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THE CONCEPTUAL FRAMEWORK OF PRODUCTION PLANNING OPTIMISATION USING FUZZY INFERENCE SYSTEM WITH TSUKAMOTO

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ABSTRACT

In today's dynamic environment, activities in manufacturing have become uncertain and complex. This is because there is always ambiguity in different states due to their diversity. In other words, the uncertainty can make the operations in the manufacturing companies become finite and result in unnecessary waste of resources in terms of money, labour or time. Therefore, production and inventory planning are essential activities to accurately predict production in the manufacturing sector. In the context of such factors, the purpose of this research is to introduce the Fuzzy Inference System (FIS) as an effective method that can assist in determining an optimal result to each fuzzy variable. The fuzzy variables of customer demand, production and inventory are used to practice the theory, synthesizing the activities in manufacturing in order to attain an effective and efficient operation in the industry. Specifically, electrical and electronics-related manufacturing companies are the engine of growth in Malaysia; therefore, FIS with Tsukamoto is implemented to facilitate and accelerate the decision-making processes within the company. In general, it is a simple method that can help to determine the optimal and appropriate quantity of manufactured goods to be handled within the operation by using the variables in the form of fuzzy numbers.

***Keywords**:* Decision Making, Fuzzy Inference System, Optimisation, Production Planning, Tsukamoto Method

INTRODUCTION

Organizations have to face the challenges of a rapidly changing market, and this results in many uncertainties for activities in the manufacturing sector (Zhao & Yu, 2011). Other than that, the requirements of the customers change over time (Li & Deng, 2011; Gunasekaran & Ngai, 2009), and lack of knowledge or insufficient information also contributes to the uncertainties (Dutt & Kurian, 2013). Ho (1989) categorizes this type of uncertainty as environmental uncertainty. Meanwhile, the production planning data can be categorised as

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variability due to variations or differences in a process or quantity. This is due to the fact that assigning an exact value for a quantity is difficult because it depends on many parameters (Dutt & Kurian, 2013). The uses of advanced information from corporate activities can support management to make more efficient and accurate decisions in order to achieve the control of operating processes, to improve the operational efficiency, and to reduce the costs of operating processes while increasing revenue in the sector (Zhao & Yu, 2011).

Fuzzy logic theory provides a very useful solution to understanding, quantifying and handling vague, ambiguous and uncertain data (Dutt & Kurian, 2013). This is supported by Mula et al. (2006), who stated that artificial intelligence-based models are of particular interest to practitioners in order to address the production planning problems under uncertainty. The fuzzy logic expresses that nothing can be firmly stated as being right or wrong; such a statement is too extreme with only two available answers. Besides that, fuzzy logic is the study of methods which correspond to a set of principles in giving meaningful information on the unconditional or approximate reasoning that can be understood in human languages (Phan & Chen G, 2000).

Syntetos et al. (2010) stated that an ideal optimization in each activity of production is very important to ensure that the operations in the company run for a longer period of time. This can also reduce any surplus or shortage in the inventory provision. The implementation of FIS with the Tsukamoto method improves the quality of strategies in manufacturing from receive of an order to supplying the needs of the marketplace by providing a fast and on-time delivery (Arnoid et al., 2012). Therefore, the aim of this research is to implement FIS with the Tsukamoto method in a manufacturing sector company to help to determine an optimal quantity of production and inventory, in order to assist with operational decision making.

The paper is organized as follows: it starts with a review of the literature on FIS, while the conceptual framework is discussed in the methodology section. Finally, some concluding remarks are made.

FUZZY INFERENCE SYSTEM

The fuzzy inference system is known by numerous other names, such as fuzzy expert system, fuzzy model, fuzzy associative memory, and simply fuzzy system (Castillo & Melin, 2008) based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning (Jang, Sun & Mizutani, 1997). The basic structure of FIS is that it consists of a fuzzification unit, a fuzzy logic reasoning unit (process logic), a knowledge base, and a defuzzification unit, as illustrated in figure 1.0. According to Castillo and Melin (2008), the basic structure of FIS consists of three conceptual components: a "rule base", which contains a selection of fuzzy rules; a "database" (or "dictionary"), which defines the membership functions used in the fuzzy rules; and a "reasoning mechanism", which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion.

