Yield Improvement on In-Mold Decoration Manufacturing through Parameter Optimization

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In-Mold Decoration (IMD) is an efficient, durable and cost effective technique for printing, painting, and forming plastic decorations. However, a large number of parameters involved in IMD manufacturing process and the complex relationship between these parameters make the determination of the optimal parameter setting a challenging task. This paper proposes a systematic framework integrating Response Surface Methodology (RSM) and logistic regression to improve the yield of IMD manufacturing process. The integrated framework becomes easy to identify the optimal parameter setting, saving a great deal of time and money in the manufacturing process. On the empirical study in collaboration with IMD company, the proposed framework shows the significant result from 10% to 87.5%, validating the viability of the proposed framework in real settings.

1. Introduction

In today's world, plastic products are pervasive almost everywhere. In-Mold Decoration (IMD) is an efficient, durable and cost effective technique for printing, painting, and forming plastic decorations. Since its introduction, IMD has rapidly become the priority choice due to its wide design flexibility and effects that cannot be achieved through other processes. Unlike the traditional printing on the surface, IMD sets the labeling and decoration between the film and the resin. The printed film is placed on one side of the mold and the molten plastic is injected onto the back of the film. The film and the plastic are then bonded as an integral unit and the decoration is embedded inside. Comparing to other methods, IMD can enhance the appearance and the durability of the finished product. More attractively, it allows the product to have multiple colors and 3D design shape on its surface, which cannot be achieved by other methods.

While IMD is advantageous in many aspects, its process usually suffers from low yields. This is mainly because IMD involves many parameters in the manufacturing process. If these manufacturing parameters are not appropriately set, the finished product can easily become defective. Specifically, as shown in Fig. 1, IMD consists of four major stages: film printing, thermoforming, trimming and injection molding; each stage further includes dozens of steps. Collectively, the whole IMD process can have 70-100 manufacturing parameters. In the current practice, the parameter setting of IMD is determined based on either a trial-and-error approach or domain engineers' personal experience. Both are biased and can easily lead to low yields.

While the parameter setting can significantly affect the yield of IMD, its determination is a challenging task. This can attribute to the following reasons. First, the number of parameters involved in the IMD process is large, leading to an astronomical number of possible manufacturing settings. For example, consider an IMD process involving 70 manufacturing parameters, each having two possible settings. There will be a total of 2^{70} possible manufacturing settings, which are too many to determine which one is the best. Second, the relationship between IMD parameters is complicated, nonlinear and unknown. To uncover this relationship, it is only possible to run experiments. However, experimentation is usually costly in terms of time and money. Third, the production output is stochastic in nature, i.e., the finished product can be defective or non-defective with the same parameter setting.

In the literature, some approaches have been proposed to deal with the parameter optimization problem arising in a number of different fields. For example, Lin[1] proposed an optimization technique based on Taguchi technique for face milling stainless steel. Three cutting parameters with multiple performances are optimized through the proposed technique. Altan[2] utilized Taguchi method, experimental design and the analysis of variance (ANOVA) to find the optimal injection molding condition for minimum shrinkage. Yin et al.[3] developed an artificial neural network (ANN) model for parameter optimization with the goal of decreasing the warpage value during PIM process. Park and Dang[4-5] used neural network and regression analysis to build the relationship between the input processes and output responses. Oktem et al.[6] found the optimal parameter for thin-shell plastic components by Taguchi method.

