Dispatching Rule In A Fuzzy Rule Knowledge-Based System For Automated Manufacturing

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Abstract

This study proposes a systematical scheme to form manufacturing fuzzy rule knowledge-based system and then to construct the dispatching fuzzy rules of jobs and vehicles in order to enhance manufacturing system operations. The manufacturing fuzzy rule knowledge-based system can assist production managers in response to the dynamics intelligently and rapidly. Owing to the quantizing qualitative information ability of fuzzy set theory, fuzzy rule knowledge-based systems are employed in exhibiting expert knowledge. The fuzzy neural network ANFIS (Adaptive network-based fuzzy inference systems) serve as learning mechanism to train the manufacturing fuzzy rule knowledge.

Keyword: Fuzzy rule, Knowledge base, Fuzzy neural network, Adaptive network-based fuzzy inference system (ANFIS), dispatching rule

1. Introduction

The growing complexity and shorter life cycle of products result in great progress on the complication of production and the related technologies in manufacturing systems (Ayres, 1991). The complexity and uncertainty are filled in manufacturing systems that seriously limit the effectiveness of conventional management and control approaches (Reid and Koljonen, 1999). The automated technologies make each manufacturing function closely interdependent (Monostori et al., 1998). In addition, manufacturing systems are full of the uncertainty and dynamic behavior. There are many tasks of messy and ill-defined problems in manufacturing in which the constraints are difficult to represent in numerical terms. The representation of these types of constraint can be facilitated by the use of AI techniques (Kerr, 1991). To solve dispatching problems with increasing complexity and uncertainty in automated manufacturing systems, using the expert system of AI plays a crucial knowledge role. Moreover, the rule-based paradigm is the most popular and the easiest to understand paradigm for codifying problem-solving knowledge (Kerr, 1991). Besides, to represent uncertainty based on fuzzy sets, fuzzy rule knowledge-based system is adopted.

A job shop manufacturing production environment has a set of n jobs $J = \{J_1, J_2, ..., J_n\}$ to be performed on a set of m machines or resources $R = \{R_1, R_2, ..., R_m\}$. The job shop-scheduling problem involves the completion of *n* jobs on *m* resources simultaneously, known as NP-hard combinatorial optimization problem (Garey and Johnson, 1979). Conventionally, one dispatching rule of jobs, such as shortest processing time (SPT), earliest due-date (EDD), etc., is good for one performance index or scheduling goal, but not proper to other production purpose (Uzsoy et al., 1993). In addition, various technological, temporal, and resource capacity constraints are often ill-defined, multiple and conflicting. Therefore, automated manufacturing shop floor needs expert's knowledge to assist in dispatching jobs.

The material transportations of shop floor are executed by automated vehicles such as automated guided vehicle (AGV), personal guided vehicle (PGV), overhead hoist transporter (OHT), etc. The issues of controlling may include dispatching, routing, and scheduling (Klein and Kim, 1996). Dispatching involves a decision rule or methodology for selecting a vehicle or station for pickup or delivery assignments. Liu and Duh (1992) proposed 'MIX' dispatching rule considering both the queue size and vehicle travel distance, which is superior to the single-attribute rule such as STT, MOQS, etc. Furthermore, they indicated that this vehicle-dispatching problem should be solved by adopting artificial intelligence technology (Liu and Duh, 1992).

However, there is no systematic approach to build membership functions and fuzzy 'if-then' rules. The parameters of membership functions referred to one fuzzy rule are traditionally adjusted by the expert's intuition or trial and error. Acquiring appropriate membership functions of fuzzy rules are laborious. Accordingly, the advantages of neural networks, such as learning non-linear relationships ability, easy generalization, fault tolerance, etc., are introduced to modify membership functions of fuzzy rules (Du and Wolfe, 1997).

Therefore, this study proposes dispatching rule using expert knowledge to assist manufacturing management and control. Furthermore, owing to the quantizing qualitative information ability of fuzzy set theory, fuzzy rule knowledge-based systems are employed in exhibiting expert knowledge. This study also applies the neuro-fuzzy inference system approach to learn and train the fuzzy rule dispatching knowledge.

