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Parameter Optimization of the Injection Molding Process Using the Taguchi Method

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Abstract

This study addresses the high defect rate (up to 99%) and the heavy dependence on operator experience in the Direct Memory Access (DMA) injection molding process. To overcome these limitations, the study applies the Taguchi method using L18 orthogonal arrays to systematically optimize six key process parameters: nozzle size, mold temperature, ejection pressure, binder chemical concentration, mold material weight, and molding time. Signal-to-noise (S/N) analysis and ANOVA were used to identify the most influential factors and determine the optimal settings. The results show a significant reduction in defect rates: delamination defects decreased from 20% to 4%, flat wire defects from 4% to 0.5%, and corrugated plastic defects from 0.6% to 0.1%. Notably, the integration of computer vision inspection and process optimization improved product quality and reduced production time. The novelty of this study lies in the systematic application of the Taguchi method to high-precision semiconductor processes and the combination with advanced testing technologies, opening up a new direction in process optimization for the industry.

Keywords

Direct Memory Access (DMA), Orthogonal array (OA), Taguchi method, Mold Plastic .

Introduction

The manufacture, research, and development of semiconductor devices, including integrated circuits, transistors, diodes, sensors, and many other electronic components, are primarily carried out by the semiconductor industry, which is a significant sector of the economy. Power semiconductors are the fundamental building blocks of integrated circuits (ICs), which are used in computers, mobile phones, tablets, networking equipment, smartphones, and other telecommunications devices (Hao et al., 2021; Knechtel et al., 2020). Products from the power semiconductor industry are widely used in technology fields, including Information technology and telecommunications. Microprocessors, memory, and other semiconductor electrical components used in consumer goods, including TVs, cameras, smart home appliances, LED lights, and more, are referred to as consumer electronics and other electrical devices (Zhong et al., 2020). Modern automobiles rely heavily on semiconductors for everything from the engine and control systems to the safety features, entertainment systems, and sensors (Bronstein et al., 2020). The development and manufacturing of electronic devices, including solar cells, lithium-ion batteries, and control electronic systems in projects are aided by the power semiconductor industry of renewable energy, renewable and recycled energy, healthcare as Medical sensors, radiation machines, diagnostic imaging machines, and health monitoring devices, all use semiconductors (Fritz et al., 2021). Power semiconductors are a measuring and control technology used in automatic measurement and control equipment in scientific measurement equipment, precision electronics, and industrial automation (Zhang & Wang, 2019). With technological advancements and increases in semiconductor device power and transparency, the power semiconductor market is changing quickly. Prominent firms in the sector encompass Intel, Samsung Electronics, TSMC, Qualcomm, Nvidia, and a wide range of multinational corporations (Iannaccone et al., 2021; Pushpakaran et al., 2020).

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Semiconductor devices require DMA (Direct Memory Access) in a wide range of applications. Data is frequently sent directly between memory and semiconductor devices, including network cards, graphics cards, hard drives, and RAID controllers, via DMA (Ma et al., 2019). Semiconductor devices can transmit data directly between memory and themselves without the need for a CPU by using DMA. Data transfer speed is accelerated, and the workload of the CPU is decreased as a result (Liu et al., 2022). Through DMA, semiconductor devices may transfer huge blocks of data fast and efficiently, eliminating the need for the CPU to process each byte of data. DMA enables the drive to send data straight to memory, bypassing the CPU, when you copy a file from a hard drive to memory (Richard, 2022). The CPU only needs to establish and set up the DMA records; after that, it can carry out other duties while the data is sent automatically. Due to its ability to boost data transmission speeds and enhance performance, DMA is essential for semiconductor devices. It lessens the workload on the CPU and enables effective data transfer from semiconductor devices without causing the system to lag (Biggs et al., 2021).

Inadequate DMA quality could have an impact on semiconductor device performance and functionality. Here are a few possible outcomes, including decreased performance as a result of DMA of low quality, which can cause data transmission to work less well. Data transmission may become sluggish or result in mistakes if DMA crashes or malfunctions (Yang et al., 2021). Device reaction times may rise, and data transmission speeds may decrease as a result. Data inaccuracies and data transfer issues may arise when the DMA is malfunctioning. When data moves between memory and a device, it could be lost or distorted. Serious issues, including system faults, the loss of crucial data, or unstable device performance, may result from this (Guzelturk et al., 2021). System crashes might occur as a result of improperly deployed or configured DMA. System crashes, unintentional reboots, and other problems with the dependability and stability of the system could result from this. Inefficient DMA execution raises power consumption, which can raise power consumption in devices. A comprehensive review also highlighted DMA reliability as a growing challenge in semiconductor manufacturing. Inadequate DMA operations or inefficient data transfers can shorten battery life or system power, waste energy, and raise power consumption. It is crucial to properly design, implement, and configure DMA and to make sure it complies with quality standards and requirements to prevent these issues (Huang, 2019). For semiconductor devices to operate reliably throughout research and manufacturing, inspection, testing, and performance assurance are crucial.

Improving quality and reducing quality costs in production is accomplished by integrating Taguchi optimization techniques and statistical methods with the use of orthogonal arrays (OA) along with analysis tables using analysis of variance (ANOVA) using samples tested in a real production environment in the manufacturing process (Zeng et al., 2021). The Taguchi empirical optimization method is highly appreciated in real production processes at manufacturing companies (Nagaraja et al., 2023). The objective of this research is to apply the Taguchi method to find optimal machining conditions in the Mold process of the DMA product line as an object for practical research. Perform parameter analysis of Injection Mold conditions at the DMA mold process with the least number of experimental studies without the need for additional equipment or supporting processes.

The DMA injection molding process has been studied extensively in various literature related to the semiconductor industry and other relevant manufacturing sectors. Many studies have focused on optimizing factors such as mold temperature, plastic pushing pressure, and binder chemical concentration to improve product quality. This includes approaches using hybrid optimization models such as Taguchi-Grey methods (Singh, 2021). However, most of these studies primarily focus on technical aspects, lacking the connection between technical adjustments and their direct impact on customer satisfaction, as well as failing to fully assess the overall benefits within the production process.

