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Six Sigma-Based Optimization of Shrinkage Accuracy in Injection Molding Processes

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Abstract**—**This paper focuses on using six sigma methodologies to reach the desired shrinkage of a manufactured high-density polyurethane (HDPE) part produced by the injection molding machine. It presents a case study where the correct shrinkage is required to reduce or eliminate defects and to improve the process capability index Cp and Cpk for an injection molding process. To improve this process and keep the product within specifications, the six sigma methodology, design, measure, analyze, improve, and control (DMAIC) approach, was implemented in this study. The six sigma approach was paired with the Taguchi methodology to identify the optimized processing parameters that keep the shrinkage rate within the specifications by our customer. An L9 orthogonal array was applied in the Taguchi experimental design, with four controllable factors and one non-controllable/noise factor. The four controllable factors identified consist of the cooling time, melt temperature, holding time, and metering stroke. The noise factor is the difference between material brand 1 and material brand 2. After the confirmation run was completed, measurements verify that the new parameter settings are optimal. With the new settings, the process capability index has improved dramatically. The purpose of this study is to show that the six sigma and Taguchi methodology can be efficiently used to determine important factors that will improve the process capability index of the injection molding process.

Keywords**—**Injection molding, shrinkage, six sigma, Taguchi parameter design.

I. Introduction

INJECTION molding is a versatile process used for molding materials into all types of different products. This process has many advantages as it can be used for a variety of materials such as metals, glasses, elastomers, but is most commonly used for thermoplastic and thermosetting plastics. Polypropylene is one of the most widely utilized raw materials in the injection molding process all over the world [1]. It is widely used because of its unique significance in its properties like having excellent moisture resistance, high strength and flexibility, while remaining at a relatively low price compared to other plastics with similar properties [1].

Along with the advantage of being able to use different materials, this technology helps with high quality part surfaces, good mechanical properties, and short product cycles [2]. This can all be done without significantly compromising part dimensions as long as the right parameters are used. Shrinkage is a serious problem with injection molded parts [3]. Even though injection molded materials indicate a shrinkage percentage range, it may not be accurate enough for certain part tolerances. In general, we may distinguish three types of shrinkage in injection molding: in-mold shrinkage (shrinkage during processing which may show up in extreme cases), as-molded shrinkage (the shrinkage just after mold opening, sometimes referred to as "mold shrinkage") and post-shrinkage (time effects during storage as physical aging, recrystallization, etc.) [3]. Here, we will focus on post-shrinkage rate.

The shrinkage of a material can be affected by a wide range of factors such as room temperature, the quality of the tool used, and the quality of the material. It can also be affected by molding parameters as injection pressure, holding time, melt temperature, and mold temperature [4]. The shrinkage of a part has a major impact on the quality and on the performance of the end product, regardless of shape and size [4]. Therefore, we need to find which parameters significantly affect shrinkage and the optimal settings for said parameters [3].

The shrinkage rate could potentially lead to a defective part, so finding the optimum parameters to eliminate the most defects is very important [5]. There have been a number of statistical models that have been developed to find optimal machining parameters such as analysis of variance (ANOVA), response surface methodology (RSM), and the Taguchi method [5]. The Taguchi methods provide an effective and standardized way to optimize designs for overall performance and quality, as well as cost [5]. Typical experimental design methods are usually very challenging because of the large amount of experimental works that have to be performed when the number of the process parameters increase, but the Taguchi-based optimization technique has produced a unique and powerful optimization discipline that differs from traditional practices [3]. The difference is that the Taguchi method has developed a specific design of orthogonal arrays to study all the process parameters with only a small number of experimental works.

II. Problem Statement

In this case study, our customer has tightened the shrinkage rate specifications in order to improve overall part quality. Our products had no problem meeting the shrinkage rate specifications of 2.5%±1.0%. However, with the new specifications of 2.5%±0.5%, most of our products have become defective parts. The process capability C_p and process capability index C_{pk} are 0.74 and 0.68, respectively. This gives us a defect rate of 3.21% which translates over to the company losing $385,200 a year because of defected parts. The goal of this case study is to reduce our defect rate, so we are aiming to

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improve the C_p and C_{pk} greater than 1. To achieve this goal, we need to revise the injection molding process to produce parts with the nominal shrinkage rate. Therefore, we will be implementing the DMAIC approach coupled with the Taguchi method. Fig. 1 shows the flowchart that illustrates the whole process of this case study.