2. Methodology

2.1 Fuzzy Rule Knowledge-Based System

A rule-based system consists of three components: a database, a rule base, and an inference engine. A fuzzy if-then rule assumes the form below:

If x is **A** then y is **B**

where **A** and **B** are linguistic value defined by fuzzy sets on universes of discourse ***X*** and ***Y*** respectively. '*x* is **A**' is called the premise, and '*y* is **B**' is called the consequence. Then, Zadeh's compositional rule of inference ($B = A \circ R$) is applied to derive consequence of a set of fuzzy if-then rules. This concept is illustrated as follows:

premise 1 (fact)：*x* is A'

premise 2 (rule)：If *x* is **A**

then

y is **B**

---

consequence ：y is B'

where **A**, **B**, A', and B' are fuzzy sets of appropriate universes. The membership function of consequence B' is denoted as follows:

$$\mu_{B'}(y) = \max_{x \in X}\left[\min\left(\mu_{A'}(x), \mu_R(x,y)\right)\right], \quad \forall y \in Y \tag{1}$$

Moreover, the neuro-fuzzy inference system approach ANFIS (Adaptive Network-Based Fuzzy Inference System) is applied to learn and train the fuzzy rule dispatching knowledge.

2.2 ANFIS: Adaptive Network-Based Fuzzy Inference System

ANFIS, a fuzzy inference system implemented in the framework of adaptive networks, can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. To illustrate the architecture of ANFIS simply, we assume that the fuzzy inference system under consideration has two inputs *x* and *y* and one output *z*. For a first order Sugeno fuzzy model, the following is a common rule base with two fuzzy IF-THEN rules:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$

The fuzzy reasoning and the corresponding equivalent ANFIS architecture are illustrated in Figure 1 and Figure 2 respectively. The ANFIS network has five layers. The node functions in each layer are described below:

Layer 1: The node function of every square node i in this layer is

$$O_i^1 = \mu_{A_i}(x) \tag{2}$$

where x is the input to node i, and A_i is the linguistic label (small, large, etc.) associated with this node function. O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i. The bell-shaped functions with maximum equal to 1 and minimum equal to 0 are usually selected as membership function O_i^1, such as

$$\mu_{A_i}(x) = \frac{1}{1+\left(\frac{x-c_i}{a_i}\right)^{2b_i}} \tag{3}$$

where $\{a_i, b_i, c_i\}$ is the parameter set. As these parameters values change, the bell-shaped functions vary accordingly to exhibit various forms of membership functions on linguistic label A_i. Parameters in this layer are referred to as premise parameters.

Layer 2: Every circle node labeled Π in this layer multiplies the incoming signals and sends the product out. For instance,

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, \; 2. \tag{4}$$

Other T-norm operators that perform generalized AND can be the node function in this layer. Each node output represents the firing strength of a rule.

Layer 3: The *i*th circle node labeled N in this layer calculates the ratio of *i*th rule's firing strength to the sum of all rules' firing strengths:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, \; 2. \tag{5}$$

The outputs of this layer are called normalized firing strengths.

Layer 4: The node function of the *i*th square node in this layer is

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{6}$$

where $\overline{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set referred to as consequent parameters.