Gap in the Research: Although optimization methods such as DOE (Design of Experiments) and RSM (Response Surface Methodology) have been widely applied in injection molding processes, several studies have applied Design of Experiments (DOE) and Response Surface Methodology (RSM) for injection molding; few have systematically applied the Taguchi method in semiconductor manufacturing. Moreover, prior work often isolates technical optimization from business outcomes such as defect rates, production efficiency, and customer satisfaction. This research bridges that gap by not only optimizing molding parameters but also measuring their direct impact on product quality and end-user satisfaction. Most current research focuses on specific aspects of the molding process but does not clarify how these factors impact overall efficiency and business outcomes (Zhao & Chen, 2020). Previous studies have primarily focused on optimizing the technical parameters of the molding process, such as mold temperature, plastic pushing pressure, and binder chemical concentration. However, the main limitation of these studies is that they often focus on specific aspects and lack a comprehensive approach to linking technical factors with actual outcomes, such as productivity improvement or customer satisfaction. Recent advancements have started to combine experimental design with AI for broader evaluations, such as surface quality prediction using DOE and machine learning (Li, 2022). Additionally, the application of the Taguchi method in these processes has not been fully and systematically explored, especially in the semiconductor manufacturing industry. As mentioned above, this study addresses these limitations by applying the Taguchi method to optimize the molding process conditions while linking the adjustment of technical parameters with practical outcomes such as product quality, production efficiency, and customer satisfaction (Kim & Lee, 2021). By implementing this optimization, the study helps reduce production time, improve productivity, and enhance the quality of the final product.

The key novelty of this research lies in the application of the Taguchi method to optimize the DMA injection molding process – a highly complex manufacturing field with stringent quality requirements. While the Taguchi method has been widely utilized across various industries, this research pioneers its use in minimizing specific defects in semiconductor manufacturing, such as delamination, flat wire defects, voids, and corrugated plastic defects. This presents a significant novelty compared to previous studies that focused on less precision-demanding production fields. Furthermore, the research not only optimizes technical parameters such as nozzle size, mold temperature, and plastic pushing pressure, but it also integrates advanced quality control processes using computer vision. This is a breakthrough as the use of AI and computer vision to inspect and analyze the final product quality dramatically improves the accuracy and speed of quality checks, reducing errors and enhancing production efficiency (Ghosh & Sinha, 2024). What makes this study particularly innovative is the development of an integrated model combining the Taguchi method with cause-and-effect analysis, along with the use of specific equipment and chemicals in the DMA production process. This allows for a more systematic and comprehensive experimental approach, reducing experimental time and defect rates, thereby boosting productivity and enhancing customer satisfaction.

This research paper is structured as follows: Section I provides an introduction. Section II presents content related to the DMA equipment manufacturing process. Section III presents the cause-and-effect analysis of the subject the research is similar to the DMA injection mold. Section IV optimizes the parameters of the DMA injection mold process using the Taguchi method. Section V presents the conclusions of the study.

Literature review

A. Direct Memory Access (DMA) Manufacturing Process

The production process of DMA (Direct Memory Access) components is carried out through 3 main processes: Process 1 (Plasma cleaning process), Process 2 (Injection Mold process), and Process 3 (Final Inspection).

Process 1 (Plasma cleaning): The process of cleaning surfaces with an affected plasma or dielectric barrier discharge (DBD) plasma produced from gaseous species is known as plasma cleaning. It uses mixtures like air and hydrogen/nitrogen as well as gases like oxygen and argon (Figure 1). The process of cleaning and sanitizing the surfaces of different materials using plasma, a state of matter in which atoms and molecules are separated and ionized, is known as plasma cleaning. It is frequently used in the industrial setting to clean materials' surfaces of contaminants, oil, grime, and other residues before conducting further procedures like electroplating, film coating, or bonding. An equipment known as a plasma cleaner or plasma etcher is frequently used to carry out the plasma cleaning procedure. By subjecting a gas or liquid that produces plasma to a strong electric field, this device produces

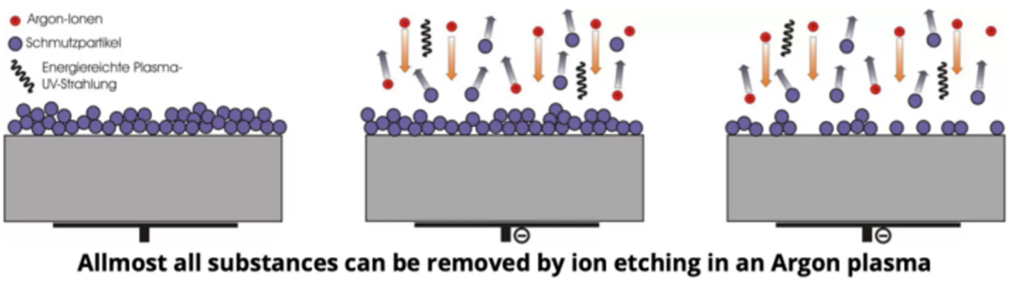


Fig. 1. Plasma cleaning process of DMA Products (Source: Author's illustration based on DMA cleaning procedure)

a plasma medium. The material to be cleaned is subsequently subjected to an impact from this plasma. The following are some of the surface impacts of plasma: Plasma cleaning helps remove surface contamination and enhances adhesion properties. In this study, it was used to ensure the surface of DMA components is clean before molding. Among the many benefits of plasma cleaning are the following: it doesn't require the use of harsh chemical cleaners, which helps to protect the environment and ensure the safety of users. the capacity to precisely and reliably clean intricate or finely textured surfaces. Capacity to remove contaminants with a high surface adherence. does not alter the fundamental characteristics of the material after cleaning. Numerous industries, including information technology, healthcare, electronics, optics, and manufacturing, use plasma cleaning.

