Optimization Plastic Mold Injection Parameters for Sprinkler Valve Production Process Using Problem Solving and Experimental Design

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Abstract

The goal of this research was to optimize the injection molding process using problem-solving technique and experimental design to determine appropriate parameters for sprinkler valve production. The analysis identified that the main cause of defects was due to inappropriate parameter settings in the injection molding process. To address this, a method was developed that began with screening factors influencing incomplete injection and burn marks on the surface of the workpiece by expert teams. Four key factors were identified: injection pressure, injection speed, end-of-fill temperature, and start-of-fill temperature. Experiment design involved a factorial 2^4 experimental design with each factor divided into 2 levels, repeating experiments 3 times, for a total of 48 experiments. Statistical analysis was conducted to determine the optimal levels for all four factors, resulting in the following optimal factor levels: injection pressure of 65 MPa, injection speed of 10 mm/s, end-of-fill temperature of 175 °C, and start-of-fill temperature of 180 °C. Additionally, the defect rate was reduced from the original 11.6% decreased to 8.7%.

Keywords: Design of experiment, Injection molding process, Sprinkler valves

I. INTRODUCTION

Currently, plastics play a crucial role in various industries, such as automotive parts, electronics, construction materials, packaging, and agriculture, significantly driving the growth of related sectors. This has led to a substantial presence of businesses in these industries in Thailand, utilizing plastic pellets as durable raw materials for manufacturing. With standardized and efficient plastic industry technologies, high-quality products can be consistently produced to compete both domestically and internationally.

Injection molding is a highly effective method for mass-producing plastic components with intricate designs and exceptional dimensional accuracy. However, improper settings of input parameters can lead to poor surface quality, reduced dimensional precision, excessive waste, and increased production time and costs. To achieve high-quality finished parts, it’s crucial to optimize these process parameters. Numerous studies have been undertaken to enhance and refine the injection molding process, enabling the production of high-quality components across various commercial machines. As such, identifying the optimal parameters is essential [1], [2].

The case study examines a factory that manufactures and distributes integrated agricultural equipment, such as sprayers, foggers, PE pipes, and PVC fittings. Through investigating issues in the plastic injection process, it was found that the highest production volume was for 1/2-inch PVC rotating sprinkler valve products, with a significant amount of waste generated. In the production of sprinkler valves, there was significant difficulty in adjustment, as some valves were challenging to fine-tune for optimal performance, making it hard to achieve the desired flow rates. Additionally, the complexity of the valve's shape hindered complete plastic injection, resulting in issues such as incomplete fills, potential air traps, and inconsistent part quality. To analyze the causes of defects, specifically flame pattern defects in injection molded parts, the use of Fishbone diagrams revealed that improper parameter settings were a significant contributing factor. This research aims to propose experimental design principles to reduce waste in the plastic injection process for spring valve production.

II. THEORIES AND RELATED RESEARCH

The Fishbone diagram, also known as a Cause-and-Effect diagram, is an essential tool in the problem-solving process, allowing teams to systematically identify and address root causes. This visual tool helps categorize potential causes of a problem, enabling teams to map out and examine the underlying factors contributing to the issue. By doing so, it facilitates discussions, prioritizes areas for further exploration, and ultimately leads to more effective solutions. Numerous studies have utilized the Fishbone diagram in the field of plastic injection molding. For example, fishbone diagram establishes a hierarchy of potential causes for defects in plastic injection products. These product defects arise from activities conducted during two primary processes: the design process and the injection molding process [3]. The Fishbone diagram highlights several issues contributing to the force problem. After discussions with manufacturing experts, it was determined that the primary causes of this issue are related to the machine, specifically concerning curing time, temperature, and pressure [4]. Employing the Six Sigma (DMAIC) methodology, data collected during the Measure phase was utilized to identify the sources of these defects and to uncover the root causes of the problem through the use of the Fishbone diagram [5]. The results indicate that the implementation of the proposed Six Sigma approach leads to a significant reduction in the rejection rate. It was observed that the quality of the final products improved substantially, with the sigma level increasing from 4.06 to 4.5. Additionally, the cost of poor quality (COPQ) was reduced by 45% [6].