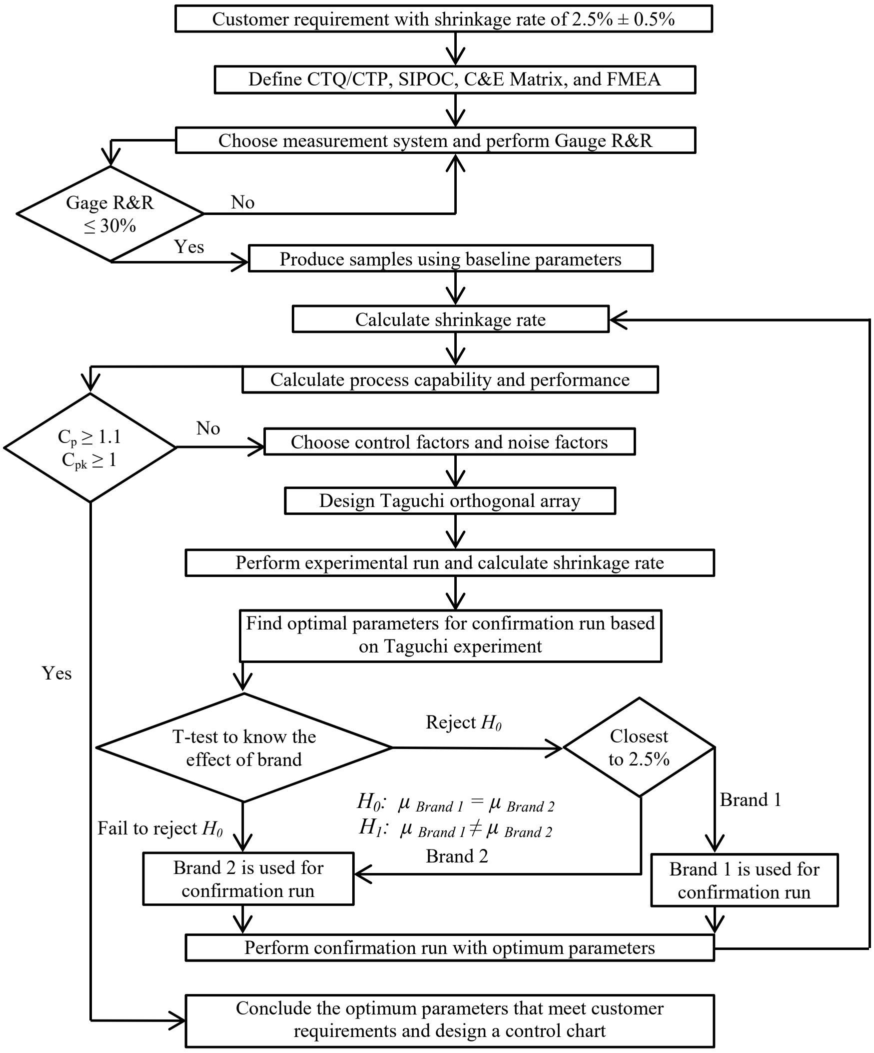

Fig. 1 Six Sigma process flowchart for injection molding

III. Experimental Procedure

In order to obtain the specified shrinkage rate while reducing cost, finding the best fit process improvement methodology is essential. Among some of the methods include Six Sigma, Re-engineering, Total Quality Management (TQM), Just-In-Time (JIT), and Poka-Yoke [6]. Re-engineering, JIT, and poka-yoke are all tools that can be used within TQM or Six Sigma. Six sigma includes all tools and philosophies of TQM but also has more advanced statistical tools, and incorporating these tools creates the opportunities for bigger and better improvements, and improvements that might not have been found with just TQM [6]. The goal of the Six sigma methodology is to improve part quality by identifying and removing the causes of defects and minimizing variability in manufacturing processes [7]. Six sigma projects follow the DMAIC approach. We first define the problem, measure the performance, analyze and identify root causes. Then, we improve the results based on analysis and control the improved process.