Process 2 (Injection Mold): Using plastic injection processes, the injection mold stage of production creates plastic products or parts out of plastic ingredients (Figure 2). Typically, this procedure entails the following steps: First, a plastic injection mold is developed according to the specifications of the finished product. The plastic material chosen and ready for the plastic injection process is known as material preparation. The molten plastic is injected into the mold as a liquid by a machine. This process is known as plastic injection. To guarantee that the resin fills the shapes and grooves on the mold and contacts the entire surface, high pressure is applied. Cooling and demolding is the process of lowering the temperature to cool and harden the plastic that has formed in the mold. Subsequently, the plastic component is removed by opening the mold. The final step of finishing involves inspecting the plastic parts, trimming any surplus material if needed, and sealing any seams or cracks. In the plastics business, the injection mold method is a popular manufacturing technique used to produce a wide range of plastic products, such as home appliances, automobile parts, electronics, and many more.

For the injection mold process to function properly and be of high quality, several critical requirements must be satisfied. An essential component of the injection mold process is temperature. To guarantee that the resin melts completely and uniformly and that the part cools down enough after injection to solidify and come out of the mold, the temperature must be properly regulated. To ensure that the resin contacts the entire mold surface and fills the grooves and shapes, pressure is applied during the plastic injection process. To ensure that the resin is firmly pressed and that the finished product is free of gaps or cracks, the pressure must be regulated suitably. During which the resin is injected into the mold and maintained under pressure is known as the injection time. This duration needs to be adjusted to give the resin enough time to fill the mold evenly and to ensure that it cools and solidifies before the mold is opened. Another crucial element is the caliber of the plastic that is injected into the mold. The resin needs to be suitable for the end application in terms of ductility, hardness, and chemical resistance. It is important to properly design the mold to make sure it has the right amount of depth, grooves, and shape to yield the desired finished product. Additionally, the material used to make the mold needs to be able to tolerate high temperatures and pressures. The particular application and the requirements of the finished product determine these and many other elements. To get the greatest outcomes, the injection mold process is a complicated one that needs to be strictly controlled and adjusted technically.

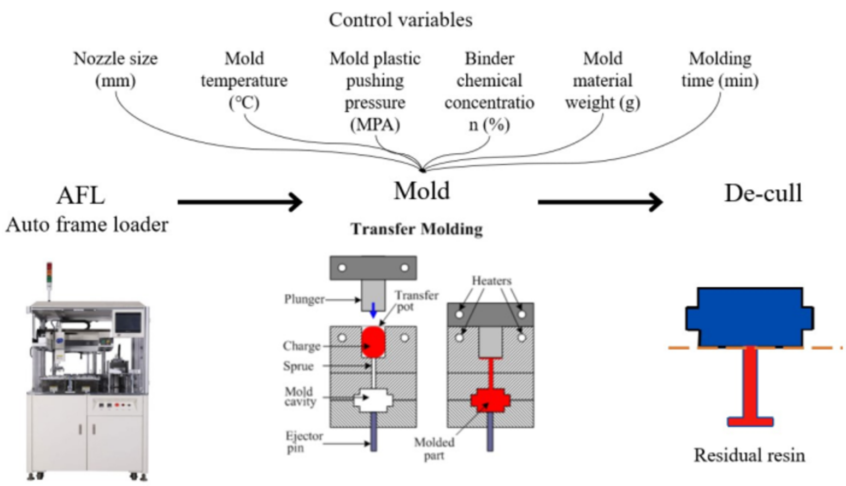


Fig. 2. DMA injection mold process (Source: Author's conceptual drawing based on injection mold setup)

Process 3 (Final inspection by computer vision): There are 4 main types of waste products generated after the injection mold process. Defect type 1 is a Split layer defect (Figure 3), occurring at a rate of 20% (1000/5000 pcs). Defect type 2 is a Flat wire defect (Figure 4), occurring at a rate of 4% (200/5000 pcs). Defect type 3 is a Void defect (Figure 5), occurring at a rate of 0.2% (10/5000 pcs), and Defect type 4 is a Corrugated Plastic defect (Figure 6), occurring at a rate of 0.6 % (30/5000 pcs). To ensure the quality of products delivered to customers, the company has invested in purchasing inspection machines using the computer vision method (Figure 7).

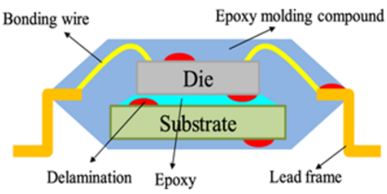


Fig. 3. Split layer defect (Source: Actual product images from experimental process)

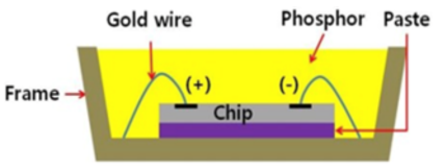


Fig. 4. Flat wire defect (Source: Actual product images from experimental process)

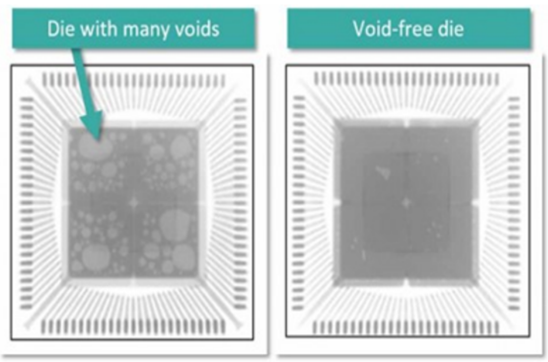


Fig. 5. Void defect (Source: Actual product images from experimental process)

Computer vision is the study of how computers can "see" and comprehend images and videos. It is a subfield of artificial intelligence (AI) and computer science. Computer vision can be used to automatically examine

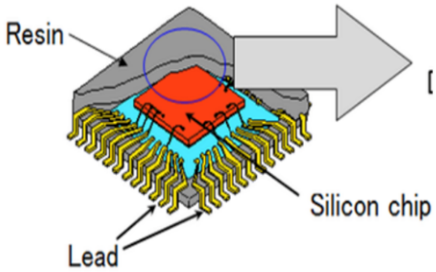


Fig. 6. Corrugated Plastic defect (Source: Actual product images from experimental process)