Design of Experiment (DOE) [7] is a statistical technique used to adjust process conditions to meet desired specifications. The fundamental principles of experimental design ensure accurate, precise, and reliable results and include three main concepts: replication, randomization, and blocking. Experimental design is applied across various objectives [8], such as optimizing process yields, identifying input variables affecting output responses, parameter adjustment, identifying factors to reduce variability, minimizing development time, and reducing overall costs. There are several formats of experimental design, with one widely utilized approach being Factorial Design [9]. This method investigates the effects resulting from the combination of all possible levels of factors in the experiment. For instance, in a case with 2 factors, if factor A has a levels and factor B has b levels, one replicate of the experiment would consist of testing all ab combinations. Factorial designs are highly efficient in examining the influence of multiple factors simultaneously and can analyze both main effects and interaction effects comprehensively.

Examples of research utilizing experimental design to optimize production conditions include efforts to reduce waste generation, determine appropriate machine parameter settings, and enhance manufacturing processes. For instance, studies have analyzed factors affecting the thickness of electroplated metal parts [10], reduced non-standard automotive part counts [11], minimized time and waste in wire edge rubber molding processes [12], identified suitable parameters for head gimbals assembly (HGA) washing processes [13], improved efficiency indices and seal-back pull forces in packaging processes [14], assessed factors influencing Napier grass cutting efficiency [15], developed efficiency in strip rubber production processes using Lean Six Sigma concepts [16]. Additionally, direct applications to plastic injection molding processes include optimizing injection molding machine settings for electronics components using 2^3 Factorial Design [17], determining suitable parameters for ABS plastic part injection using 2^{5-1} Fractional Factorial Design [18], optimizing polymer material production parameters for maximum mechanical properties and minimum shrinkage using Taguchi Design [19], and exploring conditions for reducing injection molding cycles with the aid of process simulation software [20], [21].

III. RESEARCH METHODOLOGY

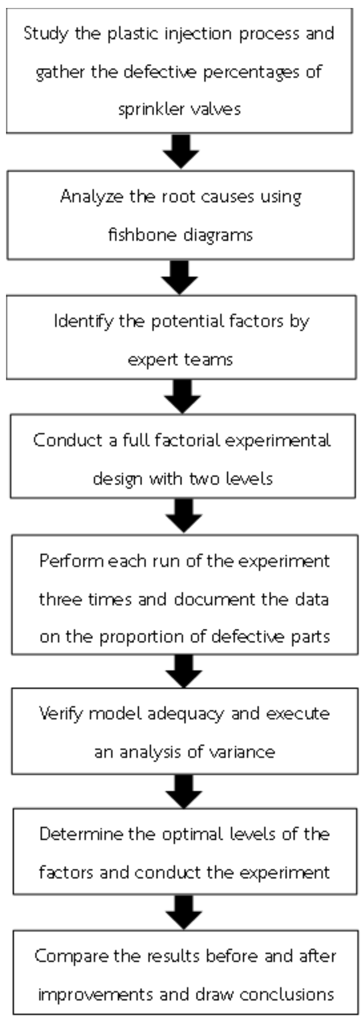

Figure 1: Steps in the research process

The research process begins with studying the operational conditions of a case study factory and identifying the nature of the encountered problems. It reviews relevant theories and research, followed by analyzing the root causes using fishbone diagrams. Recommendations for improvement are proposed by identifying appropriate parameters. Experimental design is conducted using a two-level factorial design, and injection molding experiments are performed, recording the defective rate as depicted in figure 1.