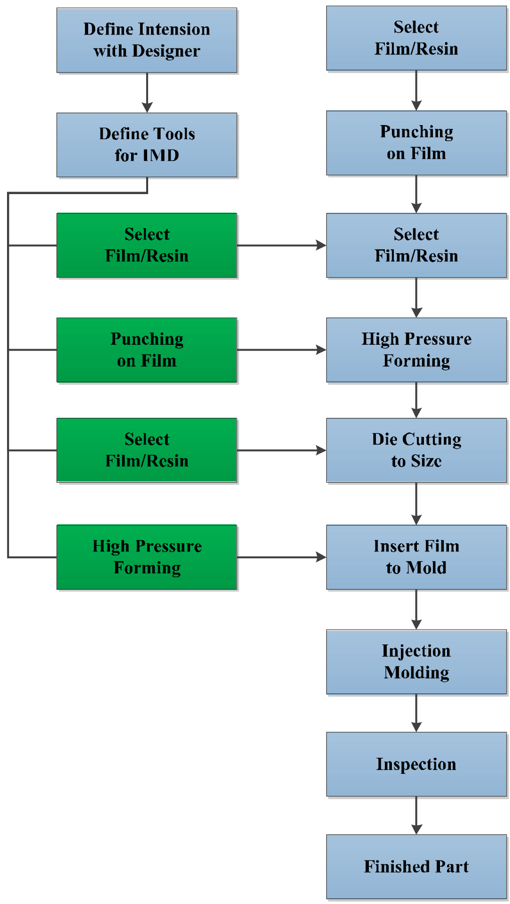

Fig. 1 The manufacturing process of IMD

Among these approaches, Taguchi method is a well-known technique for investigating the optimal parameter setting[7]. It introduces a new concept called signal-to-noise (S/N) ratio and utilizes it to quantify one product's quality. The optimal parameter setting corresponds to the one that can result in the largest S/N ratio. While Taguchi method has been widely applied to solve parameter optimization problem, it can only handle small- to medium-level problems. Moreover, it does not allow interaction effects to be estimated in the experimentation. On the other hand, artificial neural network (ANN), inspired by the biological neural network, is another popular method in parameter optimization. It is useful in building the relationship between inputs and outputs of complex systems. Many successful applications in finance, telecommunication, and manufacturing have been demonstrated. However, ANN is a data-driven approach; a large amount of data is required to produce meaningful results. For the manufacturing process where data is expensive, ANN is not applicable. Besides, ANN is a black box to analysts; the generated results can be hard to interpret.

In this research, a framework that integrates response surface methodology (RSM) [8] and logistic regression[9] is proposed to identify the optimal parameter setting to render IMD the highest yield. RSM is a sequential procedure widely used to optimize the response of interest in physical experiments[10]. Logistic regression, on the other hand, is a type of regression analysis used for predicting the outcome of categorical response variables. The basic structure of the proposed

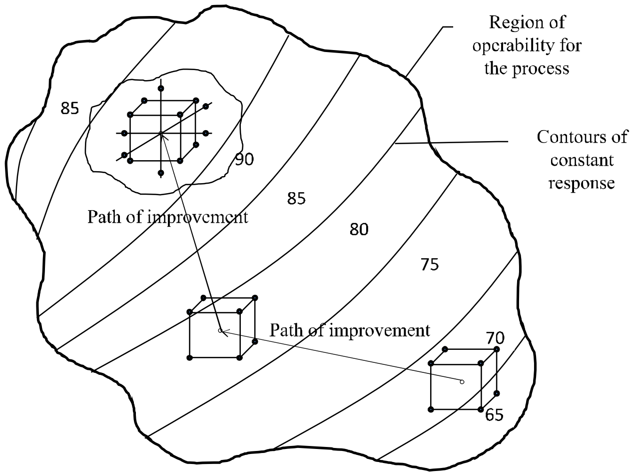

Fig. 2 The sequential nature of the proposed framework

framework is outlined as follows: instead of attempting to explore the whole parameter space in one shot, the proposed framework explores a small region in succession where designed experiments are sequentially employed and a local response surface is built to find the improved solution (parameter setting). In this research, one major difficulty for applying the traditional RSM to find the optimal parameter setting of IMD is that the output of the IMD process is categorical, i.e., the finished product can only be either defective or non-defective. By contrast, the traditional RSM assumes the response is quantitative. To address this issue, the proposed framework employ logistic regression technique to convert the categorical output of IMD into a quantitative variable, enabling the application of the response surface methodology.

Compared to the trial-and-error approach and domain engineer's judgment, the proposed framework is a scientific and systematic approach that can quickly identify the optimal parameter setting, saving a great deal of time and money in the ramp-up stage. Moreover, because the proposed framework is a design-of-experiment-based framework, it can handle large-scale problems more efficiently[8]; the interaction effects between parameters (or "factors" if in RSM terminology) can also be estimated in the experimentation. To show the viability of the proposed framework in real settings, an empirical study in collaboration with an IMD company in Taiwan is conducted. Results show that the proposed framework can significantly enhance the yield of IMD process from 10% to 87.5%. More details about the proposed framework and the empirical study will be presented in later sections.