Fig. 7. Using a computer vision machine (Source: Actual photo taken during the inspection process)

and assess the quality and features of products based on pictures or videos during product inspection. By examining product photos or videos and comparing them to predefined quality standards, computer vision quality testing can be used to assess a product's quality. Computer vision algorithms are capable of identifying scratches and other product flaws. Product dimensions can be measured by computer vision dimensional measurement, which involves processing images to calculate the lengths, areas, volumes, and distances between product components. Computer vision can be used for product identification, allowing products to be recognized and categorized from pictures or videos. It is possible to train algorithms to identify distinguishing characteristics of products and group them into distinct groups. Product component location and assembly can be inspected using computer vision positioning and assembly inspection. To make sure that the components are assembled in the proper orientation and position, algorithms can analyze photos and calculate the position and rotation of individual components. This aligns with recent research integrating AI-based visual inspection systems into plastic injection molding processes for improved defect detection accuracy (Tran, 2023).

B. DMA injection mold process experience

This research article focuses on optimizing the injection mold process. To ensure the durability of the adhesive on the surface of the DMA product, the plasma cleaning process ensures the removal of blemishes and dirt from the product under 2 gases. Figure 2 shows six conditions that impact the injection mold process. These conditions impact the injection mold process and give rise to the 4 main types of defects as above. The key chemicals and equipment used in the process are listed in Tables 1 and 2. Only those directly influencing mold quality and surface treatment were considered in the analysis.

Table 1
Chemicals used in experimental research

Chemicals	Concentration	Unit
Nickel sulfate	120%	Kg
Nickel chloride	88%	g
Boric acid	25%	g
Amino sulfonic acid	25%	g
Nickel carbonate	45%	g
Nickel anode	90%	Kg
Fluorinated anionic surfactant	35%	Lit

Table 2
Equipment used in experimental research

Equipment	Model
Ph Tester	PH-101
Heating magnetic stirrer	MH-1
Electronic precision balance	GF2000
Power supplier	LPS-301
Interfacial tension meter	K9-MKI
Contact angle meter	MODEL 683
Ultrasonic cleaning machine	L-900
Optical microscope	MM-40

Materials & Methods

Fishbone diagrams are used in cause and effect analysis, based on the 5 Whys analysis method, to find the causes that give rise to a particular problem [10] (Ilie & Ciocoiu, 2010). Cause and effect analysis, invented by Ishikawa in 1952, is widely utilized in manufacturing plants in Japan and globally (Abe et al., 1952). Typically, the team implementing continuous quality improvement in the factory proposes a cause and effect diagram, constructed using arrows to identify root causes of the arising problem.

In this study, the product quality improvement team proposes to use a cause-and-effect analysis chart to analyze errors that give rise to defects in the DMA injection mold process (Figure 8–10). The causes listed in the cause and effect diagrams are used as input for technical factors to control factors that give rise to defects in the injection mold process, such as nozzle size conditions (mm), Mold temperature (°), Mold plastic pushing pressure (MPa), Binder chemical concentration (%), Mold material weight (g), and Molding time (min). From the above conditions, if the conditions with optimal parameters are not guaranteed, 4 main defects will arise: Split layer defect, Flat wire defect, Void defect, and Corrugated Plastic defect.

This study uses the Taguchi method to optimize the injection molding process for DMA production, employing an L18 orthogonal array to minimize the number of experiments required. The key factors selected include nozzle size (8.5 mm–8.7 mm), mold temperature (195°–205°), plastic pushing pressure (10.0 MPa–10.5 MPa), binder chemical concentration (70%–90%), mold material weight (12 g–13 g), and molding time (13 minutes–17 minutes). Each experiment was repeated 3 times to ensure stability and accuracy. Signal-to-noise (S/N) ratios were calculated to evaluate the optimal level for each parameter, using the "smaller is better" approach for defects such as delamination and the "larger is better" approach for surface quality. After collecting the data, ANOVA (Analysis of Variance) was conducted to determine the significance of each factor's influence on the product outcome. The optimal parameters were then selected and confirmed through additional validation experiments.

The Taguchi method is considered the best method for optimal implementation of finding optimal conditions in production processing, contributing to improving product quality, production process quality, and productivity. The orthogonal arrays in the Taguchi method help reduce the influence of noise factors, thereby creating optimal conditions for evaluating the

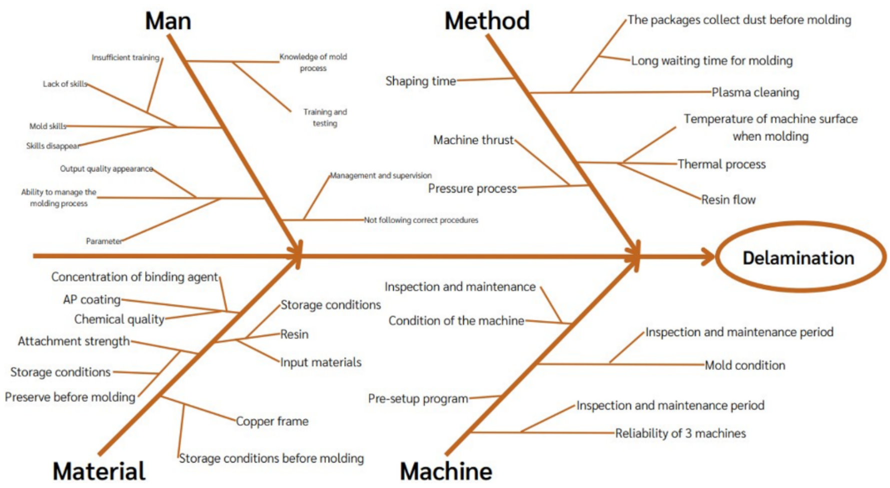


Fig. 8. Cause-and-effect diagram of Split Layer Defect (Delamination) (Source: Author's own analysis based on Ishikawa method)

