Int J Adv Manuf Technol (2015) 79:615–625
DOI 10.1007/s00170-015-6833-8

ORIGINAL ARTICLE

Approaches of fuzzy systems applied to an AGV dispatching system in a FMS

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Received: 12 August 2014 / Accepted: 18 January 2015 / Published online: 12 February 2015

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. 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 two approaches for the dispatching of AGV (automated guided vehicle) using systems fuzzy. The first use hierarchical fuzzy rule-based model building in which the main feature is to make the base of fuzzy rules is smaller and simpler but with high coverage and interpretability. The second use adaptive genetic fuzzy system with simple prediction in which the main feature is to increase the sensitivity of the system about the variables. Both approaches using multiple attributes and having the objective decrease the makespan in a FMS (flexible manufacturing system).

Keywords Automated guided vehicles · AGV dispatching · Fuzzy system · Multi-attribute · FMS · Makespan minimization

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1 Introduction

There is a widespread perception that material handling is a key component in reaching flexibility, manufacturing, energy, and agility goals. 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, and receive and distribute materials. The vehicles generally follow a path that can go in many directions and can usually be easily reconfigured 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 [1].

1.1 General problems related to AGV

automated guided vehicles (AGVs) are popular materials handling systems in automated processes, flexible manufacturing systems, and even in container handling in ports [2–4].

Many projects related to AGV have been proposed. There are several points inherent to the problem that increasingly seeks improvement for greater flexibility, competitiveness, quality, etc.

Different objectives can be found in the literature as to minimize the total transport cost of the path, minimizing travel distance or minimizing the travel time [5].

Le-Anh and De Koster [6] are presented a review of the development and control to automated guided vehicle systems. The authors cite the key issues that involve the automated guided vehicle systems, such as amount and type of vehicles, routing, position of the idle vehicle, battery management/fuel ratio, deadlock resolution, and scheduling of vehicles.

1.2 Dispatching of AGV

Dispatching is an important issue for management and control of AGV, as stated by the works [3, 6, 7] and remains today because of the amount of related research in the literature.

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 [8] presented a dispatching rule, called demand-driven (DEMD), with the main objective to meet the idle workstations, with the low number of parts in its input buffer and also workstations blocked by excess parts in its output buffer, thus, reducing idleness and possible blockages of the workstations.

Bartholdi Iii and Platzman [9] presented the rule first-encountered first-served (FEFSI) aiming to deliver loads as fast as possible for multiple AGVs operating in a simple path of closed loop.

Han and McGinnis [10] proposed the rule most significant move (MSM), which calculates the priority index for each workstation requiring transportation.

Taghaboni [11] proposed the rule most critical output queue with look ahead (MCQL) which is a variation of the rule MROQS based on a critical index and a priority index.

Over time, some researchers realized that by reflecting on more than one aspect to take decisions, they could obtain better results, as in

Kim et al. [12] proposed a dispatching rule for AGV, with the main objective of balancing workloads among workstations. They proposed an equation for this composite of several variables, involving the current state of the "shop-floor."

Tan and Tang [13] proposed a dispatching rule that consists of multiple attributes, using the fuzzy inference method called Takagi and Sugeno and also a genetic algorithm for the selection of weights between scores. The main purpose of this study was to link the fuzzy variables of the system.

Jeong and Randhawa [14] proposed a dispatching rule for AGV-type "vehicle started" composed of multiple attributes, assigning weights to each attribute by using an artificial neural network.

Benincasa et al. [15] presented a model for defining a rule for dispatching of AGV-based fuzzy systems. They considered three input variables: distance between the AGV and the workstation, the number of nodes between the AGV and the workstation, and the remaining space in the output buffer of the workstation requester. It created a rule base manually with all possible combinations.

Umashankar and Karthik [16] proposed an intelligent approach of dispatching AGVs based on multiple criteria of a fuzzy logic controller, which simultaneously takes into account various aspects in every dispatching decision. The controller operates in two phases, the first phase to determine which AGV will be selected considering the use of the AGV, the distance from the AGV to the work center, and the output buffer. If there is a tie, to resolve the conflict, the second phase considers the scheduling content and process priority.