The rest of this article is organized as follows. In Section 2, the proposed framework is introduced. In particular, the details about response surface methodology and logistic regression that are employed in the framework are discussed. In Section 3, an empirical study where the proposed framework is applied in real settings is conducted. Section 4 concludes with future research.

2. The Proposed Framework

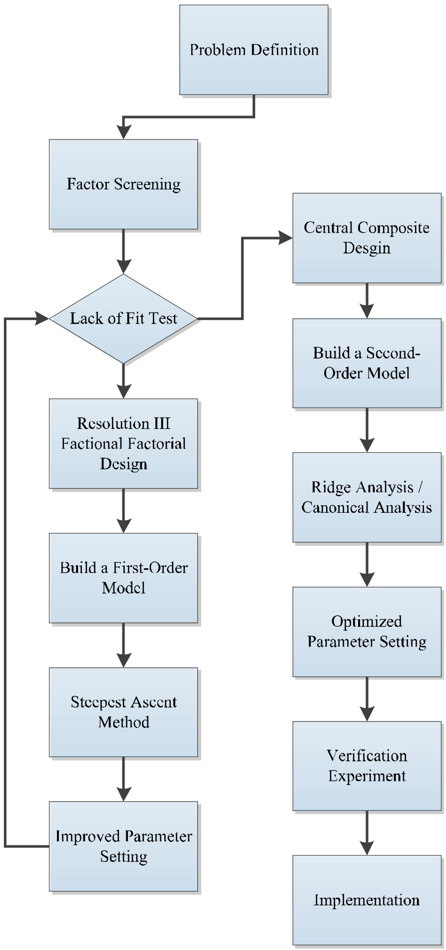

Fig. 3 The proposed framework

This section presents the proposed framework, along with some discussion about its implementation. As shown in Fig. 2, the proposed framework employs a sequential strategy to find the optimal solution. In particular, when the algorithm just gets started, a first-order model is built to represent the local response surface. The gradient of the first-order model is used to derive the "path of improvement," by which the algorithm can find the improved solution. The process is continued until there is strong evidence showing that the curvature effects are significant (i.e., a first-order model is no longer a good fit). Then, a more complicated model, i.e., a second-order model, is employed, where some statistical tools including ridge analysis and Canonical analysis can be used to locate the optimal solution.

A flowchart that illustrates the proposed framework is given in Fig. 3. In the beginning, the proposed framework requires problem definition, which entails a clear description about the problem. Specifically, analysts need to define the response and the factors that are involved in the research. Here we define the manufacturing parameters as the factors and the quality of the finished product, i.e., defective or non-defective as the response. Specifically, at a particular solution (parameter setting) x (say), let the probability that the finished products is non-defective be $\pi(x)$. The logistic regression utilizes the following link function, called logit function, to convert the binary response into a quantitative value.

$$\mathrm{logit(y)} = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) \qquad (1)$$

When building the local model, $\mathrm{logit(y)}$ is used as the response. Let the first-order model be

$$\mathrm{logit(y)} = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_i x_i \qquad (2)$$

or equivalently

$$\pi(x) = \mathrm{P}(\mathrm{y}|x_1, \cdots, x_k) = \frac{1}{1+e^{-(\hat{\beta}_0+\sum_{i=1}^{k}\hat{\beta}_i x_i)}} \qquad (3)$$

where the coefficients ($\hat{\beta}$'s) can be estimated by the maximum likelihood method [8]. Note that when the response is not normally distributed, it may not be easy to find a closed-form expression for the coefficient values that maximizes the likelihood function. Therefore, an iterative process such as Newton's method must be used in this case.

The analysis procedure starts with factor screening as a means to reduce the number of factors to be studied in the subsequent experimentation. This step is critical because the IMD process involves a large number of factors, it is necessary to identify the important factors that can significantly affect the yield of IMD. In the literature, there have been many screening designs proposed for factor screening[11]. In particular, the Resolution III fractional factorial designs can be used as screening designs for inexpensive experiments. For expensive experiments, supersaturated designs, which require only $N+1$ experimental runs for problems with N factors, can be used. Details about the Resolution III fractional factorial designs and the supersaturated designs can be found in Myers and Montgomery[8]. Note that, in addition to the screening designs, domain experts' opinions are also useful in identifying the important factors.