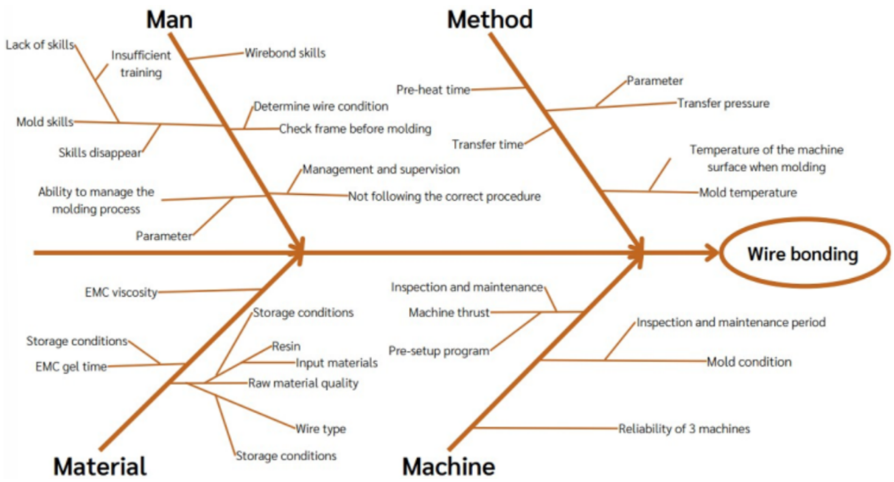


Fig. 9. Cause-and-effect diagram of Flat Wire Defect (Source: Author's analysis based on Ishikawa method)

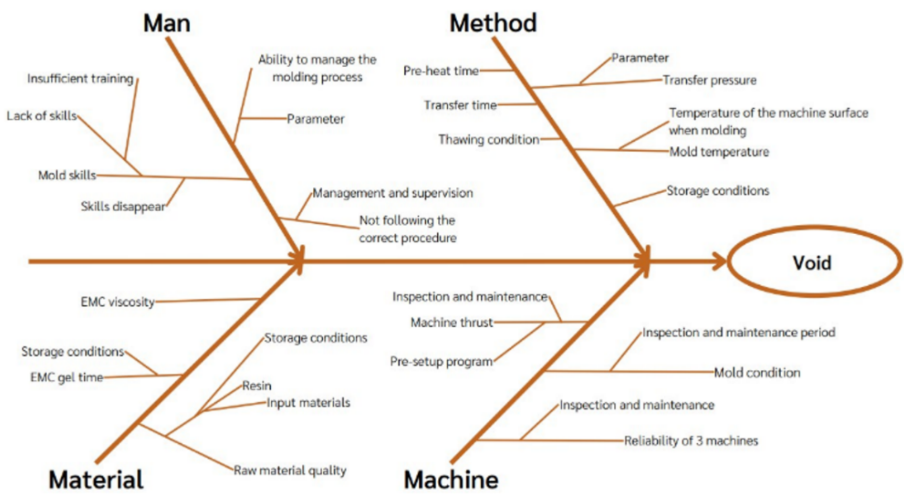


Fig. 10. Cause-and-effect diagram of Void Defect (Source: Author's analysis based on the Ishikawa method)

experimental parameters (Tab. 3). In addition, the orthogonal array also creates experimentally balanced levels compared to the Signal to Noise (S/N) index based on the logarithmic formula to improve the optimal level, creating analytical and predictive results. Experimental results are better. The "Signal" value represents the average value of the output level target, and the "Noise" value is the unwanted noise levels. The S/N ratio is calculated for the value used to evaluate the optimization level in the Taguchi experimental study.

S/N values follow the evaluation that smaller is better (Eq. 1).

$$\frac{S}{N} = -10 \times \log_{10} \left[(1/n) \times \sum \left(y_i^2 \right) \right] \tag{1}$$

S/N values follow the evaluation that larger is better (Eq. 2).

$$\frac{S}{N} = -10 \times \log_{10} \left[(1/n) \times \sum \left(1/y_i^2 \right) \right] \tag{2}$$

where, n: number of experiments, y_i: results of the ITH experiment.

Table 3
Options for selection of orthodontic array code in the Taguchi method

Orthogonal	Experimental number	Maximum number of parameters	Levels			
			2	3	4	5
L4	4	3	3			
L8	8	7	7			
L9	9	4		4		
L12	12	11	11			
L16	16	15	15			
L'16	16	5			5	
L18	18	8	1	7		
L25	25	6				6
L27	27	13		13		
L32	32	31	31			
L'32	32	10	1		9	
L36	36	23	11	12		
L'36	36	16	3	13		
L50	50	12	1			11
L54	54	26	1	25		
L64	64	63	63			
L'64	64	21			21	
L81	81	40		40		

Choosing the right and appropriate independent variables in the orthogonal array brings optimal results in the Taguchi method and helps the Taguchi method give better results than other statistical methods. Selecting the correct independent variables helps minimize the number of experimental runs while preserving the validity and comprehensiveness of the results in the Taguchi experiment, improving the accuracy of Taguchi in performing optimization without being affected by surrounding interference factors. The Taguchi method used in optimizing Injection conditions at the Mold machine is carried out according to the flow chart (Fig. 11).

