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Optimization of Flange Design for Engine Assembly Stand using RSM and NSGA-II Based on FEA Data

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ABSTRACT

This article presents the results of a research study that focused on optimizing the flange design for engine assembly stands using the Response Surface Methodology (RSM) and Nondominated Sorting Genetic Algorithm II (NSGA-II) based on finite element analysis (FEA) simulation data. The study investigated the impact of three main dimensions (d1, d2, d3) of the flange as independent variables on the mass (m, kg), Von Mises stress (V, MPa), and displacement (D, mm) as dependent variables. The regression models developed using the RSM exhibited high R^2 values of 0.9896, 0.998, and 0.9997 for m, V, and D, respectively. The multi-objective optimization results obtained through NSGA-II yielded 39 Pareto solutions, with d1 ranging from 10 to 27.43 mm, d2 ranging from 30 to 50 mm, and d3 ranging from 75 to 85 mm. These values corresponded to m values ranging from 2.93 to 7.58 kg, V values ranging from 54.8 to 342.6 MPa, and D values ranging from 0.006 to 0.270 mm. For verification purposes, Solution No.17 was selected. The results showed that the redesigned flange's mass, Von Mises stress, and displacement deviated by 0.95%, 2.28%, and 1.14%, respectively, from the optimal values obtained through the optimization process. These findings provide strong evidence for the high reliability of the optimization method employed in this study.

Keywords:
Optimization; Flange design; Engine assembly stand; Response surface methodology; NSGA II

1. Introduction

In engineering, the design of machine parts plays a crucial role in achieving optimal performance, efficiency, and reliability. Engineers face the ongoing challenge of developing machines that meet the increasing demands of higher performance, lighter weight, reduced energy consumption, and improved safety. To address these challenges, advanced computational tools and techniques are commonly employed to optimize machine designs. One such technique that has gained considerable prominence in the field is Finite Element Analysis (FEA). FEA provides engineers with a powerful computational tool to simulate and analyse the behaviour of complex systems under various operating conditions. By leveraging FEA data, engineers can optimize machine designs, resulting in improved performance, cost reduction, and increased safety [1,2].

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The optimization of machine design based on FEA data has become a focal point in recent research. This approach offers promising opportunities for enhancing machine performance, reducing costs, and improving reliability. In a study conducted by Chan *et al.,* [3], the performance of a high-precision machine tool was assessed. The evaluation involved analysing the virtual model of the machine tool created using CAD software and conducting model analysis using ANSYS Workbench software. The objective was to determine the tool's static deformation and static stiffness. The study revealed the presence of different frequencies and vibration types, indicating the existence of a weak link in the machine tool's performance. Afolabi *et al.,* [4] investigated the parameters of the fatigue life of machine shafts. The study proposed an optimal design for a machine shaft that ensures both safety and cost-effectiveness. To achieve this, a 3D model of the shaft was created using Inventor® software, employing absolute coordinates. The research findings were then compared with previous results obtained through alternative methods, including commercial FEA and calculations. Bayata and Yildiz [5] conducted a study focused on the design and optimization of various Ti-6Al-4V implant designs. The objective was to enhance the fracture resistance and service life of Ti-6Al-4V implants subjected to cyclic biting loads. FEA method was employed to optimize the design parameters of the implants and improve their performance under such loads. Many other studies have also used FEA to analyse and optimize machine structures [6-10].

Currently, many structural optimization studies have been performed through the combination of FEA data and mathematical methods such as Taguchi method, response surface methodology (RSM), artificial intelligence, Genetic Algorithm (GA) and other statistical designs. Ali, Behdinan, and Fawaz [11] developed a FEA procedure based on GA for the size and shape optimization of planar and space trusses. The study demonstrated that the GA-based FEA technique resulted in lighter structural designs in comparison to mathematical, OC, and other heuristic approaches. In a separate study, Cazacu and Grama [12] focused on optimizing the topology, size, and shape of plane trusses. They proposed a procedure and software application that utilized a genetic algorithm and FEA to evaluate the fitness function during the optimization process. Mai, Kang, and Lee [13] developed a surrogate model based on Deep Neural Networks (DNN) that was integrated with the differential evolution (DE) algorithm. This approach was applied to solve the optimum design problem of geometrically nonlinear space trusses under displacement constraints, aiming to replace conventional FEAs. The results of the study demonstrate that the proposed approach significantly reduces computational costs while ensuring convergence. Abbassi *et al.,* [14] suggested a design approach that combines FEA and Artificial Neural Network (ANN) modelling to estimate the hydroforming parameters (counterforce, axial feed, and internal pressure) of T-shaped tubes. The study establishes a strong correlation between the numerical results obtained from the FEA and the predictions generated by the ANN model. The combination of FEA and ANN is also applied in many other studies [15,16].

