Assistant Professor Parham AZIMI , PhD
E-mail: P.azimi@yahoo.com
Mehran ALIDOOST, PhD Student
E-mail: mehranalidoost@yhaoo.com
Department of Mechanical and Industrial Engineering
Islamic Azad University (Qazvin Branch)
Iran

A HEURISTIC APPROACH FOR OPTIMIZING A MULTIPLE-LOAD AUTOMATED GUIDED VEHICLE SYSTEM IN AN INTEGRATED FLEXIBLE MANUFACTURING SYSTEM

Abstract: *In this paper, we develop a heuristic for optimizing the system throughput of a multiple-load automated guided vehicle (AGV) system. This approach combines three mathematical methods such as linear regression, discrete even simulation and linear integer programming to maximize the system throughput. The proposed approach tries to find the best input parameters of a flexible manufacturing system (FMS) environment such as the AVG control strategies, fleet size, processing times and buffer capacities. This is the first time that such parameters have been linked to the system throughput in optimization process. Finally, for verifying the effect of the input parameters, we used a sensitivity analysis. As the results show, the proposed approach is efficient enough to be used in real life FMS environments.*

Keywords: *Integrated FMS, material handling systems, AGV, linear regression, Simulation, mathematical programming.*

JEL Classification: C61, C15

1. Introduction

The current tough challenge of manufacturers in consuming markets has obliged them to use flexible environment at their plant to overcome continuous changes. A typical FMS consists of major parts such as workstations (machines), material handling system (MHS) and a computer based system for integrating the last two parts. An AGV is a driverless, battery powered vehicle (usually controlled by on-board computers) and transport system used for horizontal movements. They were introduced in 1955 [1] for the first time and since then, several applications of

AGVs have been developed day by day. In these systems, a number of AGVs – which are always called as fleet size - are dedicated to some workstations and storehouses in order to transport the materials. It has been shown that this kind of MHS have been used widely in different manufacturing systems, 56% in JIT delivery systems, 13% in FMS, 12% in storage load transfer with non-AS/RS interface, 8% in AS/RS interface, 7% in progressive assembly lines, 1% in mini load AS/RS interface systems and 3% in other areas [2]. In reviewing the past works, one may find two distinct categories. The fist category deals with the design of a FMS environment. In this category some common problems such as the layout workstations, the path layout, pickup/delivery points and etc have been verified. In the second category, operational issues have been considered such as selecting the best control strategy for AGVs, the optimal fleet size, tuning the process times and buffer levels. Specially, in the second category - which has absorbed many attentions- it is very important to coordinate the workstations with material MHS simultaneously to optimize the entire system. Therefore in the second category, we are going to integrate the total system. Several researchers have stressed that efficient scheduling of material handling system is critical to the overall efficiency of FMS [3], [7], [17].The integration of material handling system (MHS) with manufacturing activities can result in manufacturing systems characterized by flexibility, high productivity and low cost per unit produced [4],[17]. Problems that address the optimal co-ordination of machine scheduling and job transporting are certainly more practical than those scheduling problems that do not take these factors into consideration. Also, to achieve global optimization between material processing and material handling activities, manufacturing planning should consider these two functions simultaneously [5], [6]. Nevertheless, the integration of MHS with FMS inevitably increases the complexity of a problem as it comprises inseparable decisions for both material processing and material handling activities [16], [17].

On the other side, most machine scheduling research studies assume either that there are an infinite number of transporters for delivering jobs or that jobs are delivered instantaneously from one location to another without transportation time involved [16]. The majority of the research work available in FMS modeling literature considers only the modeling of materials processing through work centers and assumes uninterrupted availability of material handling equipment. This could be valid for conveyorized production system but it is not reasonable for AGV-based systems [16]. Regarding the coordination between MHS and FMS, Bilge and Ulusoy [7] introduced a time window approach to simultaneous scheduling. However, due to high costs of installation of such systems, different approached have been introduced by researchers for designing and analyzing processes [8], [9]. Hulpic [10] used some activity cycle diagrams and Borenstein [11] used an intelligent DSS for the design and evaluation of flexible manufacturing systems. Chan [12] introduced an efficient approach for designing the FMS by combining simulation and multi criteria decision making methods. [13] developed a rule-based approach in this regard and [14] , [15] used similar approaches for this purpose specially when [15] addressed several benefits of multi-load AGV systems in comparison to singular ones. Lee et al. [16] showed that simulation can be a fruitful tool in FMS environments in order to determine the best control strategies. Aized [17] combined response surface method and colored Petri net approaches to optimize the system throughput. His approach considered the integration between MHS and FMS as a key factor. Ho and Liu [18] verified several pickup-dispatching rules for multiple-load AGV systems by simulation and analyze of variance methods. Their work is very similar to the one which introduced by Azimi et al. [19]. However, in [19] more control strategies were tested and they used a fuzzy TOPSIS approach for evaluating the control strategies.

In this paper, we introduce a heuristic algorithm which combines three methods such as linear regression, simulation and linear integer programming in order to optimize the system throughput in an integrated multiple-load AGV system. This algorithm has been explained in section 2. In section 3, the simulation model has been defined. In section 4, the results of the simulation model have been explained and finally, the overall conclusion is stressed in section 5.

