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Optimization of Dimensional Deviations in Wax Patterns for Investment Casting

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Abstract
Investment casting is a versatile manufacturing process to produce high quality parts with high dimensional accuracy. The process begins with the manufacture of wax patterns. The dimensional accuracy of the model affects the quality of the finished part. The present study investigated the control and optimization of dimensional deviations in wax patterns. A mold for an H-shaped wax pattern was designed and fabricated and the two most important dimensional deviations (sink marks and warpage), are investigated. Four process parameters (injection temperature, injection pressure, hold time, cooling time) affecting dimensional deviations of the wax pattern were measured. Using a 2^k factorial DOE technique, 32 experiments were designed to investigate the effect of these parameters on the two main defects in wax patterns. The results show the effect of the parameters on warpage and sink marks (output variables). The relationships between these inputs and the output variables were identified using an artificial neural network. The optimal level of each factor to minimize warpage and sink marks was determined using a multi-objective genetic algorithm. The results of this research can help decrease the time and cost of the process, dimensional deviations, and waste.

Keywords: *dimensional deviations, investment casting, multi-objective genetic algorithm, wax pattern.*

1. Introduction

Investment casting is one of the oldest manufacturing processes. Ancient Egyptians used this method to fabricate bronze statues and jewelry. In this method, the mold is destroyed by the molten metal and is, thus, also known as the lost wax process. This method is used to fabricate highly complex parts with precision. Investment casting is also suitable for producing parts that cannot be accurately produced using machining or forging operations. It is used for a variety of alloys and is appropriate for parts with specific and sensitive applications, such as in aerospace industry, where the parts must operate under extreme conditions [1].

Investment casting is used to fabricate near-net-shape parts of high quality and precision where dimensional accuracy and control of

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dimensional deviations of the finished part is essential. Shrinkage and expansion of the wax pattern, ceramic mold and the cast metal must be controlled to control dimensional deviations in the finished part [2]. Preparation of a wax pattern is the first step of investment casting and strongly affects the quality of the finished part. This quality is achieved when the model is determined to possess high dimensional accuracy and a high-quality finished surface.

The control of the parameters for injection molding significantly affects deviations in the wax pattern. In this respect, injection temperature, pressure, hold time and cooling time are considered to be the most important [3-4].

Optimization of shrinkage and expansion of wax patterns and thermoplastics have been extensively investigated [5-8]. Bisepar [9] studied shrinkage of injection molding of ABS thermoplastics used to manufacture automotive parts. Valtonen et al. [10] experimentally investigated the injection parameters of melt temperature, mold temperature, injection pressure, solidification time and injection time. ANN was then employed to select the best level of each parameter. No previous studies have been found that investigated wax pattern behavior during injection molding for investment casting.

The present study investigated four parameters (injection temperature, pressure, hold time and cooling time) affecting dimensional deviation of a part to optimize injection molding. An artificial neural network (ANN) was trained to determine the relationship between input and output parameters and a genetic algorithm (GA) was used to optimize the process. MATLAB toolbox was used to implement the algorithm.

2. Methods

The model that was designed and fabricated for the present study is based on the design of Yarlagada and Hock [11] as shown in Figure 1. This model offers easy ejection of the part from the mold and effortless distortion of the part as required for testing. The model possesses constrained and non-constrained dimensions with different shrinkage conditions. The model surface is planer-planar and has parallel walls, which facilitate measurement and decrease measurement error. The mold used to manufacture the model is shown in Figure 2.

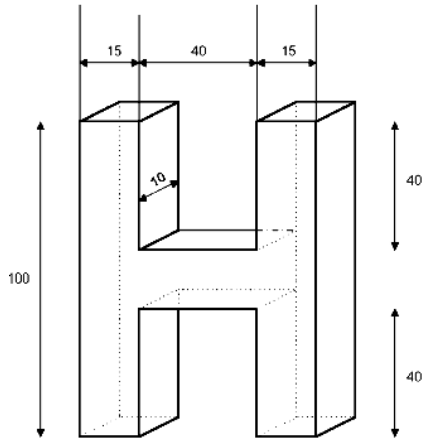

Fig. 1. Design of model for optimization

Fig. 2. Experimental mold

The type and chemical composition of the wax can affect dimensional deviation. The specifications of the wax used in this study are given in Table 1. It should be noted the results of the present testing and analysis are valid only for this type of wax and should be repeated for other types of wax and analysis. A metal mold is required for injection of the molten wax to produce the wax model. Several parameters must be controlled during injection to produce a part without defects with the dimensions required by design specifications. These parameters are injection temperature, pressure, hold time and cooling time. Table 2 shows the variation of these parameters for the present testing. Other injection process parameters were held constant and are shown in Table 3.

