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Taguchi and Grey Relational Analysis for Simultaneous Optimization of Efficiency and Thermal Management

Shraddha Sanjay Lohakare[1], Dr. Nikhil J. Rathod[2]

[1]Research Scholar, Department of Electrical Engineering Vikrant University, Gwalior

[2]Associate Professor, Department of Mechanical Engineering, Vikrant University, Gwalior

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ABSTRACT

The Taguchi design of experiments method is used in this work to systematically optimize efficiency and heat dispersion factor (HDF). An L27 orthogonal array was used to examine six control parameters, each at three levels, in order to assess their impact on system performance. The larger-is-better signal-to-noise (S/N) ratio was used to study efficiency, while the smaller-is-better criterion was used to assess HDF. To find statistically significant factors and measure their contributions, analysis of variance (ANOVA) was used. With statistical significance at the 95% confidence level, the findings demonstrate that factor C is the most important parameter affecting efficiency. While the other factors had relatively little effect, factors B and E showed moderate effects. $A_2B_2C_1D_3E_3F_3$ was found to be the best combination of parameters for optimizing efficiency. None of the characteristics were statistically significant for the heat dispersion factor, although factor F had the greatest relative impact on thermal performance. At the ideal setting $A_2B_2C_3D_3E_2F_1$, the lowest HDF was attained. A trade-off between efficiency and heat dispersion was found in a comparison analysis, especially with factor C. This suggests that multi-objective optimization is necessary in real-world applications. All things considered, the study shows that the Taguchi method is a useful and efficient technique for maximizing several performance attributes while reducing experimental effort...

Keywords: Taguchi method, efficiency optimization, heat dispersion factor, signal-to-noise ratio, ANOVA, design of experiments

1. INTRODUCTION

In many engineering applications, managing thermal behaviour while simultaneously enhancing system performance is a crucial task. Increased heat generation is frequently associated with high operational efficiency, which can have a negative impact on service life, stability, and dependability. As a result, finding the best possible balance between increasing efficiency and reducing heat dispersion has emerged as a key area of study in contemporary design and process optimization. Conventional experimental methods for performance optimization are typically time-consuming, expensive, and require a lot of trials, especially when there are several design factors. Furthermore, the identification of dominant elements influencing system responses is made more difficult by interactions between parameters. Statistical design of experiments (DOE) techniques has been widely used to systematically explore the influence of various factors with fewer experiments in order to overcome these limitations. The Taguchi approach has shown itself to be a reliable and efficient optimization tool among several DOE techniques. The Taguchi technique minimizes unpredictability due to unpredictable noise factors while identifying optimal factor levels through the use of orthogonal arrays and signal-to-noise (S/N) ratios. The technique has been widely used to enhance performance, dependability, and quality attributes in mechanical components, thermal systems, energy devices, and manufacturing processes

The impacts of six control parameters, each at three levels, on two crucial performance responses—efficiency and heat dispersion factor (HDF)—are examined in the current work using a Taguchi-based experimental framework. While HDF is viewed as a smaller-is-better characteristic to reduce heat losses, efficiency is addressed as a larger-is-better characteristic to optimize system output. To effectively support the experimental design, an L27 orthogonal array is chosen.

Each control factor's contribution and statistical significance are measured using analysis of variance (ANOVA) and signal-to-noise ratio analysis. To ascertain the relative significance of parameters and to find the best factor combinations for each performance feature, ranking analyses and response tables are also used. The paper also looks at the existence of competing parameter effects between heat dispersion and efficiency, emphasizing the need for a multi-objective optimization viewpoint.