For relevant searches in the subject, some authors claim that a negative point of dispatching rules is that their decisions are based on present information, and that further details of the processes being considered for decision making could contribute greatly.

Naso and Turchiano [17] adopted a strategy for multi-criteria decision to take into account multiple aspects in every dispatching decision. It is used for hierarchical fuzzy decision-making in conjunction with genetic algorithms to weigh the variables of greatest impact and generate the hierarchy. It was incorporated in the work a variable that the authors call chaining of tasks, which are checked destinations which lead to other services, forming a chain of tasks.

Hidehiko [18] proposed a classification system that determines a hypothesis priority using ranking to improve the efficiency of the "reasoning to anticipate the future" (RAF).

Smolic-Rocak et al. [19] presented a method for dynamic routing of supervision and control of multiple AGVs. To solve the problem of the shortest path dynamically, the dispatching method proposed uses a window of time in a vector form.

The authors Chiba et al. [20], based on the assertion that the problems related to the environment of automated guided vehicles, more specifically, the problems of modeling the path of the AGV and routing of AGVs are linked, showed a cooperative co-evolutionary approach, which considers using a genetic algorithm evolution of the two problems together.

1.3 Fuzzy system

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 [21, 22]. 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 [23–30].

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 [28] 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 [31].

In [32], a method for the automatic project of hierarchical fuzzy systems using Takagi-Sugeno inference is shown [23]. 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. [33] 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 [34] 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.

This paper proposed two different approaches of construction of fuzzy system applied on AGV dispatching in FMS. The first calculates the contribution of each variable on the system by means of an initial rule base and ,after, creates a hierarchical of rules based in contribution previously calculated. The second generates an extensive rule base and use genetic algorithm to optimize the initial fuzzy rule base.

2 Approach I—hierarchical fuzzy rule-based (HFRB) model

The approach I to construct a hierarchical rule base was developed in [33]. 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. 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 modified criterion (RMC), it is a variant of regularity criterion proposed in [34]. Thus, for each input variable Ci, there is a value of regularity criterion (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 sublevel in the hierarchy. Each sublevel takes a term and leads it to another level. For the last variable considered, the sublevels will lead toward the rule output.

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

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

2.1 Regularity criterion

As mentioned before, Sugeno and Yasukawa [34] 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.

Vieira et al. [35] 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.

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

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, and
- 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 project 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 [34].

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

where

- N is the amount of data to be clustered;
- c is number of clusters, $c \geq 2$;
- x_k, kth 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;
- u_{ik}, degree k in the given cluster i;
- m weight adjustment, varying in the range of m=[1.5, 3];

2.2 Regularity modified criterion

As described in the subsection 2.1, 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 to determine which levels of the variables will be evaluated when constructing the hierarchical rule base. In this propose, to create the model used in expression (1) from the automatic method of creating rules proposed in [36]. Thus, the same procedures are equivalent to the remaining steps of the method in the Subsection 2.1, 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 [34]. However, due to the fact that it is a method which is easy to implement and is widely known in the literature, it can be considered convenient to use.

2.3 Evaluating regularity modified criterion

As a way of evaluating this stage of the approach, the same set of data presented in [34] 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 [34], 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:

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

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 and Mendel's can generate the knowledge base from examples as a way of learning, thereby, suggesting a model for the data.

3 Approach II—adaptive genetic fuzzy (AGF) model

Some considerations make the most important considerations in developing an effective approach to the problem of vehicle dispatching in manufacturing systems. The first is the ability to consider multiple variables they are from different organizational levels. Another concern is the possibility of having more than one goal and that they can swap at runtime.

The variables to be considered often have linguistic quantifiers, and consideration of them to reach a final decision becomes a complex problem. Fuzzy logic has been used successfully in several approaches, for within its features, some features stand out as providing a mathematical framework for modeling systems loosely defined, overcomes the rigidity of classical logic allowing degrees of membership and provides core decision based on rules described in natural language.