2. The heuristic algorithm

In modern MHSs, some important criteria such as System Throughput (ST), Mean Flow Time of Parts (MFTP), Mean Tardiness of Parts (MFTP), AGV Idle Time (AGVIT), AGV Travel Full (AGVTF), AGV Travel Empty (AGVTE), AGV Load Time (AGVLT), AGV Unload Time (AGVUT), Mean Queue Length (MQL) and Mean Queue Waiting (MQW) used as the system performances [19]. But in this paper we used the system throughput for the optimization process as the objective function. The controlling mechanism of a multiple-load AGV system has been defined to create a general view on the control problem and then several rules for dispatching, delivery and load selection problems have been introduced. One of the main objectives of a control policy is to satisfy demands for transportation as fast as possible and with minimum possible conflicts between AGVs. Therefore, the following activities should be carried out by a controlling system:

- Dispatching of loads to AGVs: this problem defines the strategy for assigning the AGVs to machines (workstations) or assigning any special load to the available AGV. When an AGV is idle (i.e. it has no task to do), some requests for transportation arise in the manufacturing system. Now the problem is to assign the AGV to the best request. If the request is for delivery, the problem is called *delivery-dispatching* and if it is a pickup one then it is called *pickup-dispatching* problem. However when an AGV arrives at a P/D point for picking up some parts, another problem arise which is selecting the best load for that AGV. This problem is called *load-selection* problem.
- Route selection: by the time an AGV assigns to a specific machine, now a new problem which is selecting the best pathway from the original point to the destination. The best selected way refers to selecting a pathway to reduce transportation time and as well preventing the possible conflictions. In the literature review, There are two main categories for route selection problem which are *off-line* and *on-line* methods. Off-line methods are studied when the system information is static, i.e. there is no stochastic

event in the system. In contrast on-line controlling systems are more practical because they assume that several stochastic events like machine or AGV break downs could be happened. The on-line controlling systems are *centralized* or *decentralized*. It is centralized when the controlling system has been installed on the AGV boards and it is decentralized when the controlling system has been installed on several locations in the manufacturing cell.

- Dispatching the idle AGVs to the parking station(s).

On the other side, there are several dispatching rules in the literature [5], [19]. When an AGV is full or empty, the next task could be determined easily because the next task will be delivery (when it is full) or pickup (when it is empty). But in some situations, the AGV is half-full so the next decision should be selected among a pickup task or delivery task. In this situation, three main strategies could be developed. One is *Delivery-Task-First* (DTF) rule, which just selects delivery task. Another one is *Pickup-Task- First* (PTF) rule and the final one is *Load-Ratio* (LR). According to [19], the best rule is DTF, so in the simulation experiments, this rule has been used, i.e. a multiple-load AGV will always perform delivery task even when both delivery tasks and pickup tasks are available. For pickup-dispatching rules four major rules have been used such as *Longest-Time-In-System* (LTIS) rule (an AGV will visit the pickup point containing the load that has been in the system for the longest time), *Greatest-Queue-Length* (GQL) rule (an AGV will visit the pickup point that has the greatest number of loads waiting at its output queue), *Earliest Due Time* (EDT) rule (an AGV will visit the pickup point containing the load with the earliest due time) and *Smallest-Remaining-Processing-Time* (SRPT) rule (an AGV will visit the pickup point containing the load with the smallest remaining processing time). For delivery-dispatching problem five main rules have been used such as *Shortest-Distance* (SD) rule (an AGV will visit the delivery point to which it is the closest), *Earliest Due Time* (EDT) rule (the load that has the earliest due time will have the highest priority to be delivery by an AGV), *First-In-Queue-First-Out* (FIQFO) rule (the load that has the greatest waiting time will have the highest priority to be delivery by an AGV), *Last-In-Queue-First-Out* (LIQFO) rule (the load that has the latest waiting time will have the highest priority to be delivery by an AGV) and *Shortest -Queue-Length* (SQL) rule (an AGV will visit the delivery point that has the latest number of loads waiting at its output queue). Finally for load-selection problem, *First-In-Queue-First-Out* (FIQFO) rule (the load that has the greatest waiting time at the pickup point will have the highest priority to be picked up by an AGV has been used in the simulation experiment.
In the algorithm, first of all the design variables have been defined as follows:

- Control strategies are the first category of design variables in the optimization process. In the next section we will explain the specified control strategies that were used in the algorithm.
- The fleet size in another design variable which indicates the total number of AGVS that used in the MHS.
- The buffer level at each pickup/delivery point is another set of design variables.

- The process times at each workstation are also design variables in the algorithm.

