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Integer linear programming formulation of the vehicle positioning problem in automated manufacturing systems

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Abstract This paper addresses the problem of vehicle location (positioning) for automated transport in fully automated manufacturing systems. This study is motivated by the complexity of vehicle control found in modern integrated circuit semiconductor fabrication facilities where the material handling network path is composed of multiple loops interconnected. In order to contribute to decrease the manufacturing lead-time of semiconductor products, we propose an integer linear program that minimizes the maximum time needed to serve a transport request. Computation experiments are based on real-life data. We discuss the practical usefulness of the mathematical model by means of a simulation experiment used to analyze the factory operational behavior.

Keywords Vehicle location · Integer linear programming · Automated manufacturing · IC semiconductors · Simulation

Introduction

Material handling is a significant part of the manufacturing process in terms of both production cost and time. Indeed, the processing time of a typical job is only 5% of the manufacturing lead-time (Askin and Goldberg 2002); the remainder of the manufacturing lead-time is spent in storage and in transportation by a material handling system. In today's competitive market, most current industries face the need of automation and restrictions on the efficiency on available floor space. This trend has focused attention on the efficiency of automated material handling systems (AMHS). According to case studies provided by the Material Handling Institute (MHI 1993), benefits of building and using AMHS include labor costs saving, better schedule of work-in-process (WIP), flexible material handling, effective inventory control, greater quality assurance and safety, increased production, improved utilization of space, and flexible routing. Among the various material handling equipment used in most automated manufacturing systems, vehicle-based automated transport systems (such as automated guided vehicles or overhead transporters) are employed widely due to its flexibility in transport.

The performance of an automated material handling system is generally a decreasing function of the service time (i.e., the time between the time that a part requests transportation and the delivery time). The service time basically consists of two components: waiting time and the travel time between the pickup point and the delivery point. In addition to technology, various tactical design and operational control issues affect the performance of the transport system, including the design of the network path layout, the location of pickup and delivery points, the number of vehicles in the system, and the scheduling and routing of the vehicles. Other design issues, such as network path design, fleet size design, technology choice, etc., have also been considered in literature. The reader is referred to (Qiu et al. 2002; Le-Anh and De Koster 2004; Vis 2006) for an overview and discussion of these topics. In the following we will only focus our literature review on papers related to vehicle positioning for material handling in automated manufacturing systems. Very little has been done in literature. Only the works of Egbelu (1993), Kim (1995) and Gademann and van de Velde (2000).

This paper focuses on one of such operational issues: the location (or positioning) of vehicles. The positions of vehicles affect the empty travel times to the pickup points, and this plays a very important role in the waiting time of the

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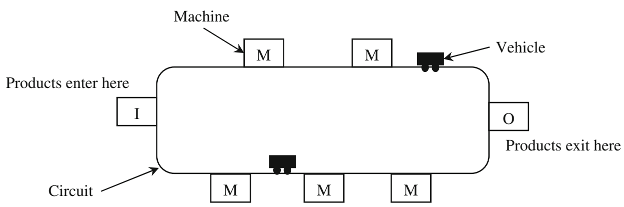

Fig. 1 Single-loop material handling network path with two vehicles and five machines

parts. Accordingly, a clever positioning of vehicles along the AMHS network may improve the performance of a vehicle-based automated transport system.

The first work on vehicle positioning was presented by Egbelu (1993) for a single loop layout (i.e., a single circuit where the pickup and delivery points are positioned along the circumference, as shown in Fig. 1). In Egbelu's paper and in subsequent works, the aim was to identify points for the positioning of idle vehicles. This author differentiated between unidirectional and bidirectional loops, and proposed a linear programming formulation for the unidirectional case and some heuristics algorithms for the bidirectional case. Kim (1995) considered the problem of positioning a single idle vehicle to minimize the average response time. The layout configuration was also a single circuit network. He showed that the problem of positioning only one vehicle can be solved efficiently. Gademann and van de Velde (2000) addressed the problem of determining the home positions for a set of m automated guided vehicles in a loop layout where n pickup points are positioned along the circumference ($m < n$). These authors defined a home position as the location where idle AGVs are held until they are assigned to the next transportation task. Mainly focused on the complexity analysis of the problem, these authors established that the problems of minimizing maximum response time and minimizing average response time are solvable in polynomial time for *any* number of vehicles in a single loop layout.