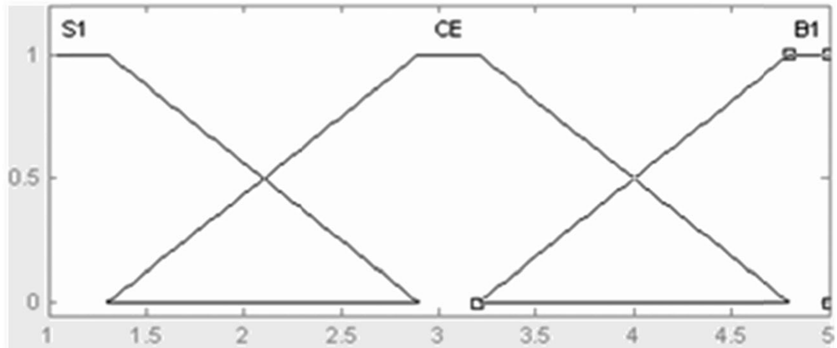

Fig. 1 Domain/area of the variables $x1$, $x2$, $x3$, $x4$, and out of range [11, 15]

Initially seeking a specialist and in literature variables with the greatest impact on production systems, such as distance, buffer, delivery date, etc. so having set the variables to be used is created fuzzy knowledge base (Fig. 2). Another important point is that fuzzy logic is favorable for integration with other computing methods, such as neural networks and evolutionary algorithms [37]. Therefore, if the rule base constructed initially not present satisfactory results, you can add other methods to refine the rule base and reaching a balance between coverage and interpretability. Because it is finding good solutions in short periods of time, the use of genetic algorithms for automatic refinement of the rule base is an option (Fig. 3).

Another advantage of this proposal is to predict the AGV dispatching, the modeling of the scenarios in Petri nets and the possibility of changing the ultimate goal, it is possible to control the stock and control its costs.

Most companies have a mix of production of different products, often coming to the hundreds. Thus, it becomes very difficult, if not impossible to make a forecast of demand for each product manufactured [38]. The company must choose, according to the manufacturing environment, demand, and management characteristics levels of its production and may be obtained from the company's financial improvements, waste reduction, and maximization of available resources [38].

Minimizing the makespan, which is produced more in less time, the stock remains at high levels, which means a higher probability of responsiveness to customers and can give rise to the creation of buffer stocks which have the function of protecting the system when demand and spare time vary over time. This favors lower costs inversely proportional to the amount stored. This case evaluated the following variables: distance, number of nodes, the input buffer, and output buffer.

Table 1 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

Working tardiness, which is produced according to demand, the stock remains at low levels, which means less chance of reducing the rates of wasting. This favors lower costs directly proportional to the amount stored. This evaluated the following variables: distance, number of nodes, chaining of tasks, and delivery date.

Distance represents a measure of distance between the AGV available and the workstation requester.

Number of nodes represents the number of nodes between the AGV available and the workstation requester. A node or intersection can be described as the junction point between two tracks, serving as a kind of semaphore to control collisions.

Input buffer and output buffer, not letting the input buffer completely empty and/or the output buffer is filling of a way of trying not to let the workstation stopped, as a result spend less time.

Chaining task is when a task leads to another, i.e., an AGV delivers a part on a workstation 1 and press a part to take to workstation 3, which in turn carries a part to workstation 7.

Delivery date, this variable is crucial for production to order and meeting deadlines.

Each input variable and output variable was divided into five symmetric triangular partitions, thus, better representing the problem.

Next, the created rule base comprised all possible among the four input variables. Four variables were divided into five partitions that is equal to a total of 625 rules, created by hand from the expert knowledge show in Fig. 3.

The genetic algorithm is used to refine the initial rule base, making a balance between interpretability x coverage.

The rules are coded by real numbers that represent the index of fuzzy sets that appear in the antecedent and consequent part of the rule. The initial population is the basis of rules established earlier.

