International Journal of Mechanical Engineering and Robotics Research

ISSN 2278 – 0149 www.ijmerr.com
Vol. 2, No. 1, January 2013


*Research Paper*

# INVESTMENT CASTING PROCESS USING FUZZY LOGIC MODELLING

**Renish M Vekariya[1]* and Rakesh P Ravani[1]**

*Corresponding Author: **Renish M Vekariya,** ✉ renishvekariya@yahoo.com

The investment casting process involves the production of engineering castings using an expendable pattern such as wax. As it is growing in size and complexity, its properties need to be controlled. However, the quality of the final casting mainly depends on the quality of wax pattern and ceramic shell. This study highlights the application of a fuzzy logic analysis in combination with Taguchi's design of experiments for prediction of quality of wax patterns in terms of linear shrinkage, surface roughness and penetration in the investment casting process. Trial experiments were conducted to confirm this approach. It has been found that the method of fuzzy logic controller modeling not only simulates the operating experiments from parametric design strategy, but also demonstrates a simple, effective, and efficient way in developing a robust quality in the product.

***Keywords:*** Wax pattern, Investment casting, Taguchi design, Fuzzy logic, Fuzzy rules

## INTRODUCTION

Metal casting is an important component of industrial production. It is usually applied to manufacture near net shape components. At present, the concept of direct/ net shape manufacturing is gaining much importance in the context of lead-time and cost reduction (Campbell, 2000). Precision casting methods such as investment casting and pressure die casting enable manufacture of near net shape parts. Investment Casting (IC), which was referred as lost wax process in the ancient years, is currently regarded as precision casting next to pressure die casting. Until mid eighties, its application in engineering component development was not significant; in fact sand casting is highly used metal casting process even today. However, in the present scenario, investment-casting application has rapidly increased specifically for near net shape manufacturing of complex and small engineering components (Beeley and Smart, 1995).

[1] Department of Mechanical Engineering, Rajkot, Gujarat, India.

The major steps in investment casting process are: injection molding of a wax pattern, ceramic shell building, dewaxing, drying, and casting (Kalpakjian and Schmid, 2008). Wax, plastic, polystyrene or frozen mercury may be used as pattern material. Wax is the most widely used pattern material for investment casting process (Wood, 1952). However, accuracy of investment casting depends on many factors like: pattern shrinkage, metal shrinkage, pattern distortion, size, shape, tree construction, gating, and expansion of ceramic shell during dewaxing and sintering. Many industries and few researchers have established these values through their experience (Nagahanumaiah *et al.*, 2003).

The accuracy of the wax patterns used in the investment casting process has a direct bearing on the accuracy achievable in the final cast part. It is essential to understand the relationship among the various controllable parameters and then the important parameters have to be identified that influence the quality of the wax pattern. Rezavand *et al.* (2007) found that in the injection step, the final dimensions of wax pattern were affected by the type of wax used, geometry of the pattern to be produced and injection process parameters chosen. Bonilla *et al.* (2001) used computer-aided heat transfer simulation to predict wax pattern shrinkages in the investment casting process. Sabau and Viswanathan (2003) determined the wax pattern dimensions from the wax's thermophysical and thermomechanical properties. The data provided in their study can be used in computer models for the numerical simulation of stress, strain, and displacement fields, and final wax pattern dimensions.

From the literature stated above, it is clear that many studies have been done by various researchers in predicting shrinkage of wax patterns in the IC process. It is desirable that the wax pattern should possess properties like least shrinkage, surface roughness and penetration. But till now, no studies have been done regarding modeling of injection process parameters in making wax patterns by the IC process that would predict the quality characteristics such as shrinkage, surface roughness and penetration, etc. beforehand.

Fuzzy reasoning is one of the powerful tools that have been used in modeling and controlling uncertain multi-criteria decision making tasks. It is based on the idea to find out a set of relations between inputs and outputs describing a process. So, the method of Fuzzy modeling expresses a nonlinear process better than any existing methods (Khrais *et al.*, 2011). Many researchers have adopted fuzzy logic techniques in their decision making problems. Park and Cho (2005) developed a fuzzy logic controller for predicting the molten steel level control of strip casting processes. Lan (2010) proposed a general optimization scheme using orthogonal array fuzzy linguistic approach to the surface roughness for CNC turning process. Hsiang *et al.* (2010) investigated the optimal process parameters that maximized Multiple Performance Characteristics Index (MPCI) for hot extrusion of AZ31 and AZ61 magnesium alloy bicycle carriers by using fuzzy-base Taguchi method. So, in the present study an attempt has been made to develop a fuzzy logic controller for prediction of quality of wax patterns with a given set of injection process parameters like injection temperature, injection pressure and holding time. It was found that the predicted and measured values are fairly close to each other. Their proximity to each other indicates that the fuzzy modelling can be effectively used to predict the quality of the wax patterns used in the investment casting process.