In this paper, we study the vehicle location problem for a general configuration of the material handling network, i.e., a network path with multiple loops interconnected (see an example in Fig. 2). To the best of our knowledge, our work is the first for which the vehicle idleness is not the unique criterion for the positioning of vehicles. Against previous works in literature, our approach divides the network path into zones and a fleet of vehicles is assigned to each of these zones in order to optimize the performance of the material handling system. This performance can be measured by minimizing the average time needed to service a request. However, this metric implies that standard deviation of the service time has to be also measured. In this paper we have chosen the maximum service time as performance metric because it is an upper bound of the actual service time of *any* transportation request.

This study is motivated by the complexity of vehicle control found in the AMHS of modern semiconductor fabrication facilities (Montoya-Torres 2005). With the arrival of 300 mm silicon wafers, the semi-conductor industry had to reconsider material handling. Standard lots of wafers became too heavy to be handled by operators without risk of musculo-skeletal disorders or product damage (Wang et al. 2003). To handle work-in-process between manufacturing operations, semiconductor manufacturers are hence installing overhead rail-based vehicles with automated storage/retrieval systems (Montoya-Torres 2006). In addition, with the interest in considering direct machine to machine pickup and delivery (called direct tool-to-tool delivery, in semiconductor terminology), such overhead rail-based automated vehicles systems run on an extended complex network path as shown in Fig. 2. The management and control of such network system becomes much more complex than previously considered in both the semiconductor literature and the general automated material handling systems literature. We propose an integer linear program that seeks to minimize the maximum time needed to serve a transport request. Some variants of the model are discussed, and its implementation on a currently in development full-automated manufacturing environment is presented.

ILP formulation

As stated before, previous works in the literature have considered the problem of locating vehicles in order to determine the points on a single loop where vehicles can park once they become idle. In this paper, instead, the network path is divided into zones and a fleet of vehicles is assigned to each of these zones in order to optimize the time required to service a transport request. The problem is inspired from a real-life fully automated integrated circuit (IC) semiconductor factory. In fact, IC makers are today affronted to the problem of optimizing the operation of the automated material handling system (AMHS), referring to increase system's productivity so as to minimize cycle time and to maximize throughput at a given service rate. This optimization may be done by the effective and efficient control of the AMHS. However, no much attention has been given to the efficiency of material handling systems within wafer factories simply because the material handling is often called a "non-value-added" activity. We know however, that without it, no value can be added. Since having the AMHS as the bottleneck of the factory is unacceptable if high throughput and short cycle times are desired, appropriate analysis techniques and tools are needed to carefully explore and plan the operation of the AMHS. The problem is approached by dividing the transportation network into zones and to assign a fleet of vehicles to each of these zones (see Fig. 3). The information about

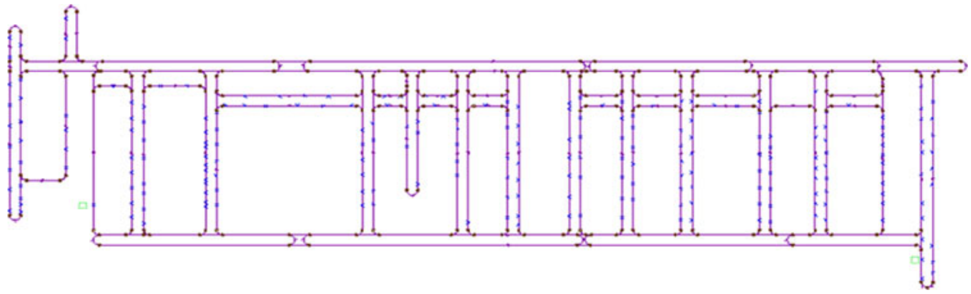

Fig. 2 Complex AMHS network path considered in this paper, more than 200 machines