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Fuzzy Theory/Fuzzification

The concept of fuzzy theory infers that it is always impossible to live without ambiguity. It is hard to know and control everything on hand all the time. This is because of sudden and unforeseen occurrences, even if we may have scheduled and outlined a direction beforehand. The reality is that uncertainty or something that is unexpected still exist.

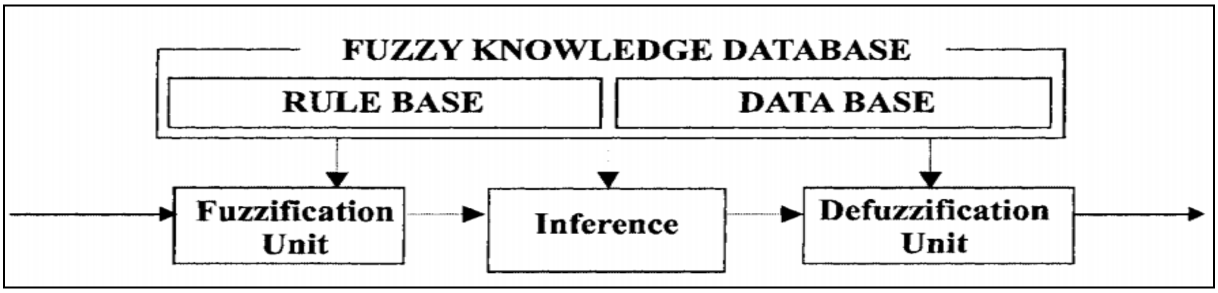

Figure 1: Basic structure of FIS (Pappis & Siettos, 2005)

Fuzzy theory can be considered as a set of principles within an extension of infinite-valued logic in the sense of incorporating fuzzy sets and fuzzy relations (Bojadziev & Bojadziev, 1995).

a) Fuzzy variables are the main elements in a fuzzy system. They are dominant elements which affect the overall system.
b) Fuzzy sets are a collection of fuzzy variables which has been directed in a specific state. It enables the description of the variables that can be restricted within a particular range that can be referred.
c) Universe sets are entire reasoning values which are permitted to manipulate the variables within them. They are a group of real digits conventionally increasing from left to right. The values can be either positive or negative.
d) The domain is a subset of the universe set within the fuzzy set. It acts as the overall range for the specific variable in which it can be included in the same series. Similarly, the domain set also increases from left to right and their values can either be presented as positive or negative.

Fuzzy if-then rule

Castillo and Melin (2008) stated that the "fuzzy if-then rule" is also known as "fuzzy rule", "fuzzy implication", or "fuzzy conditional statement". The most common and widely used interpretation considers a fuzzy rule "**if** x is A **then** y is B" where A and B are linguistic values defined by fuzzy sets on universes of discourse X and Y, respectively. Often "x is A"

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is called "antecedent" or "premise", while "y is B" is called the "consequence" or "conclusion". An example of the fuzzy if-then rule in production-planning linguistic expressions is "*if demand decreases then production is low*."

Fuzzy reasoning/Inference

Fuzzy reasoning, also known as approximate reasoning, is an inference procedure that derives conclusions from a set of fuzzy if-then rules and known facts (Castillo & Melin, 2008). The fuzzy reasoning unit performs various fuzzy logic operations to infer the output (decision) from the given fuzzy inputs. During fuzzy inference, the following operations are involved for each fuzzy rule (Pappis & Siettos, 2005):

a) Determination of the degree of match between the fuzzy input data and the defined fuzzy sets for each system input variable.
b) Calculation of the fire strength (degree of relevance or applicability) for each rule based on the degree of match and the connectives (e.g. AND, OR) used with input variables in the antecedent part of the rule.
c) Derivation of the control outputs based on the calculated fire strength and the defined fuzzy sets for each output variable in the consequent part of each rule. Several techniques have been proposed for the inference of the fuzzy output based on the rule base. The most commonly used are the Max-Min (fuzzy operator AND) fuzzy inference method and the Max-product fuzzy inference method.