Once the important factors are identified, the proposed framework employs the fractional factorial designs (Resolution III or IV) to build the first-order model with the important factors. Suppose there are k factors identified as important. Let the built first-order model be

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_i x_i \qquad (4)$$

where $\hat{\beta}_0$, $\hat{\beta}_1$,…, $\hat{\beta}_k$ are regression coefficients. Based on Eq. (4), the steepest ascent method can be performed to find the improved solution. The steepest ascent method is to search for the optimal solution along the path of improvement, which corresponds to the direction that the response $\hat{y}$ can increase most rapidly, i.e., the gradient of the first-order model. The step size with respect to each factor is determined as follows: The analyst first selects the factor that has the largest absolute regression coefficient, say factor j, and let its step size be 1. Then the step size of factor i ($i \neq j$) is determined by

$$\Delta x_i = \frac{\Delta x_j \hat{\beta}_i}{\max|\hat{\beta}_j|} \tag{5}$$

In Eq. (5), the step size of each factor is proportional to the ratio that their coefficient value is relative to the largest one. In other words, the larger their coefficient value, the bigger the step size.

For each iteration, the lack-of-fit test is performed to evaluate the appropriateness of the first-order model. When the lack-of-fit test shows that the first-order model is no longer a good fit, central composite design (CCD), which includes fractional factorial designs, includes axial points and center points, are employed to build a second-order model as follows:

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_j x_i + \sum_{i=1}^{k} \hat{\beta}_{ii} x_i^2 + \sum_{i<j}\sum \hat{\beta}_{ij} x_i x_j \tag{6}$$

Based on the second-order model that can fully characterize the local response surface, Canonical analysis is performed to locate the optimal solution. The basic idea of the Canonical analysis is to transform the second-order model into a new coordinate system with the origin at the stationary point and then rotate the axes of this system until they are parallel to the principal axes of the fitted response surface. The transformed response model is given as follows:

$$\hat{y} = \hat{y_s} + \lambda_1 w_1^2 + \lambda_2 w_2^2 + \cdots + \lambda_k w_k^2 \tag{7}$$

where the $\{w_i\}$ refers to the transformed independent variables and $\{\lambda_i\}$ are eigenvalues of the Hessian matrix of the second-order models. Details about Canonical analysis can refer to Myers and Montgomery [8].

Finally, before implementing the final solution, verification experiments are suggested to confirm the improvement that the final solution brings to the response of interest. The improvement can be evaluated by comparing the responses produced by the initial solution and by the final solution. When making comparisons, cares should be taken in selecting an appropriate number of replications in order to mitigate the effect of the sampling error.

3. An Empirical Study

In this section, an empirical study in collaboration with a company located in New Taipei City of Taiwan is conducted to demonstrate the viability of the proposed framework in real settings. Briefly, the case company manufactures many kinds of complex hi-tech plastic products (e.g., double injection, over molding or IMD) with multi-color printing, 3D design shape and light weight. Recently, the case company has applied IMD technique to produce LED panel, film keyboard, backlight logo and fingerprint frame. However, the rapid change of products presents major challenges for process engineers to identify the optimal parameter setting for each product, causing low yields. This study aims to improve the product yield through parameter optimization with the proposed framework. One product that has lowest yields (about 10%) is selected as the target product.

Table 1 Current setting, low- and high-levels of the 8 manufacturing parameters.

Factor	Symbol	Current	High	Low
force plug temp., x_1	A			
former block temp., x_2	B			
Initial pressure, x_3	C			
final pressure, x_4	D			
cavity temp., x_5	E			
nozzle temp., x_6	F			
inject pressure, x_7	G			
holding pressure, x_8	H			

An extensive discussion with domain engineers indicates that two key stages play a critical role in affecting yields: thermoforming and injection molding. Therefore, attention is placed on the parameters involved in the two stages. An analysis conducted based on historical data shows that 8 manufacturing parameters i can most affect the yield. They are listed as follows:

Thermoforming:

- Force plug temperature
- Former block temperature
- Initial pressure
- Final pressure
- Cavity temperature

Injection molding:

- Nozzle temperature
- Inject pressure
- Holding pressure

In the experimentation, the 8 manufacturing parameters are defined as the factors and the quality of the finished product is defined as the response. In particular, when the finished product is defective, the response is set as 0; otherwise, it is set as 1. The current setting of the 8 manufacturing parameters is given in Table 1 where high- and low-levels of each parameter are specified. The 8 manufacturing parameters are labeled as factors A, B,…H and $x_1, x_2, \dots x_8$ are used to denote their parameter settings (factor levels). Taking the experimental budget into consideration, the 2^{8-4} Resolution IV fractional factorial designs is chosen to fit the first-order model. The design matrix is shown in Table 2. In general, a 2^{k-p} fractional factorial design refers to the experiment that only requires 2^{k-p} runs for k factors, each having two levels. It is $1/2^p$ of the full factorial experimental design. With Resolution IV designs, no main effect is aliased with any other main effect or with any two-factor.

