Proceedings of the 2000 Winter Simulation Conference
J. A. Joines, R. R. Barton, K. Kang, and P. A. Fishwick, eds.

SIMULATION OF AN EVOLUTIONARY TUNED FUZZY DISPATCHING SYSTEM FOR AUTOMATED GUIDED VEHICLES

K.K. Tan
K.Z. Tang

Department of Electrical Engineering
National University of Singapore
4 Engineering Drive
3 117576, SINGAPORE

ABSTRACT

This paper presents the development and simulation of a novel Genetic Algorithm (GA) based methodology applied to optimal tuning of a fuzzy dispatching system for a fleet of automated guided vehicles in a flexible manufacturing environment. The dispatching rules are further transformed into a continuously adaptive procedure to capitalize the on-line information available from a shop floor at all times. The entire problem is simulated using MATLAB/ SIMULINK. The simulation results obtained show that GA is an efficient and effective tool to achieve optimal performance for the well-known NP-complete scheduling problem.

1 INTRODUCTION

Vehicle dispatching is a classical scheduling problem which has been addressed by many researchers over the years. It was first written on by Dantzig and Ramser (1956). An interesting overview of vehicle routing, scheduling and other relevant development can be found in (Bodin, 1981;1983). With the increasing proliferation in the development and applications of automated guided vehicle systems (AGVS) in various transportation and material handling industries, the nature of the problem has also become more interesting and challenging, since it is becoming more directly linked to many tangible economic performance issues. While scheduling inadequacies may usually be overcome with the commissioning of more vehicles, such practice inevitably leads to higher costs (absolute and opportunistic), and also triggers additional problems such as increased congestion in the workplace. Thus, the requirement for an effective vehicle dispatching system cannot be under-emphasized.

In this paper, we consider the simulation study of an AGVS in a manufacturing environment consisting of several workcenters performing different machining functions, a typical part or unit load visits several centers before its machining requirements are satisfied. A unit load continues to circulate in the facility between workcenters, some of which may be visited more than once by the same load, until it receives its last service. This transition of unit loads or parts generates the operational problem of routing and scheduling the AGVs within the system. The complex interaction between material flows and processes requires an efficient vehicle dispatching procedure, and the manner by which these operational control problems are resolved determines the operational efficiency of the total system.

In this paper, a simulation study will be conducted based on a flexible vehicle dispatching system developed, using a self-adapting fuzzy prioritizing approach for a fleet of AGVs operating in a multiple workcenters manufacturing environment. The dispatching rules thus designed are able to strike a compromise between the satisfaction of multiple operational criterion.. An important pre-requisite for the success and effectiveness of the fuzzy approach towards vehicle dispatching is the proper selection of scaling factors for the various operation criterion. It is difficult, with conventional analytical or numerical approaches, to obtain an optimal set of the scaling parameters, since the dispatching problem is NP-complete in nature. Moreover, the performance index may not be “well-behaved” in the multi-modal multi-dimensional search space. An effective search algorithm is thus necessary in optimizing these scaling parameters to achieve an automated dispatching system with optimal performance. To this end, GA will be useful as an optimisation tool to yield an optimal set of scaling factors for the fuzzy rules. The paper illustrates systematically the application of GA for this purpose.

2 A FUZZY VEHICLE DISPATCHING SYSTEM

The key idea in the fuzzy dispatching approach is to associate each vehicle in the system with two attributes, PARTS_IN and PARTS_OUT with the extent of demand-driven and source-driven needs of the workcenter with respect to the vehicle. These attributes are fuzzy variables (PARTS_IN, PARTS_OUT $\in$ [0, 1]) computed from a fuzzy operation on a combination of variables which are expected to influence the extent of the demand and source-driven needs of the workcenter. Decisions for material movement will be driven primarily by these attributes.