Among the design variables, the fleet size, buffer levels and process times have upper and lower limits due to the normal financial and/or technical restrictions which will be defined in details in the next section. It should be mentioned that the design variables will be used in the algorithm as the decisions variables. This algorithm starts with simulation experiments. The first goal of the algorithm is to obtain a function between the decision (design) variables and the system throughput. In simulation process, several values of each decision variable which meets the upper (U) and lower (L) restrictions are being produced randomly. We use some uniform distribution functions for each design variable in the simulation software. The upper and the lower bounds for the uniform distribution functions should be similar to the upper and the lower bound of each design variable. We used the uniform distribution functions for producing S values for each design variable because the uniform distribution function has not any bias, so it is an efficient distribution function when we have not any information about the best values for the design variables. It is similar to the process of random generation procedures in the simulation literature. At the end of simulation process, we have enough samples for starting the regression phase. Each sample is a vector which consists of distinct values of the decision variables with distinct value for the system throughput obtained from the simulation model. These samples will be used to produce the objective function by using a linear regression model. This linear function and other functional constraints will be used in a linear programming model. The optimal solution of this model will be the best values for the decision variables and the system throughput. Now, we define the algorithm as follows:

2.1 The algorithm:

Step 0) Initializing:

Denote the list of control strategies by A and assume that $|A| = n$. Now assume that:

- n denotes the number of AGVs in the system and :
$$L \leq n \leq U \tag{1}$$
Where L and U are the upper and lower bounds for the fleet size.
- There are m workstations and the process time of product i (i=1,2,…,p) at workstation j (j=1,2,…,m) is t_{ij} and :
$$L_{ij} \leq t_{ij} \leq U_{ij} \tag{2}$$
Where L_{ij} and U_{ij} are the upper and lower bounds for the process times.
- b_j denotes the buffer level at workstation j where j=1,2,…,m and :
$$L_j \leq b_j \leq U_j \tag{3}$$
Where L_j and U_j are the upper and lower bounds for the buffer levels.
- Set l=0.

Step 1) Selecting a control strategy from the A:
Set l= l+1.
Step 2) Assume that S is the sample size that we need in the regression model. Produce S samples according to the uniform distribution function for each design variable in the simulation software. Use the same upper and lower bounds for the uniform distribution functions should as ones for each design variable.

Step 3) Neglect the warm-up period and run the simulation model for S times and record the design variable values and the system throughput in each run in a spreadsheet.

Step 4) Use the mean square method to generate a linear function between the design variables and the system throughput (ST), i.e.:

$$ST_l = a_0 + a_1 n + \sum_{j=1}^{m} a_{2j} b_j + \sum_{i=1}^{p} \sum_{j=1}^{m} a_{3j} t_{ij} \quad (4)$$

Where ST_l is the system throughput under control strategy l and a_0, a_{2j}, a_{3j} are constant coefficients obtained by the mean square method.
Step 5) Formulate the following linear integer programming model for optimization:

$$Max. ST_l = a_0 + a_1 n + \sum_{j=1}^{m} a_{2j} b_j + \sum_{i=1}^{p} \sum_{j=1}^{m} a_{3j} t_{ij}$$

(1) $L \le n \le U$

(2) $L_{ij} \le t_{ij} \le U_{ij} \qquad \forall i = 1,2,\dots,p \;, j = 1,2,\dots,m$

(3) $L_j \le b_j \le U_j \qquad \forall j = 1,2,\dots,m$

(4) n, b_j, t_{ij} *are integers* $\qquad \forall i = 1,2,\dots,p \;, j = 1,2,\dots,m$

And solve the model. Indicate the optimal solution as (ST_l^*, b_j^*, t_{ij}^*).

Step 6) If l=n+1 then go to Step 7 otherwise go to Step 1.

Step 7) Selecting the best optimal solution:
The optimal solution (ST^*) which indicates the best control strategy and other optimal design variables is defined as follows:

$$ST^* = Max_{l=1,2,\dots,n}\{ST_l^*\} \quad (6)$$

Terminate the algorithm. The optimal values for each design variable are as the same the ones which belong to ST^* .

3. The simulation model

We have used the flow path layout which introduced by [18]. The flow path has been demonstrated in Figure 1. All paths are unidirectional and there is no chance to have a collision state. The pickup/delivery points are designed in a way that unloading can be done before loading tasks. Workstations 1 and 12 are entrance and sink points for products respectively. The process times have been shown in Table 1. All products have the same distribution functions at each workstation. All AGVs are multiple-load ones with load size 3 and have the same speed which is 1.8 m/s. The loading and unloading times are 30 seconds for each AGV. There are 6 different product (part) types in the model. Each product flow and the mix ratios are summarized in Table 2. We have used 10 different control strategies. These control strategies have been picked up from [19], although they tested 20 different control strategies. Since the objective function is ST in this paper, we've selected the best 10 control strategies from [19] considering system throughput criterion. Each control strategy consists of 4 different rules such as the task rule, the pickup-dispatching rule, the delivery-dispatching rule and the load-selection rule [19]. In this paper, we picked up the best ones:

- Greatest-Queue-Length (GQL) and Smallest-Remaining-Processing-Time (SRPT) have been selected as the task rules.
- First-In-Queue-First-Out (FIQFO) rule has been selected for load-selection rule.
- Shortest -Queue-Length (SQL), Earliest Due Time (EDT), Shortest-Distance (SD), Last-In-Queue-First-Out (LIQFO) and First-In-Queue-First-Out (FIQFO) rules have been selected for the deliver-dispatching rule.
- *D*elivery-Task-First (DTF) rule has been selected for the pickup-dispatching rule.