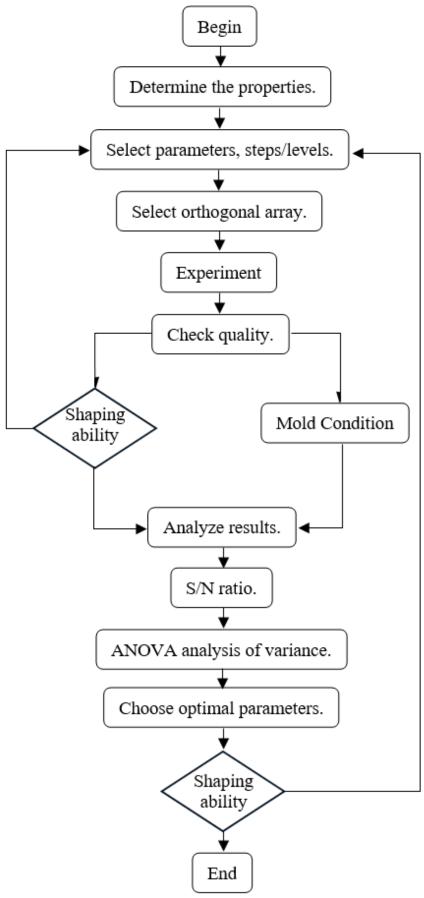


Fig. 11. Flowchart of the Taguchi optimization process (Source: Author's conception based on Taguchi methodology)

In this study, quality engineers at the company applied the Taguchi method to approach (Mitra, 2011) and analyze parameters affecting the Injection mold process of DMA products, optimizing Injection mold conditions to bring about results in reducing production time, improving product quality, improving productivity, and enhancing customer satisfaction. Experimental experiments using the Taguchi method are performed simply. However, until now, quality engineers have not paid attention to Taguchi and have not used it to analyze and optimize the production process.

A. Experimental Design

The experimental model is built based on a parametric diagram (P diagram) (Sheretov, 1999) with impact parameters such as control parameters and disturbance parameters (Figure 12). The value meets the output of the experimental research model, which is the DMA value, affected by control parameters such as nozzle size (mm), Mold temperature (°), Mold plastic pushing pressure (MPa), Binder chemical concentration (%), Mold material weight (g), and Molding time (min). The value of the control element has a set value (Tab. 4). The 6 control parameters are divided into 3 levels, but some of them contain 2 levels that are specifically set according to the control conditions of the processing machine and the technical requirements of the product. Factor A is Nozzle size (mm), which has 3 levels with corresponding values of 8.5, 8.6, and 8.7. Factor B is Mold temperature (°) with 3 levels corresponding to values in order from level 1 to level 3, which are 195, 200, and 205. Factor C is Mold plastic pushing pressure (MPa) has 2 levels corresponding to 2 values from level 1 and level 2 are 10.0 and 10.5. Factor D is Binder chemical concentration (%) with 3 levels, with values from level 1 to level 3, respectively, 70, 80, 90. Factor E is mold material weight (g) with 3 levels, with 3 values, respectively, from Level 1 to Level 3, which are 12, 12.5, and 13. Factor F is Molding time (min) has 3 levels with the corresponding values from level 1 to level 3 being 13, 15, and 17, respectively.

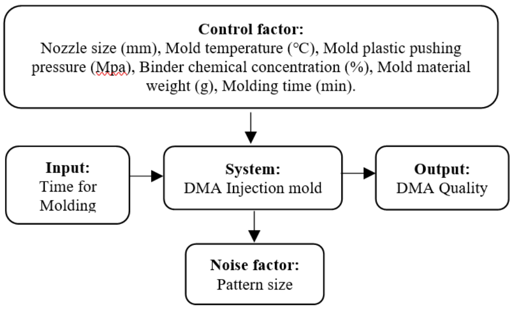


Fig. 12. Parameter diagram (Source: Author's experimental design diagram)

In Table 4, the results of the control factors include 1 factor with 2 levels and the remaining 5 factors with 3 levels. The degrees of freedom for this experimental study are 15, calculated as 1 (for the 2-level factor) plus 14 (for the 3-level factors). Therefore, the appropriate orthogonal array for the study is L18 (2^1×37), and the Taguchi experimental design used in this study is static. Details of the variables in the orthogonal network are shown in Table 5. Factor C has 2 levels, so it is arranged in the first position of the network. Orthogonally, the control factors A, B, D, E, and F have 3 levels and are arranged in the following order, respectively, from the 2nd to the 6th column. Each experimental study is repeated at the same level according to the corresponding orthogonal network, with each iteration being performed 4 times for each level in the orthogonal network.

Table 4
Control Factors and Levels

No.	Description	Level 1	Level 2	Level 3
A	Nozzle size (mm)	8.5	8.6	8.7
B	Mold temperature (°)	195	200	205
C	Mold plastic pushing pressure (MPa)	10.0	10.5	—-
D	Binder chemical concentration (%)	70	80	90
E	Mold material weight (g)	12	12.5	13
F	Molding time (min)	13	15	17

Response variable*: Defect rate (measured via computer vision system) and signal-to-noise ratio.

Table 5
Control factors and Levels in L18 (2^1×37)

No.	C	A	B	D	E	F
1	1	1	1	1	1	1
2	1	1	2	2	2	2
3	1	1	3	3	3	3
4	1	2	1	1	2	2
5	1	2	2	2	3	3
6	1	2	3	3	1	1
7	1	3	1	2	1	3
8	1	3	2	3	2	1
9	1	3	3	1	3	2
10	2	1	1	3	2	2
11	2	1	2	1	3	3
12	2	1	3	2	1	1
13	2	2	1	2	3	1
14	2	2	2	3	1	2
15	2	2	3	1	2	3
16	2	3	1	3	2	3
17	2	3	2	1	3	1
18	2	3	3	2	1	2

B. Description of Experiment and Data Analysis

The values calculated in the Taguchi method are calculated as follows:

- Computation of Signal-to-Noise (S/N) Ratio
  The Taguchi experimental analysis values are shown in detail in Table 6. Measurement trials 1 to 6 (M1–M6), representing repeated runs under the same conditions to ensure repeatability. The values 26, 46, and 48 represent observed measurement outcomes under each trial. These values correspond to quality criteria specific to the DMA molding process. In this study, noise variables refer to uncontrollable environmental or machine conditions (e.g., minor temperature/humidity fluctuations). These were not varied explicitly, but their influence is indirectly reflected in the variation across repeated runs (M1–M6). The influence values of the noise factor calculated by the value according to the S/N ratio formula are shown in detail in Table 7, and the Experimental analysis of the control parameters is shown in Figure 12.