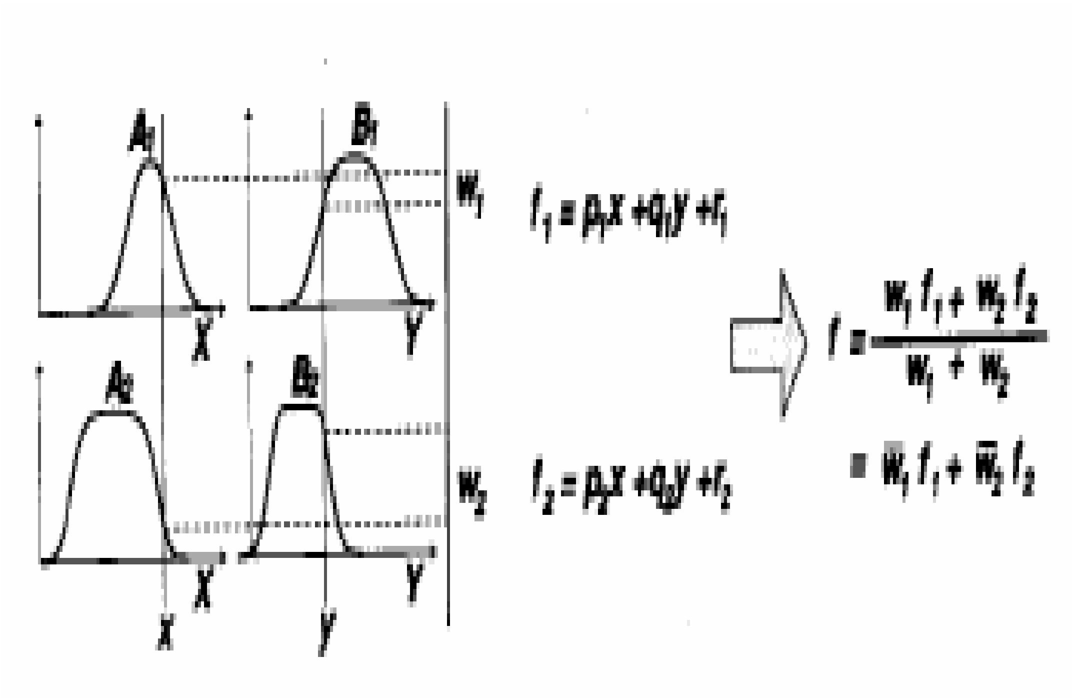

Figure 1. A two-input fuzzy model with two rules

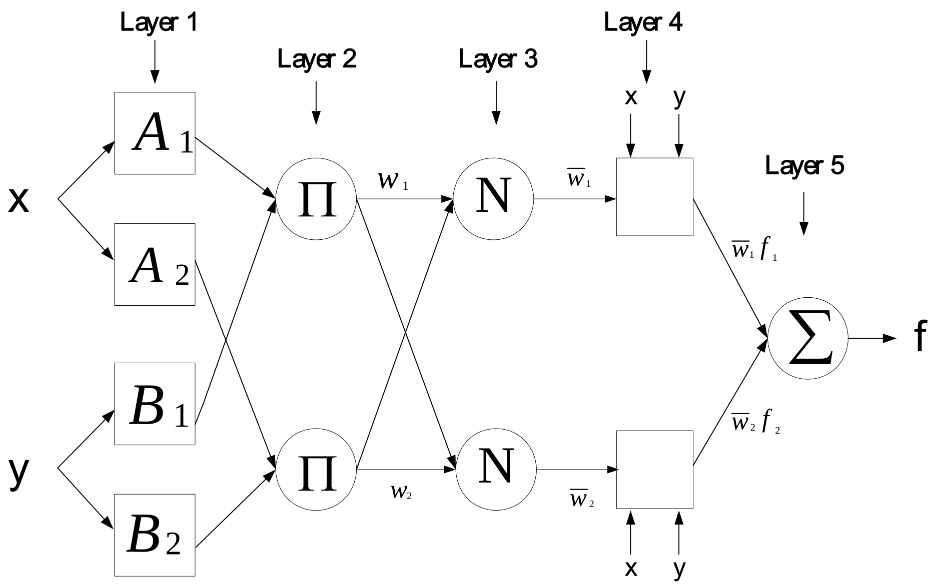

Figure 2. ANFIS Architecture

Layer 5: The single circle node labeled Σ in this layer computes the overall output as the summation of all incoming singles with function below:

$$O_1^5 = overall \quad output = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (7)$$

3. Neuro-Fuzzy Inference System Approach for Fuzzy Rule Dispatching Knowledge

To adapt the manufacturing system behavior such as scheduling strategies, the fuzzy rules are facilitated by learning from examples (see figure 3). Firstly, select the system attributes (such as the available of vehicle, the distance of vehicle, etc.) and performance indexes (such as the idle time of one machine). Secondly, get system specification and production information from MES (manufacturing execution system) database. Finally, perform manufacturing system simulation to obtain training examples for neuro-fuzzy inference system ANFIS.

