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A Hierarchical Fuzzy Rule-Based Building Model applied to a AGV Dispatching System in an FMS

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Abstract—**Excellence in manufacturing systems has been recognized as one of the main factors behind the success of industrial companies or production companies. New technology for manufacturing processes plays a significant role in this process. Achieving the potential of technological innovations in production, however, requires a wide range of management, as well as engineering issues related to the system. Material handling is a key component in reaching flexibility, manufacturing, dynamism and agility goals. The handling capacity of advanced materials is essential because without this ability of providing the material needed for the proper workstation at the right time and in the right amount, the whole plant will become "bogged down". This makes it less efficient and thus produces less profit and / or it operates at higher costs. This paper proposes a heuristic dispatching Automation Guided Vehicle (AGV) based on multiple attributes and fuzzy logic. Typically, the description of the rule base corresponds to all the possibilities of the connection between the input and output. The manual setting up of the rule base for a determined set of variables is not feasible when considering the efficiency the rules can offer in terms of performance during the inference process. It is also important to note that even for an expert in the field, the task of considering the quantitative value of the correct contribution where each rule affects the system becomes a difficult task. Taking this into account, this paper uses an approach to reduce the rules to a method of hierarchical fuzzy rules. As a means of evaluation, the proposed method is applied to a model based on fuzzy rules developed and used in AGV dispatching of a Flexible Manufacturing System (FMS).**

I. Introduction

There is a widespread perception that material handling is a key component in reaching flexibility, manufacturing, energy and agility goals. The handling capacity of advanced materials is essential because without this ability of providing the material needed for the proper workstation at the right time and in the right amount, the whole plant will become "bogged down". This makes it less efficient and thus produces less profit and / or it operates at higher costs. (Joshi & Smith, 1994).

Material handling technology to address these concerns is the Automated Guided Vehicle (AGV). An AGV is a mobile robot/vehicle used to transport materials in manufacturing environments, designed to receive and execute instructions, follow a path or track, receive and distribute materials. The vehicles generally follow a path that can go in many directions and can usually be easily re-configured according to the manufacturer's plant. Instructions for an AGV show where the vehicle should move, how to reach the destination and what to do when it arrives there (Joshi & Smith, 1994).

Fuzzy Systems, which are basically systems with variables based on fuzzy logic have been used successfully to solve problems in many areas, including pattern classification, optimization and process control [16, 17].The question of how to form a set of fuzzy rule base directly from a given set of data has attracted the attention of many researchers [2, 18-24].

Developing a fuzzy model which reproduces the representation of expert knowledge for a particular problem is not a trivial task. Therefore, the addressed problem and the variables that affect it should be studied in-depth. Many approaches have been proposed to collect data and create knowledge models to solve particular problems. Consequently, the aim is to improve the performance. Even for a specialist in the area, considering the correct contribution for each rule, creating the necessary amount of rules which represent the problem without being redundant and conflicting, becomes a hard task.

Wang and Mendel's method proposed in [14] to automatically generate a fuzzy rule base has been widely used due to it being less complex and also the fact that it produces rule bases with relatively low rates of good classification and no conflicting or redundant rules [15].

In [1], a method for the automatic project of hierarchical fuzzy systems using Takagi-Sugeno inference is shown [2]. The proposal is to define different hierarchical structures interactively using evolutionary methods, evaluate them until the best one is found among the possible candidates. The approach shows efficient results for different classes of problems such as identification, prediction and classification.

Gedeon et al. [3] propose the construction of a fuzzy rule base for the hierarchical classification problem whereby once the rule base is reduced by the proposal, the better the performance of the inference system is. More details of the method will be presented in Section II, as they are used in this paper.

Sugeno and Yasukawa [4] present an approach for qualitative modeling using fuzzy logic. Considering this, the fuzzy model (input and output variables, rule base, etc.) and the linguistic approximation modifiers (very low, more or less high, etc.) must be defined. The definition of the fuzzy model consists of identifying the structure and parameters of the functions in the domain's input.

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Analyzing the theoretical features of fuzzy logic as well as Wang and Mendel´s method, and identifying what is entailed regarding the problem of dispatching vehicles, we put forward the hypothesis that by changing the regularity criterion, we could achieve better results. Constructing the base is in accordance with the method proposed in [3], however there is a variant in the method used to determine the contribution of the variables in the system.

