{22}$$

$$d_i = \begin{cases} 1 & \text{if} \quad y_i \leq y_{i\,min} \\ \left(\dfrac{y_i - y_{i\,max}}{y_{i\,min} - y_{i\,max}}\right)^w & \text{if } y_{i\,min} \leq y_i \leq y_{i\,max} \\ 0 & \text{if} \quad y_i \geq y_{i\,max} \end{cases} \tag{23}$$

While $y_i$min and $y_i$max are the smallest and highest permitted amounts of y_i, w is a weight variable. w is a weight variable. If *w*=1, d_i rises linearly; if w<1, d_i is convex; if *w*>1, d_i is concave.

The amount of weight variable w in Eq. (22) and Eq. (23) was selected as 0.3 since a 100% outcome can be challenging to be reached [28]. The aggregate desirability value for an optimization objective function is calculated using the geometric mean of the individual desirability values associated with the multiple responses [29]:

$$DF = (d_1[y_1(x)], d_2[y_2(x)], \ldots, d_n[y_n(x)]) = \left(\prod_{i=1}^{n} d_i[y_n(x)]\right)^{\frac{1}{n}} \tag{24}$$

Where: $0 \leq d_i(y_i) \leq 1$

Therefore, we have:

$$DF = (d_1[\eta_I(x)], d_2[\eta_{II}(x)], d_3[\mathrm{X}(x)], d_4[\mathrm{SFC}(x)]$$

$$DF = \left(d_{\eta_I} \times d_{\eta_{II}} \times d_{\mathrm{X}} \times d_{\mathrm{SFC}}\right)^{\frac{1}{4}} \tag{25}$$

The restrictions considered throughout the procedure of optimization are presented in Table IX.

TABLE IX

CONSTRAINTS FOR OPTIMIZATION PROCESS

Conditions	Objective	Lower limit	Upper limit	Importance
A: T_3 (°C)	in range	350	600	3
B: P_3 (kPa)	in range	5000	15000	3
C: P_4 (kPa)	in range	5	15	3
η_I (%)	Maximized	29.29	38.15	5
η_{II} (%)	Maximized	51.85	67.61	5
X (%)	Maximized	62.71	89.68	3
SFC (kg/kWh)	Minimized	0.1982	0.2581	3

The best solutions are provided in Table X. The desirability value of 0.7086 relates to obtaining optimum thermal and exergetic efficiency with the lowest specific fuel consumption and maximum vapor quality in the provided range of design variables. For straightforward evaluation, the desirability value of every single input variable and responses connected with the prediction are displayed in Fig. 10. The outcomes of graphical optimization are displayed in Fig.11. The outlines represent the limitations determined by the criterion. Also, the graphical optimization illustrates the region of viable answer values in the parameter universe in yellow.

TABLE X
OPTIMAL SOLUTIONS

N°	Design parameters			Response parameters				Desirability
	A: T_3 (°C)	B: P_3 (kPa)	C: P_4 (kPa)	η_I (%)	η_{II} (%)	X (%)	SFC (kg/kWh)	
1	**599.96**	**14639**	**5**	**38.13**	**58.62**	**78.79**	**0.1984**	**0.7086**
2	600	14345	5	38,10	58,59	79,01	0,198	0.7031
3	596	14220	5	38,04	58,59	78,96	0,199	0.7001
4	594	14233	5	38,01	58,61	78,86	0,199	0,6993
5	599	14999	6,09	37,83	58,49	78,87	0,2	0,6884
6	599,99	14338	6,88	37,52	58,32	79,61	0,2	0,6785

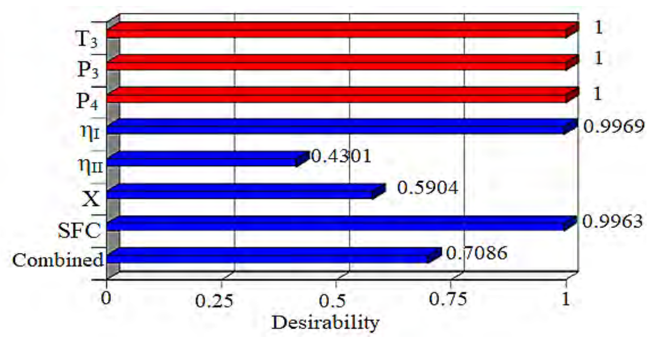

Fig. 10. Bar chart of the optimization

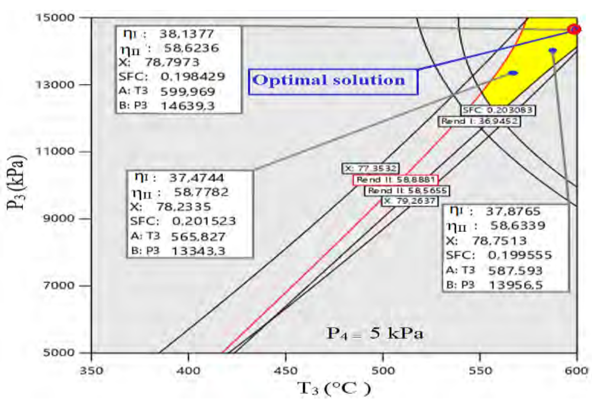

Fig. 11. Overlay plot of most desirable solution

From this evaluation, it can be determined that the turbine inlet temperature (T_3), 599.96°C, boiler pressure (P_3), 14639kPa, and condenser pressure (P_3), 5kPa are the optimum values of response variables. In contrast, the optimum value for thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X), and specific fuel consumption (SFC) are 38.13%, 58.62%, 78.79%, and 0.1984 kg/kWh, respectively.