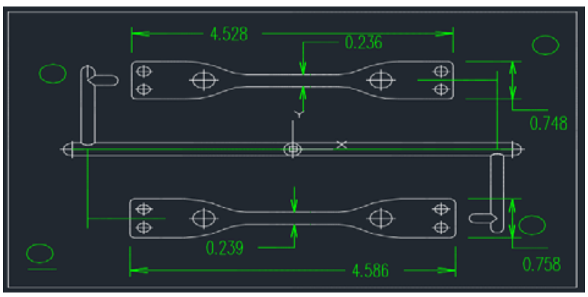

Fig. 2 AutoCAD drawing of specimen part and dimensions (In)

A. Define

The define stage is the first stage of this project. In this stage, the six sigma team acquired a drawing from the customer, shown in Fig. 2, of the required part based on the customer's specification of a length of 4.528 in., a width of 0.748 in., and a height of 0.125 in. This includes a shrinkage rate within the tolerance of 2.5% ± 1.0% on the length of the part. After this, we brainstormed root causes with a fishbone diagram and then we use a CT (critical to) Tree to further identify the problem and the processes that need to be improved in this case study.

The key parameters that could affect the shrinkage rate were listed and analyzed using the fishbone diagram, the potential failure modes were also determined. Fig. 3 shows a fishbone diagram developed based on the various processes involved. It was classified into six classifications: people, method, measurement, machine, environment, and materials and a total of 17 possible root causes that might be related to getting a shrinkage rate outside customer specifications.

TABLE I
CRITICAL TO PROCESS VS CRITICAL TO QUALITY TREE

	Shrinkage	Delivery date	Manufacturing cost
Product design	9		
Material	9		9
Delivery cost		9	9
Packaging		9	9
Inventory		4	
Melt Temp	9		9
Metering stroke	9		9
Holding pressure	9		9
Cooling time	9		9

With the potential causes identified, we can use a CT (critical to) tree to convert customer needs to measurable performance requirements. A CT tree is a tool that relates the needs that are considered important by the customer into the product and service characteristics and links these characteristics to organizational processes [8]. These help in knowing what our customers are looking for and the steps to take to ensure product quality. Key characteristics and important product parameters are defined in terms of quality, customer, and process and rated against each other. Table I shows the characteristics against each other. The CTQ (critical to quality) vs. CTP (critical to process) were compared to the process by a ranking following scale 1, 4 and 9. If a particular process has a high impact on quality, it was ranked 9, the medium impact was ranked with 4, the insignificant impact was ranked 1, and the ones with no impact were left blank.

B. Measure

In the measure phase, the focus was on the measurement system and gathering root causes of why we are getting a shrinkage rate outside the customer specifications. We decided to use the coordinate measuring machine (CMM) to measure our length because the CMM provides precise and accurate measurements. With our measurement system determined, we can conduct our gage R&R study. A gage repeatability and reproducibility (gage R&R) study was conducted by measuring the shrinkage rate of nine parts molded from the baseline parameters. The gage R&R study was performed using two appraisers and three trials for each of the seven parts, and the values were recorded. The shrinkage rate was calculated using (1), where x is the cavity length and y represents the part length. We can then convert the number into a percentage by multiplying η by 100.

$$\eta = \frac{(x-y)}{x} \tag{1}$$

The results show the shrinkage rate average of the seven parts to be 2.26 percent with an equipment variation 32.23 percent and an appraiser variation of 6.77 percent resulting in an overall 32.94 percent gage R&R with most of the variation from the equipment. This value of 32.94 percent is slightly higher than the acceptable range of 30 percent, and this indicates that there is room for improvement in our measurement process. Due to time constraints, we will continue using the CMM.

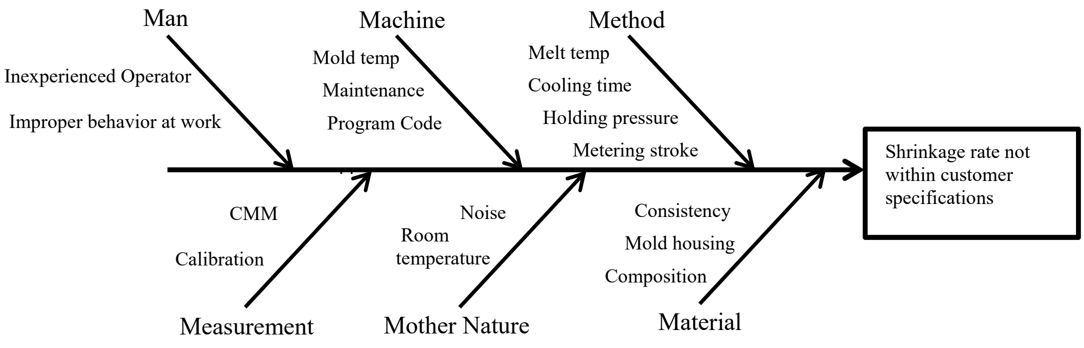

Fig. 3 Fishbone diagram

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TABLE II
FAILURE MODE AND EFFECT ANALYSIS TABLE OF THE INJECTION MOLDING PROCESS