Table 6
Experimental status

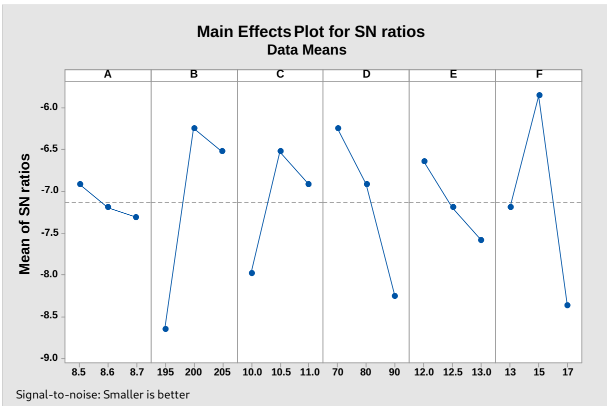
							M1	M2	M3	M4	M5	M6
							26	26	36	36	48	48
	C	A	B	D	E	F	N1	N2	N1	N2	N1	N2
1	1	1	1	1	1	1	0.85	0.83	0.90	0.94	1.04	1.03
2	1	1	2	2	2	2	0.88	0.85	1.02	0.99	1.16	1.15
3	1	1	3	3	3	3	0.94	0.91	1.15	1.15	1.23	1.13
4	1	2	1	1	2	2	0.82	0.84	0.95	0.95	1.06	1.02
5	1	2	2	2	3	3	0.89	0.82	1.07	1.06	1.19	1.18
6	1	2	3	3	1	1	0.92	0.92	1.04	1.02	1.18	1.16
7	1	3	1	2	1	3	0.88	0.87	1.0	0.98	1.12	1.08
8	1	3	2	3	2	1	0.93	0.93	1.08	1.05	1.19	1.17
9	1	3	3	1	3	2	0.87	0.87	1.0	0.99	1.11	1.09
10	2	1	1	3	2	2	0.95	0.93	1.09	1.08	1.20	1.20
11	2	1	2	1	3	3	0.88	0.83	1.03	0.95	1.09	1.09
12	2	1	3	2	1	1	0.86	0.87	1.06	1.04	1.12	1.12
13	2	2	1	2	3	1	0.81	0.82	1.05	1.03	1.13	1.14
14	2	2	2	3	1	2	0.89	0.94	1.0	1.05	1.12	1.12
15	2	2	3	1	2	3	0.80	0.81	1.05	0.99	1.09	1.14
16	2	3	1	3	2	3	0.80	0.80	0.98	0.99	1.09	1.09
17	2	3	2	1	3	1	0.82	0.83	0.97	0.98	1.08	1.08
18	2	3	3	2	1	2	0.85	0.84	1.05	1.04	1.14	1.09

The response values in the experimental study are analyzed and presented in detail in Table 8. The diagram presents the responses of the parameter control, as shown in Figure 13, and the optimal design values are presented specifically in Table 9.

Table 7
Response Table to Signal to Noise

	Signal to Noise					
	C	A	B	D	E	F
1	–14.78	–14.98	–15.93	–16.09	–15.99	–15.82
2	–15.46	–15.32	–15.89	–15.89	–15.98	–15.78
3		–15.98	–14.99	–15.90	–15.87	–16.09
S/N Contrast	0.29	0.03	0.75	0.77	0.89	0.81
Rank	5	6	4	3	1	2

(a) Data mean analysis



(b) Signal to noise analysis

Fig. 13. Response graph to signal (Source: Author's calculation based on Taguchi analysis)

Table 8
Response table to Signal

Mean						
	C	A	B	D	E	F
1	0.02187	0.02176	0.02136	0.02435	0.02019	0.02134
2	0.02318	0.02317	0.02091	0.02341	0.02134	0.02091
3		0.02521	0.02091	0.02314	0.20192	0.02132
S/N Contrast	0.00045	0.00031	0.00012	0.00213	0.00102	0.00123
Rank	5	6	4	1	2	3

Table 9
Optimal design

No.	Description	Level	Value
C	Nozzle size (mm)	C2	8.7
A	Mold temperature (°)	A3	205
B	Mold plastic pushing pressure (MPa)	B2	10.5
D	Binder chemical concentration (%)	D2	80
E	Mold material weight (g)	E3	13
F	Molding time (min)	F3	17

- The initially designed S/N values are calculated as follows

$$\begin{aligned} S/N_{\text{initial}} &= \overline{C}_1 + \overline{A}_3 + \overline{B}_2 + \overline{D}_2 + \overline{E}_3 + \overline{F}_3 \\ &= (-15.23) + (-15.83) + (-14.98) \\ &\quad + (-15.02) + (-15.23) + (-15.83) \\ &= -15.45 \end{aligned} \tag{3}$$

$$\begin{aligned} S/N_{\text{optimal}} &= \overline{C}_1 + \overline{A}_3 + \overline{B}_2 + \overline{D}_2 + \overline{E}_3 + \overline{F}_3 \\ &= (15.65) + (-15.23) + (-14.09) \\ &\quad + (-15.67) + (-15.45) + (-15.24) \\ &= -13.09 \end{aligned} \tag{4}$$

The initial parameters configured for the experimental study included C2, A3, B2, D2, E3, F3, and these parameters were optimally configured after implementing the Taguchi experimental design. The optimal improvement level of the Taguchi experimental study is $2.36 = (-15.45) - (-13.09)$.

The optimal parameters are shown in detail in Table 10.

Table 10
Prediction result

Result	S/N ratio
Initial design	–15.45
Optimal design	–13.09
Gain (Db)	2.36

C. Experimental Verification

In the experimental re-evaluation of the results of the optimal parameter levels after the Taguchi experimental design, the experimental level value is $2.37\ \text{dB} = (-13.09) - (-15.46)$. This result shows the results Design research gives optimal results. At the same time, the analysis results show that the reliability and sensitivity values are improved satisfactorily; the results are shown in Table 11.