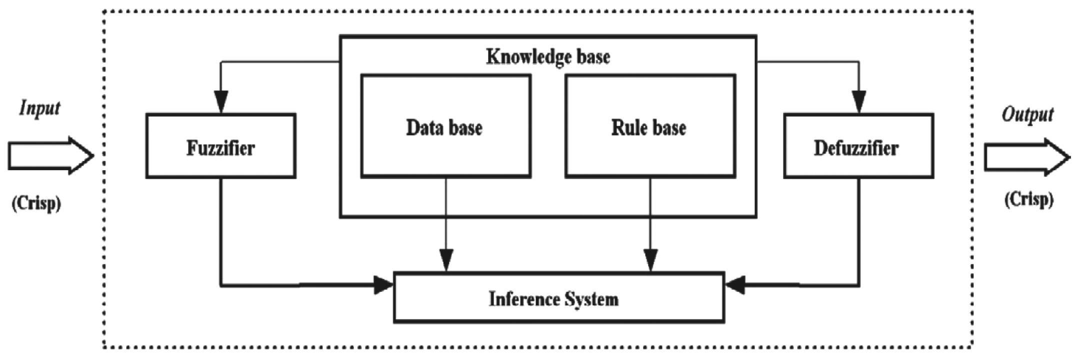
## OVERVIEW OF FUZZY LOGIC

Fuzzy Logic (FL) is one of the elements of artificial intelligence that is gaining popularity in the recent years. It was introduced in the 1930's by Jan Lukasiewicz (Xu, 2008) Fuzzy expert system based on fuzzy set theory was introduced by Zadeh (1965) as a new way to represent vagueness in everyday life. It is based on the observation that people make decisions based on imprecise and numerical information.

### Fuzzy Logic

Fuzzy models or sets are mathematical means of representing vagueness and imprecise information, accordingly the term used is fuzzy (Ravi, 2005). These models have the capability of recognizing, representing, manipulating, interpreting and utilizing data and information that are vague and lack certainty. In order to be in agreement with the real system, the fuzzy systems work on the concept of vagueness through a set of rules called the rule base, knowledge that is often available in only a heuristic form is characteristically represented and formalized in the computer programs as a set of crisp and/or fuzzy if-then rules, i.e. rules having a condition and an action component, that are then executed in parallel. Consequently, both rule based expert systems and fuzzy logic are especially applicable when a relatively comprehensive understanding of the process is available and an exact mathematical model of the process is either impossible or prohibitively expensive to develop (Juneja *et al.*, 2010). The main structure of a fuzzy rule based system is the fuzzy algorithm the fundamental concepts of which are derived from fuzzy logic (Zadeh, 1976). In general, the rule-based system is an expert knowledge-based system that contains the fuzzy algorithm in a simple rule base. The knowledge programmed in the rule base is derived from the human experience and perception. The rules represent the relationship between the inputs and the outputs of the system. The generalized structure of a fuzzy system is given by Mahapatra *et al.* (2011) and is shown in Figure 1.

**Figure 1: Structure of Fuzzy Rule Based System**



## Fuzzy Logic Controller

A fuzzy logic controller comprises of four parts: Fuzzifier, knowledge base, inference engine and defuzzifier (Mendel, 1995).

### Fuzzifier

The real world input to the fuzzy system is applied to the fuzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier converts this precise quantity into a form of imprecise quantity like large, medium, high, etc., with a degree of belongingness to it. Typically the value ranges from 0 to 1.

### Knowledge Base

The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules where as the rule base contains a number of fuzzy IF-THEN rules.

### Inference Engine

The inference system or the decision making input perform the inference operations on the rules. It handles the way in which the rules are combined.

### Defuzzifier

The output generated by the inference block is always fuzzy in nature. A real world system will always require the outputs of the fuzzy system in terms of crisp and measurable values. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

Fuzzy modeling and approximation are the most interesting fields where fuzzy theory can be effectively applied. When fuzzy modeling and approximation is applied to an industrial process, one of the key problems to be solved is to find fuzzy rules.