The fuzzy logic toolbox using the MATLAB software is employed to create the ANFIS model (see figure 4).During the training process, the parameters associated with the membership functions change (see figure 5(a) and (b)). We apply the ANFIS network to fine-tune the initial fuzzy inference matrix to converge to the optimal fuzzy inference system and to get the suitable fuzzy rules dispatching knowledge.

Then we evaluate the manufacturing system performance to verify whether the fuzzy dispatching rules are valid. If the performance is desirable, these illustrations are training examples to further enhance fuzzy rules knowledge. Otherwise, we have to perform further experiments to obtain more training examples.

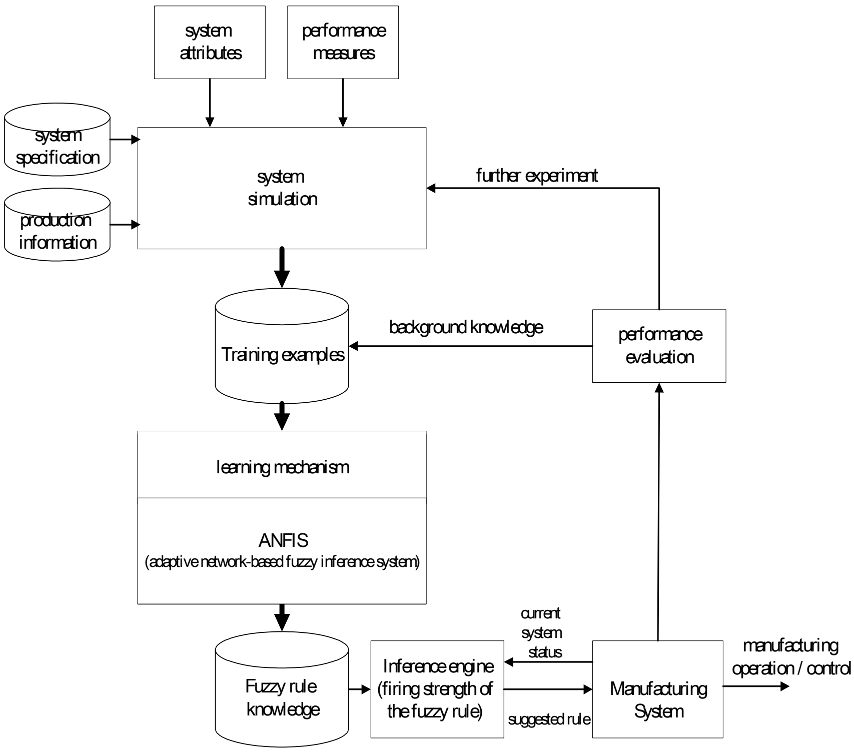

Figure 3. The fuzzy rule knowledge-based systems for dispatching in automated manufacturing