All different levels for control strategies have been summarized in Table 3. We used a coding system for referring any kind of strategies using the capital letters shown in the columns of Table 3 like [19]. For example, a strategy (or problem) T1P1D1L1 refers to a strategy where the task rule is DTF, the pickup-dispatching rule is LTIS, the delivery-dispatching rule is SQL and the load-selection rule is FIQFO. Meanwhile, in the simulation model, we used NV as a workstation-initiated approach for assigning the AGVs for the next task. All upper and lower bound can be found in Table 4. It should be mention that for stochastic events like processing times, we have just varied the mean of variables not variances, since the mean of a production facility can be adjusted easily if they lie between specified technical limits while changing the variances is much more difficult, because it needs more drastic changes like changing the machines or making it more rigid. We have used the Enterprise Dynamics V8.0 software as our simulation software. All computations were run on a PC with 2.6 GHz CPU and 2GB RAM. The warm-up period set at 48,000 seconds according to [19] and the results in Figure 2. For sampling, we set S=100, so each simulation model replicated 100 times under each control strategy. The simulation watch started from 0 to 170,000 seconds as stopping time.

4. Computational results

As an example, we set the control strategy to T1P2D1L1. According to the proposed algorithm which was explained in section 2, the first replication yield 3777 as the system throughput. Now the design variables get different values according to the uniform distribution function and the model is being replicated for 99 times (totally 100 times). All simulation results have been shown in Table 5. The results for using the mean square method have been summarized in Table 6 and Table 7. We have used the regression analysis for our calculations which have been shown in Table 8. As one may see, the correlation coefficients(R^2) are more than 0.99 which shows that the linear function has a good quality for fitness. As it was shown in Table 9, some design variables have negative and some have positive coefficients. For example the fleet size has positive influence on system throughput, since it can help the material transportations to be more efficient. So it has positive coefficient in all control strategies. Therefore, not only this explanation shows the validity of our model but also shows the importance level of each design variable in system throughput simultaneously. On the other side, increasing the buffer levels at each pickup/delivery point will result in having more parts at each workstation. This increase in parts queue will result in having more waiting times. Therefore its coefficient will be negative in all control strategies. Regarding the processing times we cannot obtain a general comment on their effects on system throughput, since each control strategy has its own characteristics on dispatching the AGVs through the workstations and on load prioritizing, sometimes increasing a process time can increase the system throughput and sometimes decreasing a process time can make better ST.
According to our example which used T1P2D1L1 as the control strategy, the optimal solution has been found by using Lingo 8.0 software as follows. Please note that we have used t_j instead of$t_{i,j}$, since all products have the same processing times at each workstations and b instead ofb_j, since we assumed that all workstations have the same buffer levels:
MODEL:

MAX =1333.136014* n +1863.40407*t1-558.93471*t2 -289.88457*t3 -
1312.1691*t4-1973.1586* t5+2201.0111*t6 -
1945.7133*t7+1164.20195*t8+5045.38866*t9-4535.8802* t10-6.25793497*b-
3508.896;

3<=n;n<= 7;

1.45<= t1;t1<=1.55;
0.95<= t2;t2<=1.05;
1.95<= t3;t3<=2.05;
0.95<= t4;t4<=1.05;
1.95<= t5;t5<=2.05;
1.95<= t6;t6<=2.05;

1.45<= t7;t7<=1.55;
1.45<= t8;t8<=1.55;
1.95<=t9:t9<=2.05;
0.95<=t10;t10<=1.05;
95<= b;b<= 105;
END (7)

The optimal solution for the design variables are as follows:

$ST_1^*= 10382.76$ $n^*= 7.000000$ $t_1^*= 1.050000$ $t_2^*=1.450000$ $t_3^*=1.950000$ $t_4^*=0.9500000$ $t_5^*=1.950000$ $t_6^* = 2.050000$ $t_7^* =1.450000$ $t_8^* =1.550000$ $t_9^* =2.050000$ $t_{10}^* = 0.9500000$ $b^*= 95.00000$

The optimal solutions have been shown in Table 10. According to the results, the best strategy is the one that AGVs select the workstation with maximum queue length (GQL rule) and distributes the load to the workstations with minimum queue length at the delivery points. On the other hand, for pickup-dispatching rule, the best strategy is maximum queue length and for the delivery-dispatching rule, the best strategy is minimum queue length. The optimal values for this strategy including the ST, buffer length and processing times have been shown in Table 10. Since the objective function is to maximize the ST, so the strategies which reduces the waiting times at workstations will be selected as the best strategy. It's why T1P2D1L1 has been selected as optimal strategy.