## Fuzzy Inference Methods

In general, two most popular fuzzy inference systems are available: Mamdani fuzzy model and Sugeno fuzzy model. The selection depends on the fuzzy reasoning and formulation of fuzzy IF-THEN rules. The most commonly known and used fuzzy inference methodology is Mamdani fuzzy model. It is based on the collection of IF-THEN rules with both fuzzy antecedent and consequent parameters (Mamdani and Assilia, 1975). The benefit of this model is that the rule base is generally provided by an expert and hence to a certain degree it is translucent to explanation and study. Sugeno fuzzy model is similar to the Mamdani method in many respects (Sugeno, 1985). The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

# EXPERIMENTAL WORK

In this work, a wax blend was produced by mixing 25% of paraffin wax, 5% of carnauba wax, 35% of microcrystalline wax, 12% of polyethylene wax and 23% of starch. All these ingredients were melted in a steel container with constant agitation in order to get homogenous melt. The molten wax blend made was poured in the vacuum wax injection machine and cylindrical wax patterns with fins were made using the silicon rubber mould, as shown in Figure 2.

**Figure 2: Silicon Rubber Mould**

The ranges of the selected process parameters were decided by conducting the experiments with one variable at a time approach. The process parameters, their designed symbols and ranges are given in Table 1. The response parameters in the present study are Linear Shrinkage (LS) in percent, Surface Roughness (SR) in nm and penetration hardness (P) in mm. Linear shrinkage, surface roughness and penetration were measured by using digital vernier calipers, surface profilometer and penetrometer respectively.

The primary experiments, comprised of 18 test trials, were designed based on the L18

**Table 1: Process Parameters and Their Values at Different Levels**

| Symbol | Process Parameters | Range | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|---|
| A | Injection Temperature | 70-80 (°C) | 70 | 75 | 80 |
| B | Injection Pressure | 0.5-0.7 (kg/cm$^2$) | 0.5 | 0.6 | 0.7 |
| C | Holding Time | 40-50 min | 40 | 45 | 50 |

**Table 2: L18 Orthogonal Array Used in the Primary Experiments**

| Trial No. | A | B | C | LS | SR | P |
|---|---|---|---|---|---|---|
| 1 | 70 | 0.5 | 40 | 2.920 | 67.4601 | 3.333 |
| 2 | 70 | 0.6 | 45 | 2.233 | 66.6954 | 2.667 |
| 3 | 70 | 0.7 | 50 | 1.445 | 71.6789 | 2 |
| 4 | 75 | 0.5 | 40 | 3.128 | 59.6365 | 4 |
| 5 | 75 | 0.6 | 45 | 2.355 | 60.0690 | 3 |
| 6 | 75 | 0.7 | 50 | 1.650 | 68.9224 | 2.333 |
| 7 | 80 | 0.5 | 45 | 3.200 | 63.9784 | 4 |
| 8 | 80 | 0.6 | 50 | 2.482 | 62.6494 | 3 |
| 9 | 80 | 0.7 | 40 | 2.889 | 52.9606 | 3.333 |
| 10 | 70 | 0.5 | 50 | 1.987 | 73.6743 | 2.333 |
| 11 | 70 | 0.6 | 40 | 2.295 | 65.4230 | 2.667 |
| 12 | 70 | 0.7 | 45 | 1.517 | 66.7417 | 2.333 |
| 13 | 75 | 0.5 | 45 | 2.735 | 62.3713 | 3.333 |
| 14 | 75 | 0.6 | 50 | 2.350 | 71.5792 | 3 |
| 15 | 75 | 0.7 | 40 | 2.333 | 58.5907 | 2.667 |
| 16 | 80 | 0.5 | 50 | 3.090 | 65.1735 | 3.667 |
| 17 | 80 | 0.6 | 40 | 2.920 | 53.8591 | 3.667 |
| 18 | 80 | 0.7 | 45 | 2.830 | 53.9163 | 3.333 |

orthogonal array. Shorter arrays would be too simple and would not produce enough data to properly analyze the process and longer arrays would complicate the experimental process. Hence, L18 orthogonal array was chosen. The assigned L18 orthogonal array with their responses is shown in Table 2. To consider the three different performance characteristics in the Taguchi method, the corresponding values of the LS, SR and MRR are processed by the fuzzy logic unit.

