OPTIMIZATION OF TEMPERATURE FLUCTUATION CONTROL IN LEGAL METROLOGY LABORATORIES USING THE TAGUCHI METHOD

Saufik Luthfianto[1*)], Sandi Satria[2], Zulfah[3], Siswiyanti[4], Tofik Hidayat[5], M. Fajar Nurwildani[6], M. Cipto Sugiono[7]
[1,2,3,4,5,6,7)] Department of Industrial Engineering
Universitas Pancasakti Tegal, Indonesia

[*)] Corresponding author email: saufik_lutfianto@upstegal.ac.id[1]

ABSTRACT Temperature fluctuations in legal metrology laboratories can affect measurement accuracy and instrument stability. This study aims to analyse and optimize the factors influencing temperature fluctuations, namely AC temperature, time duration, and lighting, using the Taguchi method with an $L9(3^3)$ orthogonal array. The experiment was conducted with three variable levels for each factor, and the results were analysed using the Signal-to-Noise (SN) ratio and Analysis of Variance (ANOVA). The findings indicate that time duration has the most significant impact on temperature fluctuation, followed by lighting, while AC temperature has a smaller effect. Although ANOVA analysis shows that none of the factors are statistically significant on the SN ratio, strong interaction effects were observed, particularly between AC temperature and time duration, as well as AC temperature and lighting. The optimal combination to minimize temperature fluctuations is selecting a longer time duration and lower lighting intensity. This study concludes that better control of time duration and lighting can improve laboratory temperature stability, contributing to enhanced measurement accuracy and energy efficiency. These findings can serve as a basis for managing metrology laboratory environments to ensure more precise and reliable measurement results.
Keywords*: Temperature fluctuation, metrology laboratory, Taguchi method, ANOVA, environmental optimization.*

INTRODUCTION

The primary function of legal metrology laboratories is to ensure that measurements remain precise and accurate, while also serving as a controlled storage environment for standard metrology instruments. Consequently, environmental conditions such as temperature and humidity must be carefully regulated. According to data from (Kementerian Perdagangan Republik Indonesia, 2024), the quality of legal metrology laboratories has shown a declining trend since 2020, with 1,692 laboratories meeting quality standards in 2020, 1,680 in 2021, 1,655 in 2022, and 1,588 in 2023. Fluctuations in temperature and humidity within metrology laboratories lead to suboptimal environmental control, which, if left unaddressed, can negatively impact measurement accuracy and precision. According to the Organisation Internationale de Métrologie Légale (OIML), permissible temperature fluctuations in metrology laboratories should not exceed ±0.7°C per hour. However, the specific variations in standardized control variables remain unidentified, posing a challenge in maintaining optimal conditions.

Research in digital metrology plays a crucial role in enhancing the reliability, efficiency, and transparency of measurement processes across various industrial and economic sectors. The digitalization of metrology, including the development of electronic infrastructure, Digital Calibration Certificates (DCC), and cloud-based metrological systems, contributes to eliminating barriers in the digital transformation of the global economy (Karthiyayini & Rajendran, 2021). Moreover, accurate and traceable measurements not only foster trust among manufacturers, consumers, and regulators but also support international trade through the harmonization of standards and the reduction of technical barriers (Rodrigues Filho & Gonçalves, 2015). In the context of the energy transition, the development of metrological systems for hydrogen is also a critical factor in ensuring measurement accuracy in the trade of more environmentally friendly gases. Therefore, research in this field impacts not only technological and economic advancements but also consumer protection, industrial efficiency, and environmental sustainability.

The digitalization of metrology, including the development of electronic metrology infrastructure, Digital Calibration Certificates (DCC), and cloud-based systems, facilitates enhanced transparency, security, and efficiency in measurement processes (Neyezhmakov et al., 2022). Furthermore, the integration of digital technologies in metrology supports the harmonization of global measurement standards, thereby impacting international trade, technological innovation, and the reduction of technical barriers (Oppermann et al., 2022). A structured calibration-certification-validation framework using a wet drum meter is applied in hydrogen metrology (Bonacina et al., 2022). This framework addresses measurement accuracy but requires further validation, scalability assessment, and long-term stability analysis. Despite challenges, it contributes to standardization efforts, supporting precise and reliable hydrogen volume and flow measurement in legal metrology.

To improve the accuracy of hydrogen refilling by integrating experimental and computational methods a hybrid metrology evaluation system is used (Kim et al., 2024). This system supports standard calibration, which encourages the adoption of fuel cells. In addition, research on thermal mass gas flow meters emphasizes measurement time rather than volume, which proposes an optimized calibration procedure to improve accuracy and efficiency in gas flow metrology (Cascetta et al., 2016). Interoperability in dimensional metrology, proposing enhancements to STEP standards for seamless data exchange (Zhao et al., 2011). A systematic review highlights legal metrology's role in trade and consumer protection, identifying regulatory gaps (Rodrigues Filho & Gonçalves, 2015). Additionally, computational modelling in precision engineering underscores the need for software certification to ensure reliable metrological computations and manufacturing quality (Linares et al., 2018).

Effective control in legal metrology laboratories is crucial for maintaining measurement accuracy, regulatory compliance, and consumer confidence. Strengthening control mechanisms ensures traceability, enhances the reliability of calibration procedures, and supports the integrity of metrological data essential for industrial applications and global trade. Therefore, a method is needed to optimize control. One of the methods used for control optimization is the Taguchi method. To address this issue, it is crucial to identify all factors influencing quality characteristics and determine optimal factor levels to minimize variance. An experimental study is necessary to evaluate the key factors affecting temperature and humidity fluctuations and establish effective control measures for optimal standardization.