When one compares the results of the current work with the ones obtained in [19], it is clear that letting the design variables to be more flexible (around 15-20%), the results will be brilliant. The best strategy at our experiments is T1P2D1L1 while it had 7th rank in [19]. At the best case (using the best strategy and the best fleet size), the ST was 1,050 units in [19] while here at the best case we have 10,244 units, i.e. the increase is 10 times more. The comparison chart between the current results and the results in [19] has been shown in Figure 3. This fact shows the effect of having a little flexibility in fleet size, processing times and buffer levels. Regarding the sensitivity analysis, we used the results of the regression coefficients (positive and negative effects) for each design variable to specify the changes in upper and lower bounds. We allowed the upper and the lower bounds of each design variable to be changed 5% to see what will be happened in the optimal solution. The results of such analysis have been shown in Table 11. In this Table, each cell shows the ST related to the strategy (the row) and the design variable (the column) after the sensitivity analysis while the Throughput column shows the ST before the sensitivity analysis. As the table shows, if we decrease the lower bound of the processing time at workstation 4 by 5% or if we increase the upper bound of the processing time at workstation 8 by 5% then the best control strategy changes to T1P2D3L1. In other cases, changing the upper and the lower bounds will not change the results. The best ST is 11,578 when we use T1P2D1L1 by increasing 5% in the fleet size. According to the results, the fleet size has the most effect on the system throughput among all strategies. The last column of this table shows the second important variable after the fleet size for each strategy.

5. Conclusions

In this paper, we have developed a heuristic algorithm by combining simulation, linear regression and integer programming methods for the first time as the optimization tool for a multiple-load automated guided vehicle system. The first contribution of this paper is that we have used several design variables simultaneously like fleet size, buffer levels at pickup/delivery points and processing times in the optimization process which optimizes the system throughput. Therefore the approach is an integrated one which connects material handling system to the FMS. The simulations results are being considered as samples for the next step which is creating a linear function between the system throughput and the design variables by the mean square method. This linear function and other functional constraints will form a linear integer model which optimizes the system throughput. For comparison purpose, we used the results obtained by Azimi et al. [19]. We used the best 10 strategies among 20 ones at their work in our model. It was shown that the best control strategy is T1P2D1L1 while this control strategy had 7th rank in [19]. The main difference is due to the flexibility provided in this paper for design variables. We allowed the design variables to be varied around 15% and the results are incredible. The system throughput was 1,050 in [19] at the best case while we could increase the ST 10 times and the ST is 10,244 at the best case here by a little flexibility in design variables. It should be mentioned that we just varied the mean of the stochastic variables like processing times not their variances. The second contribution is that the proposed approach can be used for showing the effect of each variable design in ST. Some variables like buffer levels had negative effect and some variables like the fleet size had positive effect. The amounts of these effects have been calculated also. Finally, it was shown that the fleet size has the maximum effect on the system throughput in a FMS environment. This conclusion has been obtained for the first time in the literature. Finally, we carried out a sensitivity analysis to show the validity range of the obtained results.

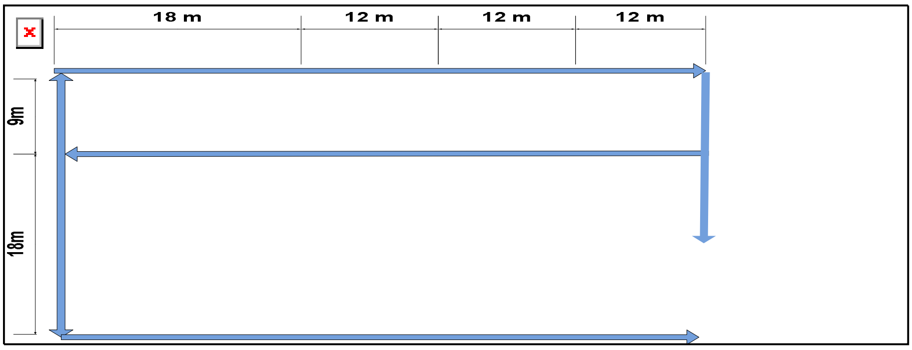

Figure 1. The flow path layout

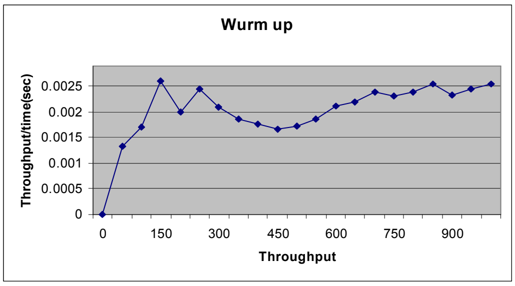

Figure 2. The warm-up diagram

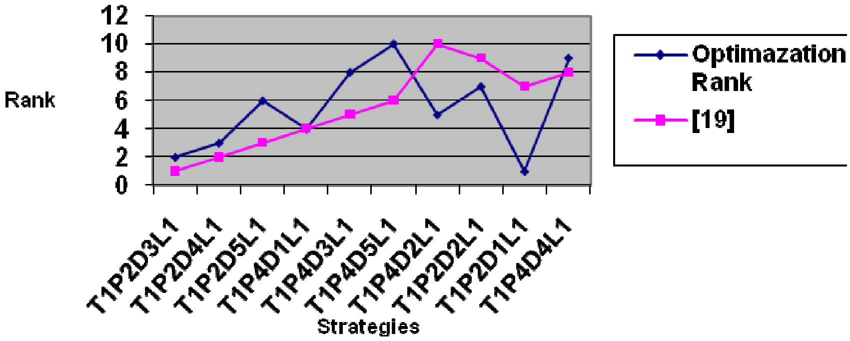

Figure 3 . Strategies Ranking

Table 1. The mix-ratio and process sequence of each part

Part Type	Mix-Ratio	Sequence
1	0.16	1-3-5-7-9-11-12
2	0.17	1-2-4-6-8-10-12
3	0.18	1-4-5-7-9-10-12
4	0.15	1-3-4-5-9-11-12
5	0.14	1-2-3-6-8-9-12
6	0.20	1-5-6-7-10-11-12

