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An Adaptive Neuro-Fuzzy Inference System for a Dynamic Production Environment under Uncertainties

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Abstract: Throughput modelling evaluates the performance and behaviour of the production systems. This study examined the potential application of Adaptive Neuro-Fuzzy Inference System (ANFIS) for modelling throughput under production uncertainties. Five significant factors were considered as the main uncertainties of production: scrap, setup time, break time, demand and lead time of manufacturing. Observations on the production uncertainties had been performed for 104 weeks in a tile manufacturing industry. The results of ANFIS model had been compared with Multiple Linear Regression (MLR) model. The results showed that ANFIS model was capable of providing adjusted R-squared of 98%, which was higher than the MLR model.

Key words: Uncertainty · Adaptive neuro-fuzzy inference system · Production throughput · Demand · Break time · Lead time

INTRODUCTION

Throughput is an important measure of production system performance. Modelling of production throughput is complex in today's dynamic production systems due to uncertainties of production line. The uncertainties of production relate to changes in demand and disturbances of production shop floors, for example, machine breakdowns and random lead times of manufacturing. Handling of production uncertainties and modelling the production throughput have a great benefit to achieve a more systematic production for approaching more reliable and robust manufacturing system. Study on production uncertainties is an opportunity for new research and development. Thus, manufacturing industries must find novel approaches to handle uncertainties quickly and effectively in order to survive global competition driven by customer-designed products [1, 2] highlighted that the models for production planning, which consider the uncertainty compared to those models that do not present uncertainty, can make superior production planning decisions. However, current theories for handling and evaluating uncertainty under production planning and control are still under debate because these theories are dependent on the time factor [3,4].

Traditionally, the tile industry was characterized by the large scale production of only certain types of products. Nowadays, however, the tile industry has been involved in the production of different types of products at different quantities. The time lost in the setup, breakdown of equipment and scraps increases the manufacturing lead time. Further, the availability of machines may differ due to the break time. Demand also constantly changes due to fluctuations from time to time. Hence, the decision making on production in consideration of fluctuations has become more and more difficult in terms of complexity. In this regard, the tile industry has been attempting to develop a new model that can answer customer orders in a timely manner by improving the delivery lead times. Many strategies and policies have been proposed to address the fluctuations and disruptions of the production system. However, most of these methods are unsustainable. The complexity of the estimation of the production throughput under uncertain conditions becomes even more difficult if the manufacturing environments involve multistage production and multiproducts. Recently a study has been focused on production sequencing and scheduling of tile products to identify a set of product families with common features due to produces a better estimation of the setup

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time. However, in this study, more uncertainties of production line were estimated using Adaptive Neuro-Fuzzy Inference System (ANFIS) and considered for throughput modeling. The focus was more on performance of production line.

Production Uncertainties: A literature review was conducted to identify significant uncertainty parameters that affect the throughput of final products and the delivery time of these final products [5]. distinguished three main types of uncertainty in manufacturing, which include uncertainty of the item throughput, mixed uncertainty of a component and delivery uncertainty [6]. presented significant uncertainty parameters in manufacturing environments in reference to demand changes, lead time variations and resource break [7]. categorized the uncertainty variables within the production facilities previously identified by [8] into internal and external disturbances. Internal disturbances include machines, tools/fixture, transport and operators. External disturbances include product variety, priority, throughput, quality, wrong time and parts for the supplier. [9] categorized manufacturing uncertainty parameters into process yield loss, quality variation, process lead time and scraps. [10] classified uncertainty variables of the production system into cancelled or rushed orders, operation time's variability and equipment breakdowns. [11] grouped four uncertainty factors into product mix, sales quantities, order delivery time and design changes.

[12] identified eight uncertainty variables that affect customer delivery performance. These variables are external late supply, internal late supply, planned setup time exceeded, machine breakdown, labor unavailability, tooling unavailability, demand batch size enlargement and customer design changes. [13] compiled uncertainty variables according to sources, such as system uncertainty, lead time uncertainty, environmental uncertainty, supply uncertainty, operation yield uncertainty, interrelationship between levels, demand uncertainty, probabilistic market demand, product sales price, capacity, breakdown, changing product mix situation, labor hiring and lay-offs, scrap, setup time, throughput uncertainty, cost parameters and quality. [2] made a list for production planning from existing models under an uncertainty environment and categorized uncertainty factors into two groups, which are analytical and conceptual. Stochastic programming was found to be the most frequently used model.

Methods for Handling Uncertainties: [4] defined modeling uncertainty as a genuine modeling decision, in which any of the existing uncertainty theories might to be applied or a "wait-and-see" approach should be adopted. Artificial intelligent approaches and machine learning techniques deal with uncertainty in manufacturing management through modeling of quantitative information [14], for example, the Petri net technique was used to relocate operations in order to use shop floor resources in the presence of machine breakdown uncertainty [15].