Several studies have employed the Taguchi method for engineering optimization. In the machining of Inconel 718, Taguchi + GRA + ANOVA was utilized to optimize cutting speed, feed rate, and depth of cut, resulting in a 64.8% increase in MRR and a 9.52% reduction in Ra (Maiyar et al., 2013). Meanwhile, the optimization of Halbach array rotors applied Taguchi + FEM to minimize weight and enhance magnetic flux density (Yu et al., 2018). In diesel engines, the Taguchi-GRA method optimizes fuel type, load, and injection pressure, resulting in a 33.26% increase in thermal efficiency, a reduction in BSFC to 0.206 kg/kWh, and lower exhaust emissions (Bylapudi et al., 2024). In hydraulic pumps, the Taguchi-L8 method compares spur and elliptical gears, demonstrating that the elliptical gear pump achieves a 120% higher flow rate, 87% improved pressure performance, and 145% lower energy consumption (Yanikören, 2025). Taguchi and PSO designs optimize injection moulding, reducing warpage and increasing efficiency (Zhang et al., 2025). The integration of Lean and Taguchi in food processing minimizes variability and improves quality (Noorwali, 2013). Taguchi's method also improves AWJ machining by fine-tuning feed rates and abrasive flow to get better material removal and surface roughness with fewer tests (Radomska-Zalas & Puzio, 2024). These studies demonstrate that the Taguchi method significantly reduces the number of experiments required while still achieving efficient and reliable parameter optimization.

The Taguchi method is applied in this study to enhance quality by reducing variation at the earliest stages of design, ensuring a more stable and controlled laboratory environment. Utilizing an $L_9(3^3)$ orthogonal array, this approach systematically evaluates the impact of three factors AC temperature, time duration, and lighting each tested at three levels across nine experimental runs. By independently analyzing these factors, the method effectively identifies optimal conditions to minimize defects and improve laboratory performance. The primary response variable, temperature fluctuation, is assessed using the "smaller is better" quality characteristic, aiming to enhance measurement accuracy and energy efficiency in legal metrology laboratories.

The novelty of this study lies in the optimization of temperature fluctuation control in legal metrology laboratories using the Taguchi method, specifically an $L_9(3^3)$ orthogonal array. Unlike previous studies that focus on general environmental stability, this research identifies time duration and lighting as the most significant factors affecting temperature fluctuations, rather than AC temperature. Moreover, the study reveals strong interaction effects between AC temperature and other variables, contributing new insights into environmental control strategies for metrology laboratories. These findings provide a quantitative basis for optimizing laboratory conditions, enhancing measurement accuracy and energy efficiency.

METHOD

The Taguchi method is an exploratory quality control approach designed to reduce high variability, offering a flexible and simplified optimization process through the use of an orthogonal array. This method aims to minimize defects and enhance overall performance. Data analysis in this study was conducted using Minitab software version 22.

Figure 1 presents a systematic diagram of the Taguchi experiment for optimizing temperature fluctuation control in a legal metrology laboratory. The process begins with the identification of control factors, where key variables influencing laboratory conditions, such as the *timer*, lighting, and AC temperature, are determined. Once these factors are identified, the experimental design phase is conducted to establish parameter variations aimed at finding the optimal combination for maintaining temperature stability. Subsequently, the experiment is carried out in the experiment execution phase, where the pre-designed conditions are tested in the laboratory. The collected data is then analyzed in the data analysis phase using statistical approaches to evaluate the effects of each factor on the desired outcome. Finally, result optimization is performed, utilizing the analyzed data to determine the most effective configuration for maintaining stable temperature conditions. This diagram provides a clear visual representation of the experimental workflow, facilitating an understanding of the optimization steps undertaken to enhance accuracy and efficiency in legal metrology.