The description of the methods proposed by [3], [4], [7] and [8] used in this study can be found in Sections II and III. As a way of evaluating, the proposal is applied to the basic rules of a fuzzy system for the problem of dispatching automated guided vehicles developed in [5] presented in Section IV. Afterwards, in Section V, the rule base generated by the proposal is applied to a hypothetical flexible manufacturing system and compared to the FIFO rule for dispatching and the original fuzzy rule base. Section VI draws the main conclusions and makes suggestions for future work.

II. Approaches

A. Constructing a Hierarchical Rule Base

The approach to construct a hierarchical rule base was developed in [3]. The first step of the method is to determine, from the set of input data, the linguistic terms that form the fuzzy rules of the system. According to the authors, for the sake of being interpreted easily and also computational simplicity, triangular functions were chosen for this purpose of representation. The rules are constructed by mapping the relationships of available inputs-outputs and the linguistic terms. As the input values cut more than one term in the field, the higher value relevance term is then considered. After generating the rules, the redundancy is eliminated. The Mamdani inference system is used in this model.

The next step of the method is to build the levels of hierarchy. Taking this into account, the contribution of each variable in the system is considered, where the top levels belong to the variable whose contribution is the most important for the fuzzy model. The contribution measure which is used is the Regularity Criterion (RC) proposed in [4]. Thus, for each input variable Ci, there is a value of RC, where the lowest value found belongs to the most important variable in the system. After determining the hierarchy of variables in the system, the construction of the base starts from the top levels. Considering the T linguistic terms of the top variable, each term generates a sub-level in the hierarchy. Each sub-level takes a term and leads it to another level. For the last variable considered, the sub-levels will lead towards the rule output. For example, for two input variables (X1 and X2), each one having T linguistic terms, and one output variable (y), the following levels are generated:

R1: If X1 is A11 then use R21
If X1 is A12 then use R22

R2: If X2 is A21 then y is B211
If X2 is A22 then y is B212

R2T: If X2 is A2T then y is B21T
If X2 is A22 then y is B2T2

The next step of the method is to reduce the rule base by eliminating certain sub-levels of the hierarchy. Taking this into account, two factors are considered:

- If the classification output is the same for all sub-levels, it can be moved to the level above the sub-level where it is located.
- If the classification output can be interpolated by two neighbors, it can also be removed.

The following example illustrates the application of these two principles. The following structure is generated considering two input variables (experience, age) and one output (salary) and each input variable has three linguistic terms:

R1: If Experience is a Few then use R21
If Experience is Average then use R22
If Experience is High then use R23

R21: If Age is Young then salary is Basic
If Age is Average then salary is Basic
If Age is Old then salary is Basic

R22: If Age is Young then salary is Basic
If Age is Average then salary is Medium
If Age is Old then salary is High

R23: If Age is Young then salary is Basic
If Age is Average then salary is Medium
If Age is Old then salary is High

Following there is the result of the rule base considering the two factors for the sub-levels' elimination:

R21: If Experience is a Few then salary is Basic
If Experience is Average then use R22
If Experience is High then salary is High

R22: If Age is Young then salary is Basic
If Age is Old then salary is High

B. Regularity Criterion

As mentioned before, Sugeno and Yasukawa [4] propose an approach for qualitative modeling using fuzzy logic. Out of all the features presented, we discuss here only the method of identifying the fuzzy model structure, which is described below.

The model structure contains the rule base, the range that the variable values assume and their respective functions in this area. From a set of input variables (x1, x2 ,..., xk), are candidates belonging to the fuzzy system, a selection is established following a determined criterion which can investigate which variables most affect the system output. The criterion used is the regularity criterion (RC). Thus, not all the variables that affect the system will belong to the fuzzy model, but only those that are most relevant.

First, the data must be divided into two groups: A and B. These groups will be used to create the fuzzy model, as the model structure is identified from the examples. The RC value is obtained by expression (1) where the variables are added one by one, considering the lowest value of the RC obtained. For each iteration of the identification algorithm, a new model according to the variables already added is created. Sub-section B in Section III establishes this principle.