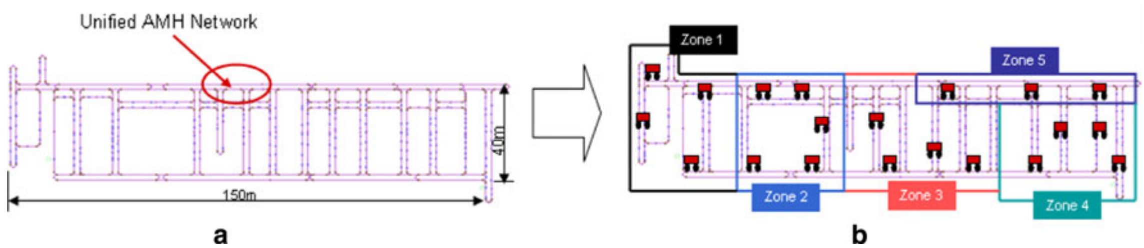

Fig. 3 Example of the zone definition problem **a** before and **b** after defining the zones geographically (note that our ILP models may define zones independently of point location)

transportation requests (demands) and vehicle behavior is aggregated. The problem is thus solved using mathematical programming (integer linear programming in our case).

Formally, the network path is defined as a graph, where nodes represent the location of machines (or transportation demand points) and arcs represent the paths in the transportation network. Two types of nodes have to be defined. First, the set of demand points (machine locations) is denoted by K and the set of points that may be centers of zones is denoted by J. The notion of center is used here with the same meaning that for facility location models found in classical Location Theory. The shortest travel time t_{ik} from vertex i to vertex k of the graph is known. The set of available vehicles is noted by V. A demand point k is said to be *covered* by point j if and only if $t_{jk} \leq T$, where $T = \max t_{jk}, \forall j \in J, k \in K$. The objective is to divide the network into P zones and to assign a fleet of vehicles to each zone.

Considerations and notation

The development of the mathematical model is based on the following considerations found in the real environment of the factory from where the problem is inspired:

- Machine layout and material flow paths are completely specified, including fixed travel distances, machine locations, and guided path directions.
- The inter-resource material flow rates in terms of load per time period are known. They are calculated from the production routings (sequence of operations) of the products to be manufactured and their demands over the manufacturing horizon.
- Whenever a transporter visits a machine or the output station of a resource group, there always exist materials to be transferred.
- Only horizontal material movements are considered (e.g., automated transport systems with automated guided vehicles, overhead transporters or automated rail carts).
- Transporters are assumed to be identical (i.e., they have identical travel speeds) and with unit load capacity.
- For the traffic management problem, the control at intersection points of the unidirectional guided path is sufficient to avoid collisions.
- Transporters and machines are supposed to be reliable.
- Preemption is not permitted, neither for manufacturing operations nor vehicle trips.
- The number of items to be manufactured during a given period is known and constant over the whole production horizon. This assumption is realistic when product release policies are defined at higher decision levels. This also allows us to formulate the objective function in order to minimize the maximum time a load waits for a vehicle. Thus, as stated by Little (1961) Law, it is easy to compute the throughput rate for the production period under study.

Before presenting the ILP formulation, the following notation is needed.

Parameters

P: number of zones
V: set of vehicles
K: set of nodes (points) in the network path

J: set of possible nodes (points) in the network path that can be the centers of zones
t_{ik}: travel time taken between each pair of points in the network path
D_k: average time per hour needed to perform *all* moves starting from point k
VC: vehicle availability per hour, i.e., the time per hour that a vehicle is available to perform transport tasks

Variables

T coverage time (i.e., the maximum time needed to serve the farthest point of a zone)
$X_j = 1$ if point j is selected as center of zone, 0 otherwise
$Y_{jk} = 1$ if point k is assigned to a created zone with point j as the center, 0 otherwise
$Z_{vj} = 1$ if vehicle v is assigned to a created zone with point j as the center, 0 otherwise