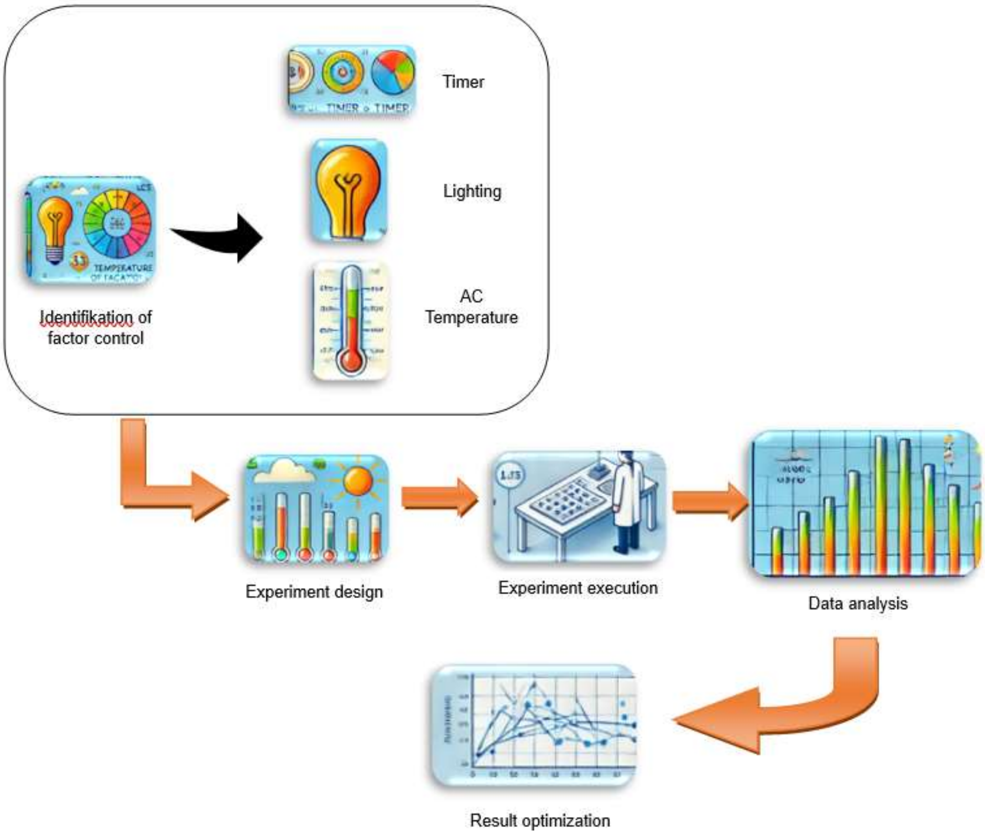

Figure 1. A sytematic research diagram

Material

The research was conducted at the Indonesian government legal metrology laboratories in February 2025. The study utilized temperature measuring devices as the primary research objects, as shown in Figure 2, while monitoring equipment, including an Internet of Things (IoT) control device, was used for data collection and analysis, as shown in Figure 3.

Figure 2. Temperature measuring devices **Figure 3. IOT Control devices**

Variable Experiment

In experimental designs, independent variables that can be controlled are referred to as control factors, while the dependent variable, which results from the influence of these factors, is called the response. The selection of control factors and response variables in this experiment is based on Table 1.

Table 1. Control factors and response

No	Faktor Kontrol	Level Faktor			Response
		1	2	3	(˚C / hour)
1	AC Temperature (X_1)	16˚C	17˚C	18˚C	
2	Time Duration (X_2)	15'	22,5'	30'	Y_{1-4}
3	Lighting (X_3)	50%	75 %	100 %	

Where, Y_{1-4} = Fourth replication of response temperature fluctuation.

Design Of Experiment

The Taguchi method is used to predict the optimal value by conducting a varied number of experiments. The Orthogonal Array (OA) is a structured arrangement of numbers in rows and columns, where columns represent the experimental parameters, and rows define the variations or factor levels. In this study, the independent variables include air conditioning temperature, time duration, and lighting, while the response variable is temperature fluctuation. The $L_9(3^3)$ Orthogonal Array is applied, where L represents the design width (Large), 9 denotes the number of experimental runs, and 3^3 indicates three control factors, each with three levels, as shown in Table 2.

Table 2. Orthogonal Array $L_9(3^3)$

Eks	Control Factors		
	X_1 (˚C)	X_2 (minutes)	X_3 (%)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

RESULTS AND DISCUSSION

Table 3. Taguchi Experiment Result

No.	Factors			Temperature fluctuation (˚C / hour)				
	AC Temperature (X_1)	Time Duration (X_2)	Lighting (X_3)					
	(˚C)	(Minute)	(%)	Y_1	Y_2	Y_3	Y_4	Y bar
1	16	15,0	50	0,6	0,58	0,6	0,60	0,60
2	16	22,5	75	0,27	0,33	0,44	0,33	0,34
3	16	30,0	100	1,2	1	1,33	1,00	1,13
4	17	15,0	75	0,53	0,55	0,6	0,53	0,55
5	17	22,5	100	1,33	1,45	1,2	1,33	1,33
6	17	30,0	50	1	1,2	1	1,00	1,05
7	18	15,0	100	0,4	0,48	0,6	0,60	0,52
8	18	22,5	50	0,8	0,96	0,88	0,80	0,86
9	18	30,0	75	1	1,12	0,97	1,12	1,05

Table 3 presents the results of a Taguchi experiment designed to evaluate the effects of three factors on temperature fluctuation (°C/hour). The investigated factors include AC temperature (X_1) in degrees Celsius, time duration (X_2) in minutes, and lighting (X_3) in percentage. Each experimental condition was tested in four replications (Y_1, Y_2, Y_3, Y_4), with the average value (Y bar) representing the mean temperature fluctuation across the replications. The table comprises nine experimental runs, each representing a unique combination of the three factors. For instance, in the first experiment, with an AC temperature of 16°C, a time duration of 15 minutes, and lighting set at 50%, the recorded temperature fluctuation ranged from 0.58 to 0.60°C/hour, with an average of 0.60°C/hour. In contrast, the third experiment, conducted at the same AC temperature but with an increased time duration of 30 minutes and maximum lighting (100%), exhibited a higher mean temperature fluctuation of 1.13°C/hour.

Overall, the results indicate that variations in AC temperature, time duration, and lighting significantly influence temperature fluctuation. Experimental conditions involving a higher AC temperature (18°C) and increased lighting intensity (100%) tend to amplify temperature fluctuation, as observed in experiment 7 (0.52°C/hour on average) and experiment 9 (1.05°C/hour on average). Conversely, conditions with lower AC temperatures (16°C) and moderate lighting (75%) result in more stable temperature fluctuations, as demonstrated in experiment 2 with an average of 0.34°C/hour.
These findings provide valuable insights into optimizing environmental conditions to minimize temperature fluctuations, offering practical implications for system stability and energy efficiency.