Vieira et al. [7] propose a change to the method at this stage of identifying the variables to calculate the RC. The selection is done in the same way: by choosing the lowest RC variable, however the highest RC variable is excluded reducing the options of choice in the next iterations. According to the authors, this feature reduces the number of interactions at each stage of the algorithm, also reducing the computational time.

$$RC = \left[\sum_{i=1}^{KA} (y_i{}^{A} - y_i{}^{AB})^2/k_A + \sum_{i=1}^{KB} (y_i{}^{B} y_i{}^{BA})^2/k_B\right]/2 \tag{1}$$

Where:

- KA and KB represent the amount of data of each group A and B;
- y_i^A and y_i^B y_i^B represent the output values of each row i of data from groups A and B;
- $y_i{}^{AB}$ represents the output values obtained by inferring the entries of row i of group A in the model created from the data of group B;
- $y_i{}^{BA}$ represents the output values obtained by inferring the input of row i in group B in the model created from the data of group A.

The fuzzy model method uses the fuzzy c-means clustering technique to determine the number of rules. By using a procedure to projection the input values in the cluster, the rules and their respective trapezoidal functions can be determined by approximation. The number of rules is obtained in relation to the number of clusters given by expression (2). The number of clusters is increased one by one, until the value obtained in S (c) reaches a local minimum. More details of this process can be obtained in [4].

$$S(c) = \sum_{k=1}^{N}\sum_{i=1}^{c} (\mu_{ik})^{m} \left(\|x_k - v_i\|^2 - \|v_i - \bar{x}\|^2\right) \tag{2}$$

Where:

- N is the amount of data to be clustered;
- c is number of clusters, c ≥ 2;
- x_k, k-th data of the data set;
- x average data $x_1, x_2, \ldots, x_n$;
- v_i vector representing the center of cluster i;
- || || standard;
- μ_{ik} degree k in the given cluster i;
- m weight adjustment, varying in the range of m = [1.5, 3];

III. Constructing a Fuzzy Rule Base Using Regularity Modified Criterion

This Section presents the main features of the proposed development. The main distinction of the approaches described so far is based on a proposal to use another method to create data models to calculate the regularity criterion. This new approach is discussed below.

A. *Regularity Modified Criterion*

As described in the sub-section "Regularity Criterion", one of the steps to identify the structure of the fuzzy system is to determine the extent of contributions or how many and which variables most affect the system output. According to this principle, this measure is used in the approach described in the sub-section " Constructing a Hierarchical Rule Base" to determine which levels of the variables will be evaluated when constructing the hierarchical rule base. In this paper, we propose to create the model used in expression (1) from the automatic method of creating rules proposed in [8]. Thus, the same procedures are equivalent to the remaining steps of the method in the sub-section "Regularity Criterion", which are: divide the data set into two groups and add the candidate variables belonging to the system one by one.

The proposed method does not include automatic identification of parameters as in [4]. However, due to the fact that it is a method which is easy to implement and widely known in the literature, it can be considered convenient to use.

B. *Evaluating Regularity Modified Criterion*

As a way of evaluating this stage of the approach, the same set of data presented in [4] was considered. As mentioned in the previous chapter, the approach proposed in this paper does not cover the generation of function parameters and therefore is a default of the areas/domains. As in [4] trapezoidal functions are defined, the same feature can also be considered. The following figure (Fig. 1) outlines the areas of input variables and their respective sets:

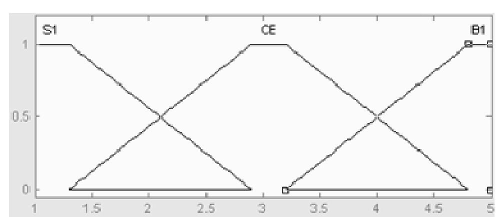

Figure 1. Domain/Area of the variables X1, X2, X3, X4 and out of range [1, 5]

Table 1 presents the results obtained by calculating the regularity criterion in its original proposal (RC) and its modified version (RCM).

TABLE I. RESULTS OBTAINED IN RC AND RCM

Iteration	*Variables*	*Value RC*	*Value RCM*
1	x_1	0.630	1.327
	x_2	0.863	2.091
	x_3	0.830	2.405
	x_4	0.937	2.966
2	$x_1 . x_2$	0.424	0.86
	$x_1 . x_3$	0.571	1.208
	$x_1 . x_4$	0.583	1.345
3	$x_1 . x_2 . x_3$	0.483	0.564
	$x_1 . x_2 . x_4$	0.493	0.598

Although the data used are the same for the RC and RCM calculations, the results are different because the definition of parameters in the dominion/area is distinct. Nevertheless, it is worth noting that what prevails here is the ability to characterize the extent of contribution of variables in the system. Thus, the method of generating Wang & Mendel's can generate the knowledge base from examples as a way of learning, thereby suggesting a model for the data.