Table 1. The specification of the wax

Grade	Filled wax B417
Producer	REMET
Filler Type	Polystyrene
Filler quantity	38% weight
Melting point	75°C
Conglition point	61°C
Viscosity at 80 C°	1000cPa
Penetration in 25 C°	3dmm
Ash content	Max. 0.03% of Weight
Color	Green

Table 2. The significant factors and their levels

Factor	Level			
	I	II	III	IV
A، Injection Temp. (˚C)	60	70	80	
B، Injection Press. (bar)	20	40	60	70
C، Hold time (S)	10	25	40	55
D، Cooling Time (S)	60	120	180	

Table 3. The constant parameters of injection molding process

Factor	Constant value
Injection Press.	50 m/s
Mould Temp.	10±2 ºC
Ambient Temp.	27±2 ºC
Injection Stroke	minimum
Clamp Press.	80 bar
Barrel Temp.	71ºC
Injection Time	1 S

The H-model used in this study had constrained and non-constrained parts. Testing showed that parts underwent two types of dimensional deviation. In one, the end parts of the wing were distorted and displaced toward each other. In another, the surfaces of the parts show evidence of substantial sinking. These deviations can be observed in Figure 3. After determining the critical areas undergoing deviation, the areas of the defects were measured and are shown in Figure 4. Area 1 shows the wing distortion inward and area 2 show the sink marks.

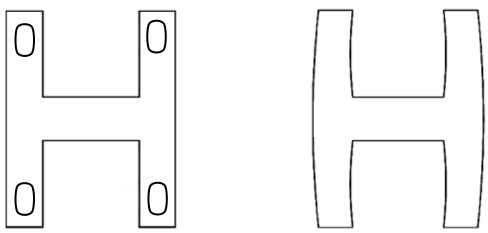

Fig. 3. Warpage and sink marks of test parts

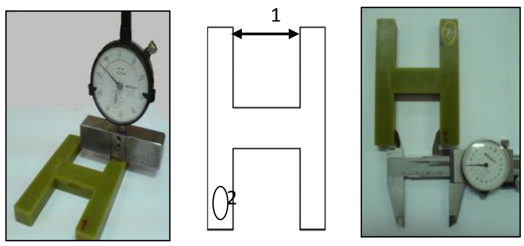

Fig. 4. Positions and areas of defects

2.1. Modeling injection wax

Classic statistical and mathematical modeling is not appropriate for predicting the behavior of wax during injection and determining the dimensional deviation of the wax pattern because of the complex and nonlinear relations between inputs and outputs. An artificial neural network (ANN) can efficiently model complex phenomena and was used in the present study. The ANN was trained using experimental data to determine the relationship between input injection parameters and distortion and sink marks as outputs. To train and test the ANN, a number of experiments were carried out to gather sufficient data to determine the levels of the parameters. Design of experiment (DOE) techniques were used for the experiments using a (3×4×4×3) full factorial approach that produced a total of 144 tests.

A two-layer ANN with a hidden layer using a sigmoid function for neurons was adopted. The linear conversion function for output and input layers is a powerful architecture that can be used for regression [12]. A perceptron ANN with feed forward back propagation was employed and is shown in Figure 5. The hidden layer consists of 25 neurons; there are four neurons in the input layer and two neurons in the output layer.

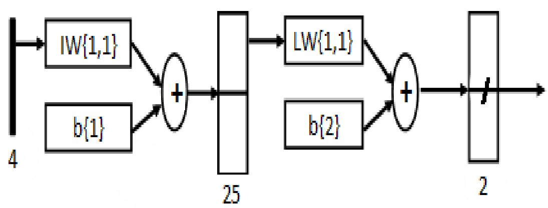

Fig. 5. Architecture of ANN

The network used the tansig function in the hidden layer and purelin linear function in the output layer. A Bayesian regularization function was used to train the ANN. Out of 144 tests, 15 experimental data-sets are used for testing and 15 sets of data for validation of the ANN. The convergence of the ANN after training is shown in Figure 6.