2.1 Takagi and Sugeno's Fuzzy Rules

The two attributes, PARTS_IN and PARTS_OUT, are inferred from a Takagi and Sugeno type of fuzzy inference. Consider the following *p* rules governing the PARTS_IN attribute of the *kth* workcenter:

$$\text{IF } x^i_{k1} \text{ is } F^i_1 \otimes \ldots \otimes x^i_{km_i} \text{ is } F^i_{km_i} \text{ THEN}$$
$$u^i_k = \alpha^i \ , \quad i = 1 \ldots p$$

with $\sum_{i=1}^{p} \alpha^i = 1$, where F^i_j are fuzzy sets, $x^i = (x^i_{k1},\ldots,x^i_{km_i})^T \in U$ are the input linguistic variables identified to affect the need of the parts inflow for rule *i*, $\otimes$ is a fuzzy operator which combine the antecedents into premises, and u^i_k is the crisp output for rule *i*. α^i is the scaling factor for rule *i*, reflecting the weight of the rule in determining the final outcome. The value of the PARTS_IN_k attribute is then evaluated as a weighted average of the u^is:

$$\text{PARTS\_IN}_k = \frac{\sum_1^p w^i_k u^i_k}{\sum_1^p w^i_k} \tag{1}$$

where the weight w^i_k implies the overall truth value of the premise of rule *i* for the input and is calculated as,

$$w^i_k = \prod_{j=1}^{m_i} \mu_{F^i_{kj}}(x^i_{kj}) \,.$$

Similarly, the *q* rules for the PARTS_OUT attribute may be formulated as,

$$\text{IF } y^i_{k1} \text{ is } G^i_1 \otimes \ldots \otimes y^i_{kn_i} \text{ is } G^i_{kn_i} \text{ THEN}$$
$$v^i_k = \beta^i \ , \quad i = 1 \ldots q$$

with $\sum_{i=1}^{q} \beta^i = 1$, where G^i_j are fuzzy sets, $y^i = (y^i_{k1},\ldots,y^i_{kn_i})^T \in V$ are the linguistic variables identified to affect the need of the parts outflow for rule *i*. v^i_k is the crisp output for rule *i*, and β^i is the scaling factor. In this case, y^i_{kj} may be the linguistic variable WAITING_TIME and G^i_j may be the fuzzy set LONG. The value of the PARTS_OUT_k attribute is then evaluated as a weighted average of the v^is:

$$\text{PARTS\_OUT}_k = \frac{\sum_1^q w^i_k v^i_k}{\sum_1^q w^i_k} \tag{2}$$

where the weight w^i_k is calculated as,

$$w^i_k = \prod_{j=1}^{m_i} \mu_{G^i_{kj}}(y^i_{kj}) \,.$$

With these attributes, the workcenters may be sorted in the order of their demand or source-driven needs. In a pull-based situation, an idle vehicle searches for the highest-inflow demand station from the PARTS_IN attribute. This station may then be paired off with a station having the highest PARTS_OUT attribute, identified from a set of stations supplying the parts to the station in demand. The converse is true for a push-based system.

2.2 Push/Pull Switching

Instead of rigidly commissioning a push or a pull-based concept in the vehicle dispatching system, it is proposed to view each of these concepts as being suited to different operating conditions, and switch between them when crossing these different operating regions. Clearly, a mechanism is needed to trigger this switch between a pull and a push-based environment, and has been formulated as follows:

- Denote SCE(k) as the set of workcenters supplying to the input buffer of workcenter k, and DES(k) as the set of workcenters to which workcenter k supply parts.
- The workcenters k_u* and k_v* are identified where

  $$\text{PARTS\_IN}_{ku*} = \max_k(\text{PARTS\_IN}_k)\,, \text{SCE}(k_u*) \not\subset \varnothing$$
  $$\text{PARTS\_OUT}_{kv*} = \max_k(\text{PARTS\_OUT}_k), \text{DES}(k_v*) \not\subset \varnothing$$

- Based on these attributes, the current state system towards a push or a pull operation may be determined. For example, a simple formulation may be to compute the following ratio

  $$\text{STRATEGY} = \frac{\text{PARTS\_OUT}_{kv*}}{\text{PARTS\_IN}_{ku*}}\,.$$

If STRATEGY > γ (where suitable values for γ may be in the range $0.6 < \gamma < 0.7$, depending on the desired level of PULL dominance), a PUSH operation may be initiated, otherwise a PULL operation will be initiated.