Multi-objective optimization methods have gained significant attention in the industry as they address the need to balance various technical requirements to achieve optimal performance[17-19]. Among them, the Nondominated Sorting Genetic Algorithm II (NSGA-II) distinguishes itself from the basic genetic algorithm by incorporating a stratification step prior to the selection operator. This stratification is based on the dominant relationship between individuals. Through the utilization of a nondominated hierarchical approach, individuals with superior characteristics are given higher chances of advancing to the next generation. Kadge [20] conducted a study to optimize the durability of a bevel gear using the FEA method. The optimized gear was then subjected to topology optimization to reduce its mass. To tackle the design optimization, a nonlinear multi-objective problem was formulated, where the number of teeth and modules were considered as the design parameters. The study employed the NSGA-II algorithm as the chosen optimization method. In another study, a multi-objective optimization method was employed for the sheet metal part fixture locating layout. The optimization process utilized a support vector regression (SVR) surrogate model in combination with NSGA-II, which is based on a parametric FEA model. The objective was to optimize the locating layout of the fixture for sheet metal parts, considering multiple objectives simultaneously [21]. The NSGA-II algorithm is also used for multi-objective optimization in many different fields [22-26].

This study focuses on optimizing the flange design for the Engine Assembly Stand (EAS) to reduce costs while ensuring durability. The analysis considers three selected dimension parameters of the flange as input variables for the optimization process. The goal is to analyse and adjust these parameters to find an optimal flange design that meets the required durability standards while minimizing production costs. The study begins by utilizing the Taguchi method to design the FEA simulation experiment to achieve this. The simulation results are then used to develop mathematical models using RSM. These models establish the relationship between the dimension parameters and the mass (m, kg), Von Mises stress (V, MPa), and displacement (D, mm). Subsequently, the NSGA-II is employed to search for Pareto-optimal solutions representing the trade-off between m, V, and D. The optimization process involves evaluating various combinations of dimensional parameters within their allowable ranges. Through simulations and analysis, the study aims to identify the optimal set of dimension values that achieve a desirable balance between durability and cost-effectiveness.

2. Materials and Methods

2.1 Engine Assembly Stand

Engine Assembly Stand (EAS) are essential tools utilized in the automotive industry for the assembly, disassembly, and testing engines. They provide a stable and secure platform for technicians to work on engines, ensuring efficiency, accuracy, and safety. The engine assembly stands were designed, including the stand frame, mounting system, rotating mechanism, lifting mechanism, tool trays and storage, adjustable height and positioning features, and safety measures, as shown in Figure 1(a). EAS is the foundation of the assembly stand, constructed from durable materials like steel to support the engine's weight and provide stability during operations. The mounting system comprises brackets, adapters, and flanges designed to securely attach the engine to the assembly stand, ensuring precise alignment and a secure fit. The rotating mechanism allows for easy engine rotation, eliminating manual repositioning and enabling technicians to access different sides and angles effortlessly.

Some assembly stands incorporate a lifting mechanism, such as hydraulic or pneumatic systems, to facilitate installing and removing heavy engine components, ensuring accurate positioning and reducing the risk of injuries during handling. Tool trays and storage compartments are commonly included in engine assembly stands, providing convenient storage for tools, components, and accessories, enhancing organization and productivity. Adjustable height and positioning features allow technicians to customize the stand's height or adjust the engine's position, improving accessibility to specific areas and reducing strain and fatigue. Figure 1(b) shows the fabricated ESA product for practical application.

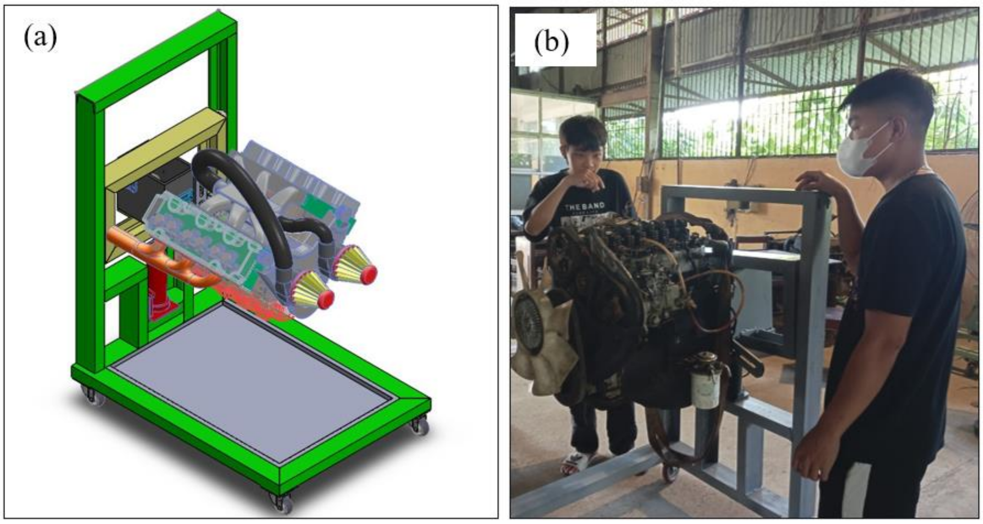

Fig. 1. Engine Assembly Stand (EAS) model (a) and manufacturing product (b) [27]

The flange used in the engine assembly and repair fixture for car engines weighing between 250 kg and 500 kg is a crucial component. It is connected to the engine using a mounting arm by M16 bolts. The main dimensions of the flange, including parameters d1, d2, and d3, are depicted in Figure 2.