Table 2. The processing-time distribution and the production sequence of each product type

Work station	Processing time distribution(min)	Work station	Processing time distribution(min)
2	N(1,0.1)	7	N(2,0.2)
3	N(1.5,0.15)	8	N(1.5,0.15)
4	N(2,0.2)	9	N(1.5,0.15)
5	N(1,0.1)	10	N(2,0.2)
6	N(2,0.2)	11	N(1,0.1)

Table 3. The levels of controlling strategies

Levels	**T**asks	**P**ickup-Dispatching	**D**elivery-Dispatching	**L**oad-Selection
1	DTF	GQL	SQL	FIQFO
2		SRPT	EDT	
3			SD	
4			LIQFO	
5			FIFO	

Table 4. The upper and the lower bounds of the design variables

Design parameters	AGV Number (n)	Processing Time in stations										Buffer capacity(b)
		t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}	
[L,U]	[3,7]	[0.95,1,05]	[1.45,1.55]	[1.95,2.05]	[0.95,1,05]	[1.95,2.05]	[1.95,2.05]	[1.45,1.55]	[1.45,1.55]	[1.95,2.05]	[0.95,1,05]	[95.105]

Table 5.Simulation output for T1P2D1L1 Strategy

Sample	Fleet size	Processing Time in stations										Buffer capacity(b)	Throughput (ST)
	n	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}		
1	3	1	1.55	2	1	2	2	1.5	1.5	2	1	105	3,777
2	6	1.05	1.45	2.05	0.95	2.05	1.95	1.55	1.45	2.05	0.95	100	7,984
3	5	1	1.55	2	1	2	2.05	1.5	1.45	2.05	1	105	6,566
4	6	1.05	1.45	2.05	0.95	2.05	1.95	1.55	1.45	2.05	0.95	95	8,023
5	4	1.05	1.45	2.05	0.95	2.05	1.95	1.55	1.45	2	0.95	95	6,635
6	4	0.95	1.45	1.95	0.95	2.05	1.95	1.45	1.45	1.95	0.95	95	6,636
7	5	1	1.45	1.95	1.05	2	2	1.45	1.45	2.05	1.05	100	6,596
8	3	0.95	1.45	1.95	0.95	2	2	1.45	1.45	2	1	105	3,776
9	5	0.95	1.45	1.95	0.95	2	2	1.45	1.45	2	1	100	6,599
10	6	1	1.45	1.95	1.05	2	2	1.45	1.45	2.05	1	105	7,940
11	6	0.95	1.45	1.95	1.05	2.05	2.05	1.45	1.45	2.05	1	105	7,941
12	5	1	1.55	1.95	1	2	2.05	1.5	1.45	2.05	1.05	105	6,560
13	3	1	1.5	2	1	2	2	1.5	1.5	2	1	105	3,796

14	4	0.95	1.5	2	1	2	2	1.45	1.55	2	1	105	5,201
15	5	1.05	1.5	1.95	1	2	2	1.45	1.55	1.95	0.95	95	6,637
16	6	1.05	1.5	1.95	0.95	2.05	1.95	1.45	1.55	1.95	0.95	95	8,021
17	6	0.95	1.45	2.05	0.95	2.05	1.95	1.55	1.45	2.05	0.95	95	8,013
18	5	0.95	1.45	2.05	0.95	2.05	1.95	1.55	1.45	2.05	0.95	100	6,593
19	4	0.95	1.45	2.05	0.95	1.95	1.95	1.55	1.45	2	0.95	100	5,196
20	4	1.05	1.55	2.05	0.95	1.95	1.95	1.55	1.45	2	0.95	100	5,200
21	6	0.97	1.52	1.97	1.03	1.93	2.03	1.53	1.42	1.97	0.93	103	7,965
22	6	1.03	1.525	2.025	1.025	2.025	2.025	1.525	1.525	2.025	1.025	103	7,958
23	6	0.98	1.475	1.975	0.975	1.975	1.975	1.475	1.475	1.975	0.975	97	8,009
24	5	0.98	1.475	1.975	0.975	1.975	2.025	1.525	1.525	2.025	1.025	97	6,618
25	5	1.03	1.475	1.975	0.975	1.975	2.025	1.525	1.525	1.975	0.975	97	6,619

Table 6. Regression Statistics

Multiple R	0.99589
R Square	0.991797
Adjusted R Square	0.983594
Standard Error	162.26
Observations	25

Table 7. ANOVA analysis

	df	SS	MS	F	Significance F
Regression	12	38199090	3183258	120.9062	1.35884E-10
Residual	12	315939.8	26328.31		
Total	24	38515030			