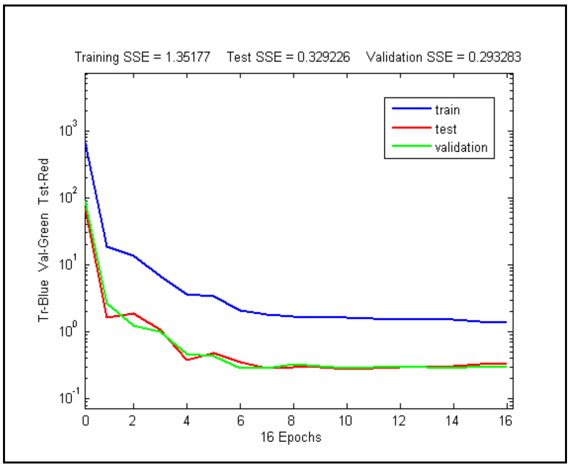

Fig. 6. Convergence of ANN

To verify performance of the ANN, the test data were introduced and the network output and error pertaining to the data were recorded. The average percentage of error for the two output sets was 12.5%. This error figure lies within an acceptable range and indicates the validity and accuracy of the model for predicting the relationship between input and output.

2.2. Parameter Optimization

The ANN was used to find a mathematical relation between input parameters and 2D deviations that show adequate accuracy. An evolutionary algorithm was applied to find the optimum level of parameters required to minimize the dimensional deviations. Injection temperature and pressure, hold time and cooling time were monitored to produce a wax pattern with minimal warpage and sink marks.

Genetic algorithms (GAs) are inspired by biological evolutionary processes that function by natural selection. A GA follows function evaluator, selection and reproduction stages. Determining the optimal parameter set is a multi-objective optimization (MOO) problem because the 2D deviations vary independently and their minimum values do not inevitably occur simultaneously. A MOO algorithm must be used if the process designer must control each individual dimensional deviation in the final pattern.

In contrast to single-objective optimization, the solution to a multi-objective problem is more of a concept than a definition. There is no single global solution and it is often necessary to determine a set of points that all fit a predetermined definition for an optimum. The predominant concept for defining an optimal point is Pareto optimality, as suggested by Pareto (1906). A point, $x \in X$, is Pareto optimal if no other point $x' \in X$ exists such that $F(x) \leq F(x')$, and $F_i(x) < F_i(x')$ for at least one function. For any given problem, there can be an infinite number of Pareto optimal points constituting the Pareto front.

A promising MOO algorithm is the multi-objective GA (MOGA). Several variations of this algorithm have been reported, of which the non-dominated sorting genetic algorithm II (NSGA II) developed by Deb et al. [13] is the most successful for a range of engineering applications. Since the aim of a MOGA search is to locate Pareto-optimal solutions, the MOO problem must be treated as a multi-modal problem. This means that the use of additional genetic operators, such as fitness-sharing and mating restrictions to locate all the peaks and valleys of the function is also required.

For the use of an ANN as a function evaluator, the MOGA uses a population size of 30, a two-point crossover rate of 0.9, a uniform mutation probability of 0.1, and the maximum number of generations as 40. Values for the decision variables and function values for the 30 Pareto optimal points are presented in Figure 7. These are all non-dominated solutions where an improvement in the value of one objectives, say warpage value, results in deterioration of another objective and vice versa.

From Figure 7 it is clear that the algorithm successfully determined optimum values in the search space of each function for the range of variation of each function.

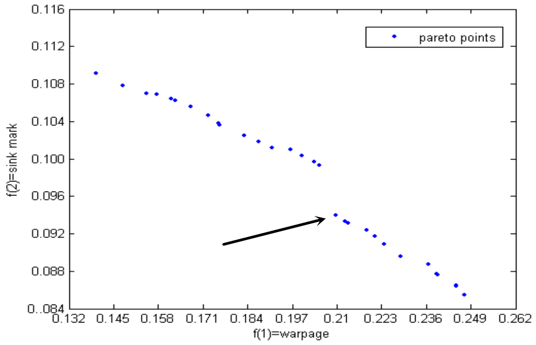

Fig. 7. Pareto front

2.3. Validation

After determining the Pareto points, the results should be validated. One point was selected for experimentation from the 30 Pareto points. Each objective function for this point must benefit from a mid-level optimum as shown in Table 4. Ten validation experiments were performed. Figures 8 and 9 show that the results from MOGA and testing are in agreement. Tables 5 and 6 give the error for each output variable.