Based on data collected retrospectively from November 2023 to January 2024, the top 5 highest defective percentages were calculated in table 1, considering both production volume and quantity of defective pieces. The product with the highest defective percentage was the 1/2-inch PVC rotating sprinkler valve, totaling 178,860 units produced with 20,747 units deemed defective, resulting in a defective percentage of 11.6%. Defective pieces primarily occurred during the plastic injection molding process. The factory did not differentiate between types of defects but categorized them collectively as “flame pattern defects”. Defective pieces were ground and mixed with PVC material for subsequent injection molding into other products.

To analyze the causes of defects or flame pattern defects in injection molded parts, a Fish Bone Diagram is employed. Interviews were conducted with relevant department heads involved in the plastic injection process, including production managers, mold department heads, injection molding technicians, quality inspection supervisors, maintenance supervisors, and research and development department heads. Causes were gathered and categorized according to the 4M principle: Man, Material, Machine, and Method. These findings are illustrated in figure 2.

Table 1: The production quantity for each model of valve

Product name	Production (pieces)	Defective (pieces)	Defective percentages
1/2-inch PVC rotating sprinkler valve	178,860	20,747	11.60
Hand-operated agricultural valve, fitting ¾ x ½	83,250	4,692	5.63
Agricultural check valve, equipment fitting 387-2	90,000	16,594	5.42
PVC-PE valve, fitting 1/2" x 16, blue (389-60R)	69,750	3,711	5.32
PVC pipe fitting, external thread ½ x ½, blue	90,000	4,459	4.96

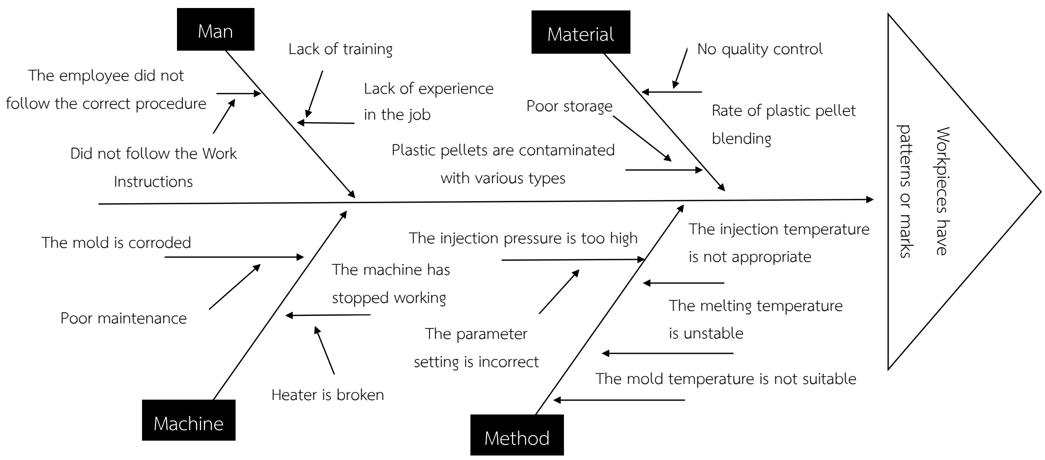

Figure 2: Fishbone diagram for analyzing the causes of problems

From the compiled causes, when ranked by significance as assessed by department heads and skilled technicians, it was found that the primary factors directly impacting the occurrence of defects were related to the Material category. These included non-standard plastic pellets, contamination from multiple types of materials, and inappropriate material mixing ratios. Method-related factors also contributed, such as improper parameter settings. Due to research and development unit constraints on disclosing material mixing formulas, this research focuses on identifying suitable parameters for the injection molding process of the 1/2-inch PVC rotating sprinkler valve by controlling consistent material mixing ratios and using the same injection molding machine.