ILP formulation

The vehicle location problem can now be formulated as an Integer Linear Program. The objective function, defined as Minimize $\left(\underset{k\in K}{\text{Maximum}} \sum_{j\in J} t_{jk}Y_{jk}\right)$, can be formulated by expressions (1) and (2) next:

$$\text{Minimize } T \tag{1}$$
$$T \geq \sum_{j\in J} t_{jk}Y_{jk} \quad \forall k \in K \tag{2}$$
$$\sum_{j\in J} X_j \leq P \tag{3}$$
$$\sum_{j\in J} Y_{jk} = 1 \quad \forall k \in K \tag{4}$$
$$Y_{jk} \leq X_j \quad \forall j \in J, k \in K \tag{5}$$
$$\sum_{j\in J} Z_{vj} \leq 1 \quad \forall v \in V \tag{6}$$
$$\sum_{k\in K} D_k Y_{jk} \leq VC \sum_{v\in V} Z_{vj} \quad \forall j \in J \tag{7}$$
$$X_j \in \{0, 1\} \quad \forall j \in J \tag{8}$$
$$Y_{jk} \in \{0, 1\} \quad \forall j \in J, k \in K \tag{9}$$
$$Z_{vj} \in \{0, 1\} \quad \forall v \in V, j \in J \tag{10}$$

The objective function (1) and the constraints (2) aim at minimizing the maximum time to cover demands. Constraints (3) ensure the use of at most P zones. Constraints (4) and (5) state, respectively, that each point in the network belongs to one and only one zone, and that a point is covered by a zone only if the zone is opened. Constraints (6) guarantee that a vehicle is assigned to at most one zone. Constraints (7) ensure that the capacity of each zone (related to the number of vehicles in the zone) is satisfied. Finally, constraints (8), (9) and (10) specify that decision variables are binary.

This formulation is closely related to the classical P- center problem in Facility Location Theory (Daskin 1995; Mirchandani and Francis 1990). Our formulation, however, differs in multiple ways:

- In the classical P-center problem, the objective is to locate (or open) P facilities by minimizing the maximal coverage distance (or time). The P facilities are in fact considered as the resources to be shared in order to satisfy demands from clients. In our case, we also want to create P zones (i.e., to divide the transportation network into P zones). However, in our model the demand of points in the network (clients in the P-center) is satisfied by a fleet of V vehicles. So, in our case, the vehicles are the resources that have to satisfy demands.
- Capacity constraints. Our formulation is not exactly the pure P-center problem since we take capacity constraints into account. Hence, we are also close from the capacitated facility location problem (CFLP), but our formulation does not consider the costs associated to opening facilities (i.e., selection of a point centre of zone). Our objective is that of the P-center.
- Global network capacity. The standard version of the CFLP considers independent capacity of facilities. In our formulation, we are interested in a global distribution of the total available capacity among the zones. Our unique constraint related to the capacity is that of the number of vehicles in the system. Hence, the zones are created according to both the zones demands and the assignment of vehicles to each zone: the global demand is distributed according to the limited vehicle fleet size.
- Discrete capacity. The formulation of the CFLP usually allows the resolution of a continuous capacity problem (e.g., according to the product to be delivered to clients). In our case, we always have discrete capacity since the objective is to distribute (assign) vehicles to the different zones created in the whole network.
- Finally, as we will see in section 3 from the experiments, our focus is on the distribution of the global capacity of created zones, and we add various criteria to the objective function in order to balance both demands between zones and vehicles in the network.