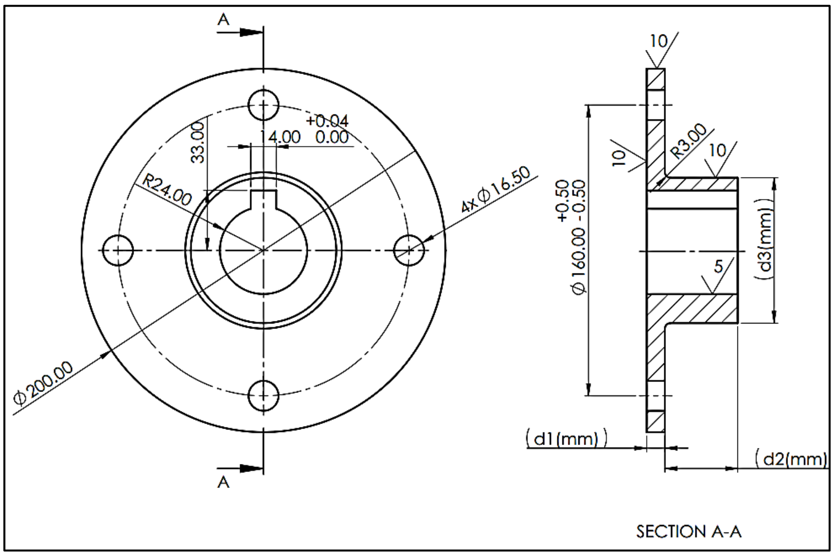

Fig. 2. Engine Assembly Stand flange dimension

The focus was on optimizing flange design to reduce costs while maintaining durability. By analysing and adjusting design parameters to find the optimal flange design that meets the required durability standards while minimizing production costs (mass). The optimization process will involve evaluating different combinations of dimensional parameters within their allowable ranges.

2.2 Methodology
2.2.1 FEA method

In this study, the input parameters d1, d2, and d3 are selected as they are considered critical in determining the performance and cost of the flange. The mass, Von Mises stress, and displacement, abbreviated as m (kg), V (MPa), and D (mm), respectively, are chosen as the output parameters of interest. FEA simulations are performed to determine the values of the output parameters under the same conditions for each combination of the input parameters. The mass (m), Von Mises stress (V), and displacement (D) are then calculated based on the simulation results.

The Taguchi method is employed in this study to design the experimental plan and carry out the experimental trials. This method is a statistical approach that allows for efficient experimentation by minimizing the number of required trials while still providing meaningful results. It involves designing an orthogonal array, which is a structured matrix that defines the combinations of input parameter levels to be tested. By systematically varying the levels of the input parameters based on the orthogonal array, the effects of each parameter and their interactions can be evaluated. Thus, a series of FEA simulations were performed using a Design of Experiment (DOE) methodology, specifically an L25 (5^3) orthogonal array. The purpose of the DOE was to systematically investigate the effects of the input parameters d1, d2, and d3 on the performance of the flange. The levels for each parameter were selected based on real product specifications, and the details are presented in Table 1.

Table 1
Input parameters and their levels of L25 (5^3) orthogonal array

No	Input parameter			Output parameter		
	d1(mm)	d2 (mm)	d3(mm)	m (kg)	V (MPa)	D (mm)
1	10	30.00	75.00	2.979	334.90	0.278
2	10	35.00	77.50	2.979	339.00	0.278
3	10	40.00	80.00	3.182	355.20	0.258
4	10	45.00	82.50	3.412	321.20	0.239
5	10	50.00	85.00	3.671	317.70	0.225
6	15	30.00	77.50	3.994	206.30	0.100
7	15	35.00	80.00	4.184	192.40	0.094
8	15	40.00	82.50	4.402	170.20	0.088
9	15	45.00	85.00	4.648	159.20	0.083
10	15	50.00	75.00	4.300	188.40	0.105
11	20	30.00	80.00	5.186	117.00	0.047
12	20	35.00	82.50	5.391	111.60	0.045
13	20	40.00	85.00	5.625	102.50	0.043
14	20	45.00	75.00	5.323	127.80	0.056
15	20	50.00	77.50	5.534	128.80	0.047
16	25	30.00	82.50	6.381	80.30	0.027
17	25	35.00	85.00	6.601	76.28	0.026
18	25	40.00	75.00	6.349	93.79	0.031
19	25	45.00	77.50	6.548	89.46	0.030
20	25	50.00	80.00	6.780	83.10	0.028
21	30	30.00	85.00	7.578	63.70	0.018
22	30	35.00	75.00	7.380	66.90	0.021
23	30	40.00	77.50	7.560	66.58	0.020
24	30	45.00	80.00	7.780	64.50	0.019
25	30	50.00	82.50	8.020	65.04	0.019

2.2.2 Response Surface Methodology (RSM) model

Response Surface Methodology (RSM) is a statistical technique that is widely used for analysing and optimizing the relationship between input variables, also known as factors, and one or more output variables, referred to as responses. RSM incorporates a systematic approach that involves conducting a series of experiments and developing statistical models to gain a comprehensive understanding of the complex relationship between the factors and responses. RSM is particularly valuable when the relationship between the factors and responses is intricate and cannot be adequately captured by straightforward linear models. It enables the exploration of interactions and nonlinear effects among the factors, leading to improved accuracy in predicting and optimizing the response variables.

