Design Optimization for Wear Minimization in Slider Pumps

SP6 – Robust Engineering

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1. Introduction

Wear is a critical challenge in the design and operation of mechanical systems, especially in components like slider pumps that undergo repetitive mechanical motion. Excessive wear not only shortens the lifespan of such systems but also increases maintenance costs and reduces operational efficiency. To address this, quality improvement strategies such as parameter design can be employed to minimize wear and enhance performance.

This project focuses on analyzing and improving the wear characteristics of a slider pump through systematic experimentation. By examining key design factors and their interactions, we aim to identify optimal design measures that reduce wear. The experiment utilizes an L8 orthogonal array with the design factors and levels outlined in Table 1, and the wear data collected under different conditions is presented in Table 2.

Table 1. Design Factors and Levels

	Design Factors	Levels
A	Material	1 and 2
B	Weight	1 and 2
C	Surface roughness	1 and 2
D	Clearance	1 and 2
E	Side Material	1 and 2
AxB	Interactions of A and B	
AxC	Interactions of A and C	

Table 2. Experimental Data for Wear

	A	B	AxB	C	AxC	D	E	Data (μm)							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**R_1**	**R_2**	**R_3**	**R_4**	**R_5**	**R_6**	**R_7**	**R_8**
1	1	1	1	1	1	1	1	12	12	10	13	3	3	16	20
2	1	1	1	2	2	2	2	6	10	3	5	3	4	20	18
3	1	2	2	1	1	2	2	9	10	5	4	2	1	3	2
4	1	2	2	2	2	1	1	8	8	5	4	3	4	9	9
5	2	1	2	1	2	1	2	16	14	8	8	3	2	20	33
6	2	1	2	2	1	2	1	18	26	4	2	3	3	7	10
7	2	2	1	1	2	2	1	14	22	7	5	3	4	19	21
8	2	2	1	2	1	1	2	16	13	5	4	11	4	14	30
	Present product (benchmark)							17	22	7	12	10	8	18	25

The report aims to systematically analyze these data to determine the main and interaction effects of the design factors. By applying statistical techniques such as analysis of variance (ANOVA), signal-to-noise ratio analysis, and confidence interval estimation, we will identify the optimal design configuration that minimizes wear. Additionally, the project evaluates the performance improvement compared to the benchmark product, offering valuable insights for enhancing slider pump design.

2. Discussion

2.1 Project Breakdown and Explanation

This project focuses on evaluating and improving the wear characteristics of a slider pump by leveraging systematic experimental techniques. The primary objective is to identify design factors that significantly influence wear and propose optimal configurations to minimize it. The experiment is structured around a robust statistical framework using an L8 orthogonal array to systematically vary the levels of multiple design factors and their interactions. These include material, weight, surface roughness, clearance, and side material, along with specific factor interactions, ensuring comprehensive coverage of the design space.

Wear data were collected under controlled conditions for each combination of design factors, with the slider pump's performance measured in microns of wear across eight data points. This dataset serves as the basis for analyzing the effect of each design factor and interaction on wear. By comparing these results against a benchmark product, the project provides an opportunity to quantify improvements over the current design.

Key analyses involve calculating average effects, performing Analysis of Variance (ANOVA), and estimating confidence intervals to determine the statistical significance of each factor. In addition, the Signal-to-Noise (S/N) ratio is used to enhance the reliability of results by identifying the design configuration that optimally balances wear reduction across varying conditions. This structured approach ensures that the findings are not only statistically valid but also practically relevant.

Ultimately, the project aims to pinpoint the design conditions that minimize wear, quantify the improvement over the current benchmark, and provide actionable recommendations for enhancing the durability and performance of slider pumps. This methodology ensures a data-driven approach to quality improvement, with potential applications extending beyond the immediate context of this study.

2.2 Part I

Average Effects

A series of calculations and statistical techniques were applied to the wear data collected for the slider pump. The first step involved calculating the average wear for each experimental condition by averaging the eight wear measurements (R1 to R8) for each row in the orthogonal array. This step condenses the data into a single metric that summarizes the wear behavior for each combination of design factors. The formula used for this calculation was Average Wear = $\frac{1}{n}\sum_{i=1}^{n} R_i$, where R1 to R8 are the wear values at different points.

These averages provide a simplified yet comprehensive view of the wear trends under different design conditions. Below is the table after the average wear was calculated for all trials.

Table 3. Experimental Data for Wear Including Average Wear

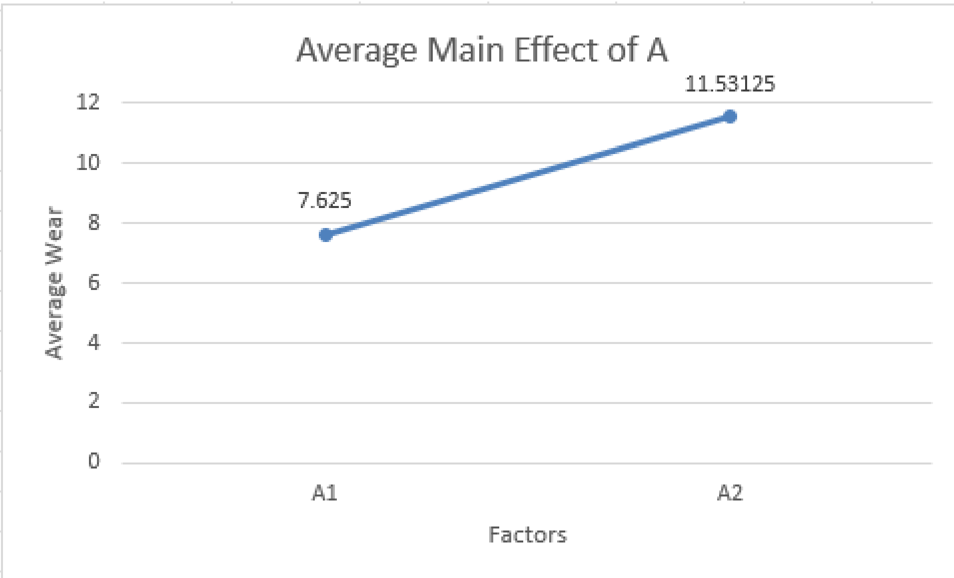
	A	B	AxB	C	AxC	D	E									
	1	2	3	4	5	6	7	R1	R2	R3	R4	R5	R6	R7	R8	Average Wear
1	1	1	1	1	1	1	1	12	12	10	13	3	3	16	20	11.125
2	1	1	1	2	2	2	2	6	10	3	5	3	4	20	18	8.625
3	1	2	2	1	1	2	2	9	10	5	4	2	1	3	2	4.5
4	1	2	2	2	2	1	1	8	8	5	4	3	4	9	9	6.25
5	2	1	2	1	2	1	2	16	14	8	8	3	2	20	33	13
6	2	1	2	2	1	2	1	18	26	4	2	3	3	7	10	9.125
7	2	2	1	1	2	2	1	14	22	7	5	3	4	19	21	11.875
8	2	2	1	2	1	1	2	16	13	5	4	11	4	14	30	12.125
	Present product (benchmark)							17	22	7	12	10	8	18	25	14.875