2.3 Optimal Weight Selection Using an Enhanced GA

As addressed in the Introduction, an important pre-requisite for the success of the fuzzy dispatching system is the selection of the scaling factors α's and β's. Manual trial-and-error adjusting of these parameters can be very time consuming and the performance of the final dispatching system maybe far from the best. For this, genetic algorithm that emulates the Darwinian-Wallace principle in natural selection and genetics is employed to obtain an optimal set of the scaling parameters. The GA evaluates performances of candidate solutions at multiple points simultaneously and has been found to be very effective in searching poorly understood and complex space for optimization in engineering applications (Dasgupta 1997, Zalzala 1998, Goldberg 1989).

Before this simulated evolution process begins, an initial population of multiple coded strings representing random scaling factors is first formed. Every such string is assigned a performance index calculated against the operational efficiency of the shop floor. At each generation of search, multiple candidates are evaluated and the search will be directed intelligently according to the Darwin's "survival-of-the-fittest" principle. Then useful search information and co-ordinates are exchanged and altered for the next generation of candidate solutions. Supported by the Schema Theory, such an evolutionary search process is proved to offer an exponentially reduced search time compared with an exhaustive search.

For faster convergence and better accuracy, individuals in each generation of the GA are further fine-tuned by going through a local hill-climbing process. This GA with improved local exploration has been successfully applied to solve engineering system identification and modeling problems. The enhanced GA was programmed in Matlab and compiled into stand-alone executable C++ source codes using Matcom to significantly reduce the program execution time. Here, integer coding with two-point crossover and tournament selection are employed for better convergence.

3 CASE STUDIES

3.1 Test Facility

The simulation analysis is based on a hypothetical facility as given in Figure 1. The facility operating data is provided in Table 1. There are 9 workcenters or departments, and a warehouse for the raw materials and finished products.

3.2 Simulation Language

The control simulation language Matlab was used for implementing the study. The language may be used for simulation of both continuous and discrete-time systems. In this case, it is applied to discrete event investigation, where the AGV guide path is modeled as a directed network consisting of nodes and arcs. Point locations in the network are uniquely identified by their Cartesian coordinates. Traffic conflicts at the load pickup/delivery points are explicitly modeled.

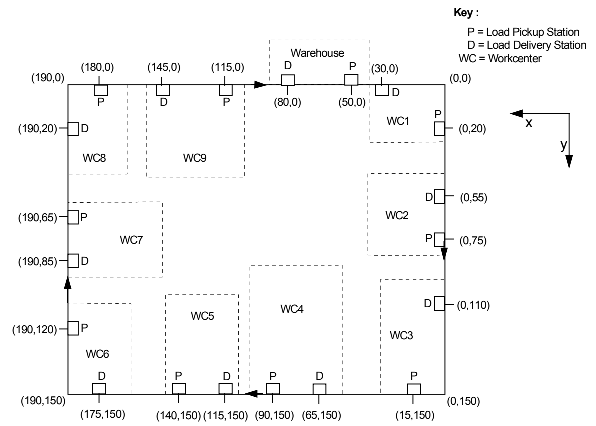

Figure 1: Layout of a Test Facility

Table 1: The Facility Operating Data

Work center	Processing Time /Unit Load (min)	Input Queue Size	Output Queue Size
1	1	3	5
2	3	2	3
3	3	2	3
4	2	3	2
5	1	1	4
6	3	2	3
7	3	2	3
8	2	3	2
9	3	4	4

Job routing = WH, WC1, (WC2,WC3), WC4, WC5, WC6, (WC7,WC8), WC9, WH
Load pickup/delivery time = 10 seconds
Vehicle length = 3 ft
Vehicle speed = 200 fpm
Pickup and delivery spur capacity = 1 vehicle.