The relationship between the input and output variables can be mathematically described by Eq. (1):

$$y=\varphi(x_1, x_2,\ldots x_n)+\varepsilon \tag{1}$$

When there are k input variables, this relationship can be reformulated into a quadratic equation as follows:

$$y=\beta_0+\sum_{i=1}^{k}\beta_i x_i+\sum_{i=1}^{k}\beta_{ii}{x_i}^2+\sum_{ij}^{k}\beta_{ij}x_i x_j+\varepsilon \tag{2}$$

In Eq. (2), the variables x_i are represented in coded form, β_i represents the coefficients for the first-order terms, β_{ii} denotes the coefficients for the quadratic terms, β_{ij} signifies the coefficients for the interaction terms within the equation, and ε accounts for the statistical error associated with the mean.

2.2.3 NSGA-II algorithm

The NSGA-II algorithm, which employs a multi-objective optimization approach, was utilized to obtain the Pareto-optimal frontier. This algorithm differs from the simple genetic algorithm by incorporating a stratification step before the selection operator. This stratification is based on the dominant relationship between individuals. By employing a nondominated hierarchical method, individuals with superior characteristics are more likely to progress to the next generation.

Additionally, the NSGA-II algorithm incorporates an elitist strategy that combines the parent population and sub-populations. This collaborative approach enables more effective competition and generation of the next generation. In this study, the NSGA-II algorithm, based on the established relationship models by RSM, was employed to optimize the input parameters d1, d2, and d3. The optimization objective was to simultaneously optimize the variables m, V, and D, which are considered as the three optimization objectives.

3. Results and Discussion

3.1 FEA data

The FEA was conducted for a total of 25 different models of flange design, and the corresponding analysis results are presented in Table 1. This table provides detailed information about various m, V, and D obtained from the FEA simulations for each of the 25 models. Figure 3 specifically showcases the analysis results for model number 25.

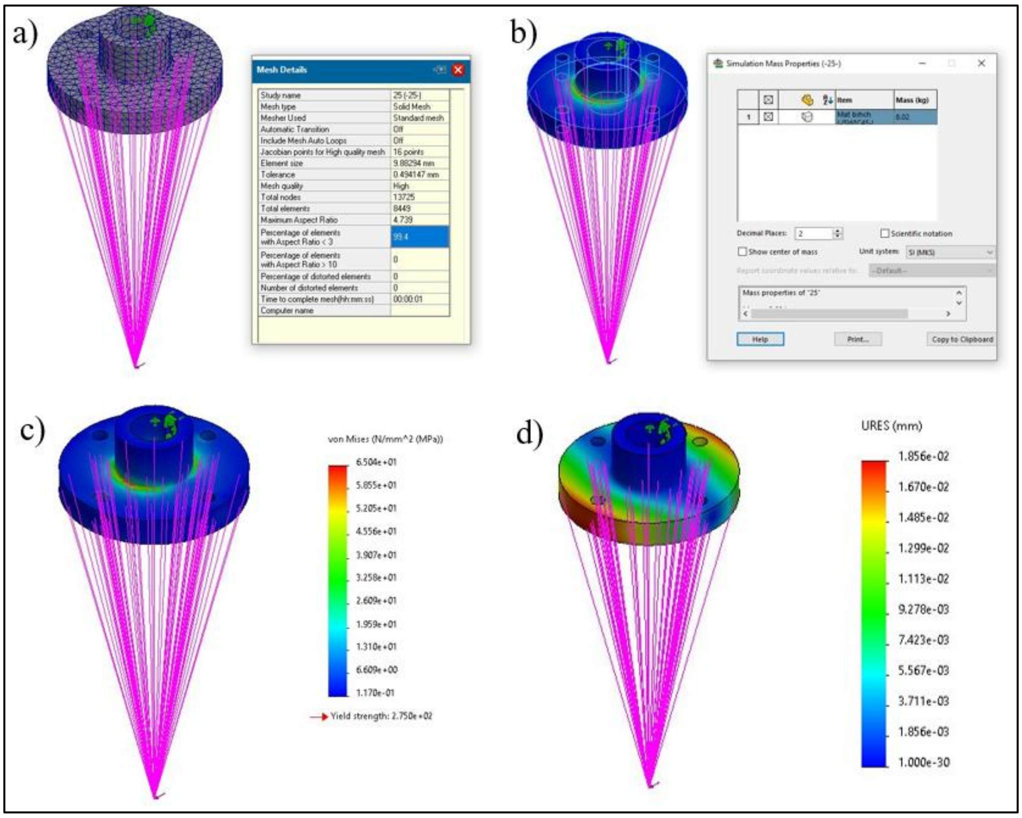

Fig. 3. The results of No. 25 model simulation: Mesh model (a), mass (b), Von Mises stress (c) and displacement (d)