The results of this study offer important new information on the key design factors influencing thermal behaviour and efficiency. In addition to providing a basis for future multi-response optimization strategies targeted at attaining balanced performance, the results can be used as a useful guideline for robust system design

2. . LITERATURE REVIEW

The Taguchi method's capacity to minimize experimental effort while identifying reliable and significant components has led to its widespread adoption as a statistical technique for process parameter optimization in engineering systems. In order to identify the ideal levels of control factors that produce desired performance characteristics under varying noise conditions (such as quality improvement and robustness) with a limited number of runs, Taguchi's experiments are traditionally designed using orthogonal arrays and signal-to-noise (S/N) ratio analysis. Taguchi-based optimization has been effectively used in thermal applications and energy systems to improve performance metrics including thermal and electrical efficiency. For instance, the Taguchi methodology was used to optimize various nanofluids and operational parameters in photovoltaic thermal (PVT) systems in order to increase electrical and thermal efficiency. ANOVA analysis was used to quantify the contributions of individual factors. Significant improvements in system efficiency were shown by the results, which also revealed flow rate and irradiance as important factors influencing performance outcomes.

Nevertheless, traditional Taguchi optimization frequently concentrates on a single quality attribute. Researchers have combined the Taguchi approach with secondary optimization frameworks to solve multi-response problems. For example, integration with Grey Relational Analysis (GRA) has been extensively documented in solar energy applications, allowing for the simultaneous optimization of several quality variables, including heat retention duration and storage efficiency in solar heating systems. To address competing objectives in design issues, hybrid approaches that combine Taguchi with utility or multi-attribute decision methods have been presented, demonstrating the method's expansion beyond single-response optimization.

Taguchi designs have also been effectively applied in mechanical engineering and production for multi-objective machining and structural performance optimization. Recent research demonstrates how Taguchi can enhance the dynamic and static properties of machine tool constructions and material processing results when paired with finite element analysis or response surface approaches.
Additionally, developments in optimization integration, including integrating Taguchi with data envelopment analysis (DEA), have demonstrated promise in effectively managing multi-response optimization with the least amount of computing strain.

The Taguchi method's capacity to directly optimize many replies without the need for other techniques is still limited, despite its widespread use. As a result, there is a general tendency in the literature toward hybrid and multi-objective frameworks, in which Taguchi functions as a strong foundation for experimental design and is supplemented with analytical methods to handle intricate engineering performance requirements. The literature currently in publication shows that the Taguchi approach is a popular and successful technique for optimizing engineering systems with several control parameters. Taguchi design of trials has been effectively used in several research to increase overall system robustness, efficiency, and thermal performance. In order to reconcile contradictory performance characteristics, a number of academics have expanded the traditional Taguchi approach by combining it with multi-objective techniques including utility theory, Grey Relational Analysis (GRA), and other frameworks for decision-making. There are still a number of research gaps in spite of these developments. First, single-response optimization is the main topic of many published studies, with a special emphasis on either efficiency enhancement or thermal behavior separately. The simultaneous study of efficiency and heat dispersion characteristics has received little attention, despite the fact that both responses are intrinsically linked and frequently show contradictory tendencies in real-world systems.

Second, despite the availability of multi-objective optimization approaches, comprehensive studies that employ separate signal-to-noise ratio and mean response analyses to quantitatively quantify the relative influence of control parameters on both performance responses are lacking. Specifically, a single experimental paradigm has not been used to adequately investigate the comparative impact of identical control parameters on efficiency and heat dispersion. Third, trade-offs and conflicting factor levels between different responses are not sufficiently discussed in a number of research that report optimal parameter values. Because real-world systems frequently demand balanced operating conditions rather than response-specific optima, this restricts the practical usefulness of such discoveries.

Additionally, fewer studies use higher-resolution designs like the L27 orthogonal array to investigate six control factors at three levels, despite the widespread use of orthogonal arrays like L9 and L18. As a result, current research may not adequately capture the combined and individual effects of various components. A thorough experimental study that simultaneously assesses efficiency and heat dispersion using a reliable Taguchi framework, identifies dominant control factors using ANOVA, and emphasizes the inherent trade-offs between performance objectives is obviously needed in light of these limitations. The main goal of the current study is to close these gaps.