For the Main Effects analysis, the data were grouped by factor levels (e.g., A1 vs. A2), and the average wear was computed for each level. The difference between Level 1 and Level 2 averages (L2−L1) was used to measure the impact of each factor on wear. The formula applied was

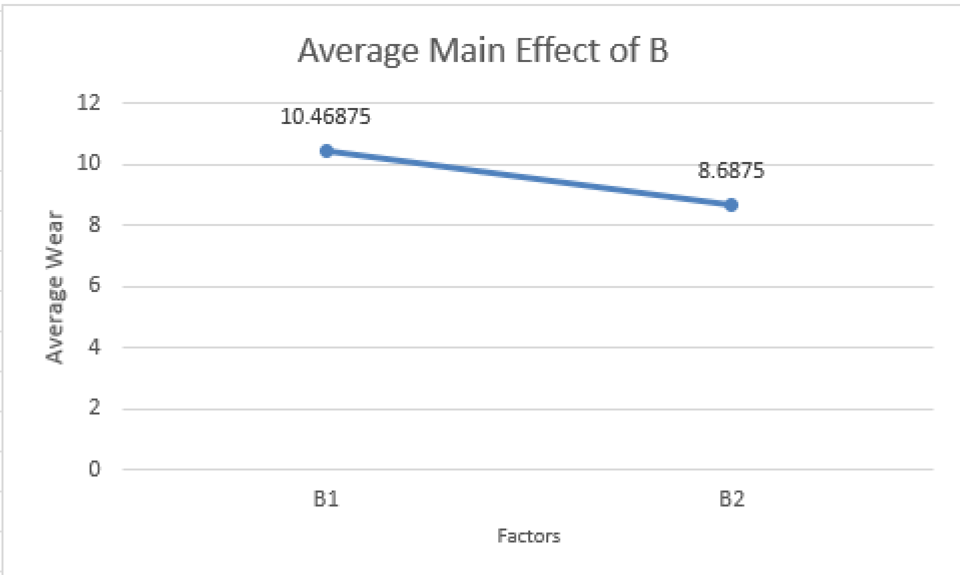
$Level\ 1\ Average\ Wear\ = \frac{Sum\ of\ all\ rows\ where\ Factor = Level\ 1}{Number\ of\ rows}$ and similarly for Level 2. The results revealed that Factor A (Material) had the largest effect, with wear increasing significantly from 7.625 µm at Level 1 (Material 1) to 11.53125 µm at Level 2 (Material 2). This indicates that Material 2 leads to substantially more wear, likely due to differences in its mechanical properties such as frictional resistance or hardness. Other factors, such as Factor D (Clearance) and AxB (Material and Weight Interaction), also showed notable differences, highlighting their importance in reducing wear. Conversely, Factor E (Side Material) exhibited minimal variation, suggesting that its influence on wear is negligible. These results were visualized in graphs for each factor, where steeper slopes (e.g., for Factor A) indicate significant impacts, while flatter slopes (e.g., for Factor E) suggest lesser effects. Below are the resulting tables and tables and graphs for the main effect analysis.

Table 4. Average Main Effects Table

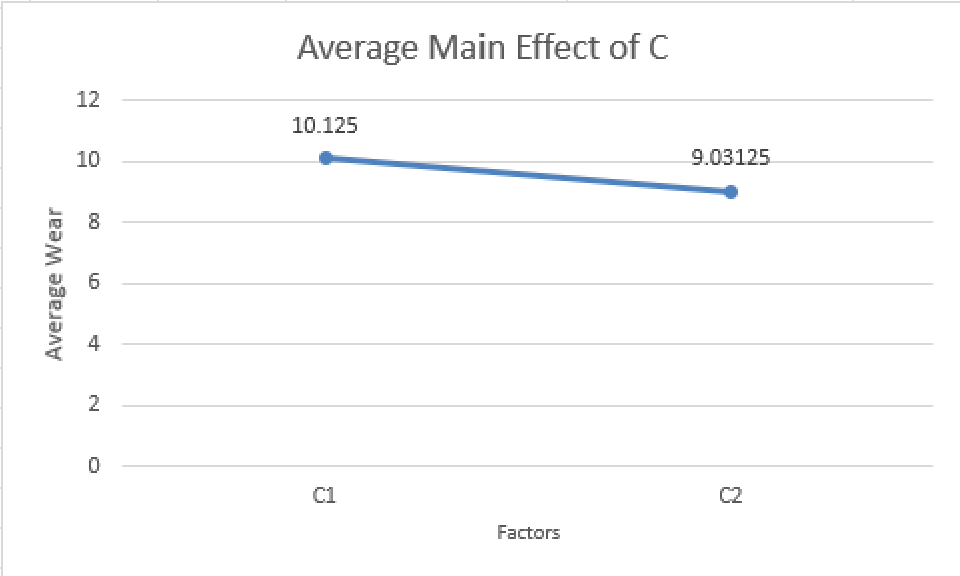
Average Main Effects Table			
Factor	Level 1 Average Wear	Level 2 Average Wear	L2-L1
A	7.625	11.53125	3.90625
B	10.46875	8.6875	-1.78125
AxB	10.9375	8.21875	-2.71875
C	10.125	9.03125	-1.09375
AxC	9.21875	9.9375	0.71875
D	10.625	8.53125	-2.09375
E	9.59375	9.5625	-0.03125