## FUZZY LOGIC MODELLING

In this work, a fuzzy-controller has been developed with three inputs and three outputs. Three input variables are Injection Temperature (IT), Injection Pressure (IP) and Holding Time (HT). Three output variables are Linear Shrinkage (LS), Surface Roughness (SR) and penetration hardness (P). Mamdani fuzzy "if-then" rule has been adopted to make the fuzzy rule base and Mamdani implication method has been used to perform inference of max-min operation. The defuzzifier uses center of gravity method to convert fuzzy data to crisp response values. Fuzzy division was performed on input and output variables by using triangular membership functions. Each input variable has three set levels, which are

**Figure 3: Block Diagram of Fuzzy-Controller**

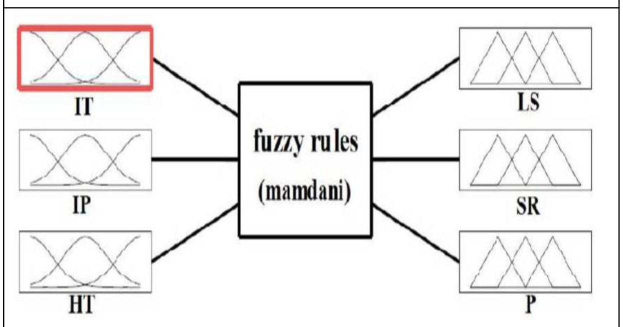



**Figure 4: Membership Function of Input Variables (a) Injection Temperature, (b) Injection Pressure, and (c) Holding Time**