IV. IMPLEMENTATION PROPOSAL

In order to evaluate the proposed method, an application was developed for the fuzzy model defined in [5]. The following sections characterize the problem addressed and the model considered.

A. *Problem Description*

An automated guided vehicle (AGV) is defined as a vehicle carrying advanced without a driver. Moreover, it is a integrated processing system which has the task of controlling the vehicle. AGVs usually move around on the factory floor on rails using specific routes. The problem of dispatching automated guided vehicles (AGVs) is to choose the best way of designating a particular AGV to transport any demand. The choice should take into account specific criteria of performance for the production system.

The first work related to the rules of dispatching AGVs was motivated by creating simple rules that evaluated a determined point system, as in: Egbelu and Tanchoco (1984); Egbelu (1987); Platzman and Bartholdi Iii (1989); Han and McGinnis (1989); Taghaboni (1989).

Over time some researchers realized that by reflecting on more than one aspect to take decisions, they could obtain better results, as in: Klein and Kim (1996); Kim et al. (1999); Kim and Hwang (1999); Tan and Tang (2000); Yamashita (2001); Jeong and Randhawa (2001); Benincasa et al. (2003); Kizil et al. (2006); Umashankar and Karthik (2006); Morandin et al. (2007).

The quantity and quality of work found in the literature shows the relevance and current topics.

B. *Definition of Fuzzy Model*

The aim of the fuzzy model proposed in [5] is to consider some input variables in order to obtain a decision in relation to the priority of service to workstations with pending resource requests. Thus, the priority value returned by the fuzzy system classifies each one of the AGVs in the manufacturing system making it possible to choose the best ranked AGV.

The rule base generated for the system corresponds to all the possibilities of relating among the input linguistic terms, i. e. 3x3x3 = 27 rules, as shown in Table II.

TABLE II. RULES

Rule	**DT**	**NN**	**ERBS**	**PE**
1	Short	Few	Big	Medium
2	Short	Few	Medium	High
3	Short	Few	Small	High
4	Medium	Few	Big	Low
5	Medium	Few	Medium	Medium
6	Medium	Few	Small	High
7	Long	Few	Big	Low
8	Long	Few	Medium	Medium
9	Long	Few	Small	High
10	Short	Medium	Big	Medium
11	Short	Medium	Medium	High
12	Short	Medium	Small	High
13	Medium	Medium	Big	Low
14	Medium	Medium	Medium	Medium
15	Medium	Medium	Small	Medium
16	Long	Medium	Big	Low
17	Long	Medium	Medium	Medium
18	Long	Medium	Small	High
19	Short	Small	Big	Low
20	Short	Small	Medium	Medium
21	Short	Small	Small	High
22	Medium	Small	Big	Low
23	Medium	Small	Medium	Low
24	Medium	Small	Small	High
25	Long	Small	Big	Low
26	Long	Small	Medium	Low
27	Long	Small	Small	High

The following measures were chosen for the input variables:

- **Distance (DT):** This represents the measure of distance in meters between the AGV and available workstation requester. This measure, as with the others considered below, is known and considered a specific layout of the factory presented in [5].

• **Number of nodes (NN):** This determines the number of nodes between the available AGV and workstation requester. A node or junction, can be described as the junction point between two tracks, serving as a kind of semaphore to control collisions.

• **Remaining space in the output buffer (ERBS):** each machine in the production system has a buffer to store pre-produced parts. Given a storage limit for the buffer, the value of the remaining vacant spaces is also considered in the fuzzy system.

PE represents the priority. For the cited variables, three evenly distributed triangular functions were used to represent each domain/area.

C. Results

In order to apply the approach, the same parameters for the input and output variables presented earlier were considered. The Mamdani inference system and center maximum defuzzification method were used. 150 lines were generated of data obtained from the fuzzy model established in [5]. Following the procedures of the method, the data set was proportionally divided into two groups. For the first step of the method, whereby the contribution of the variables is determined, the results are presented in Table III.

According to the results of the first iteration of the RCM calculation, the most important variable for the system is the space remaining in the output buffer (ERBS) followed by the variable distance (DT) and number of nodes (NN). Thus, considering the step of generating rules, the ERBS variable is at the top of the hierarchy.