Table 4. Analysis of Variance for SN ratios

Source	DF	Seq SS	Adj SS	Adj MS	F	P
AC Temperature	2	17,97	17,97	8,987	0,63	0,613
Time Duration	2	50,19	50,19	25,097	1,76	0,362
Lighting	2	25,09	25,09	12,544	0,88	0,532
Residual Error	2	28,50	28,50	14,252		
Total	8	121,76				

Table 4 presents the Analysis of Variance (ANOVA) for SN Ratios, evaluating the effects of three experimental factors AC Temperature, Time Duration, and Lighting on the observed response. ANOVA is employed to determine whether these factors have a significant effect on the variability of the SN ratio in the experiment. In this table, the Degrees of Freedom (DF) represent the number of independent categories for each factor. Each factor has DF = 2, while the Residual Error also has DF = 2, resulting in a total DF of 8 for the experiment. The Sequential Sum of Squares (Seq SS) and Adjusted Sum of Squares (Adj SS) indicate the contribution of each factor to the total variability. Among these, Time Duration exhibits the highest contribution (Seq SS = 50.19), followed by Lighting (25.09) and AC Temperature (17.97).

The Adjusted Mean Square (Adj MS) is obtained by dividing the Adj SS by the corresponding DF. The F-value is calculated by comparing the Adj MS of each factor to the Adj MS of the residual error. A higher F-value suggests a stronger effect of the factor. According to the table, Time Duration has the highest F-value (1.76), followed by Lighting (0.88) and AC Temperature (0.63). The P-value is used to assess statistical significance. Typically, if $P < 0.05$, the factor is considered to have a significant effect on the response. In this analysis, all P-values exceed 0.05 (AC Temperature = 0.613, Time Duration = 0.362, Lighting = 0.532), indicating that none of the factors have a statistically significant impact on the SN ratio.

To interpret the significance of the factors, the F-calculated values are compared against the F-table value at $\alpha = 0.05$, with DF for the factor = 2 and DF for the error = 2. Based on the F-distribution, the F-table value (5%) for (2,2) is approximately 19.00. Since all F-calculated values are considerably lower than the F-table value (0.63, 1.76, and 0.88 < 19.00), the null hypothesis (H_0) cannot be rejected. This suggests that none of the factors have a significant effect in this experiment. Although Time Duration contributes the most to variability, none of the factors are statistically significant according to the ANOVA test. This indicates that variations in the SN ratio are likely influenced by other uncontrolled factors or noise within the system.

Table 5. Response Table for Signal to Noise Ratios

Smaller is better

Level	AC Temperature	Time Duration	Lighting
1	4,1771	5,0721	1,7799
2	0,7362	2,6579	4,6162
3	2,1291	-0,6876	0,6463
Delta	3,4409	5,7597	3,9698
Rank	3	1	2

Table 5 presents the Response for Signal-to-Noise Ratios (SNR) provides an analysis of the effects of three experimental factors AC Temperature, Time Duration, and Lighting on the system's response, using the "Smaller is Better" criterion. This criterion is typically applied when the goal is to minimize variability or undesirable effects in the system. The table presents the SNR values for each factor at three different levels. For AC Temperature, the SNR values are 4.1771 (Level 1), 0.7362 (Level

2), and 2.1291 (Level 3). For Time Duration, the values are 5.0721 (Level 1), 2.6579 (Level 2), and -0.6876 (Level 3). For Lighting, the values are 1.7799 (Level 1), 4.6162 (Level 2), and 0.6463 (Level 3). The Delta values, which represent the difference between the highest and lowest SNR for each factor, indicate the impact of each factor on the response. Time Duration has the highest Delta value (5.7597), followed by Lighting (3.9698) and AC Temperature (3.4409). This ranking suggests that Time Duration is the most influential factor, as indicated by its Rank 1, followed by Lighting (Rank 2) and AC Temperature (Rank 3).

Since "Smaller is Better" is the selected criterion, lower SNR values indicate better performance in minimizing variability. The results imply that Time Duration has the greatest effect on response variation, meaning that precise control of this factor is crucial for achieving stable performance. Meanwhile, Lighting also plays a significant role, whereas AC Temperature has the least impact on the response. This response table suggests that Time Duration should be prioritized in process optimization, followed by Lighting, while AC Temperature has a relatively lower impact. These findings are essential for determining optimal factor settings to minimize unwanted variation and improve overall system performance.