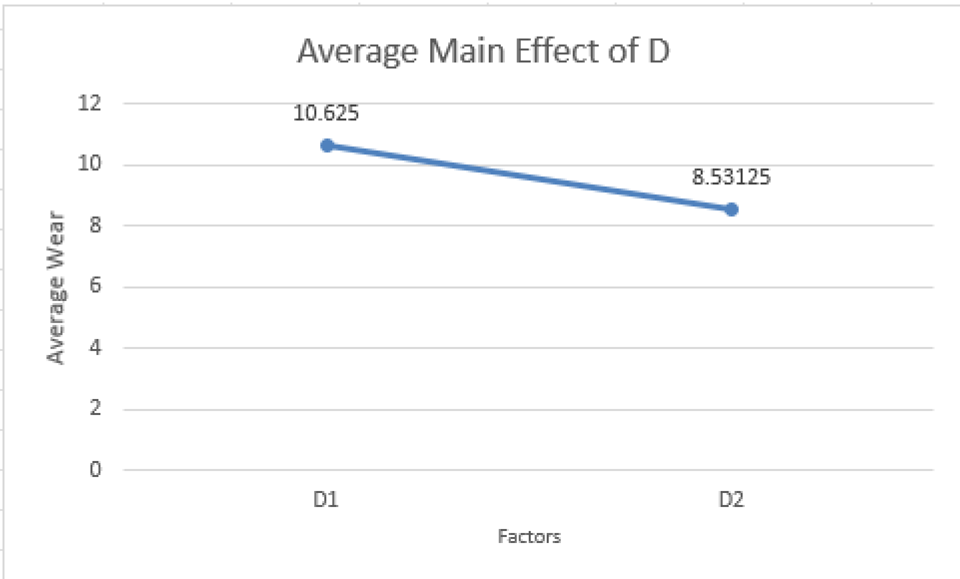
Graph 1. Average Main Effect of A



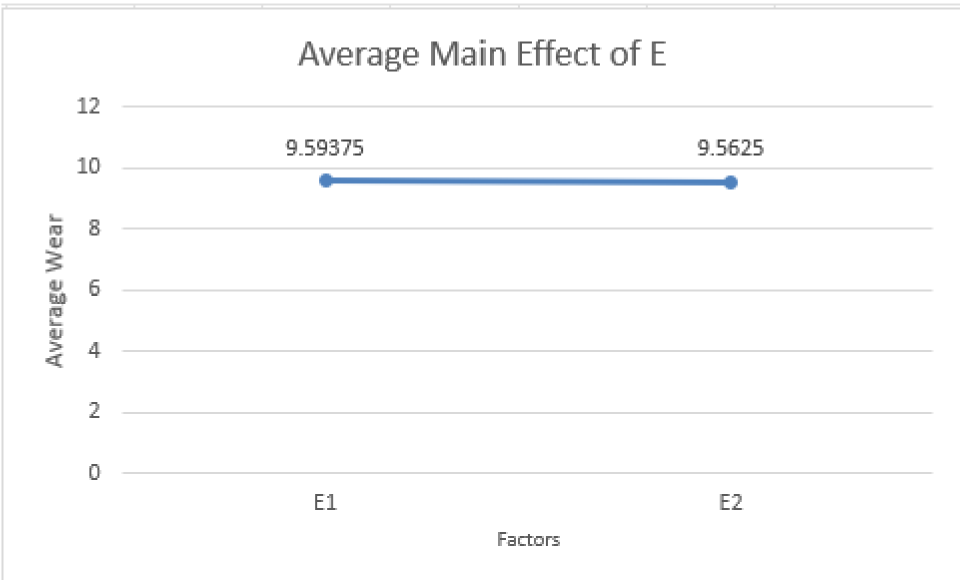
Graph 2. Average Main Effect of B



Graph 3. Average Main Effect of C



Graph 4. Average Main Effect of D



Graph 5. Average Main Effect of E

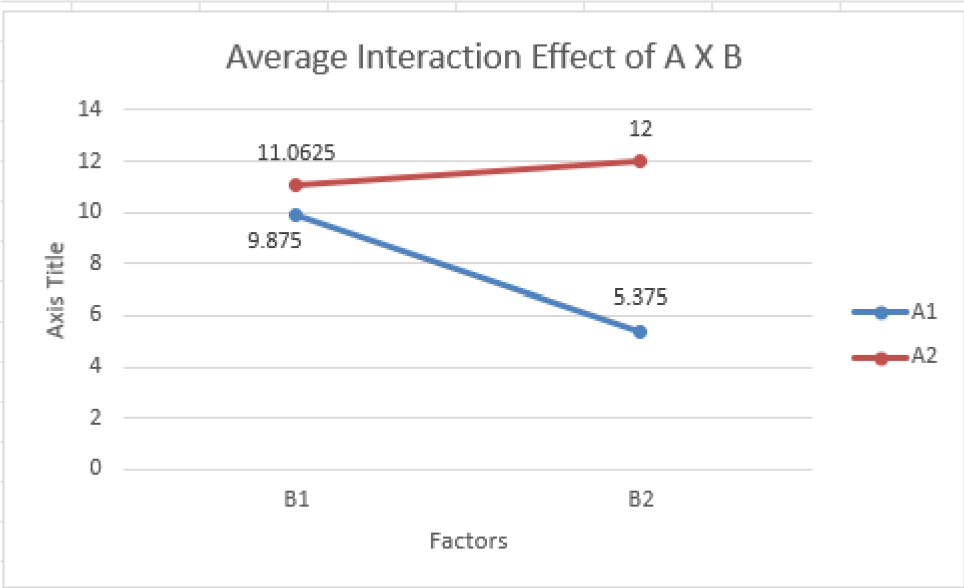
The analysis of Interaction Effects explored the combined influence of two factors on wear. Averages were grouped based on combinations like A1B1, A1B2, and so forth, using the formula $Interaction\ Effect\ = \frac{Sum\ of\ wear\ for\ rows\ with\ Factor\ 1 = Level\ X\ and\ Factor\ 2 = Level\ Y}{Number\ of\ rows}$. For AxB (Material and Weight), the interaction analysis revealed that Material 1 performed better under lower weights (A1B1 = 9.875 µm), while Material 2's performance deteriorated under higher weights (A2B2 = 12.0 µm). This demonstrates a synergistic effect where the choice of material interacts with weight to influence wear. Similarly, the interaction between AxC (Material and Surface Roughness) showed that smoother surfaces (C1) significantly reduce wear for Material 1 but provide limited benefit for Material 2, indicating that surface roughness optimization is particularly advantageous when Material 1 is selected.