3. **METHODOLOGY**

3.1 Design of Experiments

The Taguchi design of experiments (DOE) methodology is used in this study to methodically examine how various control elements affect system performance. Based on their anticipated impact on efficiency and thermal behaviour, six control factors—designated as A, B, C, D, E, and F—were chosen. Because each factor was examined at three different levels, 3^6=729 experiments were needed to complete the factorial. A Taguchi L27 orthogonal array was used, needing only 27 experimental runs, to drastically cut down on experimental effort while maintaining statistical robustness. The L27 orthogonal array permits independent main effect estimation for all chosen parameters and guarantees balanced representation of factor levels. Standard Taguchi design principles were used to define the experimental layout and appropriate factor-level combinations.

3.2 Performance Characteristics

Two performance responses were considered in this investigation:

Efficiency (η)

Efficiency represents the primary performance indicator of the system and was treated as a *larger-is-better* quality characteristic, as higher efficiency values are desirable.

Heat Dispersion Factor (HDF)

Heat dispersion factor quantifies thermal losses within the system and was treated as a *smaller-is-better* quality characteristic, since lower heat dispersion indicates improved thermal management. Each experimental run produced measured values of efficiency and heat dispersion factor, which were subsequently used for statistical analysis.

3.3 Signal-to-Noise Ratio Analysis

To evaluate the robustness of the system performance and minimize the influence of variability, signal-to-noise (S/N) ratios were calculated for both responses using Taguchi's quality loss functions.

For efficiency (*larger-is-better*):

$$\mathrm{S/N} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$$

For heat dispersion factor (*smaller-is-better*):

$$\mathrm{S/N} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right)$$

where $y_i$represents the measured response value and $n$is the number of observations per trial. Higher S/N ratios indicate improved performance and robustness for the respective quality characteristics.

3.4 Statistical Analysis

The effects of control factors on both efficiency and heat dispersion factor were analyzed using main effect plots, response tables, and delta statistics derived from S/N ratios and mean responses. Factors were ranked based on delta values to identify the most influential parameters.

To assess the statistical significance and percentage contribution of each factor, analysis of variance (ANOVA) was performed at a 95% confidence level. The ANOVA results provided F-values and P-values to identify dominant factors affecting each response.

Regression models were also developed for both S/N ratios and mean responses to establish empirical relationships between control factors and performance characteristics.

3.5 Determination of Optimal Factor Levels

Optimal levels of the control factors were determined independently for efficiency and heat dispersion factor based on the highest S/N ratios corresponding to their respective optimization criteria. The resulting optimal parameter combinations were identified using response tables and factor rankings.

The presence of conflicting optimal levels between efficiency and heat dispersion factor was analysed to evaluate trade-offs between performance objectives. This assessment provides insight into the necessity of multi-objective optimization for practical system design.

3.6 Validation and Diagnostic Analysis

Model adequacy was evaluated through residual analysis and identification of unusual observations using standardized residuals. Observations with large residuals were examined to ensure experimental consistency and reliability of the developed models.

The methodology adopted in this study provides a robust and systematic framework for identifying dominant design parameters, optimizing performance characteristics, and understanding trade-offs between efficiency and thermal behavior.

4. RESULT & DISCUSSION

4.1 Experimental Results

The experimental results obtained from the Taguchi L27 orthogonal array include measured values of efficiency and heat dispersion factor (HDF) along with their corresponding signal-to-noise (S/N) ratios. Efficiency was analyzed using the *larger-is-better* criterion, whereas HDF was evaluated using the *smaller-is-better* criterion. The calculated S/N ratios provide a measure of robustness by accounting for both the mean performance and variability of the responses.

4.2 Analysis of Efficiency

4.2.1 Signal-to-Noise Ratio Analysis

The response table for S/N ratios of efficiency shows that factor C exhibits the highest delta value (1.121), indicating that it is the most influential parameter affecting efficiency. This is followed by factors B (0.721) and E (0.493). Factors A and F show comparatively lower influence, suggesting minimal contribution to efficiency variation.