In order to validate the efficiency of desirability function approach (DF) in predicting optimal operating conditions for steam power plants, an area where traditional algorithms like Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) are commonly applied. The objective function used in this optimization for GA and PSO is formulated as:

$$F = w_1\left(\frac{\eta_I}{\eta_{I\max}}\right) + w_2\left(\frac{\eta_{II}}{\eta_{II\max}}\right) + w_3\left(\frac{X}{X_{\max}}\right) - w_4\left(\frac{SFC}{SFC_{\max}}\right) \quad (26)$$

Where the weights w_1, w_2, w_3 and w_4 are 0.3, 0.3, 0.2, and 0.2, respectively, corresponding to the relative importance of each parameter.

TABLE XI
VALIDATION OF OPTIMAL SOLUTION USING GA AND PSO

Conditions	DF	GA	PSO
T_3 (°C)	599.96	584.3302	592.6018
P_3 (kPa)	14639	14699.9871	14699.9896
P_4 (kPa)	5	5	5
η_I (%)	38.13	37.9916	38.1326
η_{II} (%)	58.62	58.9873	58.6374
X (%)	78.79	76.6484	78.3286
SFC (kg/kWh)	0.1984	0.1967	0.1981

Table XI shows the results of the optimization for the performance characteristics of the steam power plant calculated in this paper in comparison with other optimisation algorithms. As can be seen from the table, the values of the thermal efficiency (η_I), exergetic efficiency (η_{II}), vapor quality (X), and specific fuel consumption (SFC) after optimisation using GA and PSO, which represents the validity of the optimal solution. These results underscore the efficacy of DF in handling complex optimization problems in steam power plant operations, presenting a dynamic model that successfully predicts optimal conditions with substantial computational efficiency.

VI. CONCLUSION AND FUTURE WORK

In the current research, the implementation of RSM on the performance characteristics of the steam power plant carried the mathematical models of the thermal and exergetic efficiencies, vapor quality, and specific fuel consumption to explore the impacts of input variables. The regression model coupled with DF optimization was utilized to discover the best value of process variables to achieve the maximum thermal and exergetic efficiencies with the lowest SFC and maximum vapor quality. The conclusions collected as a consequence of the research may be stated below.

- The steam power plant's performance characteristics are significantly impacted by the turbine intel temperature and boiler pressure; The condenser pressure impact is minimal compared to the remaining process factors.
- The exergetic efficiency of the steam turbine power plant increases with the increase of boiler pressure and almost decreases with the increase of turbine inlet temperature.
- ANOVA outcomes reveal that the turbine inlet temperature and boiler pressure affect the thermal efficiency by 41.82% and 34.18%, respectively. The condenser pressure's effect is less significant than the other process parameters.
- The developed regression models are excellently accurate and can be used for predicting the performance characteristics of the steam turbine power plant within the limits of the design parameters studied.
- Desirability function based on multi-objective optimization asserted that the optimum value of process parameters to provide the maximum thermal and exergetic efficiencies with minimal specific fuel consumption and maximum vapor quality are in the region turbine inlet temperature, 599.96°C, boiler pressure, 14639 kPa and condenser pressure, 5 kPa with estimated thermal efficiency of 38.13%, exergetic efficiency

of 58.62%, vapor quality of 78.79% and SFC of 0.1984 kg/kWh.

- In a future work, we plan to extend the scope of the current study by investigating the effects of additional process variables on steam power plant performance. Specifically, we plan to examine variables such as feedwater temperature and the properties of alternative working fluids. These variables are expected to provide deeper insights into optimizing power plant efficiency. By exploring these areas, we hope to uncover more comprehensive strategies to enhance the operational effectiveness and sustainability of steam power plants, thus broadening the applicability and relevance of our research findings.

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NOMENCLATURE

Cp	Specific heat [kJ/kg.K]
h	Enthalpy [kJ/kg]
LHV	Lower heating value [kJ/kg]
m	Mass [kg]
$\dot{m}_f$	Fuel mass flow rate [kg/s]
$\dot{m}_s$	Steam mass flow rate [kg/s]
P	Pressure [Pa]
q_{in}	Heat supplied [kW]
SFC	Specific fuel consumption [kg/kWh]
T	Temperature [K]
W_P	Pump turbine [MW]
W_t	Work turbine [MW]
W_{net}	Net Work [MW]
X	Vapor quality [%]
Greek symbols	
η_I	Cycle thermal efficiency [%]
η_{II}	Cycle exergy efficiency [%]
η_{isP}	Pump isentropic efficiency [%]
η_{ist}	Turbine's isentropic efficiency [%]
Subscripts	
L	Liquid
s	Steam
V	Vapor
SS	Sum of squares
Df	Degrees of freedom
MS	Mean square
DF	Desirability function
d_i	Individual desirability function

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