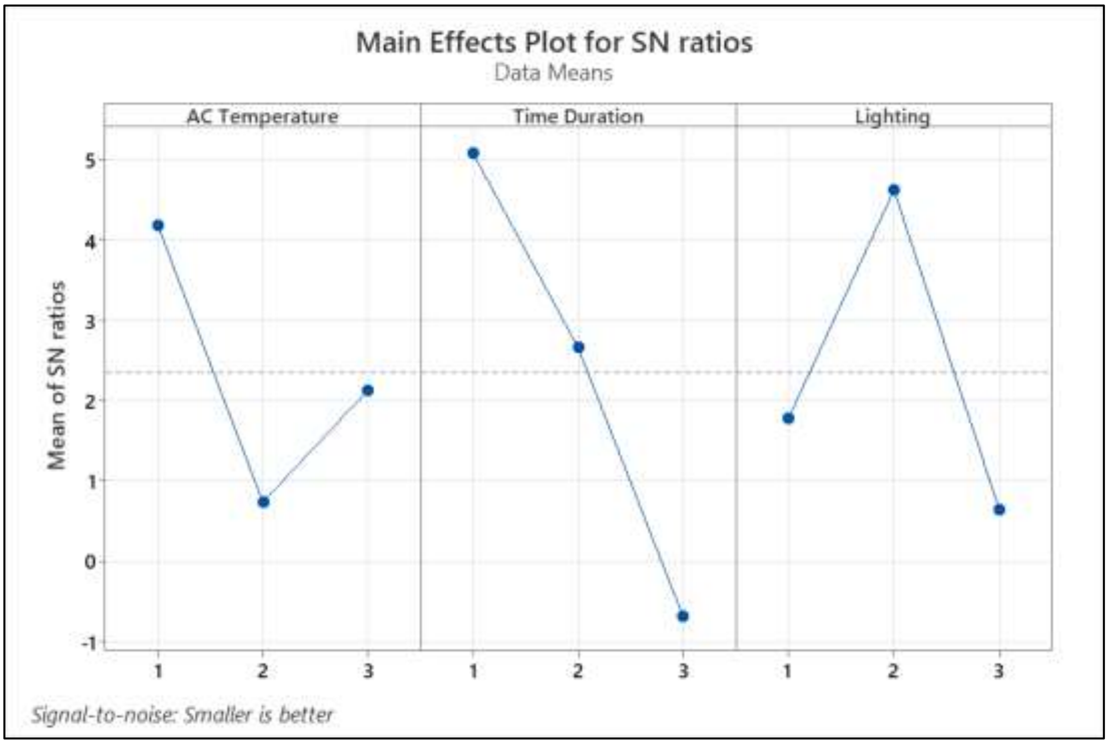

Figure 4. Main effects plot for SN ratios

The Main Effects Plot for SN Ratios illustrates the impact of three experimental factors AC Temperature, Time Duration, and Lighting—on the response variable based on their mean Signal-to-Noise (SN) ratios. The analysis follows the "Smaller is Better" criterion, indicating that lower SN ratio values are preferable for achieving optimal performance. The plot shows that Time Duration has the most significant effect, as indicated by the steepest slope, meaning that changes in time duration lead to the largest variation in SN ratios. The SN ratio is highest at Level 1 of Time Duration and decreases sharply at Level 2 before reaching its lowest point at Level 3, suggesting that Level 3 is the optimal setting. Lighting also plays a considerable role, as the SN ratio fluctuates significantly across levels, with Level 3 appearing to be the most favorable. In contrast, AC Temperature has the least impact, as its SN ratio changes are more moderate compared to the other two factors.

The trends indicate that Level 1 of AC Temperature, Level 3 of Time Duration, and Level 3 of Lighting are the most favorable settings to achieve minimal SN ratios. Overall, this plot provides valuable insights into the relative importance of each factor, confirming that Time Duration is the most influential parameter, followed by Lighting, while AC Temperature has a relatively lower impact. These findings suggest that optimizing Time Duration and Lighting is crucial in minimizing unwanted variation and improving system stability.