The main effect trends indicate that:

Efficiency improves significantly at level 1 of factor C.

Level 2 of factor B yields the highest S/N ratio.

Factors D, E, and F show moderate but non-dominant effects.

Accordingly, the optimal parameter combination for maximizing efficiency based on S/N analysis was identified as:

$$A_2B_2C_1D_1E_3F_3$$

These results suggest that controlling factor F plays a crucial role in minimizing heat dispersion.

4.2.2 Mean Response Analysis

The mean response table supports the S/N ratio findings. Factor C again shows the highest delta value (0.0876), confirming its dominant influence on efficiency. The consistency between S/N and mean response analyses indicates that improvements in efficiency are not only higher on average but also more robust against variability.

4.2.3 ANOVA for Efficiency

ANOVA results for efficiency reveal that factor C is statistically significant at the 95% confidence level, with a P-value of 0.006 for S/N ratios and 0.009 for mean responses. Factor B shows moderate influence but does not reach statistical significance at the same confidence level. Other factors contribute marginally to efficiency variation.

The coefficient of determination (R^2) values of approximately 66% for S/N ratios and 65% for mean responses indicate that the developed models adequately explain the variability in efficiency.

4.3 Analysis of Heat Dispersion Factor

4.3.1 Signal-to-Noise Ratio Analysis

For the heat dispersion factor, the response table for S/N ratios indicates that factor F exhibits the highest delta value (1.06), making it the most influential parameter in reducing HDF. Factors E (0.87) and D (0.59) follow in importance. The optimal levels corresponding to maximum S/N ratios (smaller-is-better) were identified as:

$$A_2B_3C_3D_3E_2F_1$$

These results suggest that controlling factor F plays a crucial role in minimizing heat dispersion.

4.3.2 Mean Response Analysis

The mean response analysis for HDF is consistent with the S/N analysis, where factor F again shows the highest delta value (0.607). This agreement confirms that factor F significantly affects both the magnitude and stability of the heat dispersion response.

4.3.3 ANOVA for Heat Dispersion Factor

ANOVA results indicate that none of the factors are statistically significant at the 95% confidence level. However, factor F exhibits the lowest P-value (≈0.054 for S/N ratios and ≈0.057 for means), suggesting a strong practical influence on HDF. The relatively lower R^2values (~45%) indicate that heat dispersion is influenced by additional unaccounted factors or interactions.

4.4 Trade-off Between Efficiency and Heat Dispersion

A comparison of the optimal factor levels for efficiency and HDF reveals conflicting requirements for several factors, particularly C, D, E, and F. While factor C at level 1 maximizes efficiency, level 3 minimizes HDF. Similarly, factor F favors level 3 for efficiency but level 1 for minimizing heat dispersion.

These conflicts highlight the inherent trade-off between performance enhancement and thermal management. Optimizing one response independently may adversely affect the other, underscoring the necessity for multi-objective optimization techniques to achieve balanced system performance.

4.5 Discussion of Unusual Observations

Residual and diagnostic analyses identified a small number of experimental runs with large standardized residuals for both efficiency and HDF. These deviations may be attributed to experimental uncertainties or uncontrolled noise factors. However, their limited occurrence and random distribution indicate that they do not significantly compromise the overall validity of

5. RESULTS AND DISCUSSION

5.1 Experimental Results

The experimental investigation was carried out using a Taguchi L27L_{27}L27 orthogonal array with six control factors (A–F), each at three levels. Two performance characteristics were evaluated: Efficiency (larger-is-better) and Heat Dispersion Factor (HDF) (smaller-is-better). Signal-to-noise (S/N) ratios were employed to analyze robustness and variability in system performance.