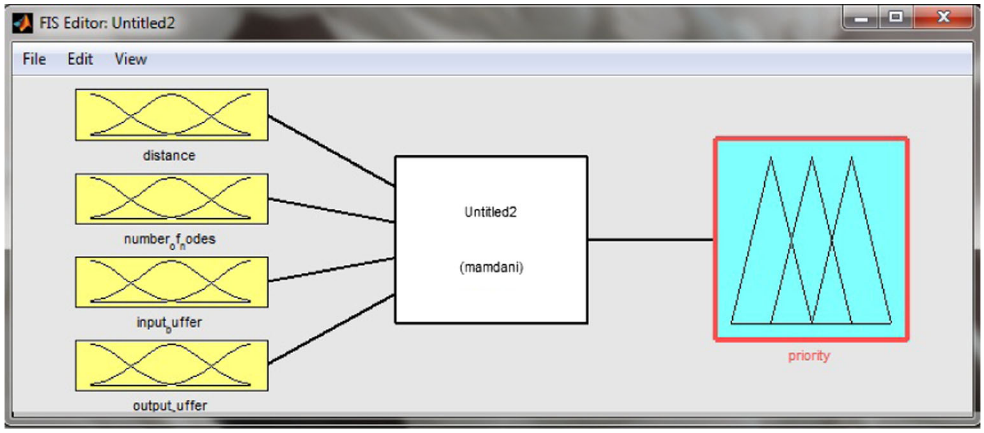

Fig. 2 Knowledge base of the makespan objective

The fitness function is defined based on an error measure, the medium square error (MSE) over a training data set, which is represented by the following expression:

$$f(C_i) = \frac{1}{2N} \sum_{y=1}^{N} \left(e_y - e_y^{'}\right)^2 \qquad (3)$$

where N is the total number of training examples, $e_y^{'}$ is the output value obtained from the system using the rule base coded in C_i and e_y is the known desired value. The best chromosome is the one that minimizes the function (3).

The genetic operators utilized in this work are one-point crossover, standard mutation, and the stochastic universal sampling selection, together with the elitist strategy.

The dynamic nature and uncertainty of the environment, only one parameter may not be ideal, then the periodic recalculation, using a score for each parameter updated in real time can bring better results [39], were added to project to the prediction, which occurs in two stages.

- First is the moment that there is a request for transportation and must be assigned to an AGV. On most systems, only the free AGVs enter the contest for shipping, which can occur is that a busy AGV will finish its task in a short time, and when this occurs, it will be in a position more feasible to fulfill the pending request. Thus, the proposal incorporates the decision these possible AGVs.
- The second is when there are one or more idle AGVs. Instead of them staying put until there is a request for transport, it does a check on processing times of the