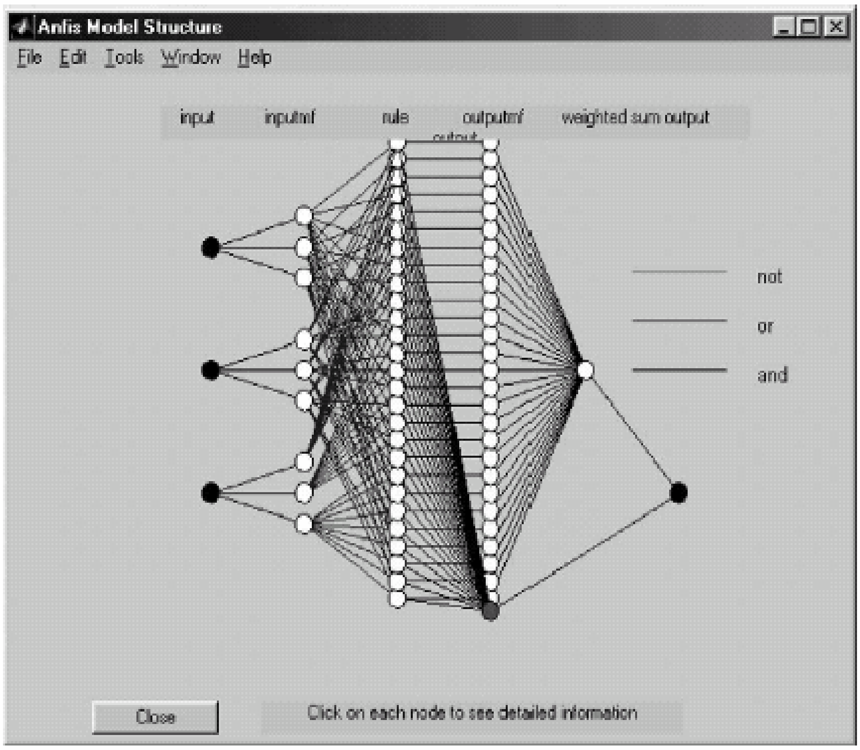

Figure 4. ANFIS network from MATLAB

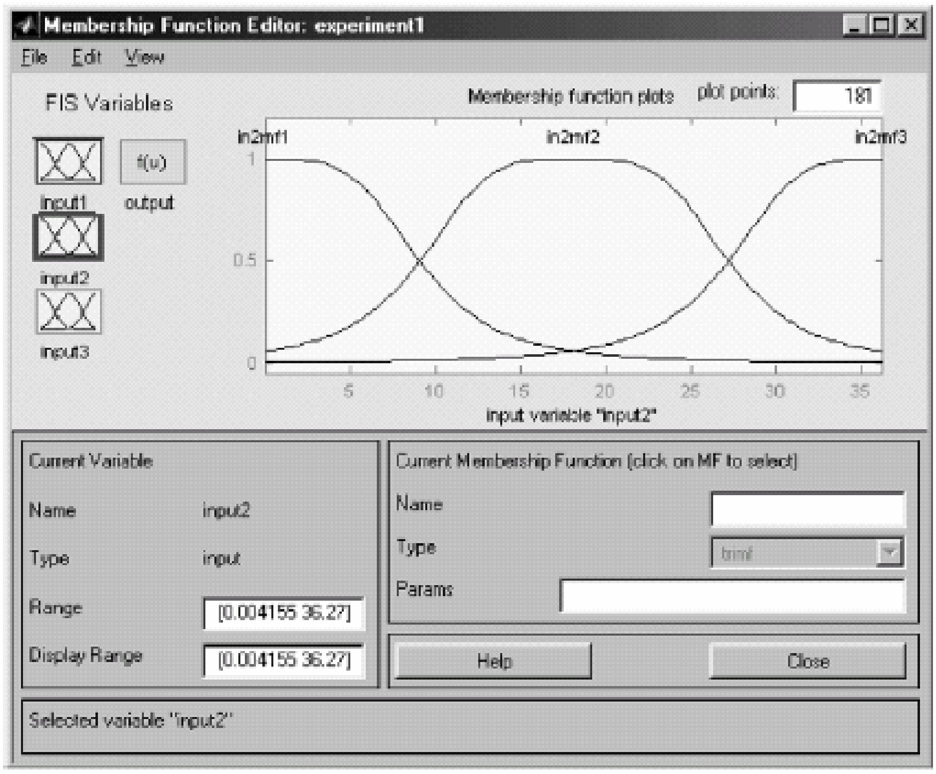

Figure 5. (a) Initial membership function

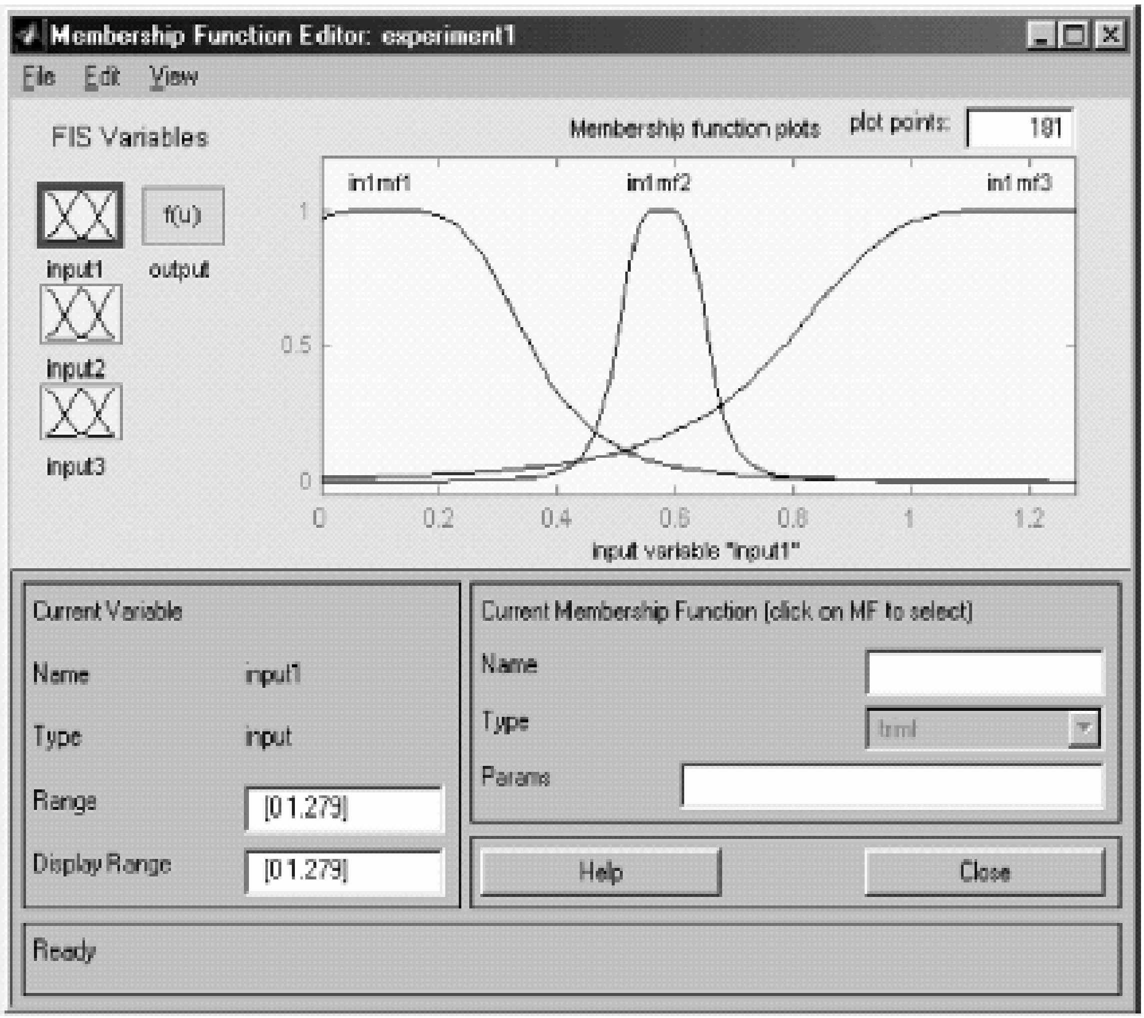

Figure 5. (b) Final membership function

4. Concluding Remarks

This study proposes a systematical scheme to form manufacturing fuzzy rule knowledge-based system and then to construct the dispatching fuzzy rules of jobs and vehicles in order to enhance manufacturing system operations. The manufacturing fuzzy rule knowledge-based system can assist production managers in response to the dynamics intelligently and rapidly.

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