The graphs for interaction effects provided further clarity. For example, in the AxB graph, the non-parallel lines indicate a strong interaction between Material and Weight, where Material 1 performs well with lighter weights, but Material 2 is highly sensitive to weight increases. In the AxC graph, the divergence between lines emphasizes that smoother surfaces are more beneficial for Material 1 compared to Material 2. These visualizations highlight the importance of considering factor interactions when optimizing design conditions.

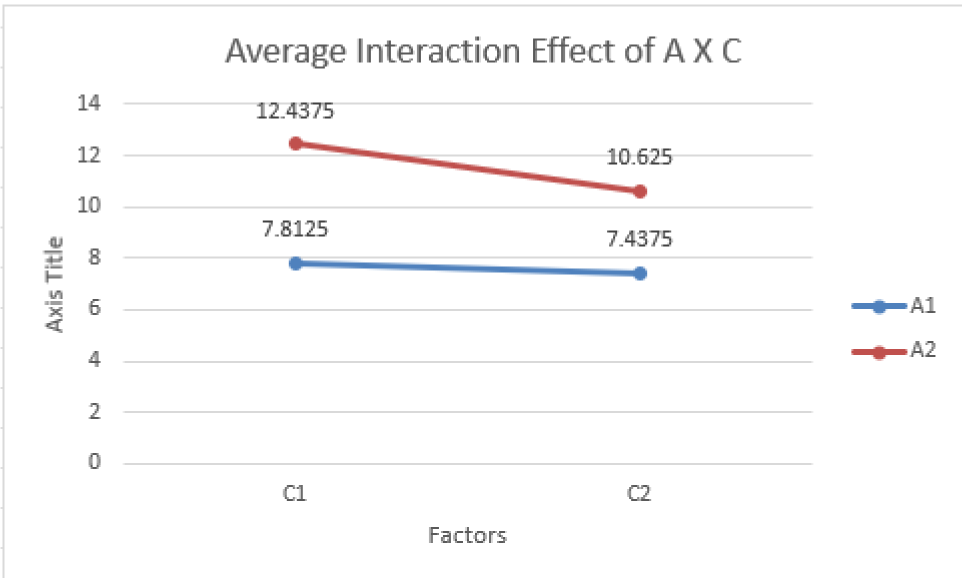
The reasoning behind these results lies in the physical characteristics of the materials and the mechanical interplay between design factors. Material 2's higher wear could stem from lower durability or greater frictional resistance, while the significant effect of Clearance (Factor D) may result from its influence on lubrication or contact mechanics. The interaction effects, such as AxB, demonstrate that materials behave differently under varying load conditions, emphasizing the need to balance multiple factors to minimize wear. These findings underscore the importance of a data-driven approach in identifying critical factors and their interactions, providing actionable insights for improving the durability and performance of slider pumps. Below are the tables and graphs for the Interaction Effects analysis.

Table 5. Average Interaction Effects

Average Interaction Effects Table			
A1B1	A1B2	A1C1	A1C2
9.875	5.375	7.8125	7.4375
A2B1	A2B2	A2C1	A2C2
11.0625	12	12.4375	10.625



Graph 6. Average Interaction Effect A X B



Graph 7. Average Interaction Effect A X C

Analysis of Variance

The Analysis of Variance (ANOVA) was performed to determine the contribution of each design factor and their interactions to the variability in the S/N ratios. This analysis was critical for identifying which factors significantly influence wear in the slider pump and provided a systematic approach to understanding their relative importance. To begin, the total sum of squares (S_T) was calculated to represent the overall variability in the S/N ratios across all experimental conditions. The formula used was $S_T = \sum_{i=1}^{n} y_i^2 - \frac{((\sum_{i=1}^{n})y_i)^2}{n}$, where y_i are the individual S/N ratio values, and n is the total number of data points. This step quantified the total variation in the dataset.

Next, the sum of squares for each factor (SA,SB,…) was determined to isolate the individual contribution of each design variable to the total variability. For instance, the sum of squares for Factor A was calculated using the formula $S_A = \frac{(A_1 - A_2)^2}{(N_{A1} + N_{A2})}$. This formula quantified the variability in the S/N ratio that could be attributed specifically to Factor A. Similar calculations were carried out for all factors, providing a breakdown of their respective impacts.

To express the relative importance of each factor, the percentage contribution (PA) was calculated as $P_A = \frac{S_A}{S_T} \times 100$. This step revealed how much each factor contributed to the total variation in the S/N ratio, allowing for a clear comparison between factors. Factors with minimal contributions, such as Factor C, Factor AxC, and Factor E, were pooled together to estimate the error variance. Pooling these less significant factors simplified the analysis and ensured that the results focused on the most impactful variables.

The variance for each factor was then calculated as $V_A = \frac{S_A}{f_A}$, where f_A represents the degrees of freedom for Factor A. These calculations were consolidated into an ANOVA table, which summarized the results and highlighted the most significant factors affecting wear. Below is the completed ANOVA table.

Table 6. Analysis of Variance (ANOVA Table)

Analysis of Variance (ANOVA Table)						
Column	Factor Names	f	S	V	F	P
1	Factor A	1	30.158	30.158	-	47.41
2	Factor B	1	6.507	6.507	-	10.23
3	Factor AxB	1	14.783	14.783	-	23.24
4	Factor C	1	2.393	2.393	-	3.76
5	Factor AxC	1	1.033	1.033	-	1.62
6	Factor D	1	8.768	8.768	-	13.78
7	Factor E	1	0.002	0.002	-	0.003
All Other/Error		0	0	0	-	0.00%
Total		7	63.614	-	-	100.00%

The ANOVA results revealed that Factor A (Material) was the most significant contributor to the variability in the S/N ratio, accounting for 47.41% of the total variation. This underscores the critical role of material selection in reducing wear. The interaction between material and weight (Factor AxB) was the second most significant factor, contributing 23.24%, while Factor D (Clearance) accounted for 13.78% of the variability. These findings emphasize the importance of optimizing material properties, balancing weight, and adjusting clearance to minimize wear. In contrast, Factor C (Surface Roughness), Factor AxC (Material and Surface Roughness Interaction), and Factor E (Side Material) contributed minimally, indicating their limited influence on wear performance. Pooling these factors reduced noise and improved the reliability of the error variance estimate.