A	B	C	D	E	F	Eff	SNRA1
1	1	1	1	1	1	0.7688	-2.28373
1	1	1	1	2	2	0.7456	-2.54988
1	1	1	1	3	3	0.7430	-2.58022
1	2	2	2	1	1	0.7520	-2.47564
1	2	2	2	2	2	0.7334	-2.69318
1	2	2	2	3	3	0.7655	-2.32110
1	3	3	3	1	1	0.5866	-4.63316
1	3	3	3	2	2	0.6238	-4.09909
1	3	3	3	3	3	0.7233	-2.81363
2	1	2	3	1	2	0.6855	-3.27985
2	1	2	3	2	3	0.7589	-2.39631
2	1	2	3	3	1	0.7977	-1.96321
2	2	3	1	1	2	0.8244	-1.67724
2	2	3	1	2	3	0.6940	-3.17281
2	2	3	1	3	1	0.6433	-3.83173
2	3	1	2	1	2	0.6654	-3.53834
2	3	1	2	2	3	0.7234	-2.81243

2	**3**	**1**	**2**	**3**	**1**	**0.7456**	**-2.54988**
3	**1**	**3**	**2**	**1**	**3**	**0.6677**	**-3.50837**
3	**1**	**3**	**2**	**2**	**1**	**0.5678**	**-4.91609**
3	**1**	**3**	**2**	**3**	**2**	**0.6211**	**-4.13677**
3	**2**	**1**	**3**	**1**	**3**	**0.7566**	**-2.42267**
3	**2**	**1**	**3**	**2**	**1**	**0.7822**	**-2.13364**
3	**2**	**1**	**3**	**3**	**2**	**0.8100**	**-1.83030**
3	**3**	**2**	**1**	**1**	**3**	**0.7234**	**-2.81243**
3	**3**	**2**	**1**	**2**	**1**	**0.6500**	**-3.74173**
3	**3**	**2**	**1**	**3**	**2**	**0.7900**	**-2.04746**

A	**B**	**C**	**D**	**E**	**F**	**HDF**	**SNRA2**
1	**1**	**1**	**1**	**1**	**1**	**4.660**	**-13.3677**
1	**1**	**1**	**1**	**2**	**2**	**4.750**	**-13.5339**
1	**1**	**1**	**1**	**3**	**3**	**7.120**	**-17.0496**
1	**2**	**2**	**2**	**1**	**1**	**4.620**	**-13.2928**
1	**2**	**2**	**2**	**2**	**2**	**5.660**	**-15.0563**
1	**2**	**2**	**2**	**3**	**3**	**5.110**	**-14.1684**
1	**3**	**3**	**3**	**1**	**1**	**3.760**	**-11.5038**
1	**3**	**3**	**3**	**2**	**2**	**4.520**	**-13.1028**
1	**3**	**3**	**3**	**3**	**3**	**5.680**	**-15.0870**
2	**1**	**2**	**3**	**1**	**2**	**5.880**	**-15.3875**
2	**1**	**2**	**3**	**2**	**3**	**4.380**	**-12.8295**
2	**1**	**2**	**3**	**3**	**1**	**4.920**	**-13.8393**
2	**2**	**3**	**1**	**1**	**2**	**5.440**	**-14.7120**
2	**2**	**3**	**1**	**2**	**3**	**4.240**	**-12.5473**
2	**2**	**3**	**1**	**3**	**1**	**4.680**	**-13.4049**
2	**3**	**1**	**2**	**1**	**2**	**4.920**	**-13.8393**
2	**3**	**1**	**2**	**2**	**3**	**4.760**	**-13.5521**
2	**3**	**1**	**2**	**3**	**1**	**4.360**	**-12.7897**
3	**1**	**3**	**2**	**1**	**3**	**5.660**	**-15.0563**
3	**1**	**3**	**2**	**2**	**1**	**5.224**	**-14.3601**
3	**1**	**3**	**2**	**3**	**2**	**4.660**	**-13.3677**
3	**2**	**1**	**3**	**1**	**3**	**4.389**	**-12.8473**
3	**2**	**1**	**3**	**2**	**1**	**4.624**	**-13.3004**