In order to guarantee a feasible solution, the total vehicle capacity in the system has to be higher than the total demand, which means that expression (11) needs to be satisfied. This equation allows us also to find the minimum number of vehicles required in the system. That is, it is possible to *a priori* compute (without solving the linear program) the minimum number of vehicles needed in the system only comparing the total transportation demand in the system with the availability (in time) of each vehicle.

$$\sum_{k \in K} D_k \leq VC \times |V| \tag{11}$$

Experiments

Simulation experiments were performed on the case study described in (Montoya-Torres 2005; Montoya-Torres et al. 2006) in order to analyze the implementation of the proposed vehicle location strategy. Experiments were run on a workstation Pentium®4 (3.4 GHz). The integer linear program (ILP) was solved using Xpress® solver (Xpress 2004). The transfer times between points are presented in a $|K| \times |K|$ matrix, where $|K| > 220$ is the total number of points in the AMHS network path. The set of points J may potentially be equal to K. However, because of computational conditions (i.e., memory space and computational time), we have set $|J| = 30$ points before running the ILP. These points were selected using a hybrid Greedy-Local search algorithm (Montoya-Torres 2008). Distances between points in the network range from 1 to 194, while demands range form 17 to 4324. The actual values of the other parameters are kept confidential and cannot be presented here.

Experiments results are presented in Table 1. It should be noted that the maximum number of zones is always open since it contributes to reducing the maximum coverage time. Vehicles are assigned based on the total demand in each zone. An important observation in Table 1 is that the use of the vehicles is very unbalanced between zones. Some vehicles are used close to 100% (e.g., 99.9% for the case with 5 zones and 24 vehicles) while others are underutilized (e.g., 67.8% for the same case with 5 zones and 24 vehicles). This comment is still valid when the number of vehicles is large (our initial simulation showed that 30 vehicles was more than enough to dynamically satisfy demands in the network). Moreover, the gap between the minimal and maximal vehicle utilization percentages increases with the number of zones to create. For 24 vehicles, the gap varies from 32.1% with 5 zones to 68.3% with 15 zones and, for 30 vehicles, from 35 to 53.1%. This is illustrated in the table by the standard deviation of the vehicle utilizations. These results are due to the fact that the mathematical model only aims at finding a set of zones and vehicle assignments that minimize the maximal coverage time, and not at ensuring a smart work balance between the vehicles. The relevance of the proposed solution can then be questioned since it is unrealistic to suppose that vehicles can be utilized close to 100% of their time. This situation may be contoured by adding both vehicle workload and demand balancing criteria in the objective function (Montoya-Torres et al. 2006). Considering these criteria, however, increase between 5 and 31 times the resolution time without adding any value to the practical (operational) applicability of the solution (i.e., zone configuration and vehicle distribution) (Montoya-Torres 2005).

Adding of cuts

In order to improve the computational time to solve the model without affecting the solution value, various cuts could be added. These cuts are presented as sets of constraints (12), (13), (14) and (15) in the model.

$$Z_{vj} \leq \sum_{k \in K} Y_{jk} \quad \forall v \in V,\ j \in J \tag{12}$$

$$X_j \leq \sum_{k \in K} Y_{jk} \quad \forall j \in J \tag{13}$$

$$X_j \leq \sum_{v \in V} Z_{vj} \quad \forall j \in J \tag{14}$$

$$Z_{vj} \leq \sum_{k=1}^{j} Z_{v-1,k} \quad \forall v \in V,\ j \in J \tag{15}$$

Constraints (12) states that a vehicle cannot be assigned to a zone if no vertex is assigned to this zone. The set of constraints (13) ensures that a zone cannot be opened if a vertex is not assigned to this zone. These two sets of constraints are also added in order to obtain more realistic solutions. Constraints (14) assure that, if a zone is open, then at least one vehicle is assigned to this zone. Constraints (15) try to tackle the symmetry problem by imposing that a vehicle can only be assigned to a zone if vehicles with lower numbers are already

Table 1 Experimental results for the ILP model

Number of vehicles	24			30		
Number of zones	5	10	15	5	10	15
Maximal coverage time	73	50	41	73	50	41
Mean vehicle utilization (%)	78.5	75.1	68.4	76.9	76.7	77.7
St. Deviation of vehicle utilization (%)	12.7	19.8	23.7	14.1	17.4	17.1
Minimal vehicle utilization (%)	67.8	38.3	29	57.1	51	44.9
Maximal vehicle utilization (%)	99.9	97	97.3	92.1	99.9	98
Mean demand of zones	12526.8	6263.4	4175.6	12526.8	6263.4	4175.8
St. Deviation of the demand of zones	7873.3	4031	2680.1	9371.7	2085.3	3269.2

assigned to zones of lower numbers. Also, these constraints ensure that vehicles not assigned to a zone are the last ones.