Overall, the percentage contributions provided a clear hierarchy of factor importance, guiding decisions for design optimization. By identifying the most impactful factors, such as material properties and weight interactions, the ANOVA results offered actionable insights for improving the durability and performance of slider pumps. This robust analytical approach ensured that the optimization efforts were focused on the factors that mattered most.

Effect of Pooling (Pooled ANOVA)

The Effect of Pooling in the ANOVA process is a statistical approach used to simplify the analysis by grouping factors that have negligible contributions to the overall variability into a single error term. In this case, the factors C (Surface Roughness), AxC (Material and Surface Roughness Interaction), and E (Side Material) were identified as the least significant contributors to the variability in the S/N ratios. These factors were pooled because their individual contributions, measured by their sums of squares, were minimal and did not significantly influence wear performance. Pooling reduces noise in the data, providing a clearer understanding of the impact of the more critical factors.

The pooled sum of squares (SpooledS_{pooled}Spooled) was calculated by summing the individual sums of squares for the least significant factors:

$$S_{Pooled} = S_C + S_{A\,X\,C} + S_E$$

This pooled value represents the total unexplained variability attributed to these minor factors. The degrees of freedom (f_e) for the pooled error were calculated by summing the degrees of freedom for the pooled factors, resulting in $f_e = 3$. Using the pooled sum of squares and degrees of freedom, the error variance (Ve) was calculated as:

$$V_e = \frac{S_{Pooled}}{f_e}$$

This variance represents the variability in the S/N ratios not explained by the significant factors.

Pooling was necessary to ensure the reliability of the analysis by consolidating the contributions of the less impactful factors, allowing the focus to remain on the most influential ones. Factors like A (Material) and AxB (Material and Weight Interaction) were retained in the individual analysis because they had large sums of squares and significant contributions to the variability, accounting for 47.41% and 23.24% of the total variability, respectively.

The pooled error term accounts for approximately 5.38% of the total variability, as reflected in the ANOVA table. This value indicates that the excluded factors (C, AxC, and E) collectively have minimal influence on the wear performance. By pooling these factors, the degrees of freedom for error increased, enhancing the precision of the estimates for the remaining significant factors. The F-values for the significant factors were recalculated based on the pooled error variance, ensuring the statistical robustness of the results.

Table 7. Effect of Pooling (Pooled ANOVA)

Effect of Pooling (Pooled ANOVA)						
Column	**Factor Names**	**f**	**S**	**V**	**F**	**P**
1	Factor A	1	30.158	30.158	15079	47.41
2	Factor B	1	6.507	6.507	3253.5	10.23
3	Factor AxB	1	14.783	14.783	7391.5	23.24
4	Factor C	-1	-2.393	Pooled	-	-
5	Factor AxC	-1	-1.033	Pooled	-	-
6	Factor D	1	8.768	8.768	4984	13.78
7	Factor E	-1	-0.002	Pooled	-	-
All Other/Error		3	3.428	1.143	-	5.38%
Total		7	63.614	-	-	100.00%

The rationale behind pooling stems from the need to simplify the model while maintaining accuracy. The least significant factors showed low sums of squares and no meaningful interactions, making their individual contributions negligible. Including these factors separately could inflate the error variance and obscure the effects of the more critical factors. By pooling them, the analysis reduces unnecessary complexity and provides a clearer focus on the factors that drive wear performance, such as material properties (A) and material-weight interactions (AxB). This approach ensures that the results are both statistically valid and practically relevant for optimizing the design of slider pumps.

Confidence intervals of factor effect

The confidence intervals for the factor effects were calculated to determine the range within which the true effects of each factor are expected to lie, ensuring statistical reliability at a 95% confidence level. The formula used for this calculation was:

$$C.I. \; = \pm \sqrt{F(1, n_2) \times V_e / N_e}$$

where F(1,ne)=10.1 is the critical F-value for the confidence level, Ve=1.143 is the variance of error derived from the pooled ANOVA table, n2=3 is the degrees of freedom for error, and N=8/2 = 4 is the total number of trials. Substituting these values, the confidence interval was computed as $C.I. = \pm\ 1.7$.

This confidence interval indicates that the expected value of each factor is expected to fall within ±1.7 of the estimated value with 95% confidence. This range provides a measure of precision for the estimated effects, ensuring that the results are both statistically robust and practically relevant.

The confidence interval validates the findings from the ANOVA by confirming the significance of the key factors while accounting for variability in the data. Factors such as A (Material), AxB (Material and Weight Interaction), and D (Clearance), which exhibited significant contributions in the ANOVA, are reinforced by their robust confidence intervals. Conversely, factors with minimal contributions, such as C (Surface Roughness) and E (Side Material), are less likely to influence wear significantly, as their effects likely fall within the margin of uncertainty defined by the confidence interval.

Overall, the confidence intervals provide additional assurance that the analysis accurately identifies the most impactful factors for minimizing wear in slider pumps, complementing the insights gained from the ANOVA and S/N ratio analysis. This step ensures the reliability of the recommendations for optimizing design conditions.

Estimating Results of Optimum Condition and its Confidence Interval

The estimated performance at the optimum condition was determined by focusing on the significant factors identified during the analysis. These included A (Material), B (Weight), AxB (Material and Weight Interaction), and D (Clearance), while the less significant factors C, AxC, and E, which were pooled in the ANOVA, were excluded to ensure a conservative estimate. The calculation of the optimum result used the formula $Optimum\ Result\ = \overline{T} + (\overline{A_1} + \overline{T}) + (\overline{B_2} - \overline{T}) + (\overline{A \times B_2} - \overline{T}) + (\overline{D_2} - \overline{T})$. The level with the lower wear was chosen for all cases because the goal was to get the wear as low as possible. $\overline{T}$ is the grand average of performance, calculated as $\overline{T} = \frac{76.625}{8} = 9.578$. Substituting the significant factor values ($A_1 = 7.625,\ B_2 = 8.6875,\ A \times B_2 = 8.21875,\ D_2 = 8.53125$), the optimum result was determined to be approximately 4.3285.