Defuzzification

Defuzzification typically involves weighting and combining a number of fuzzy sets resulting from the fuzzy inference process in a calculation, which gives a single crisp value for each output (Pappis & Siettos, 2005). Pappis and Siettos (2005) also mentioned that the most commonly used defuzzification methods are mean of maximum, centroid, and centre of sum of areas.

Kazeminezhad et al. (2005) mentioned that FIS can be used to predict uncertain systems and its application does not require knowledge of the underlying physical process as a precondition. Moreover, Nauck and Kruse (1999) mentioned that the success of FIS is due to its closeness to human perception and reasoning, as well as its intuitive handling and simplicity, which are important factors for acceptance and usability of the systems.

There are three types of FIS; Mamdani, Sugeno, and Tsukamoto. The *Mamdani* method, also known as the Max-Min method, was introduced by Ebrahim Mamdani in 1975. Meanwhile, the *Segeno* method, also known as the TSK method was introduced by Takagi-Sugeno Kang in 1985. The third one is the *Tsukamoto* method, first introduced by Tsukamoto in 1979. The

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differences between the three methods are as follows; the antecedents for, and consequences of the Mamdani and Sugeno are fuzzy sets while in the Takagi–Sugeno–Kang models, the antecedent consists of fuzzy sets but the consequence is comprised of linear equations (Tavana et al., 2013).

As stated by Castillo and Melin (2008), in the "Tsukamoto fuzzy models", the consequence of each fuzzy if-then rule is represented by a fuzzy set with a Monotone rule. As a result, the inferred output of each rule is defined as a numeric value induced by the rule firing strength.

Based on previous studies, the Tsukamoto method has been widely applied in education (Rakhman et al., 2012; Ariani & Endra, 2013), production (Firmansyah & Utami 2013), marketing (Smolova & Peach, 2010), healthcare (Kusumadewi, 2005), and banking (Kaswidjanti, Aribowo & Wicaksono, 2014).

Methodology

The study is conducted in several steps illustrated in Figure 2. There are three steps for the FIS method: Fuzzification, Inference, and Defuzzification. The Fuzzification technique begins with determining the input and output characters from the dataset of production planning. A fuzzy set is assigned for each of the input variables determined.

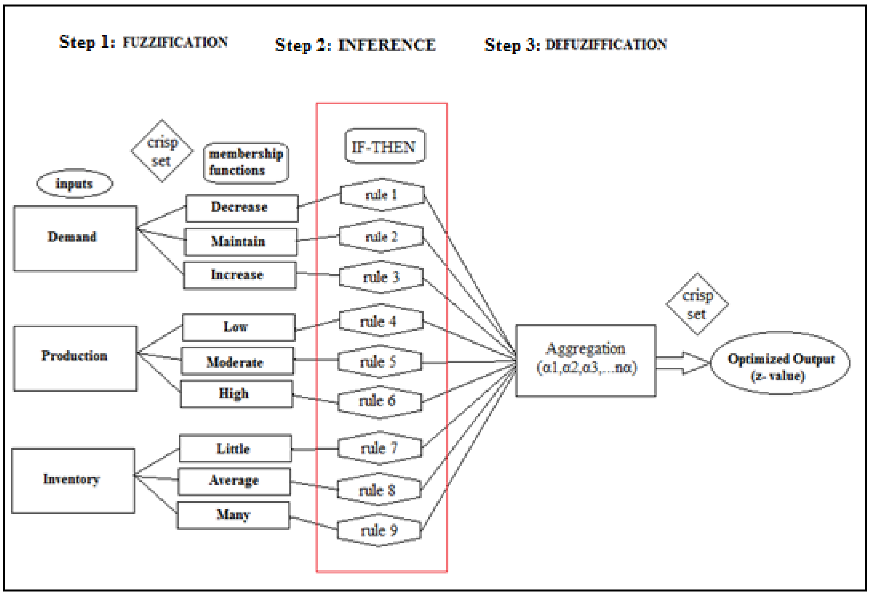

Figure 2: A Conceptual Framework FIS Tsukamoto for this study

Table 1: Criteria of Input and Output Variables

Criteria	Description	Functions
Demand	Customer Demand	Variable Input
Production	Production based on	Variable Input