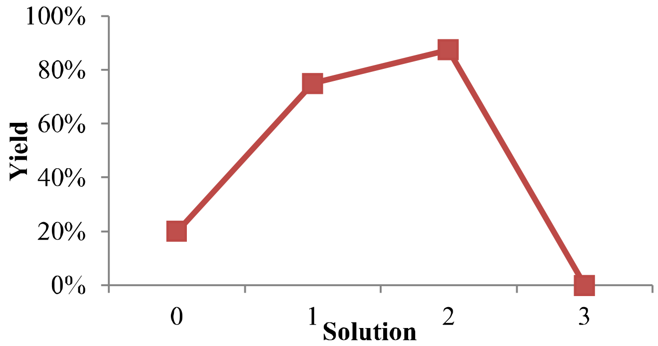

Fig. 4 The yield trend at solutions along the path of improvement

With the first-order model, the steepest ascent method is performed to find the improved solution. Specifically, the algorithm evaluates the response of the solutions step by step along the path of improvement and stops when the yield is no longer improved. In Fig. 4, it can be seen that the yield at the third solution is worse than that of the second solution, thus the algorithm stops at the second solution.

The whole process is repeated three times when the lack-of-fit test shows that the first-order model is not a good fit. Then the CCD is employed to fit a second-order model. A two-factor CCD including factorial design, axial points and center points is given in Fig. 5 for illustration purpose. In Fig. 5, the red value denotes the response at each design points. With the use of Canonical analysis and ridge analysis, the optimal solution of the second-order model is located. As shown in Table 6, the verification experiments show that the final solution can enhance the yield to 87.5%, compared to the initial solution that only has10% yield.

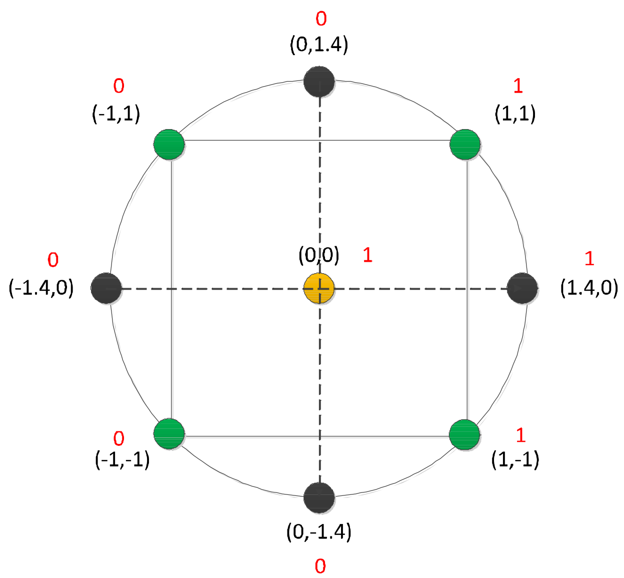

Fig. 5 The central composite design employed in the empirical study

4. Conclusions

This paper proposes a systematic framework integrating RSM and logistic regression to improve the yield of IMD manufacturing process. The integrated framework becomes easy to identify the optimal parameter setting, saving a great deal of time and money in the manufacturing process. The viability of the proposed framework is demonstrated through an empirical study in collaboration with an IMD company. Results show that the proposed framework can significantly enhance the yield from 10% to 87.5%.

Two directions are possible for future research. First, the proposed framework should be modified to handle problems that have categorical factors, in additional categorical response as shown in this paper. The challenge lies in the development of effective screening methods that work for categorical factors. Second, currently the CCD is employed for building the second model. However, CCD can be computationally demanding, especially for large-scale problems. A better experimental design that is more efficient should be investigated.

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