Adaptive Genetic Fuzzy, Predictive and Multiobjective Approach for AGVs Dispatching

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Abstract—**Excellence in manufacturing systems has been recognized as one of the main factors behind the success of industrial companies. New technologies for manufacturing processes play 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 fuzzy logic and genetic algorithms. The proposal also includes prediction task, multi-objective and modeling Petri nets causing the closest simulation of real environment.**

Keywords: Automated Guided Vehicle; AGV Dispatching; Fuzzy Logic; Genetic Algorithms.

I. INTRODUCTION

The search for competitiveness in the industrial environment has become one of the most striking features in the evolution process of production systems. Robotized manufacturing centers, distribution centers and storage of products is a practice that has been occurring in Brazil to minimize production costs, logistics and distribution, since these practices are already present in other countries with success.

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 [1].

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 sent to an AGV show where the vehicle should move, how to reach the destination and what to do when it arrives there [1].

II. 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 [10] [8] [20].

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 [19].

In Le-Anh and De Koster [25] is presented a review of the development and control of 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.

III. DISPATCHING OF AGV

Dispatching is an important issue for management and control of AGV, as stated by the works [25] [6] [10] and remains today because of the amount 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.

Egbelu [17] presented a dispatching rule, called DEMD (Demand-Driven), 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 [7] presented the rule First Encountered First Served (FEFS) aiming to deliver loads as fast as possible for multiple AGVs operating in a simple loop path.

Han and McGinnis [11] proposed the rule Most Significant Move (MSM), which calculates the priority index for each workstation requiring transportation.

Taghaboni [5] proposed the rule MCQL (Most Critical output Queue with Look ahead) 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 make decisions, they could obtain better results.

Kim et al. [23] 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 [9] proposed a dispatching rule composed 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 [2] 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. [1] 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 [14] proposed an intelligent approach of dispatching AGVs based on multiple criteria of 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 [4] adopted a strategy for multiple 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 [27] 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. [13] presented a method for dynamic routing of supervision and control of multiple AGVs. To solve the problem of shortest path dynamically, the dispatching method proposed uses window of time in a vector form.

The authors Chiba et al. [18], 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. They have presented a cooperative co-evolutionary approach, which considers a genetic algorithm for evolution of the two problems together.

IV. PROPOSAL

According to the themes discussed in previous sections, some considerations are part of the main concerns when developing an effective approach to the problem of vehicle dispatching in manufacturing systems. The first is the ability to consider multiple variables that 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 a variety of approaches and are highlighted some features like: provide a mathematical framework for modeling systems loosely defined, exceeds the rigidity of classical logic allowing degrees of membership and provides core decision based on rules described in natural language. Thus, when compared the technical characteristic with problem characteristics, we can deduce that the fuzzy logic present good results in the vehicle dispatching problem.

Initially search with the specialist and literature variables with the greatest impact on production systems, such as: distance, buffer, delivery date, etc. Once defined the variables that are used is created fuzzy knowledge base, in which each input variable and output variable are divided into five sets for a better representation. After these definitions is also built an initial rule base involving all possible combinations of input variables and uses the experience of the specialist to determine the outputs.

Another important point is that fuzzy logic is favorable for integration with other computing methods, such as neural networks and evolutionary algorithms [12]. Therefore, if the rule base constructed initially not present satisfactory results, can add other methods to refine the rule base and reach 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.

But the great advantage of this paper 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 cost.

Most companies have a production of many different products types, often coming to hundreds. Thus, it becomes very difficult, if not impossible to make a forecast of demand for each product manufactured [15]. 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 [15].

According to Martins and Alt [16], we can classify the costs of holding inventory in two categories:

Directly proportional to the amount stored:

- Storage: the more stock, more area required, plus cost of rent.
- Handling: the more inventory, more people and equipment needed to handle the inventory, plus cost of manpower and equipment.
- Waste: the more stock, the greater the chance of waste, cost more due to waste.
- Obsolescence: the more stock, the greater the chances become obsolete materials, plus costs of materials that will no longer be used.
- Robbery and theft: the more stocks, the greater the chance of materials being stolen and / or stolen, plus costs.