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	customer demand	
Inventory	Stock	Variable Input
OD	Optimised Demand	Variable Output
OP	Optimised Production	Variable Output
OI	Optimised Inventory	Variable Output

Table 1 shows the criteria of input and output variables. The input variables are Demand, Production and Inventory data. All these data are obtained from the production department. Meanwhile, the output is the optimized value for production, demand and inventory data.

Table 2: Fuzzy Sets for Input Variable

Input Variable	**Fuzzy Sets**
Demand	Decrease
	Maintain
	Increase
Production	Low
	Moderate
	High
Inventory	Little
	Average
	Many

Fuzzy sets for input variables are shown in Table 2. Fuzzy sets for Demand are DECREASE, MAINTAIN, and INCREASE. Next, the sets for Production are LOW, MODERATE, and HIGH. Meanwhile, those for Inventory are LITTLE, AVERAGE, and MANY.

Membership Functions

There is a need to apply a certain functional approach in obtaining the membership values in the fuzzy set. Kusumadewi and Purnomo (2010) state that the membership function (MF) is a curve that shows the mapping of points of data input into the membership value that has the interval between 0 and 1. The function used within this study is as follows:

i) Linear Representation

Linear Representation as shown below in Figures 3 and 4 is a set of grades which start with increasing form on the line from left to right within the domain for the increasing Linear Representation (Figure 3). For instance, its membership grade probably began with 0, following which the domain values are leveled up with higher grades of membership. Meanwhile, Decreasing Linear Representation as shown below in Figure 4 is the opposite of the Increasing Linear Representation. The highest grade of membership is leveling down from the left-hand side to the right-hand side on a straight line toward a smaller domain value.

$$\mu[x] = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ 1 & x \ge b \end{cases} \quad (1.0)$$

$$\mu[x] = \begin{cases} 1 & x \le a \\ \frac{b-x}{b-a} & a \le x \le b \\ 0 & x \ge b \end{cases} \quad (1.1)$$

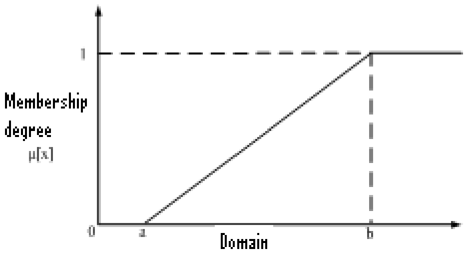

Figure 3: Fuzzy Set on an Increasing Linear Representation

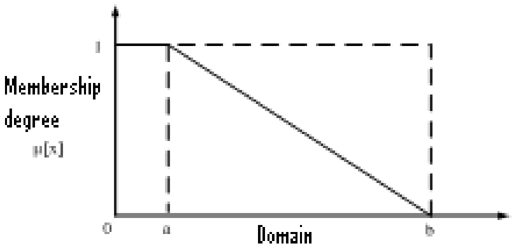

Figure 4: Fuzzy Set on a Decreasing Linear Representation

ii) Triangle Curve Representation

Triangle Curve Representation is basically a merger between two linear representations which are the Increasing Linear Representation and the Decreasing Linear Representation as shown below in Figure 5.

$$\mu[x] = \begin{cases} 0 & x \le a \text{ and } x \ge c \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & a < x < b \end{cases} \quad (2.3)$$

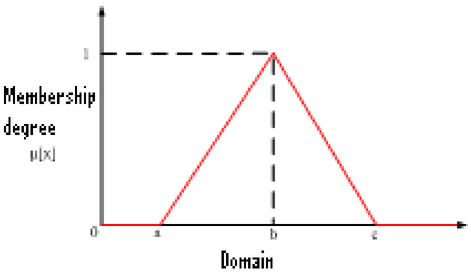

Figure 5: Triangle Curve Representations

iii) Shoulder-shaped Curve Representation is a region which is located in the middle between variables represented within an outlined triangle as shown in Figure 6.