Table 8. Regression analysis for strategies

strategies	Sum of square	Degrees of freedom	Mean square	F value	R^2
T1P2D3L1	49792780.5	12	4149398	115.844552	0.99144162
T1P2D4D1	51117181.8	12	4259765	19496.0685	0.99994871
T1P2D5D1	33628353.5	12	2802363	27530.1907	0.99996368
T1P4D1L1	41382293.9	12	3448524	673.3194	0.99851702
T1P4D3L1	30671156.5	12	2555930	164.850566	0.99397048
T1P4D5L1	28916519	12	2409710	268.053445	0.99628327
T1P4D2L1	33915276.9	12	2826273	857.501947	0.99883518
T1P2D2D1	47696556.2	12	3974713	61636.7399	0.99998378
T1P2D1D1	38199090.2	12	3183258	120.906244	0.99179697
T1P4D4L1	36909354.9	12	3075780	356.695539	0.99720433

Table 9.Decision variable coefficients

strategies	Buffer capacity	Processing Time in stations										Fleet size
		t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}	
T1P2D3L1	-17.05	210.86	-443.11	755.76	4743.2	-3398.25	1622.96	1767.81	-4912.04	1496.04	-1247.06	1229.01
T1P2D4D1	-12.00	26.89	-127.92	-119.07	-539.54	399.56	41.42	-214.21	659.84	175.87	-266.86	1347.63
T1P2D5D1	-9.23	-184.67	93.00	5.63	-76.45	111.01	37.73	-71.31	25.60	141.02	-153.43	1347.59
T1P4D1	-11.63	-532.84	1272.1	719.69	354.79	-1119.50	-1002.77	630.85	-978.05	136.50	-252.47	1129.

L1												08
T1P4D3 L1	-4.78	-92.81	1349.3	-654.94	-941.90	-172.44	-729.32	-596.61	-481.58	-152.26	705.06	1112.44
T1P4D5 L1	-12.94	-398.07	680.07	-8.45	-149.09	-169.02	-232.52	649.55	-15.47	360.36	-0.85	1092.75
T1P4D2 L1	-3.12	-274.11	998.04	926.77	1247.4	-1786.73	-737.45	496.00	-1943.96	41.71	-214.67	1118.15
T1P2D2 D1	-8.95	125.75	-12.15	-63.15	-145.11	80.68	-73.63	-154.15	120.88	32.71	-18.93	1352.50
T1P2D1 D1	-6.26	-4535.9	5045.4	1164.20	-1945.7	2201.01	-1973.16	-1312.17	-289.88	-558.93	1863.40	1333.14
T1P4D4 L1	-9.70	-890.83	496.13	715.09	172.46	378.13	18.23	828.77	165.76	556.39	-84.76	1108.82

Table 10.Integer linear programming output

strategies	Fleet size	Processing Time in stations										Buffer capacity	Throughput (ST)	Strategies Rank
	n^*	t^*_1	t^*_2	t^*_3	t^*_4	t^*_5	t^*_6	t^*_7	t^*_8	t^*_9	t^*_{10}	b^*		
T1P2D3L1	7	0.95	1.55	1.95	1.05	2.05	1.95	1.55	1.55	1.95	1.05	95	10119.51	2
T1P2D4D1	7	0.95	1.55	2.05	0.95	2.05	2.05	1.45	1.45	1.95	1.05	95	9362.303	3
T1P2D5D1	7	0.95	1.55	2.05	0.95	2.05	2.05	1.45	1.55	2.05	0.95	95	9266.027	6
T1P4D1L1	7	0.95	1.55	1.95	1.05	1.95	1.95	1.55	1.55	2.05	0.95	95	9307.691	4
T1P4D3L1	7	1.05	1.45	1.95	0.95	1.95	1.95	1.45	1.45	2.05	0.95	95	9197.881	8
T1P4D5L1	7	0.95	1.55	1.95	1.05	1.95	1.95	1.45	1.45	2.05	0.95	95	9025.201	10
T1P4D2L1	7	0.95	1.55	1.95	1.05	1.95	1.95	1.55	1.55	2.05	0.95	95	9289.989	5
T1P2D2D1	7	0.95	1.55	2.05	0.95	1.95	2.05	1.45	1.45	1.95	1.05	95	9259.966	7
T1P2D1D1	7	1.05	1.45	1.95	0.95	1.95	2.05	1.45	1.55	2.05	0.95	95	10244.44	1
T1P4D4L1	7	0.95	1.55	2.05	1.05	2.05	2.05	1.55	1.55	2.05	0.95	95	9101.589	9