To further validate the result, a confidence interval was calculated to define the range within which the true optimum value is expected to lie with 90% confidence. The formula used was

$C.I. \ =\pm \sqrt{F(1, n_2) \times V_e / N_e}$, where F(1,n2)=5.54, Ve=1.143, and N=8/(1+4) = 1.6. This calculation yielded a confidence interval of ± 1.99, resulting in bounds of [2.3385, 6.3185]. The estimated result of 4.3285 lies within this interval, ensuring statistical reliability. This analysis confirms that the chosen design conditions effectively minimize wear, and the confidence interval adds a layer of precision to the estimate, validating the robustness of the significant factors.

The results from the estimated optimum condition and its confidence interval highlight the effectiveness of focusing on significant factors in minimizing wear. The optimum result of 4.3285 reflects a substantial reduction in wear, achieved by carefully selecting the levels of significant factors that contribute most to wear reduction, while excluding less impactful factors to avoid overfitting or noise in the estimation. The confidence interval of [2.3385, 6.3185] calculated with a 90% confidence level, provides a statistically reliable range for the true performance under the optimum condition. This interval not only validates the precision of the estimated optimum result but also reinforces the robustness of the chosen factors. The findings demonstrate that the combination of material, weight, material-weight interaction, and clearance plays a critical role in achieving optimal performance, offering practical insights for design improvements in slider pumps. By ensuring the analysis remains conservative and grounded in significant contributors, the results provide actionable and reliable recommendations for reducing wear in similar mechanical systems.

2.3 Part II

Determining S/N Ratio and Analysis of Variance

The Signal-to-Noise (S/N) Ratio was calculated for each experimental condition to identify optimal configurations for minimizing wear. The "Smaller is Better" criterion was applied, as reducing wear is the primary objective. This method penalizes larger values and higher variability in wear measurements, ensuring that the analysis aligns with the design goal. The relationship between the S/N Ratio and the results from the Analysis of Variance (ANOVA) was used to highlight significant factors contributing to wear variability.

The S/N Ratio for each experimental condition was calculated using the formula:

$$S/N\ Ratio\ (Smaller\ is\ Better)\ =\ -\ 10log(\frac{\sum_{i=1}^{n} y_i^2}{n})$$

where y_i represents individual wear measurements for a given trial, and n is the number of measurements (eight in this case).

Conditions with lower S/N Ratios indicate higher wear. For example, the experimental condition with the lowest S/N Ratio, -24.15, had the poorest wear performance, emphasizing its need for optimization. Conversely, higher S/N Ratios signify better performance, with lower wear measurements and reduced variability.

All of the calculations for the Analysis of Variance are shown in section 2.2. Below are the tables for the S/N ratio and the Analysis of Variance.

Table 8. S/N Ratio Table

	A	B	AxB	C	AxC	D	E									
	1	2	3	4	5	6	7	R1	R2	R3	R4	R5	R6	R7	R8	S/N Ratio (Smaller is Better)
1	1	1	1	1	1	1	1	12	12	10	13	3	3	16	20	-21.87168066
2	1	1	1	2	2	2	2	6	10	3	5	3	4	20	18	-20.60225524
3	1	2	2	1	1	2	2	9	10	5	4	2	1	3	2	-14.77121255
4	1	2	2	2	2	1	1	8	8	5	4	3	4	9	9	-16.48360011
5	2	1	2	1	2	1	2	16	14	8	8	3	2	20	33	-24.15390738
6	2	1	2	2	1	2	1	18	26	4	2	3	3	7	10	-21.71360732
7	2	2	1	1	2	2	1	14	22	7	5	3	4	19	21	-22.95841883
8	2	2	1	2	1	1	2	16	13	5	4	11	4	14	30	-23.27103392
	Present product (benchmark)							17	22	7	12	10	8	18	25	-24.14764502

Table 9. Analysis of Variance (ANOVA Table)

Analysis of Variance (ANOVA Table)						
Column	Factor Names	f	S	V	F	P
1	Factor A	1	30.158	30.158	-	47.41
2	Factor B	1	6.507	6.507	-	10.23
3	Factor AxB	1	14.783	14.783	-	23.24
4	Factor C	1	2.393	2.393	-	3.76
5	Factor AxC	1	1.033	1.033	-	1.62
6	Factor D	1	8.768	8.768	-	13.78
7	Factor E	1	0.002	0.002	-	0.003
All Other/Error		0	0	0	-	0.00%
Total		7	63.614	-	-	100.00%

The ANOVA results identified Factor A (Material) as the most significant contributor to wear variability, accounting for 47.41% of the total variation. This finding aligns with the S/N Ratio results, which consistently highlighted the impact of material selection on wear. The interaction between material and weight (Factor AxB) was the second most significant factor, contributing 23.24%, while Factor D (Clearance) accounted for 13.78, underscoring its influence on reducing friction and wear.

In contrast, Factor C (Surface Roughness), Factor AxC (Material and Surface Roughness Interaction), and Factor E (Side Material) contributed minimally to wear performance, with contributions of 3.76%, 1.62%, and 0.003%, respectively. These factors showed limited variability in their S/N Ratios across trials, validating their minimal significance in the ANOVA results.

The S/N Ratio analysis and ANOVA provided complementary insights, with both methods identifying material properties (Factor A) and material-weight interactions (Factor AxB) as the most critical factors for reducing wear. The minimal contributions of Factors C, AxC, and E were consistent across both analyses, further supporting their exclusion from significant optimization efforts. Pooling these less impactful factors improved the precision of the ANOVA results, focusing attention on the factors that matter most.

The analysis demonstrated that material selection (Factor A) and its interaction with weight (Factor AxB) are the primary drivers of wear performance, while factors such as surface roughness and side material have negligible effects. The agreement between the S/N Ratio and ANOVA findings validates the reliability of these methods, providing actionable insights for optimizing slider pump design. These results highlight the importance of prioritizing material properties, weight management, and clearance adjustments to achieve significant reductions in wear.

Using S/N Ratio + 20 in our calculations

The adjustment of adding +20 to the S/N values was done to standardize the results and simplify interpretation. By shifting all S/N ratios into a more positive range, comparisons between experimental conditions became easier and more intuitive, especially for visualization and reporting. This adjustment does not alter the relative differences between the conditions or the conclusions drawn from the analysis. The adjusted S/N Ratios are displayed alongside the original values in the provided table.