3.2 RSM Predicting Models

Response Surface Methodology (RSM) was utilized to construct predictive mathematical equations for the dependent variables m, V, and D. The efficacy of the developed models was assessed using the coefficient of determination (R2). The resultant equations derived from the regression analysis are denoted as Eq. (3), Eq. (4) and Eq. (5) for m, V, and D, respectively, exhibiting notably high R^2 values of 0.9896, 0.998, and 0.9997 correspondingly. Figure 4 displays the residuals plot for m, V, and D. The plot reveals that the developed coefficient models exhibit statistical significance. The residuals, representing the discrepancies between the predicted and actual values, demonstrate a pattern that aligns closely with the assumptions of the regression models. This finding enhances the confidence in the accuracy of the developed models for predicting m, V, and D.

$$m = 15.01 + 0.2480 \times d1 - 0.0335 \times d2 - 0.3935 \times d3 + 0.000444 \times d1 \times d1 + 0.000458 \times d2 \times d2 + 0.002841 \times d3 \times d3 + 0.000891 \times d1 \times d2 - 0.001001 \times d1 \times d3 \quad (3)$$

$$V = -1500 - 55.8 \times d1 + 1.40 \times d2 + 59.3 \times d3 + 0.8426 \times d1 \times d1 - 0.0083 \times d2 \times d2 - 0.402 \times d3 \times d3 - 0.0406 \times d1 \times d2 + 0.138 \times d1 \times d3 \quad (4)$$

$$D = 1.28 - 0.0701 \times d1 + 0.00340 \times d2 - 0.0104 \times d3 + 0.000950 \times d1 \times d1 - 0.000053 \times d2 \times d2 + 0.000022 \times d3 \times d3 + 0.000031 \times d1 \times d2 + 0.000251 \times d1 \times d3 \quad (5)$$

In order to evaluate the effectiveness of the response surface model in capturing the statistical relationships between the design parameters and the objectives m, V, and D, a comprehensive verification process was conducted using the ANOVA (Analysis of Variance) test.

In this study, the ANOVA test was applied individually to analyse the three objectives: m, V, and D. The corresponding results of the ANOVA analysis for m, V, and D can be found in Table 2, Table 3 and Table 4, respectively. These tables present detailed information, such as the source of variation, sum of squares, degrees of freedom, mean squares, F-values, and p-values associated with each response surface model. The results show that the p-values for all three response surface models were significantly smaller than the conventional significance level of 0.05. This indicates a high level of statistical significance for these models. The small p-values suggest that the observed variations in objectives m, V, and D can be confidently attributed to the influence of the design parameters captured by the respective response surface models.

Table 2
Analysis of Variance for m

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	8	62.2827	99.985%	62.2827	7.7853	12914.94	0.000
Linear	3	62.2429	99.921%	62.1692	20.7231	34377.06	0.000
d1	1	61.2083	98.260%	61.2083	61.2083	101537.15	0.000
d2	1	0.6160	0.989%	0.4431	0.4431	734.99	0.000
d3	1	0.4186	0.672%	0.4255	0.4255	705.81	0.000
Square	3	0.0136	0.022%	0.0297	0.0099	16.44	0.000
d1×d1	1	0.0086	0.014%	0.0086	0.0086	14.31	0.002
d2×d2	1	0.0019	0.003%	0.0069	0.0069	11.43	0.004
d3×d3	1	0.0031	0.005%	0.0166	0.0166	27.46	0.000
2-Way Interaction	2	0.0262	0.042%	0.0262	0.0131	21.74	0.000
d1×d2	1	0.0180	0.029%	0.0261	0.0261	43.25	0.000
d1×d3	1	0.0082	0.013%	0.0082	0.0082	13.64	0.002
Error	16	0.0096	0.015%	0.0096	0.0006		
Total	24	62.2924	100.000%				

Table 3
Analysis of Variance for V

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	8	234788	98.49%	234788	29349	130.09	0.000
Linear	3	203255	85.26%	203170	67723	300.19	0.000
d1	1	201756	84.63%	201756	201756	894.29	0.000
d2	1	78	0.03%	6	6	0.03	0.872
d3	1	1422	0.60%	1377	1377	6.10	0.025
Square	3	31376	13.16%	31397	10466	46.39	0.000
d1×d1	1	31064	13.03%	31064	31064	137.69	0.000
d2×d2	1	30	0.01%	2	2	0.01	0.921
d3×d3	1	282	0.12%	332	332	1.47	0.243
2-Way Interaction	2	157	0.07%	157	78	0.35	0.711
d1×d2	1	2	0.00%	54	54	0.24	0.631
d1×d3	1	155	0.07%	155	155	0.69	0.419
Error	16	3610	1.51%	3610	226		
Total	24	238398	100.00%				