Process Step/Input	Potential Failure Mode	Potential Failure Effects	SEV	Potential Causes	OCC	Current Controls	DET	RPN
Material placed in hopper	Wrong material	Incorrect properties	5	Wrong material setup	2	Operator sees problem and controls	5	50
Heating bands melt plastic	Wrong setup temperature	Cold temperature clogs machine	8	Set temperature too low	4	Operator sees problem and controls	7	224
		High temperature burns material	8	Set temperature too high	4	Operator sees problem and controls	7	224
Screw forces melted plastic through sprue	Incorrect shot size setup	Unfilled mold cavity	6	Metering stroke incorrect	5	Operator sees problem and controls	8	240
Part solidifies	Holding pressure time	High solidification leads to high cycle time	2	Set cooling time too long	4	Operator sees problem and controls	7	56
		Low solidification leads to defected part	5	Set cooling time too short	4	Operator sees problem and controls	7	140
Part ejection from mold	Part sticks to top mold	A stop in process to remove the part	4	Failure to apply non-stick spray	2	Operator sees problem and controls	4	32
	Ejector pins in incorrect location	A stop in process to remove the part	4	Mold design	3	Mold design inspection	4	48

A cause-and-effect (C&E) matrix helps us identify which factors affect the outcomes of shrinkage rate. In the C&E matrix, we multiply the customer importance with rankings and final output number is ranked. With these relationships visible and quantified, we can identify the most influential inputs as key parameters input variables (KPIV). From the C&E matrix, the cooling time (s), melt temperature (f), holding time (s), and metering stroke (in) are defined as KPIV. The C&E Matrix also provides the initial input to the failure mode and effect analysis.

The next step is to conduct the failure mode and effect analysis (FMEA). The main idea of FMEA is to determine the potential failure modes in the process, as well as their causes and effects. The FMEA of the injection molding process is shown in Table II. This was done to help identify potential failure modes that could affect the injection molding process and the effect of such failures, the risk to customers if these processes fail and how to control them to ensure a better quality product. An FMEA uses three criteria to assess a problem; how severe the problem is, the frequency of the problem, and the detection rate of the problem [9]. The severity is ranked from 1-10 with a low number and high number translating to low impact and high impact respectively. The occurrence is also ranked from 1-10 with a low number meaning that it is not likely to occur and a high number meaning that it is more likely to occur. The detection is ranked from 1-10 with a high number meaning hard detection and a low number meaning easy detection. The RPN is the product of the three factors and the highest numbers are the processes that we must improve upon factors, three levels, and one noise factor were used. Our four controllable factors are the cooling time (s), melt temperature (f), holding time (s), and metering stroke (in). Our one uncontrollable factor, or noise factor, is the brand of material. This is represented with brand 1 and brand 2.

TABLE III
MAIN AND NOISE FACTORS

Designation	Variable	Unit	Level 1	Level 2	Level 3
A	Cooling time	sec	10	13	16
B	Melt Temperature	f	380	400	420
C	Holding time	sec	6	8	10
D	Metering stroke	in	2.6	2.7	2.8
	Non- Controllable Factors				
1		Brand 1			
2		Brand 2			
Output				Shrinkage rate	

TABLE IV
TAGUCHI L_9 ORTHOGONAL ARRAY

	Main Factors				Noise Factors			
N	A (Cooling time)	B (Melt temperature)	C (Holding time)	D (Metering stroke)	Brand 1	Brand 2	$\bar{Y}$	S/N Ratio
1	1(10)	1(380)	1(6)	1(2.6)	0.026	0.024	0.025	25.153
2	1(10)	2(400)	2(8)	2(2.7)	0.024	0.023	0.023	39.482
3	1(10)	3(420)	3(10)	3 (2.8)	0.023	0.022	0.023	30.511
4	2(13)	1(380)	2(8)	3 (2.8)	0.024	0.023	0.023	31.749
5	2(13)	2(400)	3(10)	1(2.6)	0.022	0.022	0.022	49.427
6	2(13)	3(420)	1(6)	2(2.7)	0.024	0.025	0.024	35.956
7	3(16)	1(380)	3(10)	2(2.7)	0.022	0.026	0.024	20.387
8	3(16)	2(400)	1(6)	3 (2.8)	0.024	0.023	0.023	30.037
9	3(16)	3(420)	2(8)	1(2.6)	0.022	0.024	0.023	22.275