Inversely proportional to the amount stored:

- Cost of production: buying in larger quantities, the greater the chances of getting lower prices.
- Preparation costs: by producing in large scale, it uses the same resources to produce a larger amount, reducing the unit cost.

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. Favorable to reduce the costs inversely proportional to the amount stored. In this case are evaluated the four variables: distance, number of nodes, the input buffer and output buffer.

Working tardiness, which is produced according to demand, the stock remains at low levels, which means less chance of reducing the rates of wasting. Favorable to reduce the costs directly proportional to the amount stored. In this case are evaluated the four variables: distance, number of nodes, chaining of tasks and delivery date.

Due to the dynamic and uncertain environment, only one parameter may not be ideal, and then the periodic recalculation, using a score for each parameter updated in real time can bring better results [22], therefore was added to the project the prediction, which occurs in two stages.

First it 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 tends to happen 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 stand still until there is a request for transport, it does a check on processing times of the workstations, selects those with a shorter time to finish the task, makes the calculation of priority and forwards the AGV before the workstation to request transportation.

The Petri net modeling makes the experiment closer to the real factory environment. Modeling in Petri nets the scenario that will apply the method, set up each workstation and each node of the transportation routes are resources to be used by a vehicle at a time, that happens in real factories and often neglected 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) at the same time.

V. Implementation of the Proposal

First the fuzzy knowledge base was created for each goal by using the specialist's knowledge.

For the objective of makespan was considered the variables: distance, number of nodes, input buffer space and output buffer space. It's shown in Figure 1 the fuzzy system created in Matlab for the makespan objective.

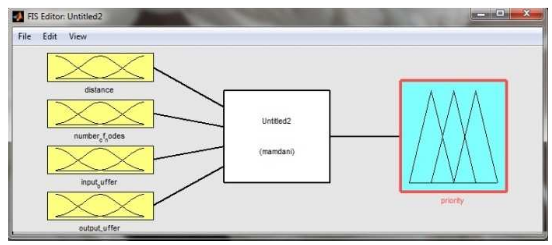

Fig. 1. Knowledge base of the makespan objective.

For the objective of tardiness, was considered the variables: distance, number of nodes, chaining tasks and delivery date. It's shown in Figure 2 the fuzzy system created in Matlab for the tardiness objective.

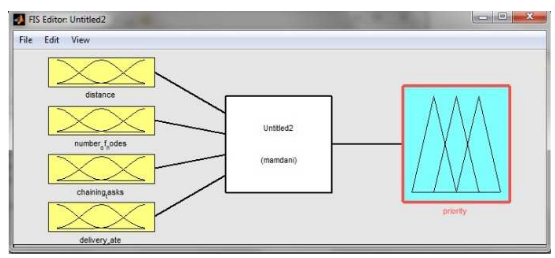

Fig. 2. Knowledge base of the tardiness objective.

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

Number of nodes: represents the number of nodes between the available AGV and the requesting workstation. 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 space and output buffer space: not letting the input buffer empty and / or the output buffer full are ways not to leave the workstation stopped, as a result spend less time.

Chaining task: when a task is connected with another task, i.e. an AGV unloads a part on workstation, still in workstation 1 load another part to take on the workstation 3, on the workstation 3 makes unloading and loading another part for workstation 7.

Delivery Date: this variable is crucial for production to order and meet deadlines.

Each input variable and output variable were divided into five symmetric triangular partitions, thus better representing the problem. It's shown in Figure 3 the database of a variable created in Matlab.

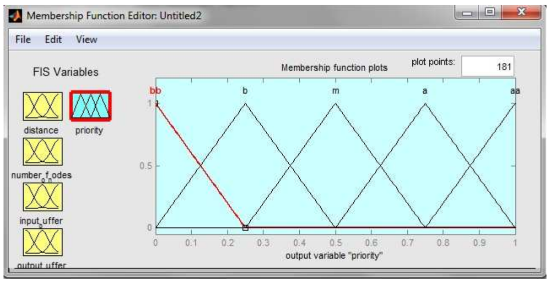

Fig. 3. Symmetric triangular partitions of the variables.

