Chapter 39
To Predict Surface Roughness and Linear Shrinkage of Die Casting Process by Using of Fuzzy Algorithm Model

Narendra Krishania and Anil Kumar Birru

Abstract This research paper narrates a manually constructed Mamdani based on fuzzy algorithm model for envisaging surface roughness and linear shrinkage of die casting, so that defects can be refrained from the casting in terms of surface finish and dimensions. A set of rules established by the help of mathematical model have been used to derive two fuzzy controllers which are being used in this process. With the help of this fuzzy algorithm, high production rate and high quality of products can be obtained by controlling process parameters. Confirmation experiments reveal that these fuzzy logics are able to attain optimum grouping of the process parameters. Hence, the quality of casted products in die casting process can be improved to a greater extent by this approach. The predicted surface roughness and linear shrinkage by this model had an error of only 3.55 and 6.02%, respectively, which was confirmed by checking the validity of the model developed by performing confirmation experiments. This proposed model can be reasonably utilized by the industries involved in die casting around the world to increase the overall effectiveness of the process and product.

Keywords Fuzzy logic · Orthogonal array · Surface roughness · Linear shrinkage

39.1 Introduction

Metal casting is a vital part of industrial production. It is generally used to develop near net shape component. Nowadays, the theory of direct/net shape manufacturing is attaining great importance in terms of lead time and cost reduction [1].

The die casting is an economical and efficient method offering a wide range of shapes than any other process. During manufacturing a metal part, the shapes of the

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metals depend upon the injection temperature and liquid level. Die casting parameters like injection temperature, moisture level, injection pressure, and liquid level by using embedded controller. In the conventional system, the die casting parameters are measured by manual. The process of die casting involves five main stages which are clamping, injection, cooling, ejection, trimming. Basically, non-ferrous alloys are die casted like alloys of aluminium, alloys of copper, alloys of magnesium, and alloys of zinc. Die casting machines used are of two types—one is hot chamber machine (alloys with low melting temperature are die casted like zinc) and cold chamber machine (alloys with high melting temperature are die casted, like aluminium). Several engine components and pump components are manufactured using die casting.

Accuracy of die casting is affected by many factors like injection pressure too high, injection temperature too high, cooling time too short, low pouring temperature, clamp force too low, ejection force too high, non-uniform cooling rate.

To recognize the significant controllable process parameters which influence the quality of the casted products, it is essential to understand and find out the relationship among these controllable process parameters and quality of the casted products. The selection of the suitable process parameters for making qualitative casted products is one of the primary challenges in casting industry. It is very difficult to set appropriate process parameters with consideration of multiple performance characteristics and to depend on large amount of experimental operations. Therefore, it is important to effectively obtain the optimal process parameters to reduce trial and error time and consuming cost in the casting process [2].

Fuzzy reasoning is one of the prevailing tools which is used for modelling and governing undefined multi-criterion conclusion-making problems. It is grounded on the notion to obtain a set of association between inputs and outputs describing a procedure. So, the technique of fuzzy modelling conveys a nonlinear course better than several existing process [3]. Fuzzy logic techniques have been implemented by a number of researchers in their conclusion-making glitches. A fuzzy logic controller for forecasting the level regulator of molten steel in strip casting methods was created by Park and Cho [4]. With the aid of orthogonal array fuzzy linguistic approach, a general optimization system was implemented in the CNC turning operation for surface by Lan [5]. With the help of fuzzy-based Taguchi technique, Hsiang et al. [6] discovered the optimal process parameters that were maximizing the multiple performance characteristic index (MPCI) for hot extrusion of AZ31 and AZ61 magnesium alloy bicycle carriers [7, 8]. So, in the present study an effort has been made to create fuzzy logic controllers for estimation of quality of casting products with some provided set of process parameters like injection temperature, injection pressure, and time. It was originated that the predicted and measured values are in close proximity [9–12]. The closeness of results implies that the fuzzy modelling technique is efficient to estimate the quality of the patterns used for die casting.