The stochastic method was introduced by [16] to deal explicitly with uncertainty and to make decisions that are less sensitive to the variations in input data. Stochastic programming using demand as a random variable has been found as the most popular trend recently in the production planning for manufacturing industries [17-20] formulated a stochastic model under demand uncertainty. The levels of demand uncertainty were probability specified [21] presented a method that uses stochastic integer programming to meet demand uncertainty. Their efforts involve simple enumeration of a few discrete cases to handle uncertainty in demand [22] pointed out that the degree of uncertainty and complexity is very high in a remanufacturing system. The stochastic dynamic model was used to determine the quantities to be remanufactured at each period.

[23] simulated a few models using WITNESS software to analyze the various effects of two main uncertainty variables, machine breakdown and lead time variability. They concluded that machine breakdown has a greater effect on the production throughput, whereas lead time uncertainty has a greater influence on the cycle time. Later, [24] considered a production system under machine breakdown and quality variation. They examined the effect of common processes on the throughput and cycle time using the same method (WITNESS software). They found that the variation in the level of common processes in the system has a significant effect on the production throughput and cycle time. Using simulation methodology, [25] examined the performance of a manufacturing environment under demand and lead time uncertainties. The effects from the use of different lot sizing rules were also considered. These uncertainties were concluded to be addressed using appropriate lot-sizing rules. [26] developed a simulation model to examine the interaction effects of demand and supply uncertainties. These uncertainties were modeled in terms of changes in lot size, timing, planned orders and policy

fence on several system performance measures, such as late deliveries, number of setup times, ending inventory levels and component shortages. System performance was concluded to be significantly affected by demand changes and supply uncertainties. [27] examined the effect of uncertainty in operational release planning on the total duration. A combination method of Monte Carlo simulation and process simulation was proposed. They concluded that every uncertain variable individually increases the make span. Further, for any combination of uncertainty variables, their effects are always greater than when their individual effects are considered.

In multiproduct environments that involve more than one type of uncertain variable, the analytical approach is replaced by expert system methodologies, such as Fuzzy logics. Fuzzy programming was applied for planning production in a multisite environment under uncertain capacities and demands by [28-30] used Fuzzy modeling to investigate customer demand and external supply uncertainties. [31] presented a Fuzzy multiobjective optimization approach to maximize the satisfaction level of multiple objectives in a supply chain under an uncertain product demand. [32] presented a Fuzzy method for determining production process availability by considering process failures and machine breakdown.

MATERIALS AND METHODS

ANFIS was applied for estimating the parameters of significant variables in order to examine the effects of these parameters on the production throughput. The ANFIS model categorized the input space into Fuzzy subspaces and maps the output using a set of linear functions. ANFIS is a Fuzzy mapping algorithm based on the Tagaki–Sugeno–Kang Fuzzy inference system [33, 34]. ANFIS has been successfully used for mapping the input–output relationship based on available data sets [35]. The system acquires its adaptability by utilizing a hybrid learning method that combines back propagation and least mean square optimization algorithms. The ANFIS model output matches the system output with a minimum Root Mean Square Error (RMSE). Using a learning process, ANFIS can determine the mapping relation between an input and output data set in order to identify the optimal distribution of membership functions; the relation involves a premise and a consequent part [36]. ANFIS, which was developed by [37], is a universal approximate that incorporates Sugeno type Fuzzy inference systems into adaptive neural networks. ANFIS uses the power of two patterns, namely, artificial neural networks and Fuzzy logic, in a single framework and simultaneously overcomes their own shortcomings.

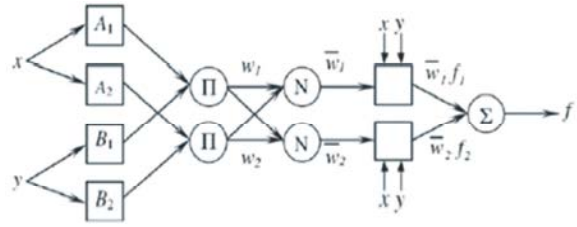

Fig. 1: ANFIS structure with two rules [17]

Table 1: Datasets for ANFIS

Dataset	Quantity
Training	64
Checking	20
Testing	20
Total	104

In this study, the data set collected for over 104 observations in 104 weeks included scrap, setup time, break time, demand and lead time of manufacturing. Our data set was categorized into three groups as shown in Table 1. The training set was assigned to build the ANFIS model. The checking data set was used to ensure that the trained model is a suitable representation of the target system and to avoid overfitting of the system to the training data set. Actually, overfitting occurs when the model is too much trained such that the mapping between the input and the output data has lost its generalization capability to fit any data that was not trained on [38].

The solution procedure of ANFIS is briefly presented in Fig. 1. Two inputs and one output are assumed.

Where

x, y : Inputs,
fi : Output, i= 1, 2,
Wi : Weight, i= 1, 2,
A and B : Fuzzy sets.

For a first order Sugeno Fuzzy model, a common rule set with two fuzzy if–then rules in (1) and (2) was assumed [37].