Based on the analysis by expert teams, factors influencing and impacting the issue of patterned defects in molded parts, specifically within the Method category, were identified. The experimenters utilized parameters related to machine settings as experimental design factors (Figure 3), which encompassed four specific factors:

1. Injection Pressure 2. Injection Speed
3. End Stage Injection Temperature
4. First Stage Injection Temperature

In this study, a full factorial experiment with 2 levels (2^4 Full Factorial Experiment) involving 4 factors was conducted, resulting in 16 experimental runs. Each experiment was replicated 3 times, totaling 48 experimental runs. The experiments were randomized using statistical analysis software. The response variable measured was the proportion of defective parts, with a confidence level of 95% (α = 0.05).

During actual injection molding, it was observed that the injection molders adjust all four factors when encountering defective parts during production. These adjusted values differ from those specified in the standard production documents. Subsequently, the molders record these adjusted values in the Condition Document. Therefore, the researcher collected data retrospectively from these documents spanning three months from November 2023 to January 2024. The researcher defined the factor levels based on the minimum and maximum values to establish low and high levels for each factor, as shown in the table 2.

Table 2: Factor level categorization

Factors	Factor Level		Unit
	Low (-)	High (+)	
Injection Pressure (A)	55	65	MPa
Injection Speed (B)	10	20	mm/s
End Stage Injection Temperature (C)	175	185	°C
First Stage Injection Temperature (D)	170	180	°C

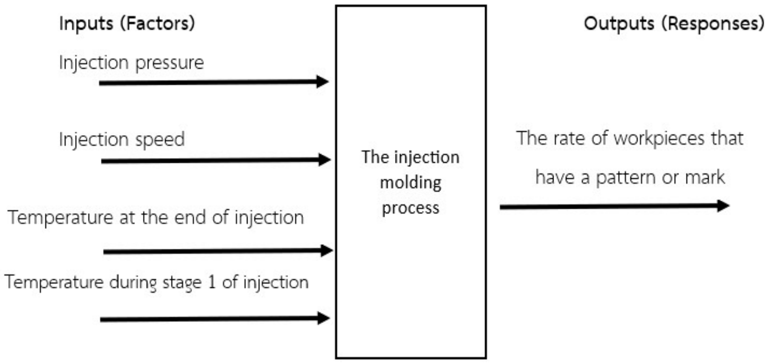

Figure 3: Experimental design factors

IV. STATISTICAL ANALYSIS RESULTS

A. Experimental Results

From the designed full factorial experiment (24) with each experiment replicated 3 times, totaling 48 experiments, each experiment involved 100 pieces, resulting in a total of 4,800 pieces as shown in the table 3.

B. Model Adequacy Checking

The validation of the experimental design entails verifying the accuracy and appropriateness of the data obtained from the experiments. This is assessed based on the principle that $\varepsilon_{ij} \sim NID(0, \sigma^2)$, where the residuals derived from the experimental data exhibit a normal distribution, are approximately centered around zero, and the variance σ^2 remains constant. These conditions ensure the reliability and validity of the experimental data. The results of the ε_{ij} verification are illustrated in figure 4.

Table 3: The response value of each experiment

StdOrder	RunOrder	Blocks	A	B	C	D	Response
16	1	1	65	20	185	180	0.05
42	2	1	65	10	175	180	0.02
32	3	1	65	20	185	180	0.06
26	4	1	65	10	175	180	0.01
21	5	1	55	10	185	170	0.19
5	6	1	55	10	185	170	0.20
36	7	1	65	20	175	170	0.05
20	8	1	65	20	175	170	0.06
1	9	1	55	10	175	170	0.05
28	10	1	65	20	175	180	0.10
9	11	1	55	10	175	180	0.11
13	12	1	55	10	185	180	0.07
18	13	1	65	10	175	170	0.07
35	14	1	55	20	175	170	0.13
40	15	1	65	20	185	170	0.10
25	16	1	55	10	175	180	0.13
19	17	1	55	20	175	170	0.15
30	18	1	65	10	185	180	0.14
33	19	1	55	10	175	170	0.07
41	20	1	55	10	175	180	0.14
11	21	1	55	20	175	180	0.07
7	22	1	55	20	185	170	0.11

Table 3: The response value of each experiment (Cont.)