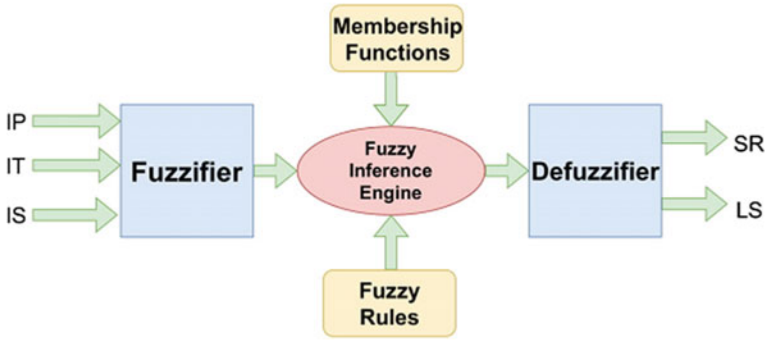

Fig. 39.1 Structure of three inputs two outputs' fuzzy logic

39.1.1 Fuzzy Logic Overview

Mamdani method is the most used fuzzy inference. Initially, one of the first fuzzy processes to regulate a steam engine and boiler was developed by Mamdani and Assilia in [13–15]. A fuzzy logic arrangement consisting of three inputs and two outputs is developed for this study which is shown in Fig. 39.1 [16]. Following steps are followed to execute Mamdani fuzzy inference:

(a) fuzzification of the input variables,
(b) rule output are evaluated and aggregated, and
(c) defuzzification.

Mamdani fuzzy rule is described as:

$$\text{Rule 1: If } y_1 \text{ is } M_1,\ y_2 \text{ is } N_1 \text{ and } y_3 \text{ is } O_1 \text{ then } z_1 \text{ is } P_1 \text{ and } z_2 \text{ is } Q_1 \text{ else}$$
$$\text{Rule 2: If } y_1 \text{ is } M_2,\ y_2 \text{ is } N_2 \text{ and } y_3 \text{ is } O_2 \text{ then } z_1 \text{ is } P_2 \text{ and } z_2 \text{ is } Q_2 \text{ else}$$
$$\text{Rule } n\text{: If } y_1 \text{ is } M_n,\ y_2 \text{ is } N_n \text{ and } y_3 \text{ is } O_n \text{ then } z_1 \text{ is } P_n \text{ and } z_2 \text{ is } Q_n \text{ else}$$

where M_i, N_i, O_i, P_i, and Q_i are termed as fuzzy subsets which are described by the analogous membership function [17–20].

39.2 Experimental Work

By performing the experiment with single variable at a time approach, the span of the particular process parameters is determined. The designed symbols and ranges of the process parameters are provided in Table 39.1. In the present study, the response parameters considered are surface roughness (SR) in μm and linear shrinkage (LS) in percentage.

Table 39.1 Factors and levels used in the experiments

Factor	Description	Unit	Range	Level 1	Level 2	Level 3
A	Pouring temperature	°C	650–750	650	700	750
B	Injector pressure	Bar	120–240	120	180	240
C	Plunger velocity	m/s	1.2–3.8	1.2	2.5	3.8

Table 39.2 L_9 orthogonal array used in the primary experiments

Experiment no.	A	B	C	SR	LS
1	650	120	1.2	48.5541	1.412
2	650	180	2.5	55.8354	1.384
3	650	240	3.8	63.0352	1.204
4	700	120	1.2	58.2841	2.974
5	700	180	2.5	65.3251	2.575
6	700	240	3.8	73.7327	2.045
7	750	120	1.2	61.0512	3.715
8	750	180	2.5	66.0263	3.315
9	750	240	3.8	75.1121	3.012

The primary experiments were conducted using nine test trials; these nine test trials were designed on the basis of L_9 orthogonal array. The reason of choosing L_9 orthogonal array is that shorter arrays are not capable of producing ample data to appropriately analyse the method since they are too simple and longer arrays would create complexity for the trial method. The response of assigned L_9 orthogonal array is shown in Table 39.2. In order to consider the three unlike performance characteristics in Taguchi method, corresponding values of the surface roughness (SR) and linear shrinkage (LS) are processed by the fuzzy logic unit.

39.2.1 Fuzzy Logic Modelling

In this work, three inputs and two outputs are used to evolve a fuzzy controller. Pouring temperature (PT), injector pressure (IP), and plunger velocity (PV) are three input variables, and surface roughness (SR) and linear shrinkage (LS) are two output variables. To make the fuzzy rule base, Mamdani fuzzy "If-Then" declarations for 27 rules has been considered, and to execute inference of max–min operation, Mamdani implication method has been adopted. To change fuzzy data to crisp response values, the centre of gravity method has been used by the defuzzifier. By acquiring triangular membership function, fuzzy division of input and output variables is carried out. Block diagram of fuzzy controller is shown in Fig. 39.2. This has been developed by MATLAB.