Table 11. Sensitivity analysis of the decision variables

strategies	AGV Number (+5%)	Processing Time in stations (±5%)										Buffer capacity (-5%)	Throughput(Z)	Important decision variable
		t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}			
T1P2D3L1	11349	10182	10194	10365	10208	10201	10289	10357	10157	10142	10131	10205	10119.51	X_4
T1P2D4D1	10710	9376	9371	9395	9373	9364	9382	9389	9368	9369	9364	9422	9362.303	Buffer capacity (Y)
T1P2D5D1	10614	9274	9273	9267	9270	9268	9272	9270	9266	9271	9275	9312	9266.027	X_{11}
T1P4D1L1	10779	9711	9722	9850	9737	9779	9785	9716	9761	9942	9809	9740	9307.691	X_4
T1P4D3L1	10310	9233	9205	9222	9228	9234	9207	9245	9231	9265	9203	9222	9197.881	X_{10}
T1P4D5L1	10118	9025	9043	9026	9058	9037	9034	9033	9026	9059	9045	9090	9025.201	Buffer capacity (Y)
T1P4D2L1	10408	9301	9292	9387	9315	9327	9379	9352	9336	9340	9304	9306	9289.989	X_4
T1P2D2D1	10612	9261	9262	9266	9268	9264	9264	9267	9263	9261	9267	9305	9259.966	Buffer capacity (Y)
T1P2D1D1	11578	10338	10306	10272	10310	10343	10355	10342	10303	10497	10471	10275	10244.44	X_{10}
T1P4D4L1	10210	9106	9129	9110	9143	9103	9121	9110	9137	9126	9146	9150	9101.589	Buffer capacity (Y)

REFERENCES

[1] **Müller, T. (1983),** ***Automated Guided Vehicles***. IFS (Publications) Ltd./Springer-Verlag, UK/Berlin;
[2] **Sezen, b (2003),** ***Modeling Automated Guided Vehicle System in Material Handling***. Dogus Üniversitesi Dergisi, 4 (2), 207-216;
[3]**Jawahar, N., Aravindan, P., Ponnambalam, S. G. and Suresh, R. K. (1998),** ***AGV Schedule Integrated with Production in Flexible Manufacturing Systems***. International Journal of Advanced Manufacturing Technology, 14, 428–440;
[4]**Seo, Y. and Egbelu, P. J. (1999),** ***Integrated Manufacturing Planning for an AGV-based FMS.*** International Journal of Production Economics, 473–478;
[5]**Sabuncuoglu, I., & Hommertzheim, D. (1992),** ***Dynamic Dispatching Algorithm for Scheduling Machines and Automated Guided Vehicles in a Flexible Manufacturing System***. International Journal of Production Research (30/5), 1059–1079;
[6]**Aized, T., Takahashi, K. and Hagiwara, I. (2007),** ***Modelling and Analysis of an Integrated Automated Guided Vehicle System Using Colored Petri Net***. World Congress on Engineering, 1038–1043;
[7]**Bilge, U. and Ulusoy, G. (1995),** ***A Time Window Approach to Simultaneous Scheduling of Machines and Material Handling System in an FMS***. Operations Research (43/6), 1058–1070;
[8]**Boris S and David S. (1993),** ***Controlling Flexible Manufacturing Systems Based on a Dynamic Selection of the Appropriate Operational Criteria and Scheduling Policy.*** International Journal of Flexible Manufacturing System, 18(1), 1-27;
[9]**Spano M.R, O'Grady P.J. and Young R.E (1993),** ***The Design of Flexible Manufacturing System***. Computer in Industry, 21, 185-98;
[10]**Hulpic V. and Paul R.J. (1994),** ***Simulation Modeling of Flexible Manufacturing Systems Using Activity Cycle Diagrams***. Journal of the Operation Research Society, 45(9), 1011-23;
[11]**Borenstein D. IDSSFLEX (1998),** ***An Intelligent DSS for the Design and Evaluation of Flexible Manufacturing Systems***. Journal of the Operational Research Society, 49(7), 734-44;
[12]**Chan F.T.S., Jiang B. and Tang N.K.H. (200),** ***The Development of Intelligent Decision Support Tool to Aid the Design of Flexible Manufacturing Systems***. International Journal of Production Economics, 65(1), 73-84;
[13]**Anglani A., Grieco A., Pacella M. and Tolio T. (2002),** ***Object-oriented Modeling and Simulation of Flexible Manufacturing Systems: A Rule-based Procedure.*** Simulation Modeling Practice and Theory, 10(3), 209-34;
[14]**Meinert T.S., Taylor G.D. and English J.R. (1999),** ***A Modular Simulation Approach for Automated Material Handling Systems***. Simulation Practice and Theory, 7(1), 15-30;

[15]**Bilge, U. and Tanchoco, J. M. A. (1997),** ***AGV Systems with Multi-load Carriers: Basic Issues and Potential Benefits***. Journal of Manufacturing Systems, 16(3), 159–174;
[16]**Lee H. and Cheon M.U.M.I. (2009),** ***The Simulation Design and Analysis of a Flexible Manufacturing System with Automated Guided Vehicle System***. Journal of Manufacturing Systems, 28, 115_122;
[17]**Aized T. (2009),** ***Modelling and Performance Maximization of an Integrated Automated Guided Vehicle System Using Colored Petri Net and Response Surface Methods*** . Computers & Industrial Engineering, 57, 822–831;
[18]**Ho, Y.C. and Liu, H.C. (2006),** ***A Simulation Study on the Performance of Pickup-dispatching Rules for Multiple-load AGVs***. Computers and Industrial Engineering, 51, 445-463;
[19]**Azimi P., Hale, H. and Alidoost M. (2010),** ***The Selection of the Best Control Rule for a Multiple-Load AGV System Using Simulation and Fuzzy MADM in a Flexible Manufacturing System*** . Modelling and Simulation in Engineering, Volume 2010, doi:10.1155/2010/821701.