Rule 1: If x is A1 and y is B1, then $f1 = c1 + \alpha_1 \times + \beta_1 y$. (1)

Rule 2 : If x is A2 and y is B2, then f2 = c2 + $\alpha_2 \times$ + β_2y. (2)

Where

F1 : First order polynomial, the output of the rule 1,

F2 : Second order polynomial, the output of the rule 2,

α_i and β_i : Coefficients of inputs, i= 1, 2,

ci : Constant parameters, i= 1, 2,

Finally overall output was calculated in equation (3).

$$f = \frac{w1f1 + w2f2}{w1 + w2} => \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i} \quad (3)$$

The construction of the ANFIS model was implemented in MATLAB, which comprises Fuzzification by determining the type and the number of membership functions [39]. The subtractive clustering method proposed by [40] was used to partition the universe of discourse for input variables and then to generate the Fuzzy Inference System (FIS). The number of Fuzzy rules required for FIS construction and their associated membership parameters was minimized using the subtractive clustering method for three rules. The next step was training of the inputs to minimize the RMSE and to adjust the shape of the membership functions. The hybrid learning algorithm was used to develop the ANFIS model. This algorithm consisted of back propagation for the input parameters associated with input membership functions and least squares estimation for the parameters associated with output membership functions. The learning process stoped when a maximum number of training iterations (epochs) was achieved. The best ANFIS model was selected based on a lower RMSE for both the training and checking data sets, in which the RMSE was under control and was not increased according to [41, 42].

RESULTS

Three Gaussian membership functions for each input were developed and the parameters for each input were estimated in Table 2.

Table 3 summarizes the estimated coefficients of the Sugeno linear function.

The Sugeno linear functions were formulated for all three clusters, shown in (4) until (6).

Table 2: Inputs estimated parameters

Inputs	Membership functions	Cluster	σ	μ
Break time	Gaussian	Low	93.51	291
		Medium	93.52	312
		High	93.51	334
Demand	Gaussian	Low	2897	8079
		Medium	2897	12450
		High	2897	16750
Lead Time	Gaussian	Low	112.1	5668
		Medium	112.1	5713
		High	112.1	5758
Setup time	Gaussian	Low	6.185	195
		Medium	6.196	200
		High	6.188	205
Scrap	Gaussian	Low	642.2	4390
		Medium	642.2	4770
		High	642.2	5158

Table 3: Estimated coefficients of Sugeno linear function

Production throughput estimated	Inputs' coefficients of Sugeno linear function					
Clusters	β_0	β_1	β_2	β_3	β_4	β_5
Low	-207500	32.69	0.924	31.43	86.6	0.220
Medium	20140	0.213	0.9	3.396	14.8	-0.15
High	5066	-3.05	0.875	-0.10	-2.55	-0.41

Table 4: Estimated coefficients of MLR

Output	Inputs' coefficients of Sugeno linear function					
Production throughput estimated	β_0	β_1	β_2	β_3	β_4	β_5
	-1289	-0.86	0.906	-0.15	15.8	0.0476

Table 5: Comparison of ANFIS and MLR

Model	R^2
MLR	97%
ANFIS	98%

$$P_{Low}(t) \sim -207500 + 32.69B(t) + 0.9246\,D(t) + 31.43\,L(t) + 0.2209S(t) \quad (4)$$

$$P_{Medium}(t) \sim 20140 + 0.2138B(t) + 0.9\,D(t) + 3.396\,L(t) + 14.86\,Se(t) - 0.1577S(t) \quad (5)$$

$$P_{High}(t) \sim 5066 - 3.0556B(t) + 0.8758\,D(t) + 0.1014\,L(t) - 2.553\,Se(t) - 0.4157S(t) \quad (6)$$

Where

P = Production throughput,

B = Break time,

D = Demand,

L = Lead time of manufacturing,

Se = Setup time,

S = Scrap.

Table 4 summarizes the estimated coefficients of the Multiple Linear Regression (MLR) function.

The MLR based on the coefficient estimated in Table 4 was formulated in equation (7).

$$P(t) \tilde{} -1289-0.86B(t) + 0.906\ D(t) -0.15\ L(t) + 15.8\ Se(t) + 0.0476\ S(t) \quad (7)$$

Table 5 presents the accuracy of both MLR and ANFIS models using adjusted R-squared.

The results demonstrated that the ANFIS inference was capable to produces with higher accuracy compared with the MLR model.

CONCLUSION

An adaptive Neuro-Fuzzy inference system model for modelling production throughput was developed using a real data set collected from a tile industry. The ANFIS model predicted with 98% accuracy compared with the multiple linear regression model. Studies based on the results of ANFIS have shown that Neuro–Fuzzy systems were robust for dealing with production uncertainties. It can be applied as a reliable method in uncertain manufacturing environments because of its flexible and adaptive capability. Further studies may be achieved by establishing a wider database, including additional input variables and examining in another dynamic manufacturing industry.

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