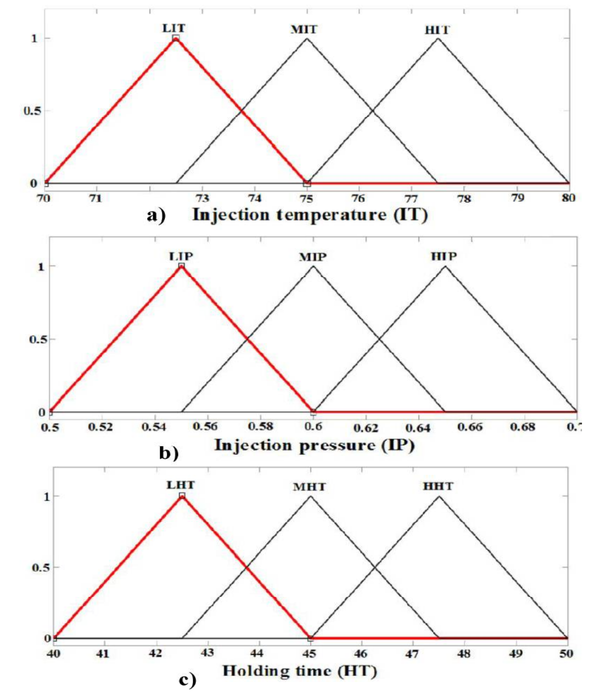



**Figure 5: Membership Function of Output Variables (a) Linear Shrinkage, (b) Surface Roughness, and (c) Penetration**

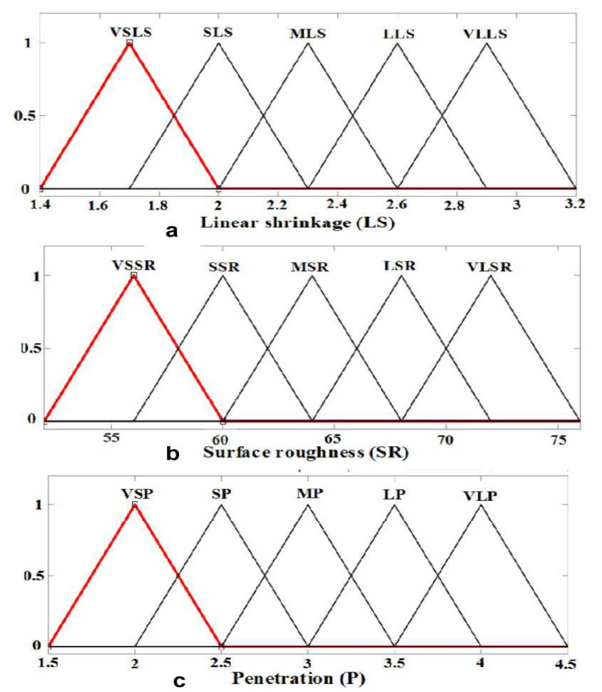


**Table 3: Input-Output and Fuzzy Intervals**

| S. No. | System's Linguistic Variable | | Linguistic Values | Fuzzy Interval (Min-Average-Max) |
|---|---|---|---|---|
| 1. | Inputs | Injection Temperature (°C) | Low | 70-72.5-75 |
| | | | Medium | 72.5-75-77.5 |
| | | | High | 75-77.5-80 |
| | | Injection Pressure (kg/cm$^2$) | Low | 0.5-0.55-0.6 |
| | | | Medium | 0.55-0.6-0.65 |
| | | | High | 0.6-0.65-0.7 |
| | | Holding Time (min) | Low | 40-42.5-45 |
| | | | Medium | 42.5-45-47.5 |
| | | | High | 45-47.5-50 |
| 2. | Outputs | Linear Shrinkage (%) | Very Small | 1.4-1.7-2 |
| | | | Small | 1.7-2-2.3 |
| | | | Medium | 2-2.3-2.6 |
| | | | Large | 2.3-2.6-2.9 |
| | | | Very Large | 2.6-2.9-3.2 |
| | | Surface Roughness (nm) | Very Small | 52-56-60 |
| | | | Small | 56-60-64 |
| | | | Medium | 60-64-68 |
| | | | Large | 64-68-72 |
| | | | Very Large | 68-72-76 |
| | | Penetration (mm) | Very Small | 1.5-2-2.5 |
| | | | Small | 2-2.5-3 |
| | | | Medium | 2.5-3-3.5 |
| | | | Large | 3-3.5-4 |
| | | | Very Large | 3.5-4-4.5 |

Low (L), Medium (M) and High (H). Each output variable has five set levels, which are Very-Small (VS), Small (S), Medium (M), Large (L) and Very-Large (VL). Figure 3 describes the block diagram of fuzzy-controller, which has been developed using MATLAB software. Figure 4 and Figure 5 refer to membership function of the three inputs and the three outputs. The fuzzy intervals for inputs and outputs are shown in Table 3.

A set of fuzzy rules have been constructed for predicting the responses namely, linear shrinkage, surface roughness and penetration of the wax patterns in IC process. These rules are based on the actual experimental results found with given set of inputs. By taking the max-min compositional operation, the fuzzy reasoning of these rules yields a non-fuzzy output as shown in Figure 6.

**Figure 6: Fuzzy Inputs and Prediction of Outputs**

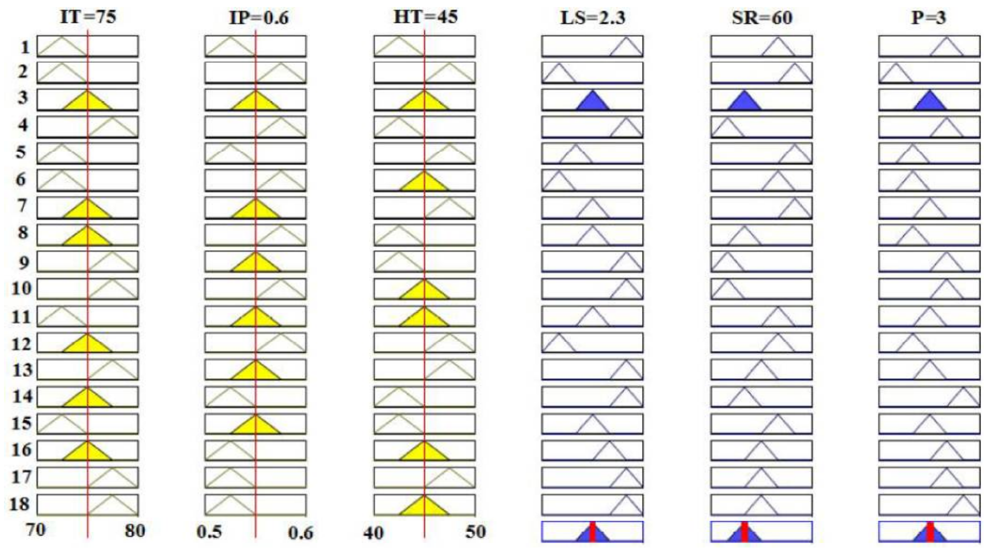



**Table 4: Comparison of Results Between the Actual and the Predicted Values**

| S. No. | Injection Process Parameters | | | Experimental Values | | | Fuzzy Predicted Values | | | % Error | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IT | IP | HT | LS | SR | P | LS | SR | P | LS | SR | P |
| 1. | 77 | 0.5 | 46 | 2.471 | 68.91 | 2.67 | 2.68 | 65.5 | 3.00 | 7.80 | –5.21 | 11.00 |
| 2. | 72 | 0.6 | 50 | 1.890 | 66.70 | 2.33 | 1.71 | 71.9 | 2.01 | –10.53 | 7.23 | –15.92 |
| 3. | 73 | 0.7 | 45 | 1.550 | 62.48 | 2.33 | 1.70 | 68.0 | 2.50 | 8.82 | 8.11 | 6.80 |