3	**2**	**1**	**3**	**3**	**2**	**5.782**	**-15.2416**
3	**3**	**2**	**1**	**1**	**3**	**5.629**	**-15.0086**
3	**3**	**2**	**1**	**2**	**1**	**4.924**	**-13.8464**
3	**3**	**2**	**1**	**3**	**2**	**5.621**	**-14.9963**

5.2 Analysis of Efficiency

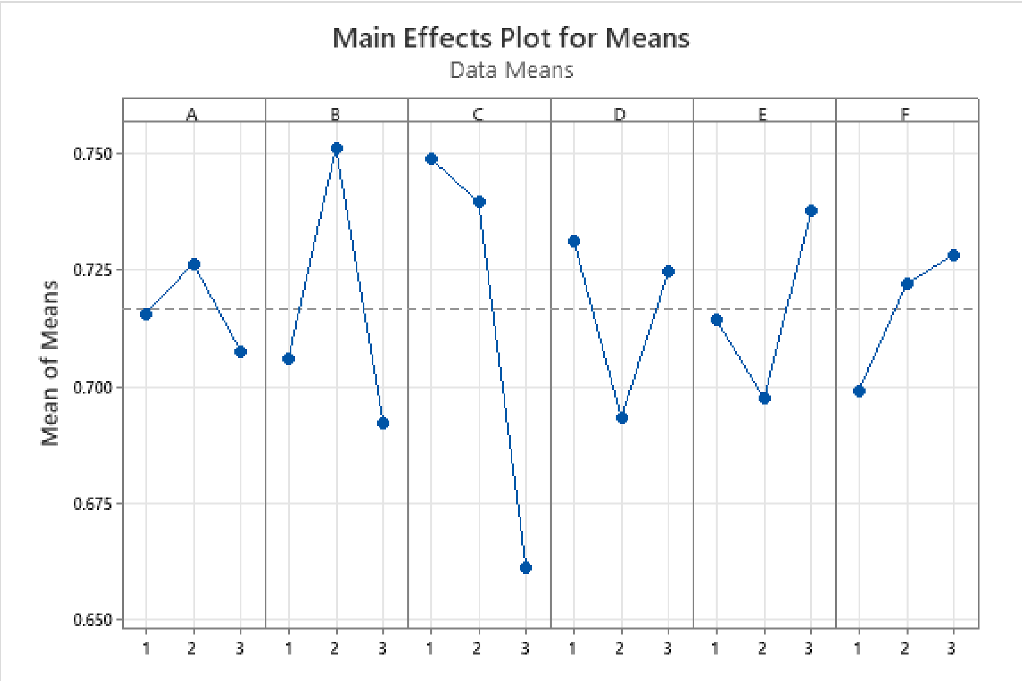
5.2.1 Signal-to-Noise Ratio Analysis

For efficiency, the larger-is-better quality characteristic was selected. The response table for S/N ratios indicates that factor C exhibits the highest delta value (1.121), ranking first among all factors. This confirms that factor C has the strongest influence on efficiency. Factors B and E follow with moderate influence, while factors A, D, and F show comparatively lower effects.

The factor significance ranking for efficiency based on S/N ratio is:

{C > B > E > D > F > A}

Level	A	B	C	D	E	F
1	0.7158	0.7062	0.7490	0.7314	0.7145	0.6993
2	0.7265	0.7513	0.7396	0.6935	0.6977	0.7221
3	0.7076	0.6924	0.6613	0.7250	0.7377	0.7284
Delta	0.0188	0.0589	0.0876	0.0378	0.0400	0.0291
Rank	6	2	1	4	3	5



5.2.3 Main Effects and Optimal Levels

From the response tables, the optimal levels for maximizing efficiency are determined as:

A2B2C1D3E3F3\boxed {A_2 B_2 C_1 D_3 E_3 F_3} A2B2C1D3E3F3

At this combination, the system achieves the highest robustness and average efficiency. The regression model developed for efficiency explains approximately 66% of the total variation, indicating an acceptable predictive capability for engineering applications.