StdOrder	RunOrder	Blocks	A	B	C	D	Response
44	23	1	65	20	175	180	0.12
22	24	1	65	10	185	170	0.12
39	25	1	55	20	185	170	0.09
43	26	1	55	20	175	180	0.05
37	27	1	55	10	185	170	0.17
4	28	1	65	20	175	170	0.04
34	29	1	65	10	175	170	0.06
12	30	1	65	20	175	180	0.09
17	31	1	55	10	175	170	0.04
38	32	1	65	10	185	170	0.08
46	33	1	65	10	185	180	0.13
15	34	1	55	20	185	180	0.08
14	35	1	65	10	185	180	0.12
48	36	1	65	20	185	180	0.08
31	37	1	55	20	185	180	0.06
23	38	1	55	20	185	170	0.07
29	39	1	55	10	185	180	0.07
24	40	1	65	20	185	170	0.09
45	41	1	55	10	185	180	0.05
47	42	1	55	20	185	180	0.04
10	43	1	65	10	175	180	0.03
6	44	1	65	10	185	170	0.09
3	45	1	55	20	175	170	0.14
27	46	1	55	20	175	180	0.04
2	47	1	65	10	175	170	0.08
8	48	1	65	20	185	170	0.07

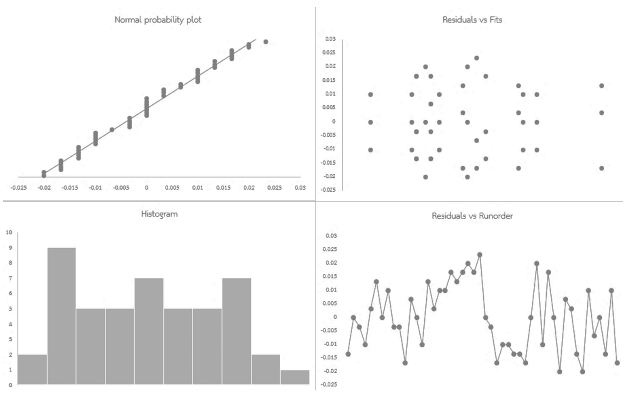

Figure 4: Residual plot

From the Normal Probability Plot, it was observed that the residuals exhibit a straight-line distribution, indicating a normal distribution. This allows for the estimation that the data follows a normal distribution pattern.

From the scatter plot of residuals compared to the fitted values, it was observed that the distribution of residuals remains consistent across all positions, without any apparent trend. Therefore, it can be concluded that the data exhibits variance stability.

From the scatter plot of residuals compared to the observation order, it was found that the distribution of residuals exhibits a pattern of independence or cannot be precisely modeled. This indicates independence of residuals.

C. Analysis of Variance

The results of the variance analysis of the full factorial experimental design (24) at a 95% confidence level are depicted in figures 5 and 6.

From the variance analysis of the 2^4 full factorial experimental design, it was found that factors influencing the defect rate of products, with a P-value less than the significance level of 0.05, are divided into interactive effects of 2 factors and main effects. The interactive effects of the 2 factors include pressure and speed (AB), pressure and end temperature (AC), pressure and temperature at stage 1 (AD), speed and end temperature (BC), and end temperature and temperature at stage 1 (CD). This results in significant main effects of pressure (A), speed (B), end temperature (C), and temperature at stage 1 (D) on the defect rate of products. The model's decision-making coefficient (R-Square) is 91.99%, indicating that the regression model can effectively explain the variability in the response variable around its mean [3]. When plotting the relationship between each factor level (Factorial Plots) that influences the defect rate of patterned products, as depicted in figures 7 and 8. Figure 7 showed that, considering the main effects, increasing pressure (A), increasing speed (B), increasing the temperature at stage 1 (D), and decreasing the end temperature (C) resulted in a reduction in the defect rate.