3.3 Computation of Attributes

In this simulation, the input variables chosen for the computation of the PARTS_IN attributes are:

- Length of time before incoming queue is empty, **LT_IN**

- Shortest travel distance of vehicle to source workcenters, and to the workcenter concerned, **STD_IN**.
- Shortest length of time before the outgoing queue of source workcenters is full, **SLT_IN**
- Number of parts completed already by the workstation, **PC_IN**.

The 4 rules formulated for the computation of the **PARTS_IN** attribute for the kth workcenter are:

IF $\mathbf{LT\_IN_k}$ is SHORT, THEN $u_k = \alpha_1$
IF $\mathbf{STD\_IN_k}$ is SHORT, THEN $u_k = \alpha_2$
IF $\mathbf{SLT\_IN_k}$ is SHORT, THEN $u_k = \alpha_3$
IF $\mathbf{PC\_IN_k}$ is LOW, THEN $u_k = \alpha_4$

PARTS_IN is then computed as in (1).

The input variables chosen for the computation of the **PARTS_OUT** attributes are:

- Shortest length of time before outgoing queue of workcenter is full, **SLT_OUT**.
- Shortest travel distance of vehicle to workcenter concerned, and to target workcenters, **STD_OUT**.
- Length of time before the incoming queue of destination workcenter is empty, **LT_OUT**.
- Number of parts completed already by the workstation, **PC_OUT**.

Similarly, the 4 rules formulated for the computation of the **PARTS_OUT** attribute for the kth workcenter are:

IF $\mathbf{SLT\_OUT_k}$ is SHORT, THEN $v_k = \beta_1$
IF $\mathbf{STD\_OUT_k}$ is SHORT, THEN $v_k = \beta_2$
IF $\mathbf{LT\_OUT_k}$ is SHORT, THEN $v_k = \beta_3$
IF $\mathbf{PC\_OUT_k}$ is LOW, THEN $v_k = \beta_4$

PARTS_OUT is then computed as in (2).

Here, $\alpha_1 \ldots \alpha_4$, $\beta_1 \ldots \beta 4$ are the scaling parameters for the fuzzy dispatching system, which will be tuned by the enhanced GA described in Section 2.3 to achieve an optimal shop floor productivity. The membership functions are made time varying according to the set of assigned tasks at any point in time. In our approach, a linear interpolation between the maximum and minimum values of the variables serves as the membership function. As an example, consider the following STD_IN variable:

$$\mu_{SHORT}(STD\_IN_k) = \frac{STD\_IN_k - \min(STD\_IN)}{\max(STD\_IN) - \min(STD\_IN)}\ .$$

3.4 Rule Comparison

The performance of the proposed GA-Fuzzy dispatching system was compared with the demand driven (DEMD) rules and the fuzzy approach with scaling factors fine tuned via a trial and error approach. The rule comparison was carried out under the following three different cases.

3.4.1 Case I

Given an equal number of vehicles, the same facility scenario, and the same length of time or shift duration, how does the facility throughput compares between the two sets of rules? Throughput is defined as the total number of parts completed and removed from the facility shop floor during the shift. The following parameters were used for Case I analysis:

1. The facility operates a two-hour shift.
2. Three vehicles are in use.
3. Infinite number of loads were available for processing at time, t = 0.

3.4.2 Case II

Given the same conditions as in Case I, how long does it take for the facility to produce a known number of parts under the two sets of rules? The analysis was done with 3 vehicles and 30 parts or unit loads to be produced and centers on the determination of the length of time it will take the facility to produce the 100 parts under each of the dispatching methodology. The facility operating duration is a measure of the rule's ability to accelerate the unit loads through the facility.