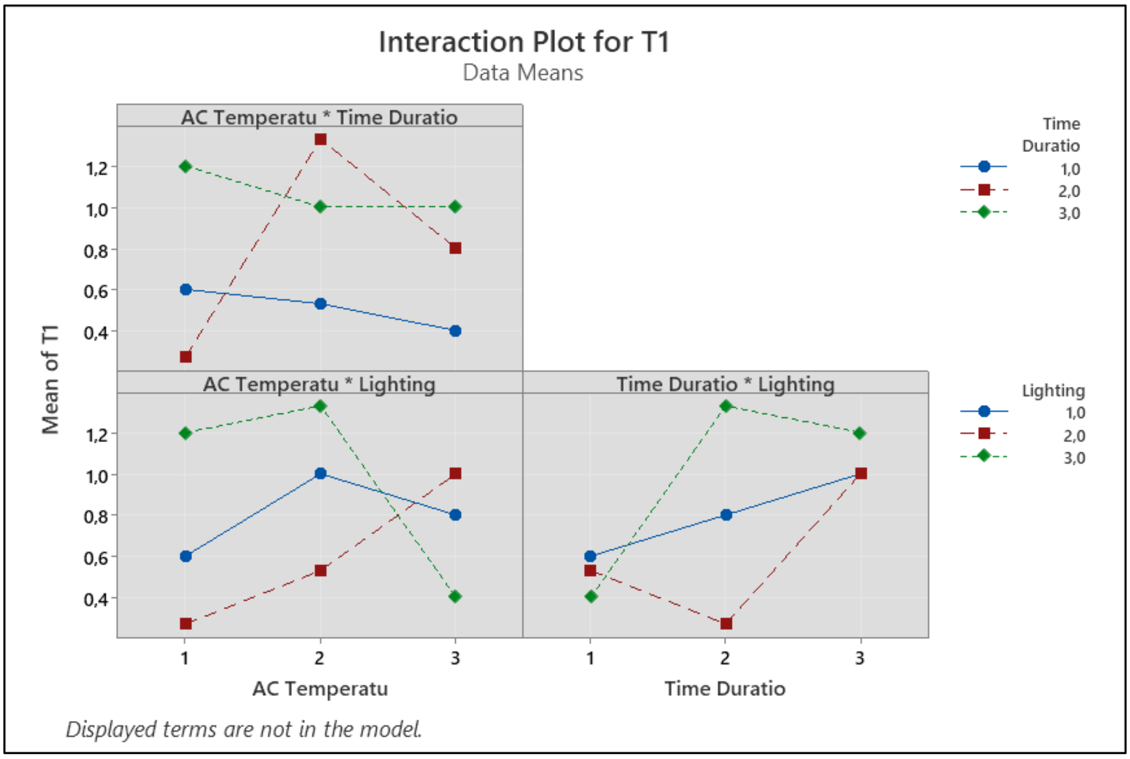

Figure 5. Interaction plot for temperatur 1

Figure 5 presents the interaction effects between three experimental factors: AC Temperature, Time Duration, and Lighting on the response variable T1. The plot consists of three subplots, each representing the interaction between two factors: AC Temperature × Time Duration, AC Temperature × Lighting, and Time Duration × Lighting. Interaction effects are evident when the lines in the plots are non-parallel or intersect, indicating that the influence of one factor on T1 depends on the level of the other factor. In the AC Temperature × Time Duration plot, significant interaction is observed as the lines cross, particularly at Time Duration Level 2.0, where the response peaks at AC Temperature Level 2. This suggests that the effect of AC Temperature on T1 is not consistent across different levels of Time Duration. Similarly, in the AC Temperature × Lighting plot, Lighting Level 3.0 exhibits a sharp increase at AC Temperature Level 2, followed by a decrease at Level 3, further indicating an interaction effect.

This pattern suggests that the impact of AC Temperature is influenced by different Lighting conditions.

The Time Duration × Lighting plot also shows non-parallel trends, confirming interaction effects between these two factors. The most noticeable interaction occurs at Lighting Level 3.0, where the response variable T1 reaches its peak at Time Duration Level 2 and decreases sharply at Level 3. This indicates that the effect of Time Duration on T1 is not independent but varies depending on Lighting conditions. The presence of strong interaction effects in these plots highlights that T1 is not solely influenced by individual factors but also by their interactions. Among the observed interactions, the most significant effect appears between AC Temperature and Time Duration, as indicated by the considerable fluctuations in response values. These findings underscore the importance of considering interaction effects in experimental optimization, as ignoring them may lead to incorrect conclusions about the influence of each factor.

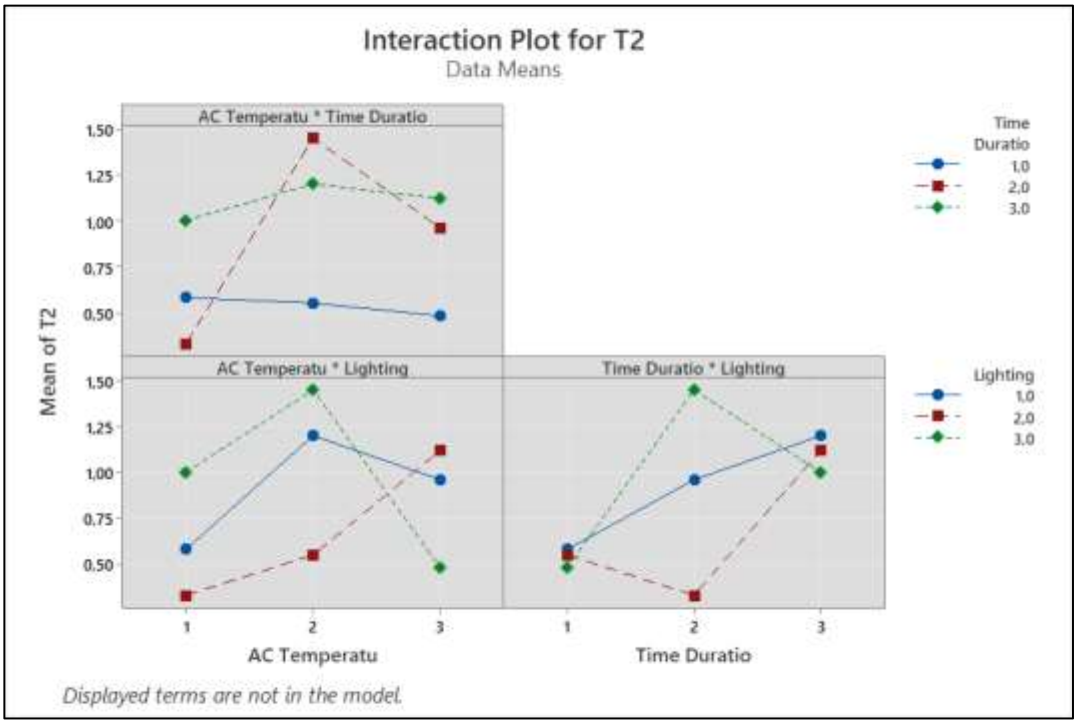

Figure 6. Interaction plot for temperature 2

Figure 6 illustrates the interaction effects between three experimental factors: AC Temperature, Time Duration, and Lighting on the response T2. This graph consists of three subplots, each depicting the interaction relationship between two factors: AC Temperature × Time Duration, AC Temperature × Lighting, and Time Duration × Lighting. The presence of interactions between these factors is indicated by non-parallel or intersecting lines, suggesting that the effect of one factor on T2 depends on the level of the other factor.