Table 4
Analysis of Variance for D

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	8	0.186809	96.83%	0.186809	0.023351	61.13	0.000
Linear	3	0.146410	75.89%	0.145771	0.048590	127.20	0.000
d1	1	0.144826	75.07%	0.144826	0.144826	379.12	0.000
d2	1	0.000345	0.18%	0.000045	0.000045	0.12	0.736
d3	1	0.001239	0.64%	0.000853	0.000853	2.23	0.155
Square	3	0.039500	20.47%	0.039588	0.013196	34.54	0.000
d1×d1	1	0.039492	20.47%	0.039492	0.039492	103.38	0.000
d2×d2	1	0.000004	0.00%	0.000091	0.000091	0.24	0.631
d3×d3	1	0.000004	0.00%	0.000001	0.000001	0.00	0.959
2-Way Interaction	2	0.000899	0.47%	0.000899	0.000449	1.18	0.334
d1×d2	1	0.000381	0.20%	0.000031	0.000031	0.08	0.780
d1×d3	1	0.000517	0.27%	0.000517	0.000517	1.35	0.262
Error	16	0.006112	3.17%	0.006112	0.000382		
Total	24	0.192921	100.00%				

The ANOVA results also indicate that d1, d2, and d3 have a significant influence on the variable m. Additionally, the factors d1 and d3 are found to have a significant impact on both V and D. This conclusion is supported by the corresponding P-values, which are below the threshold of 0.05, indicating statistical significance. However, it is primarily the variable d1 that influences the variables m, V, and D. This suggests that d1 plays a crucial role in determining the values of m, V, and D, while the influence of d2 and d3 on these variables is relatively less significant.

Table 5
Input conditions and objectives of multi-objective

Input	Objective
10≤d1≤30	Objective 1: Min (m)
30≤d2≤50	Objective 2: Min (V)
75≤d3≤85	Objective 2: Min (D)

3.3 Multi-Objective Optimization

The formulation of the multi-objective optimization model for the design parameters (d1, d2, d3) using the NSGA-II algorithm, considering m, V, and D as the optimization objectives, based on the established relationship models by the RSM method, is as follows in Table 5.

The objective is to minimize the values of m, V, and D by finding the optimal values for the design parameters d1, d2, and d3. The specified constraints on the design parameter ranges must be satisfied. To achieve this, the NSGA-II algorithm will be employed to search for Pareto-optimal solutions. These solutions will offer a trade-off between the three objectives, ultimately leading to an optimal design configuration.

The implementation of the NSGA-II algorithm involved utilizing the optimization tool provided by the MATLAB software. To configure the algorithm, various control parameters were chosen, such as the population size, maximum number of generations, crossover probability, and mutation probability. The "maximum generations" parameter dictates the number of iterations the algorithm will undergo before terminating. The "crossover probability" parameter determines the frequency of crossover operations. Higher values of this parameter facilitate faster convergence, while lower values result in slower convergence. Lastly, the "mutation probability" parameter governs the likelihood of random perturbations occurring in individual solutions. This study selected the following parameter values: a population size of 100, a mutation probability of 0.25, a crossover probability of 1.0, and a maximum generation number of 500. These particular values were chosen to achieve a reasonable convergence rate during optimization.