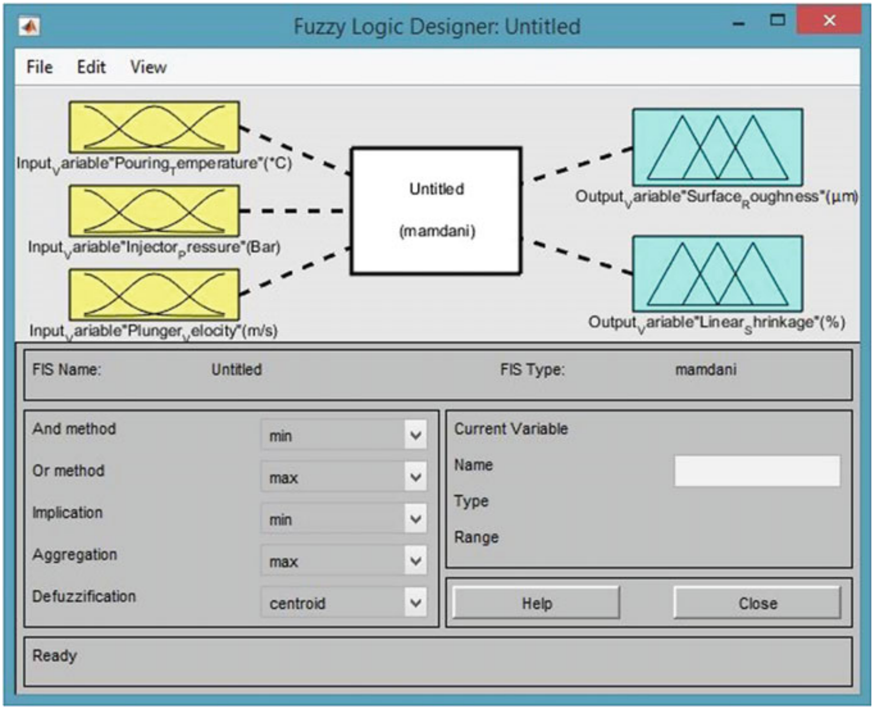

Fig. 39.2 Block diagram of fuzzy controller

Membership functions of the three inputs are small (S), medium (M), and large (L), and membership functions of the two outputs are very small (VS), small (S), medium (M), large (L), and very large (VL). Input and output functions are shown in Figs. 39.3 and 39.4. Table 39.3 shows the fuzzy intervals for input and output for forecasting the response, namely surface roughness (SR) and linear shrinkage (LS) of the casted products in die casting process. By taking into account the max–min combinational operation and with provided set of inputs, experimental results are originated on which these fuzzy rules are established. A non-fuzzy output is provided by the fuzzy reasoning of these rules as shown in Fig. 39.5.

Validation of Fuzzy Model Prediction

Three experiments were performed with different combination of the input process parameters which were not incorporated in the training set (randomly chosen). In Table 39.4, the corresponding experimental responses are measured and listed. From the fuzzy controller, the response values are again acquired for the same set of input process parameters. Then, to find out the extent by which the fuzzy controller is working, the percentage of error was calculated. The experimental and the predicted result obtained from the Mamdani fuzzy model has been plotted on graph as shown in Fig. 39.6. Also, bar graph has been drawn between experimental and fuzzy predicted data as shown in Fig. 39.7.