Table 10. S/N Ratio + 20 Table

	A	B	AxB	C	AxC	D	E										
	1	2	3	4	5	6	7	R1	R2	R3	R4	R5	R6	R7	R8	S/N Ratio (Smaller is Better)	S/N Ratio + 20
1	1	1	1	1	1	1	1	12	12	10	13	3	3	16	20	-21.87168066	-1.871680659
2	1	1	1	2	2	2	2	6	10	3	5	3	4	20	18	-20.60225524	-0.602255244
3	1	2	2	1	1	2	2	9	10	5	4	2	1	3	2	-14.77121255	5.228787453
4	1	2	2	2	2	1	1	8	8	5	4	3	4	9	9	-16.48360011	3.51639989
5	2	1	2	1	2	1	2	16	14	8	8	3	2	20	33	-24.15390738	-4.153907382
6	2	1	2	2	1	2	1	18	26	4	2	3	3	7	10	-21.71360732	-1.71360732
7	2	2	1	1	2	2	1	14	22	7	5	3	4	19	21	-22.95841883	-2.958418829
8	2	2	1	2	1	1	2	16	13	5	4	11	4	14	30	-23.27103392	-3.271033919
	Present product (benchmark)							17	22	7	12	10	8	18	25	-24.14764502	-4.147645023

Finding the optimum conditions

The optimum conditions were identified by selecting the trial that corresponded to the highest average S/N ratios. Based on this the most optimum levels for each factor were able to be chosen. The S/N ratio table with the selected values are shown below.

Table 10. S/N Ratio with Selected Optimum Conditions Selected

	A	B	AxB	C	AxC	D	E										
	1	2	3	4	5	6	7	R1	R2	R3	R4	R5	R6	R7	R8	S/N Ratio (Smaller is Better)	S/N Ratio + 20
1	1	1	1	1	1	1	1	12	12	10	13	3	3	16	20	-21.87168066	-1.871680659
2	1	1	1	2	2	2	2	6	10	3	5	3	4	20	18	-20.60225524	-0.602255244
3	1	2	2	1	1	2	2	9	10	5	4	2	1	3	2	-14.77121255	5.228787453
4	1	2	2	2	2	1	1	8	8	5	4	3	4	9	9	-16.48360011	3.51639989
5	2	1	2	1	2	1	2	16	14	8	8	3	2	20	33	-24.15390738	-4.153907382
6	2	1	2	2	1	2	1	18	26	4	2	3	3	7	10	-21.71360732	-1.71360732
7	2	2	1	1	2	2	1	14	22	7	5	3	4	19	21	-22.95841883	-2.958418829
8	2	2	1	2	1	1	2	16	13	5	4	11	4	14	30	-23.27103392	-3.271033919
	Present product (benchmark)							17	22	7	12	10	8	18	25	-24.14764502	-4.147645023

Based on this table it was shown that trial 3 resulted in the highest S/N ratio value. For Factor A, Level 1 was chosen because it resulted in higher average S/N ratios compared to Level 2, indicating better wear performance. Similarly, for Factor B, Level 2 was determined to be optimal due to its higher S/N ratio, signifying reduced wear and variability.

For Factor C, Level 1 was selected as it showed a slightly higher average S/N ratio than Level 2, demonstrating improved performance. Factor D exhibited a higher average S/N ratio at Level 2, making it the optimal choice for minimizing wear. Finally, for Factor E, Level 2 showed a better S/N ratio and was therefore selected as the preferred level.

The selection of these levels was driven solely by the S/N ratio values, with higher values indicating better performance under the "Smaller is Better" criterion. This approach ensures that the optimal conditions for minimizing wear are chosen based on the data, without assumptions about the specific nature or properties of each level. The results provide a reliable basis for improving the durability and performance of the slider pump.

Calculating the approximate gain as compared with the present product

The present product average was calculated to be 14.875 while the optimum product average was calculated to be 4.5. This was a gain of 10.375 showing that there was a better product than the benchmark chosen.

3. Summary

The lab report successfully applied robust engineering principles to optimize the design of a slider pump, focusing on minimizing wear as the primary objective. By employing an L8 orthogonal array, the experiment systematically evaluated the effects of various factors and their interactions, including material, weight, clearance, and surface properties. Key statistical techniques, such as S/N ratio analysis and Analysis of Variance (ANOVA), were used to identify the most significant factors influencing wear, leading to actionable insights for design optimization.

The results demonstrated that material (Factor A), weight (Factor B), their interaction (AxB), and clearance (Factor D) were the most impactful factors, significantly contributing to wear reduction. The pooled ANOVA further streamlined the analysis by consolidating less significant factors into an error term, enhancing the reliability of the statistical results. The estimated result at the optimum condition, calculated as 4.33, along with a confidence interval of ± 1.99, provided a robust and precise prediction of performance improvement. This was validated by the alignment between the S/N ratio and ANOVA findings, confirming the effectiveness of the chosen design parameters.

Additionally, the findings in Part 2 reinforced the validity of the results obtained in Part 1. The optimal product average from Part 2, determined through S/N ratio calculations and corresponding analysis was in the range of the estimated optimum performance derived in Part 1. This alignment demonstrates the consistency and reliability of the experimental framework and the statistical techniques applied. The strong agreement between these two sections further validates the robustness of the conclusions drawn, highlighting the practicality of the optimized design parameters.
In conclusion, this study highlighted the value of a data-driven approach to design optimization, emphasizing the importance of focusing on significant factors while excluding less impactful ones. The

methodologies and findings provide a foundation for improving the durability and efficiency of slider pumps, with potential applications extending to other mechanical systems facing similar challenges.