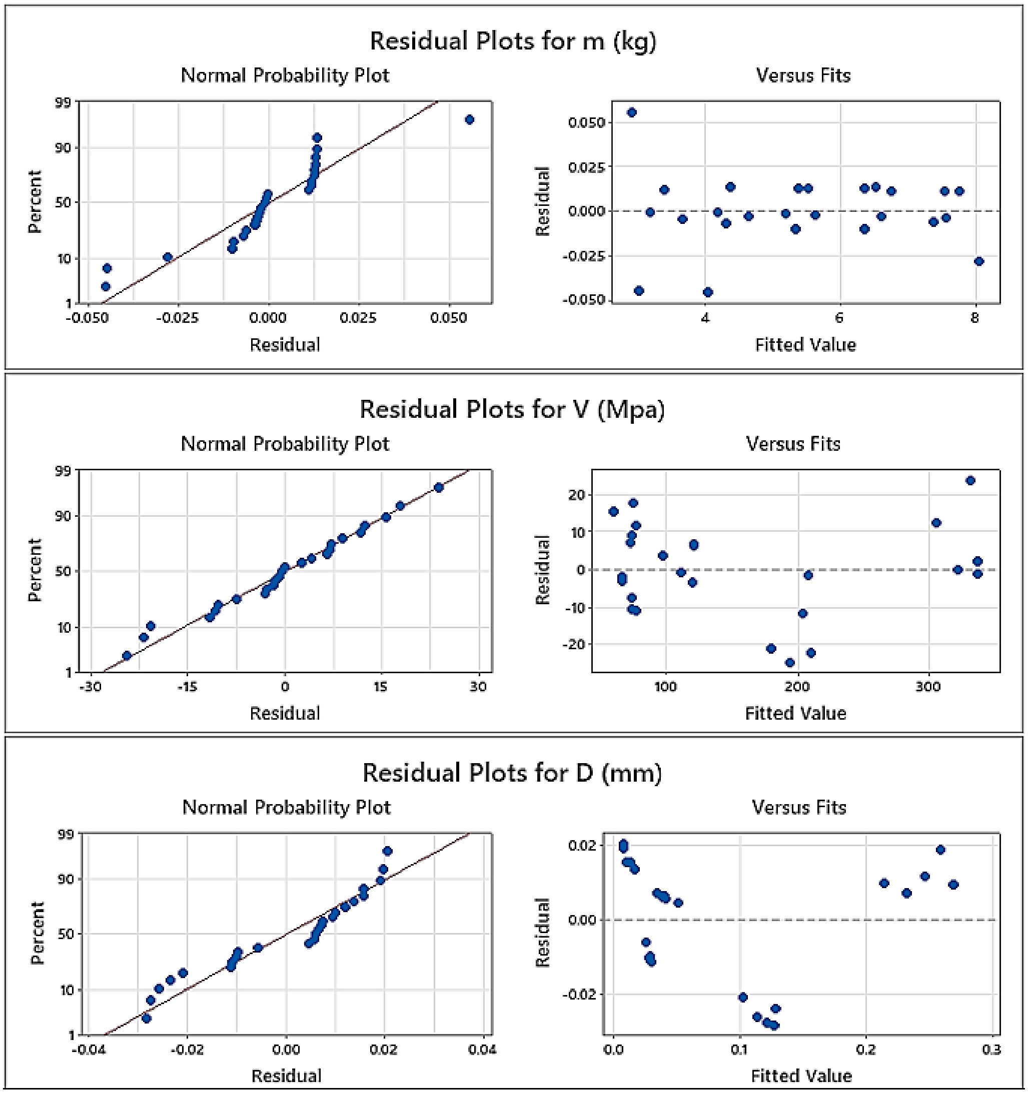

Fig. 4. The residuals plot for m, V, and D

Figure 5 presents the optimal results obtained through the application of the NSGA-II algorithm. The first objective exhibited a range of 2.9 to 7.6 kg. The second objective displayed a variation spanning from 54.8 to 342.6 MPa and the third objective showcased a range of 0.01 to 0.27 mm. These ranges were derived from the analysis of 39 Pareto solutions, which are detailed in Table 6.