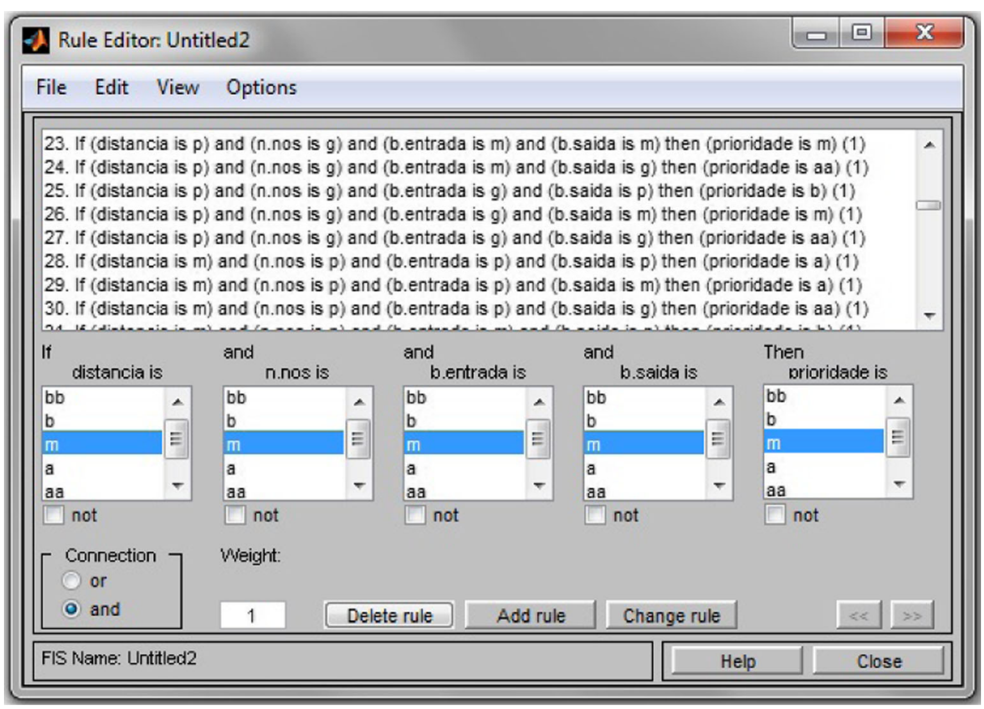

Fig. 3 Initial rule base

workstations, selects those with a shorter time to finish the task, it is the account of priority and sends the AGV already even before the workstation makes the request for transport.

Basic modeling in Petri nets, the scenario that will apply the method, appears to each workstation, and each node in the transportation routes is a resource to be used by a vehicle at a time, that happens in real factories and often disregarded in studies in the literature, which can load and unload more than one vehicle on the same workstation at the same time, or two vehicles passing through a node (intersection) in the same time.

4 Computer experiments

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. The factory was simulated in Simio software based on the model shown in Fig. 4, and Petri net model was created in CPNtools software (Fig. 5).

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; and the considered AGV is a unit load device.

Table 2 shows the distance between the points of loading, unloading, and workstations. Table 3 shows the number of nodes (crossings) between the points of loading, unloading, and workstations.

Table 4 shows the sequence of production for each product.

All matrices support for creating a dynamic allocation table to help control and dispatching AGVs.

The aim of the fuzzy model proposed in [15] 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., $3\times3\times3=27$ rules.

Based in [15], the implementation using a fuzzy rule hierarchy was analyzed, 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 [15]. In order to apply the approach, the same parameters for the input and output variables presented earlier were considered. The Mamdani inference system