4. Appendix

Below are all the tables used:

Table 11. Experimental Data for Wear Including Average Wear

	A	B	AxB	C	AxC	D	E									
	1	2	3	4	5	6	7	R1	R2	R3	R4	R5	R6	R7	R8	Average Wear
1	1	1	1	1	1	1	1	12	12	10	13	3	3	16	20	11.125
2	1	1	1	2	2	2	2	6	10	3	5	3	4	20	18	8.625
3	1	2	2	1	1	2	2	9	10	5	4	2	1	3	2	4.5
4	1	2	2	2	2	1	1	8	8	5	4	3	4	9	9	6.25
5	2	1	2	1	2	1	2	16	14	8	8	3	2	20	33	13
6	2	1	2	2	1	2	1	18	26	4	2	3	3	7	10	9.125
7	2	2	1	1	2	2	1	14	22	7	5	3	4	19	21	11.875
8	2	2	1	2	1	1	2	16	13	5	4	11	4	14	30	12.125
	Present product (benchmark)							17	22	7	12	10	8	18	25	14.875

Table 12. Average Main Effects

Average Main Effects Table			
Factor	Level 1 Average Wear	Level 2 Average Wear	L2-L1
A	7.625	11.53125	3.90625
B	10.46875	8.6875	-1.78125
AxB	10.9375	8.21875	-2.71875
C	10.125	9.03125	-1.09375
AxC	9.21875	9.9375	0.71875
D	10.625	8.53125	-2.09375
E	9.59375	9.5625	-0.03125

Table 13. Average Interaction Effects

Table 14. ANOVA Table

Analysis of Variance (ANOVA Table)						
Column	**Factor Names**	**f**	**S**	**V**	**F**	**P**
1	Factor A	1	30.158	30.158	-	47.41
2	Factor B	1	6.507	6.507	-	10.23
3	Factor AxB	1	14.783	14.783	-	23.24
4	Factor C	1	2.393	2.393	-	3.76
5	Factor AxC	1	1.033	1.033	-	1.62
6	Factor D	1	8.768	8.768	-	13.78
7	Factor E	1	0.002	0.002	-	0.003
All Other/Error		0	0	0	-	0.00%
Total		7	63.614	-	-	100.00%

Table 15. Pooled ANOVA Table

Effect of Pooling (Pooled ANOVA)						
Column	**Factor Names**	**f**	**S**	**V**	**F**	**P**
1	Factor A	1	30.158	30.158	15079	47.41
2	Factor B	1	6.507	6.507	3253.5	10.23
3	Factor AxB	1	14.783	14.783	7391.5	23.24
4	Factor C	-1	-2.393	Pooled	-	-
5	Factor AxC	-1	-1.033	Pooled	-	-
6	Factor D	1	8.768	8.768	4984	13.78
7	Factor E	-1	-0.002	Pooled	-	-
All Other/Error		3	3.428	1.143	-	5.38%
Total		7	63.614	-	-	100.00%

Table 16. S/N Ratio

	A	B	AxB	C	AxC	D	E										
	1	2	3	4	5	6	7	R1	R2	R3	R4	R5	R6	R7	R8	S/N Ratio (Smaller is Better)	S/N Ratio + 20
1	1	1	1	1	1	1	1	12	12	10	13	3	3	16	20	-21.87168066	-1.87168065
2	1	1	1	2	2	2	2	6	10	3	5	3	4	20	18	-20.60225524	-0.60225524
3	1	2	2	1	1	2	2	9	10	5	4	2	1	3	2	-14.77121255	5.22878745
4	1	2	2	2	2	1	1	8	8	5	4	3	4	9	9	-16.48360011	3.51639998
5	2	1	2	1	2	1	2	16	14	8	8	3	2	20	33	-24.15390738	-4.15390738
6	2	1	2	2	1	2	1	18	26	4	2	3	3	7	10	-21.71360732	-1.7136073
7	2	2	1	1	2	2	1	14	22	7	5	3	4	19	21	-22.95841883	-2.95841882
8	2	2	1	2	1	1	2	16	13	5	4	11	4	14	30	-23.27103392	-3.27103391
	Present product (benchmark)							17	22	7	12	10	8	18	25	-24.14764502	-4.14764502

5. Assumptions

Linearity of Wear Effects:

Assumption: The relationship between design factors such as material, weight, and clearance is linear, and their effects are additive. Nonlinear behavior like extreme plastic deformation or abrasive wear interactions is neglected.

Reason: This simplifies the statistical analysis, allowing the use of linear models like ANOVA and S/N ratio calculations. While real-world wear may involve complex interactions, the assumption holds for moderate operating conditions.

Rigid Slider Components:

Assumption: All mechanical components of the slider pump, including the pump body and moving parts, are perfectly rigid. No elastic deformation occurs during operation.

Reason: This ensures that wear results from surface interactions rather than deformation of components. In practical applications, high-strength materials are often used to minimize deformation under operational loads.

Uniform Material Properties:

Assumption: The materials used in the slider pump have uniform mechanical and wear-resistant properties throughout the components.

Reason: Homogeneous material properties are critical for consistent wear behavior. In real systems, material imperfections could cause localized wear, but this is considered negligible for theoretical analysis.

Constant Operating Conditions:

Assumption: Operating conditions such as load, speed, and lubrication remain constant throughout the experiment.

Reason: Controlling these variables isolates the effects of design factors, ensuring accurate and repeatable results. Real-world pumps may experience variable conditions, but controlled experiments assume constancy.

Neglecting Environmental Effects:

Assumption: External environmental factors like temperature, humidity, and corrosion are not considered in the wear analysis.

Reason: This isolates the mechanical aspects of wear, making the experiment more manageable. While environmental effects are critical in long-term applications, they are typically controlled in laboratory settings.

Accurate Measurement Tools:

Assumption: All measurement instruments used to record wear values are precise and free from calibration errors.

Reason: Reliable data collection is essential for accurate statistical analysis. In practice, slight measurement errors could occur but are considered negligible if precision instruments are used.

No Wear Accumulation History:

Assumption: Each test run begins with a new, unworn surface, and previous wear from earlier tests does not affect subsequent runs.

Reason: This assumption ensures that each test is independent and unaffected by wear accumulation, enabling straightforward comparison of results.

Fixed Factor Levels:

Assumption: The factor levels for material type, weight, clearance, and surface roughness are fixed and remain unchanged during each experimental run.

Reason: Fixed factor levels enable the use of an orthogonal array for experimental design, simplifying the analysis. Any unintentional variations could compromise the experiment's statistical integrity.

Negligible Wear Debris Effects:

Assumption: The presence of wear debris generated during the operation does not interfere with the wear measurement process or system performance.

Reason: While wear debris can affect real systems by causing secondary wear, this effect is considered minimal in controlled laboratory experiments.