Experiments were conducted to analyze the actual impact of the proposed cuts on computational resolution time. Results are presented in Table 2. We can observe an improvement with cuts (13) and (14) of between 11 and 89% when there are 24 vehicles in the system and between 10 and 40% with a fleet size of 30 vehicles. With constraints (12) and (15), we expected to decrease the resolution time. However, this was not always the case. An improvement of 49% was obtained with expression (12) when there were 24 vehicles and the network was divided in 15 zones. Besides, although cut (15) did not aid to decrease the computational time, its interest is mainly concerned with the order in which vehicles are assigned to created zones. In a dynamic decision context, this may help the central transport control system to manage the vehicles at any time the configuration of zones is updated.

Operational implementation

The solution obtained by applying the ILP formulation can then be implemented at the operational level to analyze and control the dynamic behavior of vehicles when servicing transport requests. There are three main different types of rules: vehicle management, vehicle dispatching and vehicle routing. Since the transport network path has been divided into zones with a given number of vehicles, we first need to implement an efficient control policy in order to determine how vehicles will move between and within those virtual zones. We compared various such policies (Montoya-Torres 2005). The dominating policy consists on to allow vehicles to only serve transportation requests from point k belonging to its assignment zone given by the ILP (i.e., $Y_{jk} = 1$). Once vehicle v has delivered a job into another zone, it has to request authorization to now serve transportation demands in this "new" zone. This authorization is given only if the current number of vehicles is less than the tactical number. Otherwise, the vehicle leaves its previous zone and can now serve any load waiting for transportation at *any* point in the factory, according to the dispatching rule implemented, as explained in next paragraphs. The consequences of a vehicle leaving a zone to enter another one will not be debated here. According to the definition of the ILP model, this obviously reduces the capability for the penalized zone to serve future transport requests, while it increases the traffic in the beneficial zone. In real implementation, the system should automatically re-affect the vehicle to its initial zone after an extraordinary transport request.

The second type of control rules concerns the traditional vehicle dispatching rules analyzed in the literature (Qiu et al. 2002). Two situations may arise. The first situation is called "vehicle-initiated task assignment" and deals with the problem of matching a vehicle v to a task when multiple loads (i.e. lots) are simultaneously waiting for pickup in the points of the zone j assigned to the vehicle ($Z_{vj} = 1$). Under this category we used the current location first come first serve (CL-FCFS) rule. This means that an idle vehicle first looks for work at its current location. If no load is waiting to be transported at this point, then transportation requests are served sequentially in chronological order as they have been received. The second dispatching situation is called "load-initiated task assignment" and deals with the problem of matching a task in zone j to a vehicle v when multiple empty vehicles are idle and waiting for a task assignment. Under this category, the rule implemented in our model was the longest idle vehicle (LIV) rule. This rule assigns the highest dispatching priority to the vehicle that has remained idle the longest among all the idle vehicles. The main advantage of this rule is its workload balancing effect on all participating vehicles.

Once vehicles have been assigned to serve transport requests, the third problem to be resolved at the operational level is the vehicle routing problem, i.e., a route has to be selected to conduct the vehicle from its current location to the pickup point and then to the final destination (Qiu et al. 2002). In current manufacturing practice, this vehicle routing

Table 2 Impact of cuts on computational time (s)

Number of vehicles	24			30		
Number of zones	5	10	15	5	10	15
Without cuts	197	482	190	134	241	43
With (12)	339	767	96	581	739	197
With (13)	175	270	103	203	190	30
With (14)	174	265	20	120	200	26
With (12) and (13)	440	804	279	552	880	265
With (13) and (14)	207	333	49	156	248	38
With (12), (13) and (14)	428	689	307	539	669	79
With (15)	544	4398	26110	437	7612	4014