In the AC Temperature × Time Duration plot, it is observed that for Time Duration Level 2, there is a sharp increase in T2 at AC Temperature Level 2, while for Time Duration Levels 1 and 3, the changes in T2 remain relatively stable. This pattern indicates that Time Duration Level 2 has a significant influence on T2, but this effect is not consistent across all levels of AC Temperature.

Meanwhile, in the AC Temperature × Lighting plot, the interaction between these two factors is quite evident as the lines exhibit opposite trends. At Lighting Level 3, there is a sharp increase at AC Temperature Level 2, followed by a decrease at Level 3. Conversely, at Lighting Level 2, a different pattern emerges with a peak at AC Temperature Level 3. This suggests that the effect of AC Temperature on T2 is strongly influenced by lighting conditions.

In the Time Duration × Lighting plot, a clear interaction is observed at Lighting Level 3, where T2 increases significantly at Time Duration Level 2 and then decreases at Level 3. In contrast, at Lighting Level 2, there is a sharp decline at Time Duration Level 2, which differs from the other Lighting levels. These varying patterns confirm the interaction between Time Duration and Lighting, where the effect of each factor is not independent but is influenced by the level of the other factor.

The most significant interactions appear to occur in the AC Temperature × Time Duration and AC Temperature × Lighting combinations, where the differences in T2 values are substantial and the variation across levels is inconsistent. These results indicate that optimizing parameters to achieve the best T2 value must consider interaction effects between factors, rather than focusing solely on their individual effects.

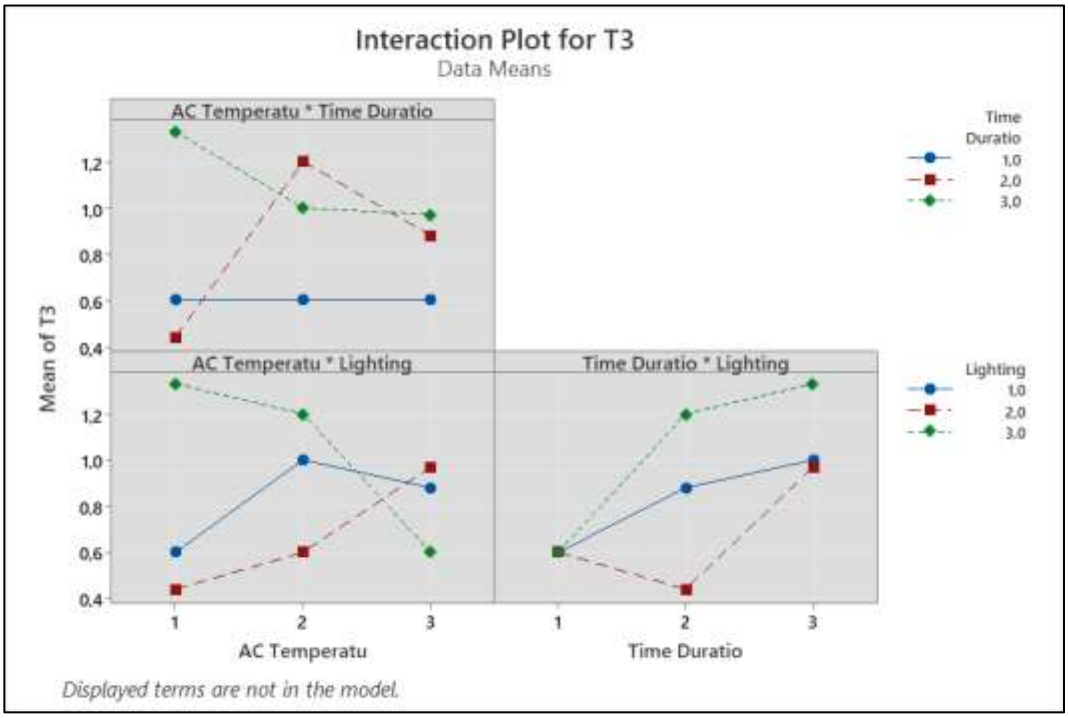

Figure 7. Interaction plot for temperature 3

Figure 7 presents the interaction effects of three experimental factors: AC Temperature, Time Duration, and Lighting on the response T3. This plot consists of three subplots, each illustrating the interaction between two factors: AC Temperature × Time Duration, AC Temperature × Lighting, and Time Duration × Lighting. The presence of interaction effects is indicated by non-parallel or intersecting lines, which suggest that the effect of one factor on T3 depends on the level of the other factor. In the AC Temperature × Time Duration plot, the trend for Time Duration Level 1 remains stable across different AC Temperature levels. However, for Time Duration Levels 2 and 3, there is a significant fluctuation. Time Duration Level 3 starts at a high T3 value and then decreases as AC Temperature increases, whereas Time Duration Level 2 exhibits a sharp increase at AC Temperature Level 2 before decreasing again at Level 3. These variations suggest a strong interaction effect, where the influence of Time Duration on T3 is not consistent across different AC Temperature levels.

The AC Temperature × Lighting plot shows a clear interaction effect. For Lighting Level 3, there is a peak at AC Temperature Level 2, followed by a decline at Level 3. Conversely, Lighting Level 2 has a different trend, showing an increasing pattern at AC Temperature Level 3. This indicates that the effect of AC Temperature on T3 is strongly dependent on the lighting conditions, suggesting that different lighting levels result in different responses for the same AC Temperature levels. In the Time Duration × Lighting plot, an interaction effect is evident as the trends for different lighting levels differ significantly. Lighting Level 3 shows a sharp increase in T3 at Time Duration Level 2, while Lighting Level 2 exhibits a contrasting trend with a decrease at Time Duration Level 2 before increasing at Level 3. The differences in these trends confirm that the relationship between Time Duration and T3 is affected by Lighting conditions.