5.2.2 Analysis of Variance (ANOVA)

ANOVA results for the S/N ratios of efficiency reveal that factor C is statistically significant with a p-value of 0.006, indicating a dominant contribution to performance improvement at a 95% confidence level. Factor B shows moderate influence with a p-value close to the significance threshold, whereas the remaining factors do not exhibit statistically significant effects.

Similarly, ANOVA for mean efficiency values confirms that factor C remains significant (p = 0.009), demonstrating consistent influence across both mean performance and variability reduction.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	0.001604	0.001604	0.000802	0.26	0.774
B	2	0.017059	0.017059	0.008529	2.77	0.097
C	2	0.041673	0.041673	0.020836	6.78	0.009
D	2	0.007381	0.007381	0.003690	1.20	0.330
E	2	0.007278	0.007278	0.003639	1.18	0.335
F	2	0.004217	0.004217	0.002108	0.69	0.520
Residual Error	14	0.043032	0.043032	0.003074		
Total	26	0.122242				

5.2.3 Main Effects and Optimal Levels

From the response tables, the optimal levels for maximizing efficiency are determined as:

{A_2 B_2 C_1 D_3 E_3 F_3}

At this combination, the system achieves the highest robustness and average efficiency. The regression model developed for efficiency explains approximately 66% of the total variation, indicating an acceptable predictive capability for engineering applications.

5.2.4 Discussion on Efficiency Behavior

The strong influence of factor C suggests that it directly governs the primary energy transfer or conversion mechanism of the system. Operating at level C1C_1C1 significantly enhances efficiency, while deviations to higher levels result in noticeable performance deterioration. Factors B and E influence secondary operational characteristics, contributing to moderate performance improvement.

5.3 Analysis of Heat Dispersion Factor (HDF)

5.3.1 Signal-to-Noise Ratio Analysis

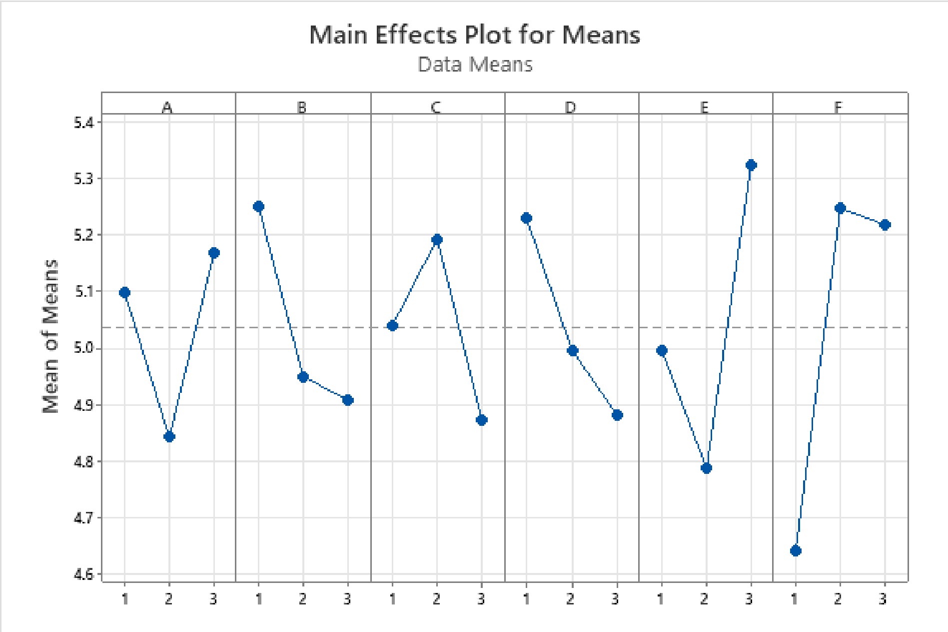
For heat dispersion factor, the smaller-is-better criterion was adopted. The S/N ratio response table indicates that factor F exhibits the highest delta value (1.06), ranking first among all factors. Factors E and D follow in importance, while factors A, B, and C have relatively minor effects.