Then created the rule base comprising all the possibilities between input variables, in other words, four input variables divided into five partitions is equal to a total of 625 rules, created by hand from the expert's knowledge. It's shown in Figure 4 a sample of the initial rule base created in Matlab.

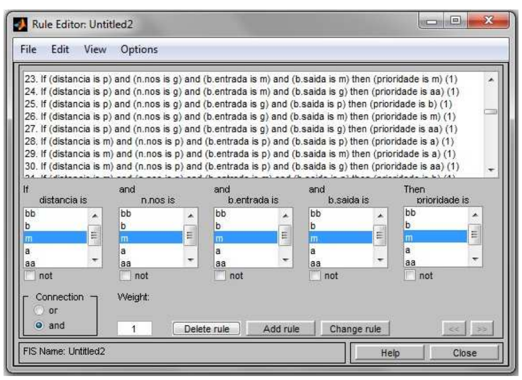

Fig. 4. Initial rule base.

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.

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:

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

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 minimize the function (1).

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

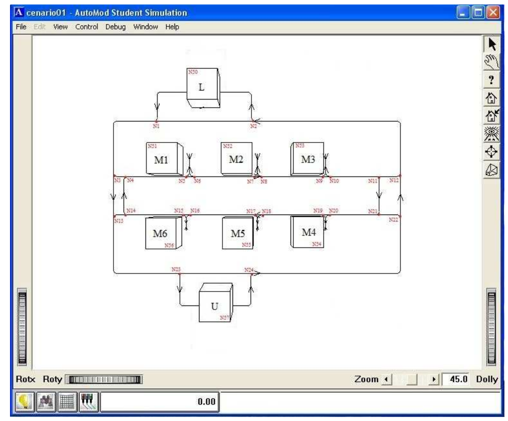

Fig. 5. Factory layout the proposal is implemented.

Figure 5 depicts the layout application built on a simulation tool, and Figure 6 represents the same layout modeled in Petri nets in CPNtools.

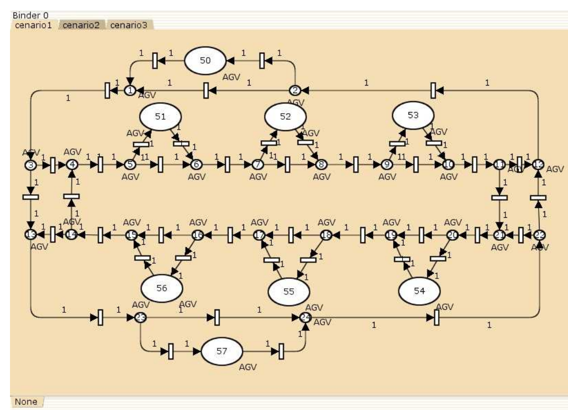

Fig. 6. Factory layout modeled in Petri nets.

To supplement the information environment we have: an matrix of processing times of workstation, scripts matrix of products, matrix of distance between the workstation, matrix of number of nodes, and the matrix of paths, where the system searches these data to begin the process of decision making.

At Table 1 it's presented a sample of paths between all points of the system, including the travel time between each point.