Design summary

factors 4	base design 4, 16
runs 48	replicates 3
block 1	center pts (total) 0

Analysis of variance

Source	DF	adj SS	adj MS	F-value	P-value
Model	15	0.080392	0.005359	24.50	0.000
Linear	4	0.015492	0.003873	17.70	0.000
A	1	0.004408	0.004408	20.15	0.000
B	1	0.001875	0.001875	8.57	0.006
C	1	0.004800	0.004800	21.94	0.000
D	1	0.004408	0.004408	20.15	0.000
2way interactions	6	0.024658	0.004110	18.79	0.000
AB	1	0.001008	0.001008	4.61	0.039
AC	1	0.002133	0.002133	9.75	0.004
AD	1	0.006075	0.006075	27.77	0.000
BC	1	0.012033	0.012033	55.01	0.000
BD	1	0.000075	0.000075	0.34	0.562
CD	1	0.003333	0.003333	15.24	0.000
3way interactions	4	0.008208	0.002052	9.38	0.000
ABC	1	0.000133	0.000133	0.61	0.441
ABD	1	0.002408	0.002408	11.01	0.002
ACD	1	0.004033	0.004033	18.44	0.000
BCD	1	0.001633	0.001633	7.47	0.010
4way interactions	1	0.032033	0.032033	146.44	0.000
ABCD	1	0.032033	0.032033	146.44	0.000
Error	32	0.007000	0.000219		
Total	47	0.087392			

Model summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0147902	91.99%	88.24%	81.98%

Figure 5: Variance analysis results

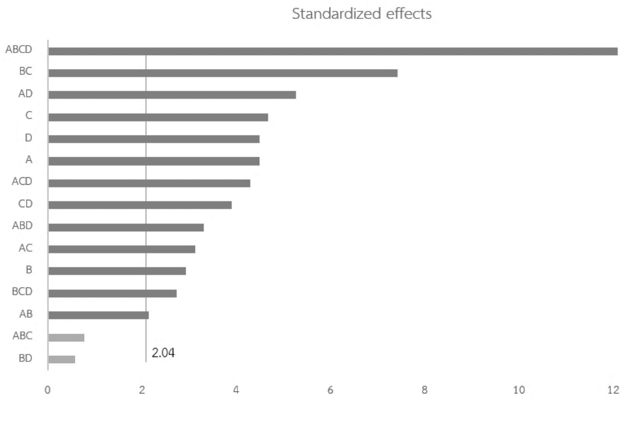

Figure 6: Pareto chart showing significant factors

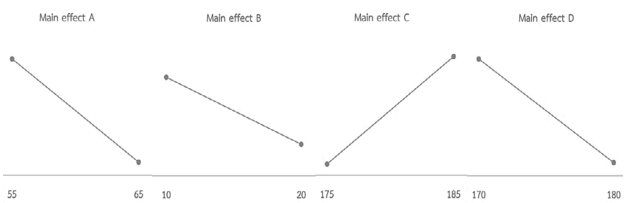

Figure 7: Main effects

Figure 8 illustrated apparent interaction effects. The results indicated that the interaction effects for AB, AC, AD, BC, and CD were statistically significant. Meanwhile, the interaction for BD was not significant.