Table 4. The conditions of the Pareto point selected for validation experiments

Factor	value
Injection Press. (bar)	64.5
Injection Temp. (ºC)	73
Hold Time (S)	42
Cooling Time (S)	135
Warpage (mm)	0.206
Sinkmark (mm)	0.094

Table 5. MOGA and Experimental results for sinkmark

Experiment No.	MOGA Results (mm)	Exp. Results (mm)	Error (%)
1	0.094	0.10	6
2		0.09	4.4
3		0.11	14.5
4		0.08	17.5
5		0.10	6
6		0.09	4.4
7		0.09	4.4
8		0.11	14.5
9		0.09	4.4
10		0.11	14.5
Average	0.094	$\bar{X}$ =0.097	9.1

Table 6. MOGA and Experimental results for warpage

Experiment No.	MOGA Results (mm)	Exp. Results (mm)	Error (%)
1	0.206	0.23	10.4
2		0.25	17.6
3		0.18	14.4
4		0.2	3
5		0.22	6.3
6		0.2	3
7		0.19	8.4
8		0.21	1.9
9		0.91	8.4
10		0.21	1.9
Average	0.206	$\bar{X}$ =0.208	7.5

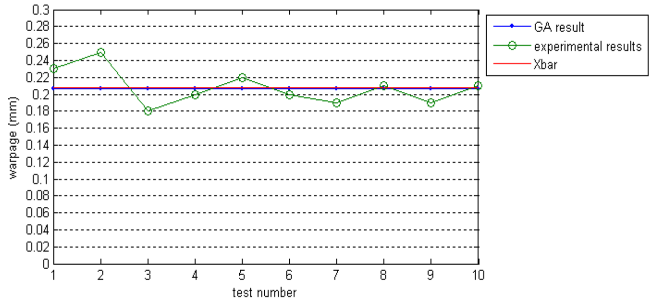

Fig. 8. Results of warpage of MOGA and testing

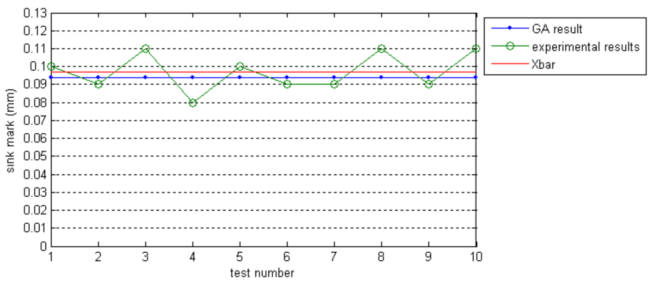

Fig. 9. Results of sink mark from MOGA and testing

For the selected Pareto point, the value of warpage was 0.206 mm and for sink marks was 0.094 mm. The average error between the experimental and MOGA results was 9.1% for warpage and 7.5% for sink marks, which shows the validity of the optimum values found. Table 7 shows the average values for warpage and sink marks prior to and after optimization. The results indicate a decrease in warpage and sink marks of 41% and 52%, respectively, after optimization. This is a significant improvement in the process. It can be said that MOGA helped determine the optimum set of process parameters in the search space and strongly decreased the incidence of defects.

Table 7. Optimized versus non-optimized values for warpage and sinkmark

	Prior to Optimization	Optimized value (mm)	Improvement (%)
Warpage	0.351	0.208	41
Sink	0.201	0.094	53

3. Summary and Conclusion

This study used a hybrid system comprising an ANN and a GA to optimize the process parameters for injection of wax patterns used for investment casting. DOE was used to design a set of experiments to generate results for training the ANN. The optimum set of parameters for minimum warpage and sink marks significantly decreased the level of defects. A pattern was produced that was closer to design specifications and allowed fabrication of a ceramic mold that improved the quality of the parts. The results of this research can be used to decrease manufacturing lead time, waste, and production costs. The methodology can be adopted by manufacturing companies for investment casting, especially for producers of turbine blades.

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