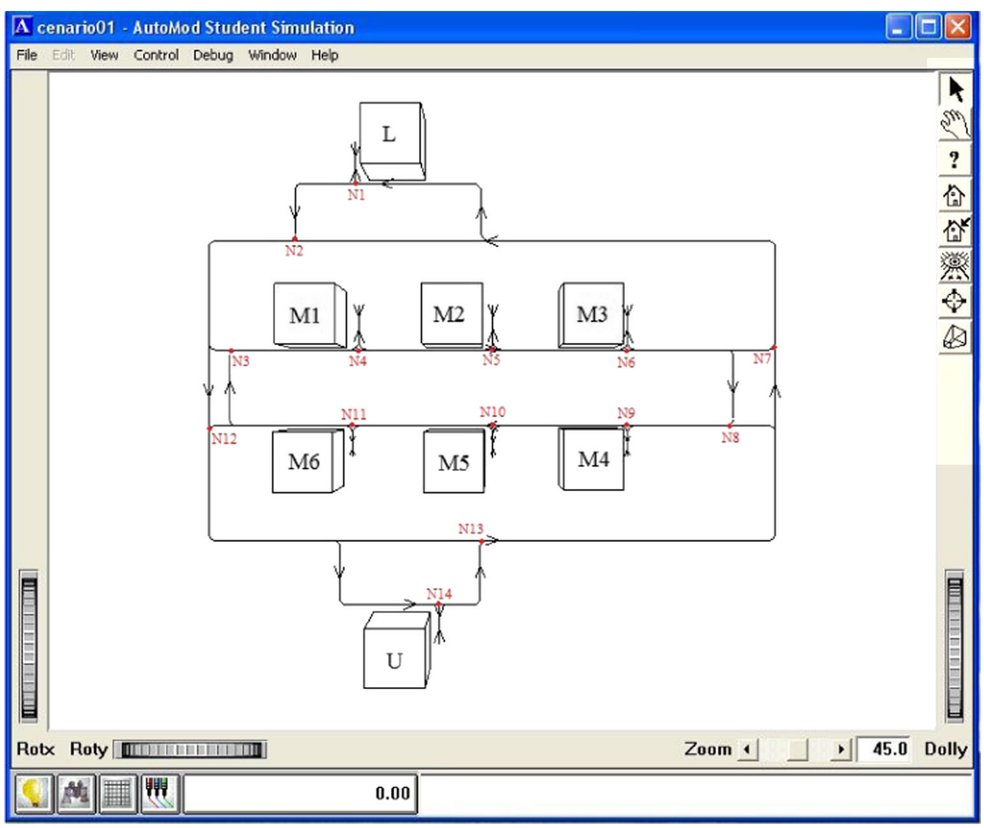

Fig. 4 Factory layout the proposal is implemented

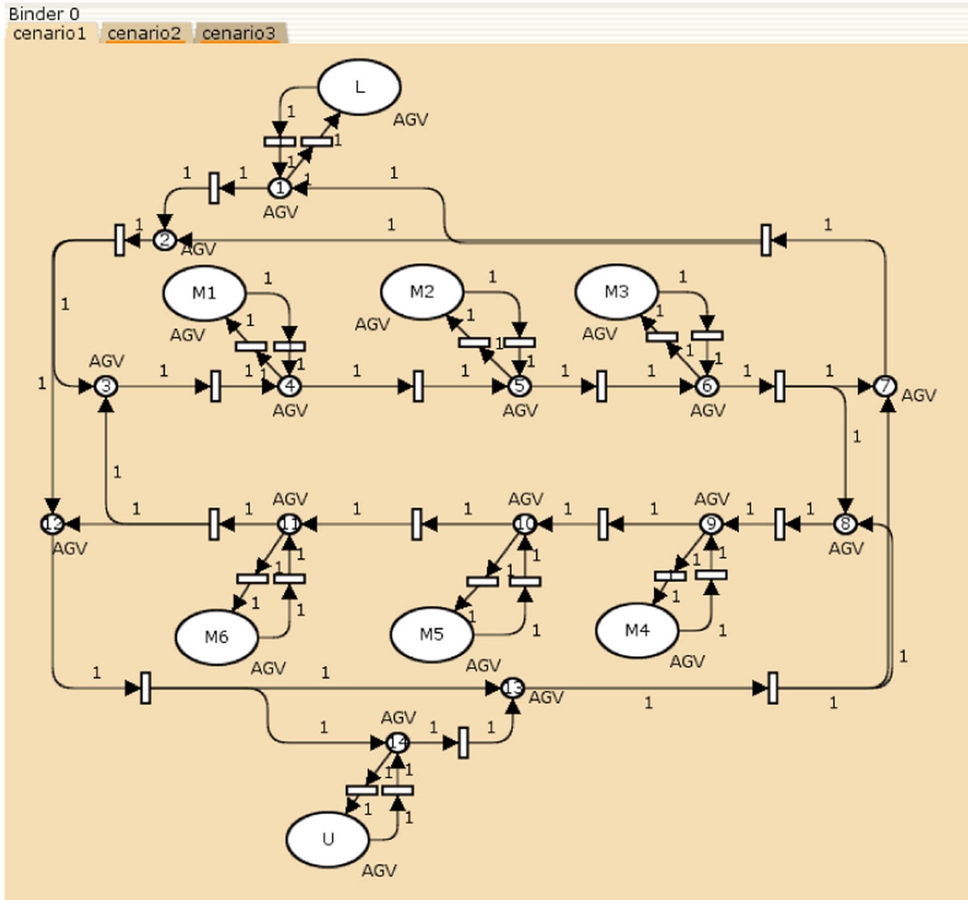

Fig. 5 Factory layout modeled in Petri nets

and center maximum defuzzification method were used. To be able to perform the intrinsic analysis of the method, 150 lines were generated of data obtained from the fuzzy model established in [15]. 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 5. All fuzzy systems were implemented in MATLAB software.

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.