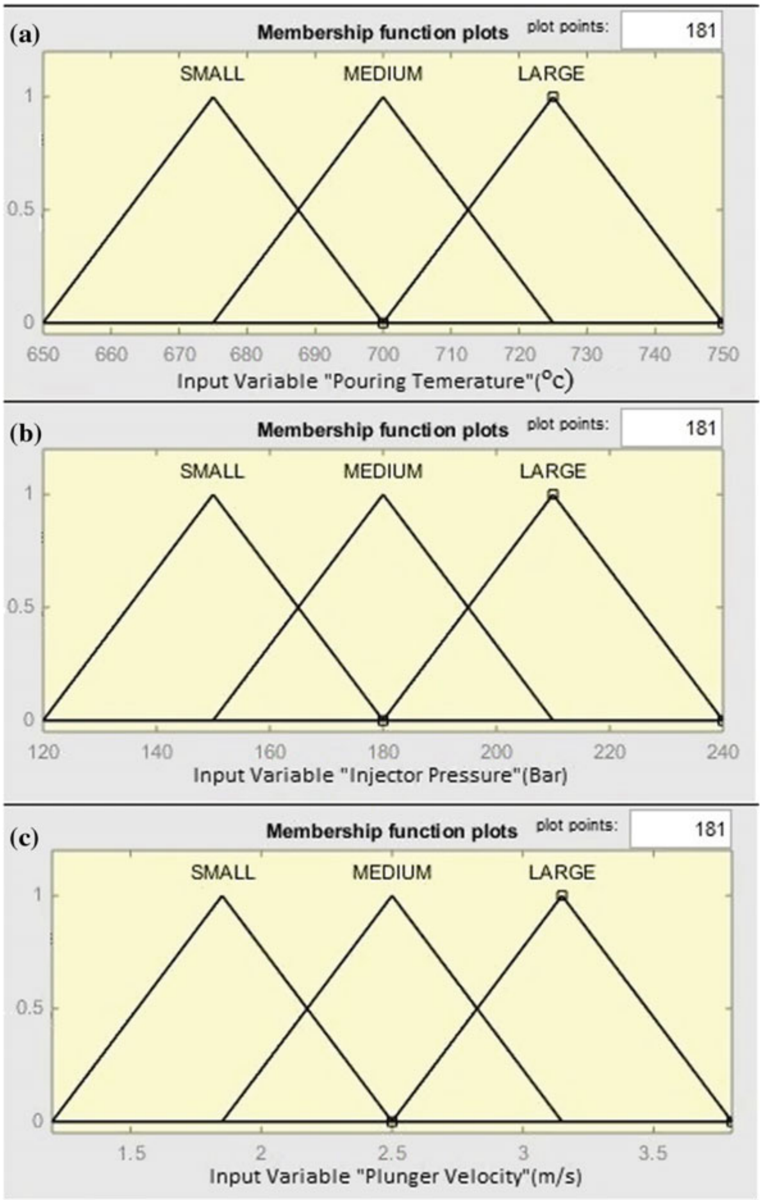

Fig. 39.3 Membership function of input variables: **a** pouring temperature, **b** injector pressure, and **c** plunger velocity

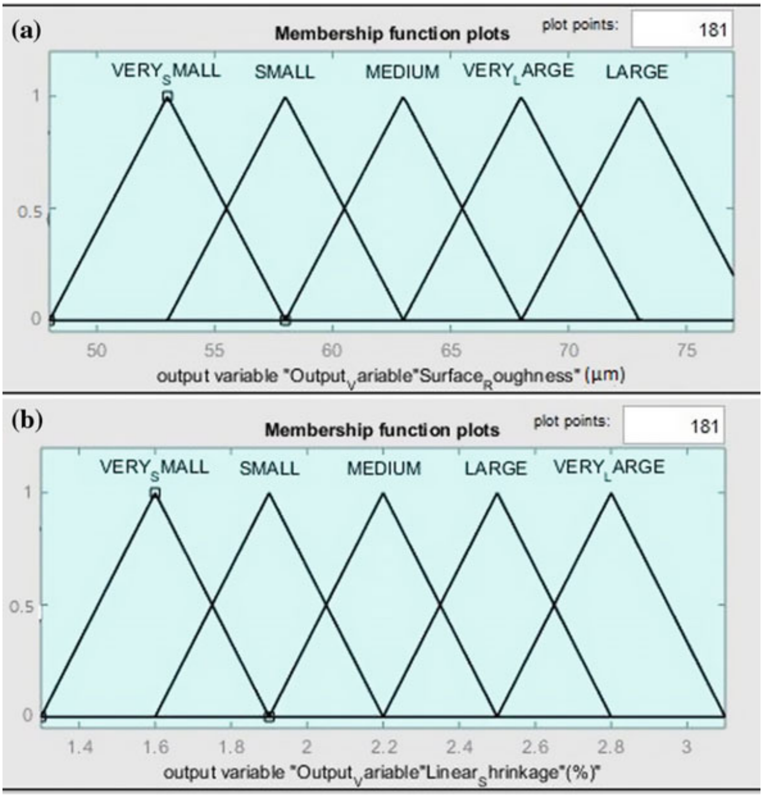

Fig. 39.4 Membership function of output variables: **a** surface roughness and **b** linear shrinkage

Table 39.3 Input output and fuzzy intervals

S. no.	System's linguistic variable		Linguistic values	Fuzzy interval (min–average–max)
1	Inputs	Injection speed	Small	650–675–700
			Medium	675–700–725
			Large	700–725–750
		Injection pressure	Small	120–150–180
			Medium	150–180–210
			Large	180–210–240
		Injection time	Small	1.2–1.85–2.5
			Medium	1.85–2.5–3.15
			Large	2.5–3.15–3.8