3.4.3 Case III

Given the same conditions as in Case I and a production target over a fixed time period, how many vehicles are required to meet the production target under the two sets of rules? The conditions for the analysis are the following:

1. There are a fixed number (30) of unit loads to be produced.
2. The production of the fixed number of unit loads must be satisfied within the time interval specified (2 hours).

If all other factors remain the same, it seems that the number of vehicles required will be a function of the dispatching rule in force, since the rules act differently with the vehicles.

3.5 Simulation Results

The scaling parameters obtained via trial and error approach is shown in the second row of Table 2. To achieve an automated weights selection and to improve the performance of the dispatching system, the enhanced GA described in Section 2.3 has been run for 50 generations with a population size of 50. The obtained weighting parameters at the end of the evolution are given in the third row of Table 2.

Table 2: A Comparison of the Scaling Parameters

Scaling factors	α1	α2	α3	α4	β_1	β_2	β_3	β_4
Manual setting [1]	0.1	0.5	0.2	0.2	0.2	0.5	0.1	0.2
Enhanced GA	0.02	0	0.71	0.27	0	0.03	0.96	0.01

Based on the scaling factors in Table 2, the performances of the various dispatching methods were compared and summarized in Table 3. It can be seen that the developed GA-Fuzzy dispatching methodology has outperformed the other two approaches for all the three cases under studied.

Table 3: Comparison Results of Various Dispatching Methods

	DEMD	**Fuzzy**	**GA Fuzzy**	**% Improvement** (GA-Fuzzy vs Fuzzy)
Case I: Throughput	16	27	32	18.52 %
Case II: Production	2.99	2.14	1.89	12 %
Case III: Vehicles	9	5	3	40 %

4 CONCLUSIONS

This paper considers the simulation study of a GA-tuned fuzzy dispatching system for a fleet of automated guided vehicles operating in a flexible manufacturing environment with multiple workcenters. Dynamic and adaptive vehicle dispatching strategy has been implemented to fully utilize the on-line information available from the shop floor at all times. Simulation results obtained show that the GA-fuzzy dispatching system has outperformed other conventional approaches for all the three different case studies.

REFERENCES

Bodin, L., and B. Golden. 1981. Classification in vehicle routing and scheduling. *Networks* 11: 97-108.

Bodin, L., B. Golden, A. Assad, and M. Ball. 1983. Routing of vehicles. *Computers and Operations Research* 10: 79-115.

Dantzig, G. B., and J. H. Ramser. 1956. The truck dispatching problem. *Management Science* 6: 80.

Dasgupta, D., and Michalewicz, Z. 1997. *Evolutionary Algorithms in Engineering Applications*. Berlin: Springer-Verlag.

Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimisation and Machine Learning*. Reading, MA: Addision-Wesley.

Tan, K. C., and Li, Y. 1997. Evolutionary system identification in the time-domain. *Proc. I.Mech.E., Part I, Special Issue on Applications of Genetic Algorithms to Engineering Systems*, 211(4): 319-323.

Tan, K. C., Li, Y., Gawthrop, P. J., and Glidle, A. 1997. Evolutionary grey-box modelling for practical systems. *Second IEE International Conference on Genetic Algorithms in Engineering System Innovations and Applications,* Glasgow, U.K., pp. 369-375.

Zalzala, A. M. S., and Fleming, P. J. 1998. *Genetic Algorithms in Engineering Systems*. IEE Control Engineering Series 55, England.

AUTHOR BIOGRAPHIES

K.K. TAN is an Assistant Professor with the National University of Singapore. His research interests are in the areas of control system modeling and simulation. His email address is <kktan@nus.edu.sg>.

K.Z. TANG is a professional officer with the National University of Singapore. He is currently pursuing a Ph.D. degree. .His research interests are in the area of discrete and continuous system modeling and simulation.