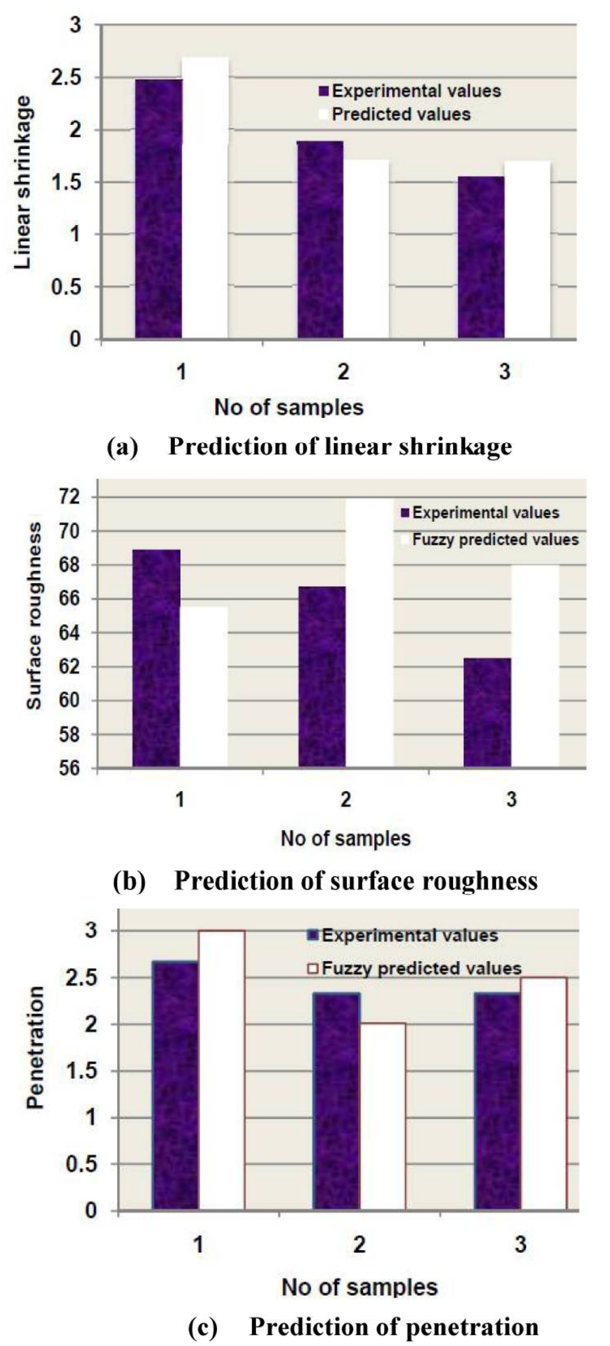
## VALIDATION OF FUZZY PREDICTION

Three experiments were conducted with different combinations of the input process parameters which were not included in the training set (randomly selected). The corresponding experimental responses were measured and listed in Table 4. The response values were again obtained from the fuzzy controller for the same set of input process parameters. Then, the percentage of error was calculated to know the extent by which the fuzzy controller is working. Graph is plotted between the experimental and the predicted results from the Mamdani fuzzy model, as shown in Figure 7.

## DISCUSSION

In this work, a fuzzy logic controller using Taguchi orthogonal design has been developed to predict the quality characteristics namely, linear shrinkage, surface roughness and penetration of wax patterns in the IC process. Prediction results suggest that Mamdani inference method predictions are satisfactory. Inference was based on maximum error calculated. So, it has been proved to be an effective and powerful tool for improving the quality and reliability of the entire process. The predicted values of fuzzy output can be further precisely predicted by increasing the number of experiments. It can also be used for optimization of multiple performance quality

**Figure 7: Experimental vs Fuzzy Predicted Values of (a) Linear Shrinkage, (b) Surface Roughness, and (c) Penetration**




characteristics. The present work can be extended to forecast other responses such as coefficient of thermal expansion, tensile strength of wax patterns, etc., with different process parameters and pattern materials, to test the ability of the expert systems in prediction of the outputs.