(continued)

Table 39.3 (continued)

S. no.	System's linguistic variable		Linguistic values	Fuzzy interval (min–average–max)
2	Outputs	surface roughness (µm)	Very small	48–53–58
			Small	53–58–63
			Medium	58–63–68
			Large	63–68–73
			Very large	68–73–78
		linear shrinkage (%)	Very small	1.3-1.6–1.9
			Small	1.6–1.9–2.2
			Medium	1.9–2.2–2.5
			Large	2.2–2.5–2.8
			Very large	2.5–2.8–3.1

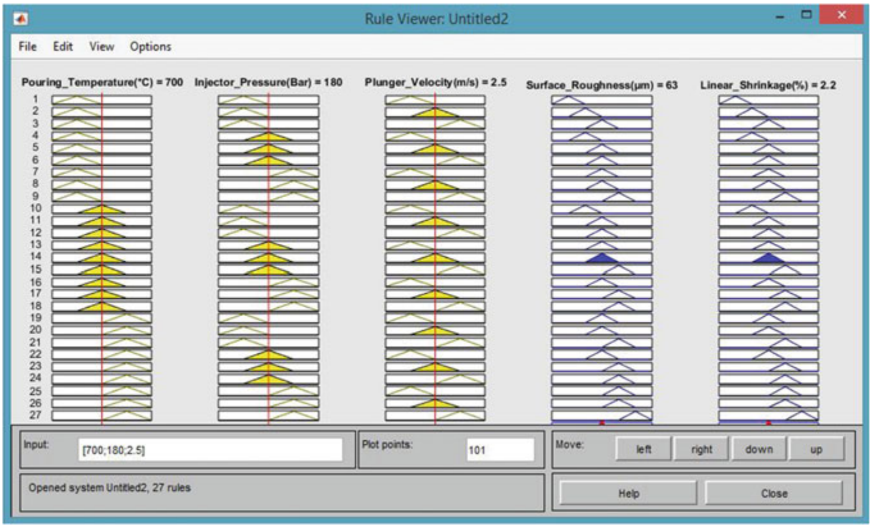

Fig. 39.5 Fuzzy inputs and prediction of outputs

Table 39.4 Comparison of results between the actual and the predicted values

S. no.	Injection process parameter			Experimental values		Fuzzy predicted values		% error	
	PT	IP	PV	SR	LS	SR	LS	SR	LS
1	650	120	1.2	48.554	1.412	52	1.5	7.09	6.23
2	700	180	2.5	65.325	2.075	63	2.2	3.55	6.02
3	750	240	3.8	75.112	3.012	79	3.3	5.17	9.56