C. Analyze

Equation (2), the nominal the better equation, is used to calculate the signal-to-noise ratio, where η is the response, $\bar{Y}$ is the average of the shrinkage rate measurements, and s^2 is the variance of the shrinkage rate data.

$$\eta = 10log(\frac{\bar{y}^2}{s^2}) \quad (2)$$

An L_9 orthogonal array shown in Table IV is used to organize the parameters affecting the process and the levels at which they are varied.

TABLE V
RESPONSE TABLE

	A	B	C	D
Shrinkage rate				
Level 1	0.0239	0.0242	0.0243	0.0235
Level 2	0.0233	0.0229	0.0232	0.0239
Level 3	0.0234	0.0234	0.0231	0.0232
S/N ratio				
Level 1	31.72	25.76	30.38	32.29
Level 2	39.04	39.65	31.17	31.94
Level 3	24.23	29.58	33.44	30.77

For the shrinkage rate, the value in each column that is close to .025 is chosen. For the signal-to-noise (S/N) ratio, the largest value in each column is chosen. The predicted shrinkage rate, based on the formula $Y_{Predictted} = \bar{Y}_{A2} + \bar{Y}_{B3} + \bar{Y}_{C1} + \bar{Y}_{D2}) - 3\bar{Y}_{all}$, from the first set of parameters $A_1B_1C_1D_2$ is 2.58%. The predicted shrinkage rate percentage from the second set of parameters $A_2B_2C_3D_1$ is 2.22%. Since our customer requires shrinkage rate to be closest to 2.5%, we choose $A_1B_1C_1D_2$ as the optimal setting shown in Table V.

After finding our optimal settings, we have to conduct hypothesis testing. The hypothesis testing is conducted to see if the material brand has a significant effect on the shrinkage rate. A t test is conducted as we compare two means from two sample groups. The hypothesis is shown where $\mu_{\text{Brand 1}}$ represents the mean of the old cutting and $\mu_{\text{Brand 2}}$ represents the mean of the new cutting tool.

- H_0: $\mu_{\text{Brand 1}} = \mu_{Brand\ 2}$
- H_1: $\mu_{\text{Brand 1}} \neq \mu_{Brand\ 2}$

The calculations for the t-test were calculated using (3), where $\bar{x}_1$ represents material brand 1 and $\bar{x}_2$ represents material brand 2. S^2 is the pooled sample variance and n_1 and n_2 are the sample size [10].

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2(\frac{1}{n_1}+\frac{1}{n_2})}} \quad (3)$$

TABLE VI
CONFIRMATION RUNS WITH OPTIMAL PARAMETER SETTINGS

Run #	1	2	3	4	5	6	7	8	9	10	11	12	Average
Shrinkage rate	.0237	.0245	.0259	.0232	.0239	.0265	.0275	.0252	.0248	.0269	.0240	.0239	.02502

Using 99% confidence interval and a degree of freedom of 17, the t-test value was calculated, and the result was 0.225, with a critical region of 2.898. From the t-test calculations, the test statistic value 0.225 does not exceed the critical region value of 2.898, so we fail to reject the null hypothesis. This tells us that there is no significant difference between the two brands. Since the average shrinkage rate of Brand 2 is closer to our nominal, we will be using Brand 2 to run our confirmation runs.

D. Improve

With defined the optimum parameters, confirmation runs are followed to verify if the products have a shrinkage rate closer to the desired. 12 parts were molded using the optimal parameters. The confirmation parts were then measured using the CMM to measure the length of all the pieces. The results of the confirmation runs are recorded in Table VI.

The average shrinkage rate for the confirmation run parts is 2.502% and a standard deviation of 0.14%, which is very close to the nominal value 2.5%. We calculated the new C_p and C_{pk} to be 1.19 and 1.17, respectively. We also plotted a capability analysis graph in Fig. 4 to visually see that the processs has been improved.