TABLE I
MATRIX OF PATHS

Paths										
	Beginning									Destination
path	**N50**	0	0	0	0	0	0	0	0	**N50**
time	0	0	0	0	0	0	0	0	0	0
path	**N50**	N1	N3	N4	N5	0	0	0	0	**N51**
time	0	6	18	1	7	0	0	0	0	1
path	**N50**	N1	N3	N4	N5	N6	N7	0	0	**N52**
time	0	6	18	1	7	7	1	0	0	1
path	**N50**	N1	N3	N4	N5	N6	N7	N8	N9	**N53**
time	0	6	18	1	7	7	1	1	7	1
path	**N50**	N1	N3	N13	N23	0	0	0	0	**N57**
time	0	6	18	8	18	0	0	0	0	6
path	**N51**	N6	N7	N8	N9	N10	N11	N12	N2	**N50**
time	0	1	7	1	7	1	7	1	26	6
path	**N51**	0	0	0	0	0	0	0	0	**N51**
time	0	0	0	0	0	0	0	0	0	0
path	**N51**	N6	N7	0	0	0	0	0	0	**N52**
time	0	1	7	0	0	0	0	0	0	1
path	**N51**	N6	N7	N8	N9	0	0	0	0	**N53**
time	0	1	7	1	7	0	0	0	0	1
path	**N51**	N6	N7	N8	N9	N10	N11	N21	N20	**N54**
time	0	1	7	1	7	1	7	8	7	1
path	**N52**	N8	N9	N10	N11	N12	N2	0	0	**N50**
time	0	1	7	1	7	1	26	0	0	6
path	**N52**	0	0	0	0	0	0	0	0	**N52**
time	0	0	0	0	0	0	0	0	0	0

At Table 2 it's presented the distance between the points of loading, unloading and workstations.

TABLE II
MATRIX OF DISTANCE BETWEEN THE WORKSTATION

Distance								
	L	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**U**
L	0	33	41	49	72	80	88	56
M1	57	0	9	17	40	48	56	88
M2	49	78	0	9	32	40	48	80
M3	41	70	78	0	24	32	40	72
M4	117	40	48	56	0	9	17	49
M5	109	32	40	48	78	0	9	41
M6	101	24	32	40	70	78	0	33
U	72	101	109	117	41	49	57	0

At Table 3 it's presented the number of nodes (intersection) between the points of loading, unloading and workstations.

TABLE III
MATRIX OF NUMBER OF NODES

Number of Nodes								
	L	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**U**
L	0	6	8	10	14	16	18	6
M1	10	0	4	6	10	12	14	18
M2	8	12	0	4	8	10	12	16
M3	6	10	12	0	6	8	10	14
M4	14	10	12	14	0	4	6	10
M5	12	8	10	12	12	0	4	8
M6	10	6	8	10	10	12	0	6
U	6	10	12	14	6	8	10	0

Table 4 shows the sequence of production for each product.

TABLE IV
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

All matrices are used as support for creating a dynamic allocation table to help control the AGV dispatching.

The objective of makespan was compared with paper Benincasa et al. [1], who had the same goal. At Table the results are presented.

TABLE V
RESULTS TABLES

Production of five lots (25 parts)			
Qtd. AGVs	Makespan Benincasa[1]	Makespan Proposal	% gain of the Proposal
1	6086	5060	16,86
2	4720	4392	6,95
3	4576	4268	6,73
Production of ten lots (50 parts)			
1	12418	9487	23,60
2	9360	8193	12,47
3	9199	7980	13,25
Production of twenty-five lots (125 parts)			
1	29198	25300	13,35
2	23298	18373	21,14
3	22443	18306	18,43
Production of fifty lots (250 parts)			
1	56782	48660	14,30
2	45996	38874	15,48
3	44572	35798	19,69

To validate the goal tardiness was programmed production of many products, each lots of product with a different delivery date. Running the simulation, the method has proven effective to program each lots of products according to their takt-time, producing all of their due delivery dates, leaving time windows in case there is a need to fit of urgently production lots.

VI. Conclusions

Based on the related research to perform the optimization and represent knowledge, this paper proposes a genetic fuzzy model for dispatching of AGVs which includes prediction, multiple objectives and modeling with Petri nets. Based on the characteristics of the problem addressed and techniques concepts used, there is the sticking between both. Concluded that the inclusion of prediction task brings gains in time, including the multiple objective method gains flexibility and robustness, and modeling in Petri nets makes the tests are closer to real conditions.

The advantage of the proposed tardiness is to align production with demand, managing to reduce inventory costs and always meeting the deadlines for applications.

The advantage of the proposed makespan is to explore the maximum of all resources, managing to reduce manufacturing costs and produce large batches in shorter period of time.

The advantage of this work is to have two methods that achieve good results separately and can be changed or merged at any time, depending on the flow of the industrial production.

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

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