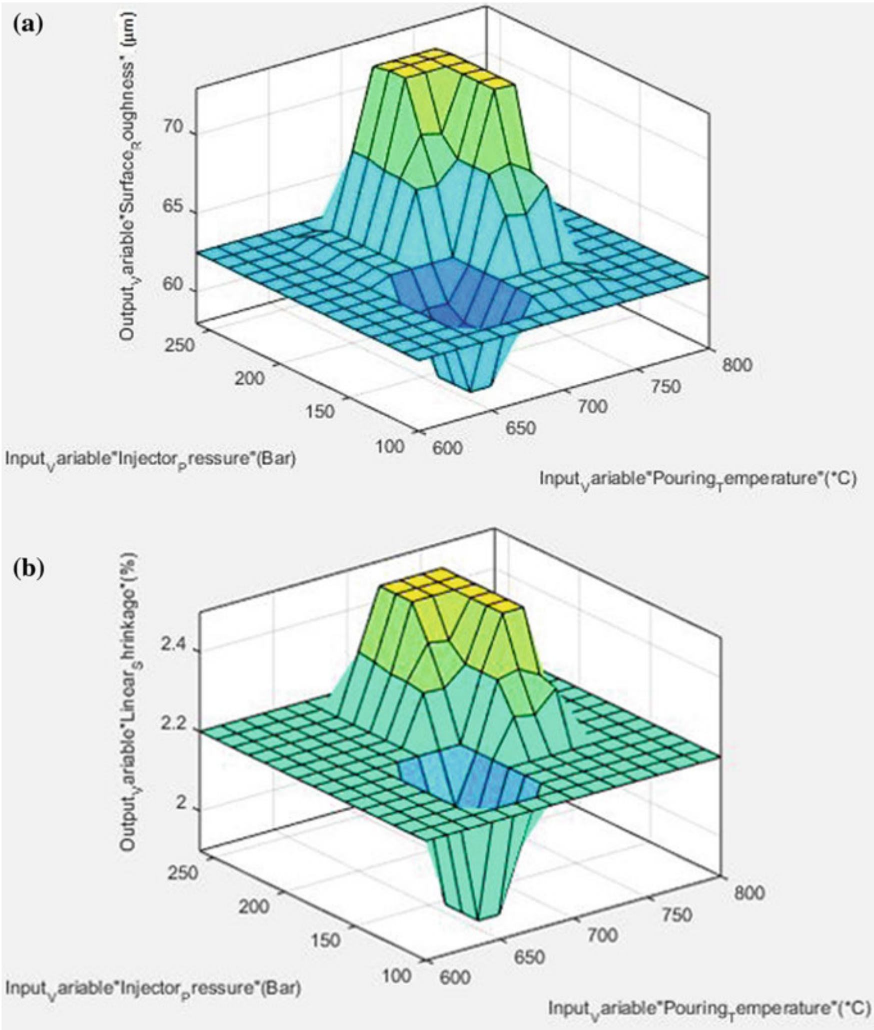

Fig. 39.6 Predicted surface roughness and linear shrinkage by fuzzy logic in relation to parameters change: **a** pouring temperature and injector pressure and **b** pouring temperature and injector pressure

39.3 Discussion

In this work, to predict the quality characteristics, namely surface roughness and linear shrinkage of casted product in die casting process, a fuzzy logic controller using Taguchi orthogonal array design has been developed. Prediction results show that Mamdani inference was on the basis of maximum error calculated. So, for

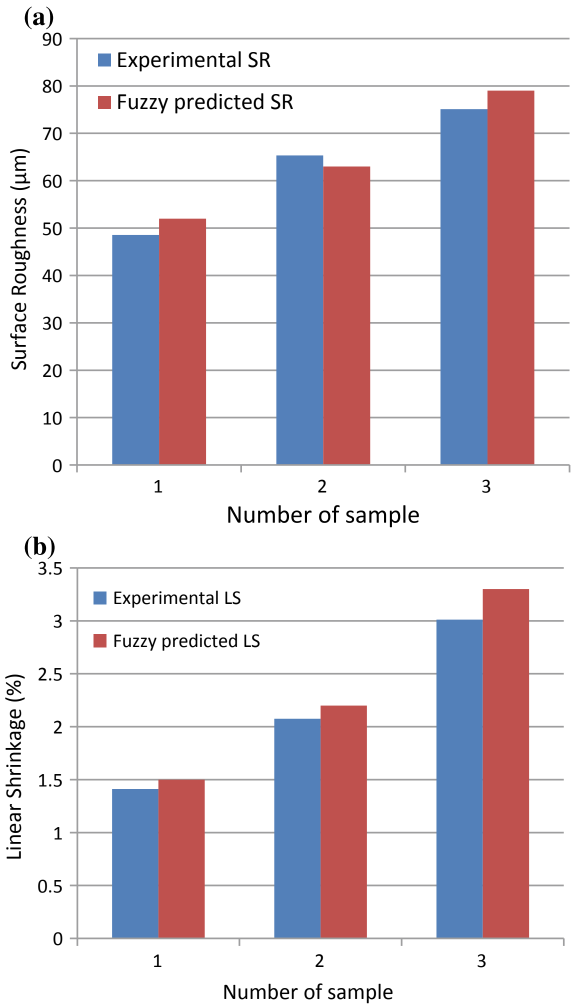

Fig. 39.7 Prediction of **a** surface roughness and **b** linear shrinkage

improving the quality and reliability of the entire process, it has proved to be an effective and powerful tool. By enhancing the number of experiments, the anticipated values of fuzzy output can be further precisely predicted. It is also very useful and can also be used for the optimization of multiple performance quality process parameters and casted product material, to test the ability of the expert systems in prediction of the outputs.

39.4 Conclusion

From the present study, resulting conclusions are summarized as follows:

- The capability of generalization and prediction of pattern characteristics within the range of experimental data such as surface roughness and linear shrinkage of casted product in die casting process have been shown with the help of Mamdani fuzzy inference.
- Industries which are using the experience of skilled workers can use a set of fuzzy rules which further result in improvement in forecasting ability of the process.
- For automation of the process, this methodology seems to be beneficial.

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