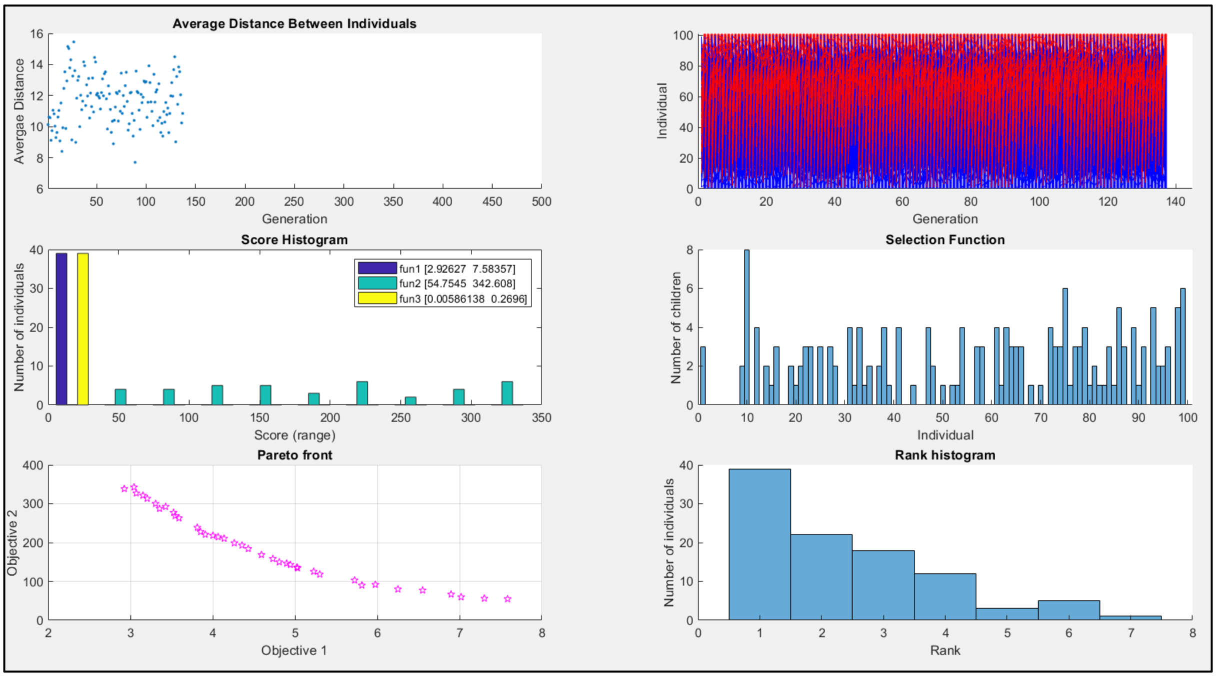

Fig. 5. Multi-objective optimization results using NSGA-II

Based on the material's yield strength, the displacement requirements of the flange during operation, and the objective of minimizing mass, the study chose the No. 17 model with design parameters d1 = 20.08 mm, d2 = 36.64 mm, and d3 = 77.68 mm. The resulting mass of this design is 5.23 kg, with a Von Mises stress of 125.4 MPa and a displacement of 0.048 mm. To verify the effectiveness of the chosen parameters, the flange model was modified accordingly, and a FEA simulation was performed. The analysis revealed that the mass, Von Mises stress, and displacement of the redesigned flange are 5.28 kg, 122.6 MPa, and 0.0487 mm, respectively. These values deviate by 0.95%, 2.28%, and 1.14% from the optimal values obtained through the optimization process. These results provide strong evidence for the high reliability of the employed optimization method in this particular study.

Table 6
The optimal design parameters and 39 Pareto-optimal solutions

No.	d1 (mm)	d2 (mm)	d3(mm)	m (kg)	V (MPa)	D (mm)
1	10.00	30.00	75.00	2.93	338.4	0.270
2	25.01	50.00	84.92	7.02	59.8	0.006
3	27.43	50.00	85.00	7.58	54.8	0.012
4	10.00	30.00	75.00	2.93	338.4	0.270
5	12.77	33.34	77.29	3.59	263.1	0.183
6	13.78	33.71	77.46	3.81	238.7	0.158
7	14.70	34.21	77.03	4.00	218.3	0.138
8	18.02	34.25	82.45	4.94	142.9	0.064
9	25.39	46.12	83.55	6.90	66.8	0.010
10	10.01	41.34	75.96	3.04	342.6	0.264
11	14.56	31.78	75.48	3.91	220.8	0.146
12	11.39	35.31	77.02	3.31	300.1	0.221
13	14.26	33.52	75.07	3.85	227.8	0.155
14	17.64	31.19	82.14	4.81	149.7	0.068
15	15.73	36.88	79.74	4.36	193.1	0.109
16	11.48	35.39	79.58	3.43	292.4	0.208
17	20.08	36.64	77.68	5.23	125.4	0.048

18	19.27	34.87	77.85	5.02	136.2	0.057
19	26.23	50.00	84.93	7.30	56.2	0.008
20	12.17	35.56	78.42	3.53	277.2	0.194
21	17.14	33.60	82.13	4.73	158.4	0.077
22	10.65	36.44	76.82	3.15	321.6	0.243
23	25.29	38.17	81.47	6.55	77.2	0.013
24	22.97	36.61	80.91	5.98	91.6	0.020
25	19.37	32.76	78.40	5.03	134.2	0.054
26	24.52	30.41	82.01	6.25	80.0	0.010
27	15.56	36.04	78.66	4.26	198.8	0.116
28	10.92	35.54	76.88	3.20	313.4	0.235
29	14.82	33.96	78.31	4.07	214.4	0.132
30	21.43	39.51	81.46	5.72	103.0	0.029
31	12.55	33.89	77.12	3.54	268.8	0.189
32	10.47	35.31	75.74	3.07	327.0	0.253
33	21.67	33.86	84.10	5.81	90.0	0.023
34	14.59	32.50	81.30	4.14	210.4	0.126
35	17.77	34.32	82.57	4.90	146.2	0.067
36	16.14	34.97	80.05	4.43	184.0	0.100
37	20.62	32.07	78.72	5.30	118.2	0.039
38	17.27	36.90	76.99	4.59	168.4	0.089
39	11.88	34.81	75.15	3.35	287.3	0.215

4. Conclusion

This study focused on optimizing the flange design for an engine assembly stand using RSM and the NSGA-II algorithm based on FEA data. The Taguchi method was employed to design the FEA simulation experiment, and RSM was used to develop a mathematical model that establishes the relationship between the three main dimensions of the flange and the mass (m, kg), Von Mises stress (V, MPa), and displacement (D, mm). Subsequently, the NSGA-II algorithm was utilized to search for Pareto-optimal solutions representing the trade-off between the variables m, V, and D by evaluating various combinations of dimensional parameters within their allowable ranges. The results showed that the regression models derived from the RSM method exhibited notably high R^2 values for m, V, and D, indicating high predictive accuracy. Moreover, the application of NSGA-II for multi-objective optimization yielded 39 Pareto solutions that encompassed diverse values of d1, d2, and d3, corresponding to the output parameters. To verify the effectiveness of the chosen parameters, solution No.17 was selected for testing. The results showed that the redesigned flange's mass, Von Mises stress, and displacement were 5.28 kg, 122.6 MPa, and 0.0487 mm, respectively. These values deviated by 0.95%, 2.28%, and 1.14% from the optimal values obtained through optimization. These results provide strong evidence for the high reliability of the employed optimization method in this particular study.

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