Table 11
Experimental verification result

Result	S/N ratio
Initial design	–15.46
Optimal design	–13.09
Gain (Db)	2.37

Results

The study shows significant improvement in the DMA injection molding process through the Taguchi method, optimizing key parameters. Critical factors like nozzle size, mold temperature, and plastic pushing pressure were vital for improving product quality. For instance, increasing the mold temperature to 205° reduced delamination defects from 20% to below 10%. Similarly, optimizing binder chemical concentration to 90% and mold material weight to 13g reduced defects like flat wire and corrugated plastic. The Signal-to-Noise (S/N) ratio improved by 2.36 dB, showing better process stability, while ANOVA highlighted binder concentration and material weight as key factors. Compared with initial conditions, defect rates dropped significantly, especially delamination, improving both quality and production efficiency. However, limitations such as environmental factors (room temperature, humidity) were not controlled, suggesting further research. Future studies could explore additional parameters like cooling time or injection speed. The results imply that the Taguchi method can be widely applied to industries like automotive and electronics, emphasizing lean production and continuous improvement to enhance efficiency and consistency.

Table 12 shows that all types of defects are significantly reduced after optimization. Delamination defects are reduced by 80%, flat wire defects are reduced by 87.5%, void defects are eliminated (reduced by 100%), and corrugated defects are reduced by 83.3%. These results demonstrate the obvious effectiveness of the parameter optimization process. The Taguchi method has helped to improve the overall product quality.

Table 12
Comparison of Defect Rates Before and After Optimization

Type of Defect	Before (%)	After (%)	Improvement (%)
Delamination	20	4	–80
Flat wire defect	4	0.5	–87.5
Void defect	0.2	0	–100
Corrugated defect	0.6	0.1	–83.3

Discussion

The results show that the Taguchi method can effectively identify the most influential factors (e.g., binder concentration, mold temperature) with fewer experiments compared to full factorial DOE. This is especially beneficial in semiconductor production, where trial costs are high. Unlike RSM, which requires complex modeling, Taguchi provides a straightforward implementation, allowing practitioners to apply it in real-time process optimization.

Theoretical Basis of the Taguchi Method

The Taguchi method is based on fluctuation control and noise reduction by optimizing the signal/noise ratio (S/N), which makes the production process more stable without changing the entire system. The use of the L18 orthogonal matrix allows for to reduction of the number of experiments while ensuring high accuracy, as demonstrated in the study with an improvement in the S/N ratio from –15.45 dB to –13.09 dB.

Theoretical Basis of Chemical Bonding and Mechanical Strength

Research shows that the concentration of the binder chemical directly affects the surface durability and anti-delamination ability of the product according to the chemical bonding theory. At the same time, optimizing the mold material mass at 13g helps to distribute pressure more evenly in the mold, reducing defects such as air bubbles or plastic ripples according to the force distribution theory.

Analysis of variance (ANOVA) confirmed that factors such as mold temperature and chemical concentration had a significant impact on product quality, contributing to improved process reliability. The reduction in production variation, demonstrated by the improvement in S/N ratio from –15.45 dB to –13.09 dB, stabilized quality and increased production efficiency according to quality management theory.

Conclusions

Optimizing mold temperature conditions during production brings many important benefits such as reducing product defects (cracking, shrinkage, deformation), shortening curing time, increasing efficiency and reducing energy costs. The appropriate temperature also helps to prolong mold life and improve product uniformity in size and material properties. Good temperature control contributes to reducing scrap rates, thereby improving the quality and competitive position of the enterprise. In addition, to ensure accurate and repeatable optimization results, it is necessary to strictly control external factors such as environmental conditions, measuring equipment, data monitoring, and repeatable testing.

The study optimized the DMA molding process by combining machine operation experience, causal diagrams, and the Taguchi method, which improved product quality, productivity, and customer satisfaction. The results showed that the signal-to-noise ratio (S/N) increased by 2.36 dB, confirming the effectiveness of the experimental design compared to traditional methods.

When applying the Taguchi method to optimize mold thermal conditions in production, some limitations should be noted. If the model does not reflect reality, the optimization results may be inaccurate. This method often limits the number of factors and levels, and important factors may be missed. Determining the optimal level is sometimes difficult, and the data obtained also requires high statistical skills to analyze. In addition, the Taguchi method is not flexible when the process or raw material changes, and the initial setup cost can be high. External factors such as temperature and environmental humidity, if not well controlled, will affect the reliability. Repeating the test without a clear quality control process can also lead to erroneous results.

Although the study has achieved significant results in optimizing the DMA injection molding process, there are still certain limitations. First, external environmental factors such as room temperature and humidity are not fully controlled, which may affect the experimental results. Second, the study only focuses on 6 main technical parameters, without considering other factors such as cooling time or injection speed. Third, the application of the Taguchi model is mainly based on the assumption that the influencing factors are independent, which may not fully reflect the complex production reality. Finally, the experiments were conducted under specific production conditions in a factory, so further validation studies in different production environments are needed to increase the generalizability of the results.

The article provides some future research directions when applying the Taguchi method to optimize mold thermal conditions in production. The directions include integrating IoT and AI technology to automate data collection and analysis, building advanced simulation models to predict the influence of temperature, and multi-objective optimization to balance quality, cost, and time. In addition, the effectiveness of Taguchi should be studied with new materials (such as composites, bioplastics), performing sensitivity analysis of factors, improving cooling methods, and controlling actual production conditions. Research should also evaluate the role of personnel training, quality control from raw materials to final products, and combining Taguchi with other methods such as Six Sigma or Lean to improve overall production efficiency.

The advancement of knowledge: The study not only applies the Taguchi method to optimize technical parameters but also clarifies the relationship between technical factors and output results such as defect rate, surface quality, and customer satisfaction. This helps to expand the understanding of the causal relationship in the semiconductor molding process, which has not been systematically studied before.

On practical value: The study provides an optimal set of parameters that can be applied directly to the production line without changing the equipment, helping to reduce costs and improve quality. The model combining the Taguchi method and cause-and-effect analysis can be applied to many industries that require high quality, such as automobiles, electronics, and biomedicine. This contributes to increasing production efficiency and customer satisfaction.

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