The strongest interaction effects are observed in the AC Temperature × Time Duration and AC Temperature × Lighting plots, where non-parallel trends suggest a significant dependency between these factors. This analysis highlights that optimizing T3 requires considering the combined effects of multiple factors rather than treating them independently.

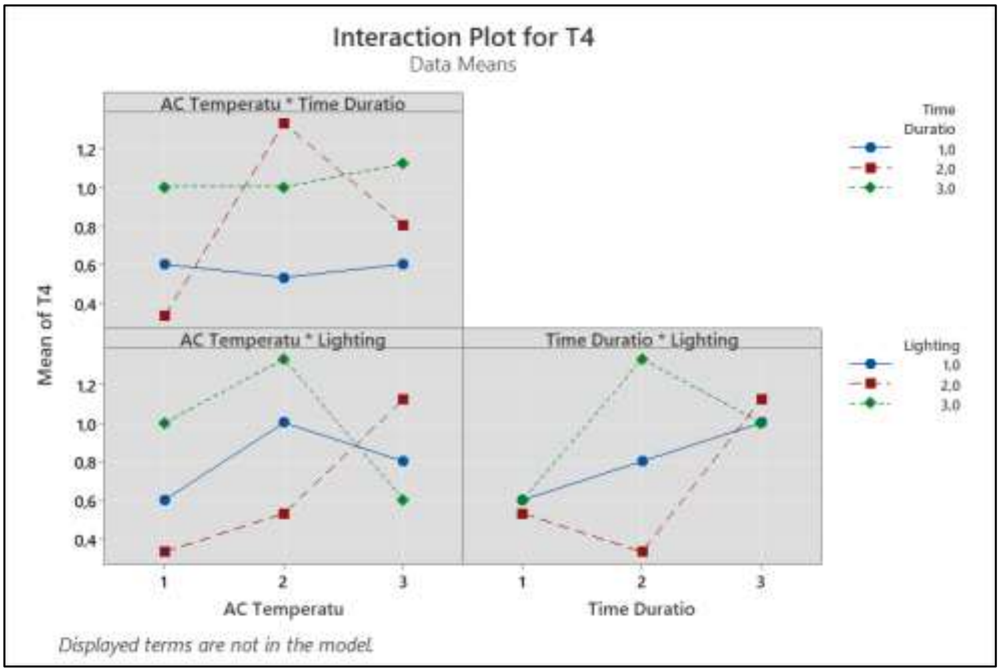

Figure 8. Interaction plot for temperature 4

Figure 7 illustrates the interaction effects between three experimental factors: AC Temperature, Time Duration, and Lighting on the response T4. The plot contains three subplots, each representing the interaction between two factors: AC Temperature × Time Duration, AC Temperature × Lighting, and

Time Duration × Lighting. Interaction effects are identified by non-parallel lines, which indicate that the effect of one factor on T4 depends on the level of another factor.

In the AC Temperature × Time Duration plot, the response for Time Duration Level 1 remains relatively stable across different AC Temperature levels. However, for Time Duration Level 2, there is a sharp increase at AC Temperature Level 2, followed by a decrease at Level 3. Time Duration Level 3, on the other hand, starts high at AC Temperature Level 1, remains stable at Level 2, and increases slightly at Level 3. These variations suggest a strong interaction effect, where the influence of Time Duration on T4 is inconsistent across different AC Temperature levels.

The AC Temperature × Lighting plot shows a significant interaction effect, particularly for Lighting Level 3, where the response peaks at AC Temperature Level 2 and then decreases at Level 3. In contrast, Lighting Level 2 follows an increasing trend, reaching its highest value at AC Temperature Level 3. This indicates that the effect of AC Temperature on T4 is highly dependent on the lighting conditions, meaning that different lighting levels yield different responses at the same AC Temperature levels. The Time Duration × Lighting plot also shows noticeable interaction effects. Lighting Level 3 exhibits a sharp increase in T4 at Time Duration Level 2, whereas Lighting Level 2 follows a different pattern, decreasing at Time Duration Level 2 before increasing at Level 3. The differences in these trends confirm that the relationship between Time Duration and T4 is influenced by Lighting conditions.

Overall, the strongest interaction effects are seen in the AC Temperature × Time Duration and AC Temperature × Lighting plots, where non-parallel lines suggest that these factors do not act independently. This suggests that optimizing T4 requires a careful balance between AC Temperature, Time Duration, and Lighting to achieve the desired outcomes.

CONCLUSION

The experimental results indicate that time duration has the most significant impact on temperature fluctuation, followed by lighting, while AC temperature has a smaller influence. ANOVA analysis reveals that although these factors contribute to temperature variation, none of them have a statistically significant effect on the SN ratio. However, strong interaction effects were observed, particularly between AC temperature and time duration, as well as AC temperature and lighting. Based on the response analysis and main effects plot, the optimal combination to minimize temperature fluctuations is by selecting a longer time duration and lower lighting intensity, whereas AC temperature has a relatively smaller impact compared to the other two factors. Overall, this study demonstrates that better control of time duration and lighting can help maintain temperature stability in metrology laboratories, thereby improving measurement accuracy and energy efficiency.

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