TABLE III. RESULTS

Iteration	Variables	Value RCM
1	DT	4.042
	NN	8.787
	ERBS	2.878
2	ERBS – DT	17.084
	ERBS - NN	8.836

After the stage of generating and eliminating the rules, which follow the procedures described in Section II, the final rules were:

R1: If ERBS is Small then PE is Low
If ERBS is Medium then use R22
If ERBS is Large then use R23

R22: If DT is Short so PE is High
If DT is Average then PE is Average
If TD is Long then PE is Low

R23: If TD is Long then PE is Average
If DT is not Long then PE is High

As the results show, the initial 27 original rules are reduced to 8rules, which is a very significant reduction in terms of the system inference performance. Note that the variable Number of Nodes (NN) is no longer considered on the basis of hierarchical rules, as its values are inherently linked to the variable distance, i. e. for a short distance, there are few nodes on the path to be travelled by the vehicle. Although it is common sense that it is affirmative, only with the results is it possible to establish a consistent evaluation and a better adjustment of the variables and the model.

V. APPLICATION OF THE METHOD

The flexible manufacturing system (FMS) case considered in the study was built in a software simulation. The FMS consists of six manufacturing machines with a limited production buffer, an AGV, a loading station and an unloading station, as shown in Fig. 2.

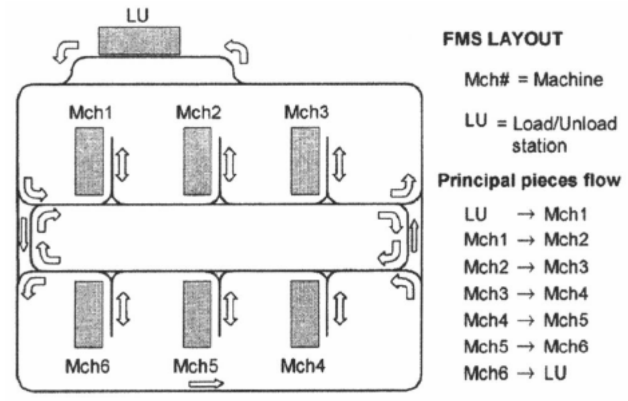

Figure 2. The flexible manufacturing system layout (Morandin, 2006)

The dispatching rules proposed here were tested and validated in this FMS. It was defined that the total number of parts to be produced is 375 pieces, including 25 pieces of each type. The pre-production sequence is C, B, D, E, A, C, B, 0, E, A, C, B, D, E and A.

• For the simulation tests, the following conditions were considered:

• There is only one operation at a time in a workstation.

• The capabilities of the machine buffer are limited.

• The travel distance between the workstations and AGV are known and the AGV speed is constant.

• Each type of piece requires a set of tools.

• The installation times are constant.

• The considered AGV is a unit load device.

Based on this hypothetical situation, the implementation using a fuzzy rule hierarchy was analyzed, and was described in this paper and compared to the application of the FIFO rule (first in - first out), described in the literature as simple rules, and compared to the original fuzzy rule. Table IV presents the result of the implementation, showing each time slice, which was the quantity of products produced by each technique.

TABLE IV. SIMULATION OF RESULTS

Time (hours)	Quantity produced		
	FIFO	FUZZY	FUZZY HIERARCHICAL
0	0	0	0
10	54	57	62
20	109	114	124
30	157	167	179
40	207	226	238
50	256	281	293
60	308	338	345
63			
65			375
68	349	375	
74	375		

VI. CONCLUSIONS

Based on the related research to perform the optimization and represent knowledge, this work proposes a hierarchical construction model of a rule base using the regularity modified criterion. Initially, based on the characteristics of the problem and the concepts proposed by Wang and Mendel, it can be concluded that by changing the regularity criterion, the order of variable evaluation according to the hierarchical rules would change, thus achieving better results. First, we observed the effectiveness of the method to measure the contribution of each variable in the system and create the rule base, in which the method has proven effective. Subsequently, we applied the rule base obtained from the problem of dispatching vehicles in the hypothetical FMS. Observing the results in Table IV, it can be concluded that the proposal obtained a better result, producing the same amount of products in less time.

Considering future work, it is recommended that the proposed method should be applied to more complex and larger flexible manufacturing systems to observe the behavior of keeps effective, also adding more variations to the simulation parameters making the problem more realistic. Another important contribution would be to improve the identification model fuzzy system using an approximation method of the parameters of the variable domains from the set of input data. This would make it possible to have a better representation of the input values and a better characterization of the contribution variable measure.

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