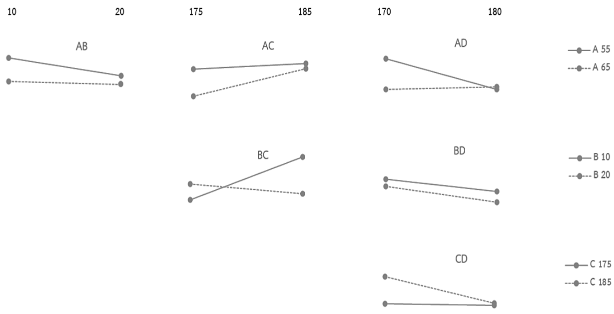

Figure 8: Interaction effects

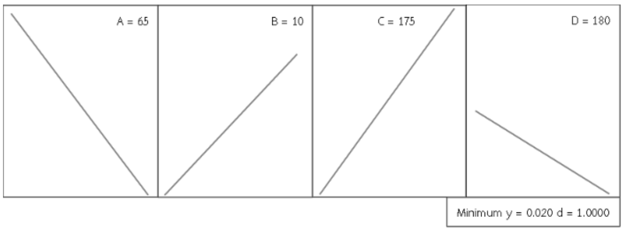

Figure 9: Response outcomes of appropriate factor levels

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
y	Minimum		0.03	0.2	1	1

Solution

Solution	A	B	C	D	y fit	Composite desirability
1	65	10	175	180	0.02	1

Multiple response prediction

Variable setting

A	65
B	10
C	175
D	180

Response	Fit	SE fit	95% CI	95% PI
y	0.02	0.00854	(0.00261,0.03739)	(-0.01479,0.05479)

Figure 10: Results of output optimization point

After conducting preliminary factor screening experiments, it was determined which factors influence the occurrence of defects in the products. Subsequently, appropriate factor levels were identified for use in the plastic injection molding process using Response Optimization methodology. The response analysis was performed with a Minimize Goal approach, setting the acceptable lower limit of defects to 0.03 and the upper limit to 0.2, as illustrated in figures 9 and 10.

Analysis of experimental results using Response Optimization and summarization of the optimal factors for each factor as follows:

Based on the above analysis, the optimal levels of factors for parameter adjustment are determined as follows: pressure at 65 MPa, velocity at 10 mm/s, end injection temperature at 175 °C, and first stage injection temperature at 180 °C. These adjustments resulted in minimizing the defect ratio to a minimum of 0.020 or 2%. The overall satisfaction with the response outcomes, measured by the composite desirability (D), ranges between 0 and 1. A value of D equal to 1 indicates complete satisfaction with the response outcomes [22].

Comparing the results before and after optimization, it was found that in April 2024, when the experiment was designed by adjusting all 4 parameters to match actual injection conditions, out of 4,800 injected pieces, there were 418 defects, accounting for 8.7% as shown in the table 4. The experimental results indicated a reduction in the defect rate. However, there were limitations related to a small production size due to limited material availability, time constraints, and the challenges of interrupting the predetermined production schedule. A comparison of the parameter values specified in the original standard and the newly proposed values was presented in the table 5.

Table 4: Result comparisons before and after improvement

Periods	Production (pieces)	Defective (pieces)	Percent defective
November 2023 - January 2024	178,860	20,747	11.6%
April 2024	4,800	418	8.7%

Table 5: Comparison of parameters

Comparison	Pressure (MPa)	Speed (mm/s)	End Temp (°C)	First Temp (°C)
Standard Document (Old)	80	10	185	175
Proposed Setting (New)	65	10	175	180

V. CONCLUSION

Design of a 2^4 full factorial experiment for manufacturing 1/2-inch rotating PVC sprinkler valves, which originally had a maximum defect rate of 11.6%. Upon adjusting all four parameters—pressure, speed, end injection temperature, and first stage injection temperature—based on actual injection conditions, conducted in April 2024, the defect rate decreased to 8.7%. Using Response Optimizer, the suitable parameter levels identified were: pressure at 65 MPa, speed at 10 mm/s, end injection temperature at 175 °C, and first stage injection temperature at 180 °C. These adjustments resulted in a defect rate lower than the target. The researchers will propose implementing these parameter adjustments to the factory as a case study for consideration in developing new production standards. Recommended research tasks include: conducting more experiments for result verification minimizes the chances of errors caused by random sampling, analyzing new ingredient compositions to reduce production costs and cost components, maintaining and preparing molds for operational readiness, exploring techniques for optimizing multiple parameters, and developing adaptive algorithms that enhance product quality and reduce waste.

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