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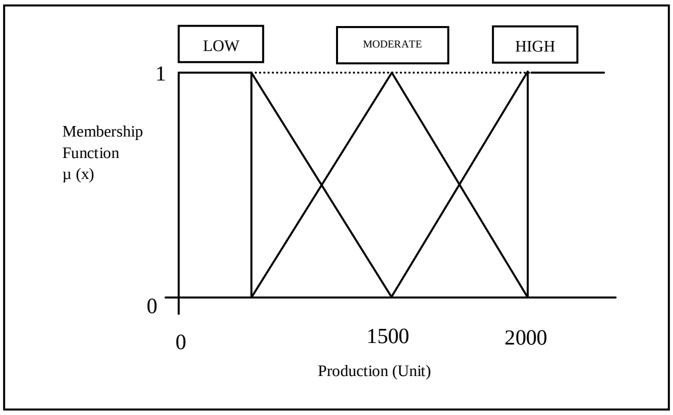

Figure 6: Shoulder-shaped Curve Representation

(iv) Operator of Fuzzy Set (AND)

There are several operations specifically defined for the combination of, and modification to, conventional fuzzy sets. A two-operational set results in membership values which are named as fire strength or α- predicates. For AND operator, the smallest membership function value among the aspects of the set is taking in order to practice it.

The second step is conducting inferences by making rules based on available data (Turban et al., 2004). In this stage, fuzzy rules that describe the local behaviour of the mapping is determined as follows:

[R1] IF Demand DECREASE And Inventory MANY Then Production LOW
[R2] IF Demand DECREASE And Inventory AVERAGE Then Production LOW
[R3] IF Demand DECREASE And Inventory LITTLE Then Production LOW
[R4] IF Demand MAINTAIN And Inventory MANY Then Production LOW
[R5] IF Demand MAINTAIN And Inventory AVERAGE Then Production MODERATE
[R6] IF Demand MAINTAIN And Inventory LITTLE Then Production HIGH
[R7] IF Demand INCREASE And Inventory MANY Then Production HIGH
[R8] IF Demand INCREASE And Inventory AVERAGE Then Production HIGH
[R9] IF Demand INCREASE And Inventory LITTLE Then Production HIGH

Based on the nine rules above, INFINITY and z values for each rule will be determined. INFINITY is a membership value of each rule antecedent, while z is the estimated value of goods to be produced from each rule. Each variable needed to identify a maximum value and minimum value of input variables.

The last step is defuzzification. This step determines the crisp output using an average defuzzification centralized method. The Z value obtained in this stage shows the amount of optimized data for each input variable. This step is analyzed once the production planning data are collected.

CONCLUSION

The paper focused on designing the FIS with the Tsukamoto Method for production planning optimisation in electrical and electronics- related manufacturing company in order to achieve effective and efficient operations in the presence of environmental uncertainty and variability of data. According to Dutt and Kurian (2013), fuzzy logic theory is a powerful tool for handling uncertainty. FIS consists of three steps - fuzzification, inference, and defuzzification. In the fuzzification step, input variables are customer demand, production, and inventory quantity. Meanwhile, fuzzy sets for each input are decrease, maintain and increase for customer demand, low, moderate and high for production and little, average, and many for inventory. Therefore, membership functions for this study are three trapezoidal (low, moderate and high). Nine rules perform the inference procedure and given facts to derive a reasonable output or conclusion. Finally, the centralized method is used in defuzzification to attain optimized quantity for production, inventory, and demand.

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