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

Table 2 Matrix of distance between the workstation

Distance	L	M1	M2	M3	M4	M5	M6	U
L	0	34	42	50	74	82	90	58
M1	58	0	10	18	42	50	58	90
M2	50	78	0	10	34	42	50	82
M3	42	70	78	0	26	34	42	74
M4	118	42	50	58	0	10	18	50
M5	110	34	42	50	78	0	10	42
M6	102	26	34	42	70	78	0	34
U	74	102	110	118	50	58	66	0

Table 3 Matrix of number of nodes

Number of nodes	L	M1	M2	M3	M4	M5	M6	U
L	0	4	5	6	8	9	10	4
M1	5	0	2	3	5	6	7	9
M2	4	6	0	2	4	5	6	8
M3	3	5	6	0	3	4	5	7
M4	7	5	6	7	0	2	3	5
M5	6	4	5	6	8	0	2	4
M6	5	3	4	5	7	8	0	3
U	4	6	7	8	4	5	6	0

Table 4 Scripts matrix of products

Product	Route	Sequence				
1	1	L	1	3	5	U
1	2	L	2	3	5	U
2	1	L	2	3	4	U
2	2	L	1	2	5	U
3	1	L	1	2	6	U
3	2	L	2	4	5	U
4	1	L	1	4	5	U
4	2	L	3	4	5	U
5	1	L	1	4	6	U
5	2	L	2	4	6	U

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 eight rules, which is a very significant reduction in terms of the system inference performance.

In approach AGF, each input variable was divided into five partitions, and the rule base comprises all possibilities among the input variables, equal to a total of 625 rules. To refine these rules, we used the genetic algorithm implemented in MATL AB with some settings like

- Creating the new population of the genetic algorithm applies elitism rate of 20 %, crossing a central rate of 80 %, the mutation occurs after about 5 % of the cross choosing a random gene, and population selection method is tournament.
- Each new population obtained is applied in the order of AGVs problem, and the evaluation function achieved by each population is stored. The stopping criterion can happen in three ways:

Table 5 Results obtained in RCM

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

Table 6 Final results

Qtd. AGV	FIFO Makespan	Benincasa [15] Makespan	HFRB Makespan	AGF Makespan
Production of five lots (25 parts)				
1	6319	6001	5580	5060
2	4702	4479	4187	4092
4	4781	4598	4169	4068
Production of ten lots (50 parts)				
1	12,219	11,604	10,440	9487
2	8918	8493	7871	7980
4	9042	8670	7802	7793
Production of 25 lots (125 parts)				
1	31,223	29,401	27,489	25,300
2	21,330	20,133	18,824	18,373
4	21,431	20,295	18,855	18,306
Production of 50 lots (250 parts)				
1	67,089	61,269	59,778	55,660
2	44,861	41,271	39,620	38,874
4	43,253	39,902	37,906	35,798

- First: if the value of the evaluation function of a determinate population is equal to or less than the predetermined value
- Second: if after 15 consecutive generations, the evaluation function of the population have not improved
- Third: if it reached the maximum number of iterations 100

Thus, after applying the optimization, the rule base end goal makespan, that initially had 625 rules, was with 280 rules. The obtained makespan using the approaches in this paper, as well the makespan value obtained in the two literature papers in some different cases, is shown in Table 6.

5 Conclusion and future work

Based on the related research to perform the optimization and represent knowledge, this work proposes the approach I based in the 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, it can be concluded that the proposal obtained a better result, producing the same amount of products in less time compared to the other techniques. It is noteworthy that this application can also cause the rule base to become smaller, thus facilitating the understanding of expert and reducing processing time.

Based on the related research to perform the optimization and represent knowledge, this paper proposes the approach II fuzzy genetic model for AGVs dispatching including prediction, multiple objectives, and modeling with Petri nets. Initially, based on the characteristics of the problem and the concepts the techniques used, it was concluded that including the prediction would gain time, including the multiobjective, the method would gain in strength and modeling in Petri nets brings another view to the implementation of the problem.

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. Also, it is recommended to develop a policy to control the maintenance and supply of AGV, as well as the best location in the layout for this.

Acknowledgments The authors thank the Coordination of Improvement of Higher Education Personnel (CAPES) for providing scholarship and the project INCT SEC the support and investment in research.

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