## CONCLUSION

The conclusions resulting from the present study are summarized as follows:

- Mandany-Fuzzy inference system has shown the capability of generalization and prediction of pattern characteristics such as linear shrinkage, surface roughness and penetration of the wax patterns in IC process within the range of experimental data.
- The maximum deviations between experimental and fuzzy predicted values are minimal.
- In the industries, the experience of a skilled worker can be replaced by a set of fuzzy rules which may lead to improvement in forecasting ability of the process.
- The methodology can be helpful for automation of the process.

## REFERENCES

1. Beeley P R and Smart R F (1995), *Investment Casting*, Institute of Materials, London, UK.
2. Bonilla W, Masood S H and Iovenitti P (2001), "An Investigation of Wax Patterns for Accuracy Improvement in Investment Cast Parts", *International Journal of Advanced Manufacturing Technology*, Vol. 18, pp. 348-356.
3. Campbell J (2000), "The Concept of Net Shape for Casting", *Materials and Design*, Vol. 21, pp. 373-380.

4. Hsiang S H, Lin Y W and Lai J W (2010), "Application of Fuzzy-Based Taguchi Method to the Optimization of Extrusion of Magnesium Alloy Bicycle Carriers", *Journal of Intelligent Manufacturing*.
5. Juneja P K, Ray A K and Mitra R (2010), "Fuzzy Control and Neural Network Control of Limekiln Process", *International Journal of Electronics Engineering*, Vol. 2, No. 2, pp. 305-306.
6. Kalpakjian S and Schmid S (2008), *Manufacturing Processes for Engineering Materials*, Pearson Education Incorporation, New Jersey.
7. Khrais S, Al-Hawari T and Al-Araidah O (2011), "A Fuzzy Logic Application for Selecting Layered Manufacturing Techniques", *Expert Systems with Applications*, Vol. 38, pp. 10286-10291.
8. Lan T S (2010), "Fuzzy Linguistic Optimization on Surface Roughness for CNC Turning", *Mathematical Problems in Engineering*, pp. 1-10, Hindawi Publishing Corporation.
9. Mahapatra S S, Nanda S K and Panigrahy B K (2011), "A Cascaded Fuzzy Inference System for Indian River Water Quality Prediction", *Advances in Engineering Software*, Vol. 42, pp. 787-796.
10. Mamdani E H and Assilia S (1975), "An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller", *International Journal of Man-Machine Studies*, Vol. 7, pp. 1-13.
11. Mendel J M (1995), "Fuzzy Logic Systems for Engineering: A Tutorial", *IEEE Proceedings*, Vol. 83, pp. 345-377.
12. Nagahanumaiah, Ravi B and Mukherjee N P (2003), "Tool Path Planning for Investment Casting of Functional Prototypes/Production Molds", *National Conference on Investment Casting*, CMERI, Durgapur.
13. Park Y and Cho H (2005), "A Fuzzy Logic Controller for the Molten Steel Level Control of Strip Casting Processes", *Control Engineering Practice*, Vol. 13, pp. 821-834.
14. Ravi B (2005), "Metal Casting Computer Aided Design and Analysis", Printice Hall of India, New Delhi, India.
15. Rezavand S A M and Behravesh A H (2007), "An Experimental Investigation on Dimensional Stability of Injected Wax Patterns of Gas Turbine Blades", *Journal of Material Processing and Technology*, Vol. 182, pp. 580-587.
16. Sabau A S and Viswanathan S (2003), "Material Properties for Predicting Wax Pattern Dimensions in Investment Casting", *Materials Science and Engineering*, Vol. 62, pp. 125-134.
17. Wood R L (1952), "Investment Castings for Engineers", Reinhold Publishing Corporation, New York.
18. Xu D (2008), "Applications of Fuzzy Logic in Bioinformatics", Imperial College Press, London, UK.
19. Zadeh L A (1965), "Fuzzy Sets", *Information and Control*, Vol. 8, pp. 338-353.
20. Zadeh L A (1976), "A Fuzzy-Algorithm Approach to the Definition of Complex or Imprecise Concepts", *International Journal of Man-Machine Studies*, Vol. 8, pp. 249-261.