The influence ranking for HDF is:

{F > E > D > C > A > B}

Level	A	B	C	D	E	F
1	5.098	5.250	5.041	5.229	4.995	4.641
2	4.842	4.949	5.194	4.997	4.787	5.248

3	5.168	4.908	4.874	4.882	5.326	5.219
Delta	0.326	0.342	0.320	0.348	0.539	0.607
Rank	5	4	6	3	2	1



5.3.2 Analysis of Variance (ANOVA)

ANOVA results for HDF show that none of the factors are statistically significant at the 95% confidence level. However, factor F presents the highest F-value, indicating that it has the strongest relative effect on heat dispersion. The lower R^2 values suggest that heat dispersion is influenced by multiple interacting parameters and possibly external environmental factors.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	0.5294	0.5294	0.2647	0.54	0.595
B	2	0.6282	0.6282	0.3141	0.64	0.542
C	2	0.4611	0.4611	0.2305	0.47	0.635
D	2	0.5644	0.5644	0.2822	0.58	0.575
E	2	1.3297	1.3297	0.6649	1.36	0.290
F	2	2.1071	2.1071	1.0535	2.15	0.154
Residual Error	14	6.8671	6.8671	0.4905		
Total	26	12.4870				

5.3.3 Optimal Levels for Minimum Heat Dispersion

Based on S/N ratio analysis, the optimal parameter combination for minimizing heat dispersion factor is identified as:

{A_2 B_2 C_3 D_3 E_2 F_1}

This combination minimizes thermal losses and enhances thermal stability.

5.3.4 Heat Dispersion Behaviour Discussion

Factor F's predominance suggests that it plays a direct part in controlling heat dissipation or thermal regulation. Heat dispersion is decreased when operating at level F1F_1F1, whereas thermal losses are increased at higher levels. While the other parameters have little effect, factors E and D have a moderate effect on the thermal pathway.

6. CONCLUSION

Using an L27L_{27}L27 orthogonal array, the current work used the Taguchi design approach to examine the impact of six control parameters on efficiency and heat dispersion factor (HDF). Regression modelling, ANOVA, and signal-to-noise ratio analysis were employed to assess factor significance and performance robustness.

Factor C is the most important parameter for efficiency, contributing the most variance of all the factors, according to the larger-is-better criterion. For both S/N ratios and mean values, ANOVA verified factor C's statistical significance at the 95% confidence level. While variables A, D, and F had relatively little effects, factors B and E demonstrated substantial influence. $A_2B_2C_1D_3E_3F_3$ was found to be the ideal parameter combination for optimizing efficiency, offering the best average performance and robustness.

None of the factors were statistically significant at the 95% confidence level when the heat dispersion factor was examined using the smaller-is-better criterion. But according to delta values and F-statistics, factor F had the greatest impact, suggesting that it plays a major role in regulating thermal dispersion. $A_2B_2C_3D_3E_2F_1$ was shown to be the best combination for decreasing HDF, which enhanced thermal stability and decreased thermal losses.

A comparison of the two replies shows that there is a trade-off between efficiency and heat dispersion, especially related to factor C, where different amounts are favoured for each response's best performance. This emphasizes how multi-objective optimization methods are required to provide a balanced operating condition appropriate for real-world applications.

All things considered, the Taguchi methodology turned out to be a useful and methodical instrument for determining crucial elements, lowering experimental effort, and improving system performance. The study's conclusions offer insightful information for operational control and design improvement targeted at increasing efficiency while preserving acceptable thermal behaviour..

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