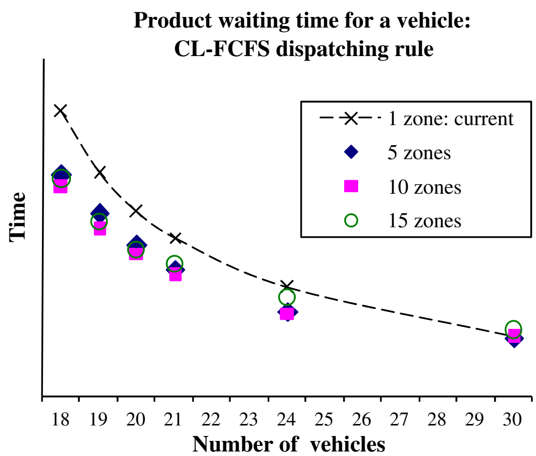

Fig. 4 Results of the ILP operational implementation using simulation

Table 3 Diminution on product waiting time for a vehicle

Number of zones to locate vehicles	Number of vehicles in the system					
	18	19	20	21	24	30
5-zone (%)	20	17	16	18	20	2
10-zone (%)	24	23	21	22	21	2
15-zone (%)	21	19	19	15	9	9
Average (%)	22	20	19	18	17	1

problem is very often solved by selecting the shortest path, unless this path is congested. In our case, some preliminary simulations showed that the shortest path is also the fastest path (Montoya-Torres et al. 2005).

Results of implementing the ILP solution at the operational level are shown in Fig. 4, representing the evolution of the average time a vehicle needs to service a transportation request by a product against the number of vehicles in the system. The fleet size (number of vehicles in system) is defined as a parameter in the design of experiments. The current number of vehicles in the factory is considered as the reference scenario (its value is kept confidential). The 1-zone line (dot line in Fig. 4) represents the reference scenario without the implementation of the ILP location strategy. This is the current vehicle control strategy implemented at the factory. Points in the figure represent the different vehicle distribution scenario by locating them in 5, 10, and 15 zones. In Table 3, we can observe, for a given number of vehicles, the relative improvement on the product waiting time. It is to notice that the larger the number of vehicles, the shorter the waiting time. This is explained by the fact that having a lot of vehicles in the factory increases the possibility of serving a transport request in a short amount of time. Thus, the impact of the implementation of the vehicle location strategy using this ILP formulation is especially interesting in order to reduce the investment needed on transportation resources (Montoya-Torres et al. 2009).

Concluding remarks

In this paper, we addressed the problem of vehicle location in complex automated transport systems. Instead of traditional research works which only considered a single loop, our focus was on a complex network path with multiple loops interconnected. The study was motivated by the configuration of the automated material handling system found at a large-scale semiconductor manufacturing facility. We proposed a mathematical formulation and discussed its practical implementation. The model presented here approached the problem at a tactical level. The system is divided in zones and vehicles are affected to those zones. It should be noted that although the results obtained from the model are encouraging, a better balancing for the number of vehicles within each zone can be obtained. To do this, we can add a constraint that takes into account the maximum fleet size in the zone as a variable in the model. The models should be tested with different sets of data, especially for the set J of possible zone-centers. For the experiments of this paper, these points were first selected using a greedy-local search algorithm, whose applicability is discussed in (Montoya-Torres 2005). Interesting research can be done on more intelligent strategies, as meta-heuristic approaches (e.g., taboo search, genetic algorithms, grasp) that have shown to be efficient for solving other location-like problems. This approaches will be use to select these points in order to improve the objective function in a short amount of time that may be used for dynamic decision-making. In addition, another interesting research subject is the finding of some dominance properties for the selection of these points.

Finally, an interesting point of this study was the implementation of the ILP solution at the operational level so as to study the dynamic behavior of vehicles. The operational level required the coupling of the solution with a discrete-event simulation model in order to analyze the dynamics of the manufacturing system.

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