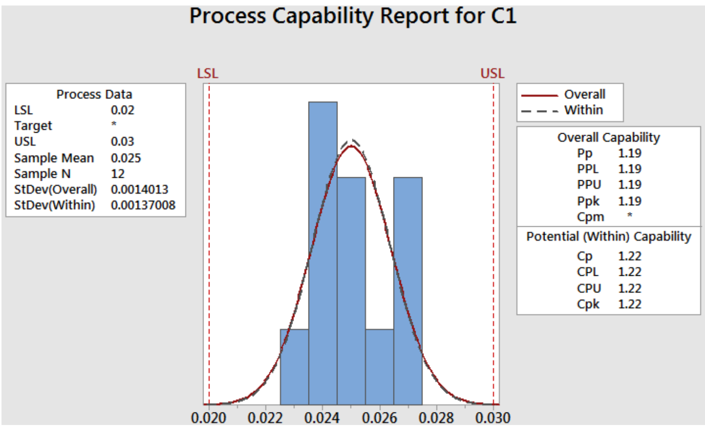

Fig. 4 Process capability graph of optimal parameters

E. Control

Now, the optimal parameters have been verified; it is essential to control the process. We have created an SPC (statistical process control) chart for the process to identify if a part is outside of the specification limits. The upper control limit (UCL) for X-bar equals 2.69% and the lower control limit (LCL) for X-bar equals 2.31%. The UCL for R equals 0.69% and the LCL equals 0%. The process has been improved and is now capable of making the parts meet the customer's desired shrinkage rate. It is important to keep this process improved and to ensure that it does not go out of control. To do this, a control chart for the X-bar and R-bar was created and is shown in Fig. 5. The UCL, CL, and LCL are shown in blue, red, and green, respectively.

Date	May 31								
Time of Day		8:00	9:00	10:00	11:00	12:00	1:00	2:00	3:00
Sample Group #		1	2	3	4	5	6	7	8
Sample Measurements Value of X	1								
	2								
	3								
	4								
	5								
Sum									
Average X-bar									
Range *R*									

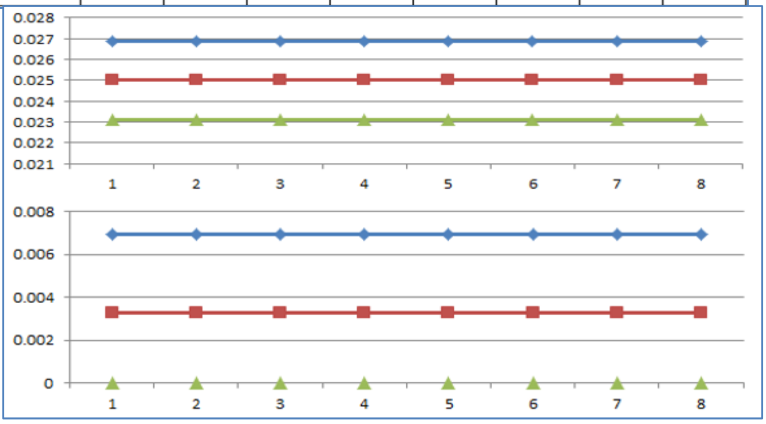

Fig. 5 Statistical process control chart for injection molding process

IV. Conclusion

In this project, we investigated the significance of cooling time, melt temperature, holding time, and metering stroke on the shrinkage rate. Using the Taguchi experiment, the optimal parameter values are calculated as cooling time (10 s), melt temperature (380 f), holding time (6 s), and metering stroke (2.7 in). From the hypothesis testing conducted, we can conclude that the brand of material has no significant effect on the shrinkage rate. So, we chose to use the brand that had a shrinkage rate average closest to our customer's nominal specifications. Using these parameters, we produced injection molded parts with an average shrinkage rate of 2.502%, which is within the specified limits of 2.5% ± 0.5%. The implemented six sigma methodologies helped in improving the C_p value from 0.74 to 1.19 and increased the C_{pk} value from 0.68 to 1.17. This reduced our defect rate from 3.21% to 0.04%, thus, saving our company $380,000 a year. This case study indicates that the DMAIC approach is very effective in improving the process so that it can manufacture parts within customer specifications and the customer can even tighten their specifications.

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