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ORIGINAL ARTICLE

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Modularized simulation for lot delivery time forecast in automatic material handling systems of 300 mm semiconductor manufacturing

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Abstract The more accurate the forecast is to lot delivery time, the more effective it is in fab scheduling. In fab operations, scheduling is the major impact factor of tools capacity allocation, tools utilization control and bottleneck management. However, there is no effective method to estimate delivery time in 300 mm automatic material handling systems (AMHS) operation. Computer simulations are authentic, but they are either too complex to model fab operations as well as the whole AMHS, or too time-consuming to simulate with a full-scaled fab model. This paper proposes an analytic methodology to estimate the loop-to-loop delivery time for differentiated lots in a 300 mm AMHS environment. Combining simulation and statistics techniques, we develop a modularized simulation method (MSM) for delivery time forecast of priority lots. Numerical experiments based on data from a local 300 mm manufacturing fab are conducted. Simulation demonstrates that the MSM has credible results in estimating lot delivery times. The time differences between MSM and simulation for both priority lots and regular lots are 0.2 s and 0.1 s, respectively. Using the MSM method to forecast AMHS delivery time is a great contribution for streamlining shop floor operations, such as scheduling and dispatching, for eliminating time delays in the 300 mm automatic environment.

Keywords AMHS · Delivery time forecast · 300 mm semiconductor manufacturing · Simulation

Notations

x: Transport job index
i, j, l: OHT loop index
w_{xl}: Waiting time of job x at loop l
$\overline{W}_l$: Average waiting time of loop l
b_{xl}: Blocking time of job x at loop l
$\overline{B}_l$: Average blocking time in loop l
U_{xl}: Theoretical (without any delay) delivery time of job x at loop l
D_x: Total delivery time of job x
s_l: Estimated standard deviation of delivery time in loop l
MSEW_l: Mean square error of waiting times in loop l
MSEB_l: Mean square error of blocking time in loop l
τ: Hoisting time
η: Loop switching time between any two loops
$\overline{d}_l$: Average transport distance in loop l
d_{xl}: Transport distance of job x in loop l
υ_l: Number of vehicles in loop l
Ω_l: Percentage of prioritized transport jobs in loop l
ρ_l: Loading (transport job arrival rate) of loop l
α: Risk level

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1 Introduction

Accurate forecast of production activities is crucial to streamline semiconductor fab operations. Otherwise, it is difficult to predict production cycle time. Although many researchers and practitioners have put effort into cycle time control and management [1–4], it is still a challenge to determine the production cycle time. Due to the complicated dynamics of a wafer fab, the estimate of cycle times usually rely on empirical experiences, historical data analysis and statistical projection [3], or computer simulation [4]. Human experiences are straightforward but it is difficult to explain their induction process, and heavily depend on the decision makers. Statistical inferences based on historical data are more analytic but still questionable because of highly-coupled interactions among lots. Computer simulations are either too complex to model fab operations as well as the whole AMHS, or too time-consuming to simulate with a full-scaled fab model.

Since the 200 mm semiconductor manufacturing era, automatic material handling systems (AMHS) have played an important role in both the interbay lot delivery as well as the management of in-process inventory. Lot transportation time in the interbay AMHS becomes a non-neglectful factor to the production cycle time. However, it is either unknown or difficult to predict the transport time in a complicated AMHS. In order to eliminate unnecessary transport delays in AMHS, hand-carrying is sometimes adopted to speed up the transportation of lots. In 300 mm semiconductor manufacturing, the capability of automatic tool-to-tool delivery is considered a must [5, 6]. Lot transport time between consecutive operations can no longer be neglected in such a fully automated operational environment. Seamless collaboration is expected between lot scheduling and material transfer to optimize equipment utilization and product cycle times. An effective solution methodology is needed to determine lot transport time in 300 mm AMHS.

Due to occasional process changes and pilot or risk production, semiconductor manufacturing suffers from frequent process experiments or inspections. A lot will be granted as high priority, named as hot lot or super hot lot, for process characterization, or design validation before releasing a new product for production, or customers' special request. High priority lots are very important to both fab operations and services to customers. Operations of high priority lots can be either preemptive against regular operations, or resource-reserved for no-wait services.

Among the proposed AMHS solutions, overhead hoist transport (OHT) is one of the promising technologies in realizing fab-wide automatic tool-to-tool transportation. We adopt OHT as our study vehicle for 300 mm AMHS. Different from the popular 200 mm AMHS solutions of over head shuttle (OHS) and automatic guided vehicle (AGV), it is very difficult to implement mechanisms of shortcut and bypass in an OHT intrabay loop because (1) the length of an intrabay loop is shorter than that of an interbay, (2) at least four OHT service points (loadports) have to be replaced in order to add one pair of shortcuts, and (3) at least two service points are needed for each bypass. All of these may reduce the number of loadports, as well as that of processing equipment to be installed within a loop. This reduction of processing equipment will result in lower utilization in the expensive cleanroom space and is ineffective in fab layout design. A typical OHT intrabay loop is, therefore, designated as a simple directed graph as depicted in Fig. 1.

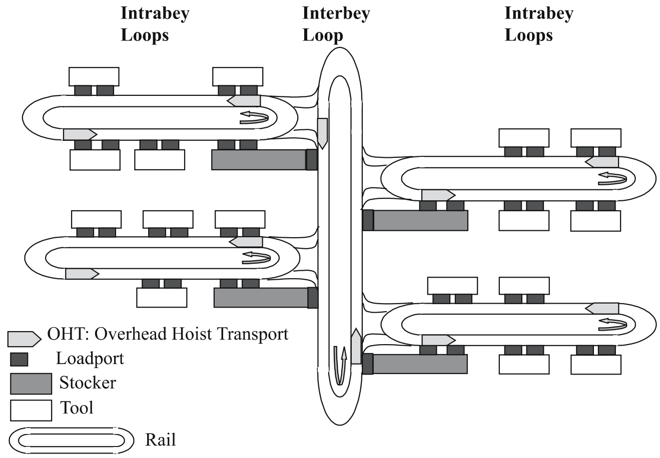

Fig. 1. Top view of an OHT configuration

Many research efforts have been devoted to the automation of material handling systems in both 300 mm interbay and intrabay [6–10]. Most of them focus on the design concept for effective integration of fab layout and AMHS in 300 mm semiconductor manufacturing. Cardarelli and Pelagagge [11] developed a simulation tool for design and management optimization of automatic interbay material handling and storage systems in wafer fabs. They used generalized probability density functions which are fitted with the observations from monthly historical data in a wafer fab as the scenarios to evaluate the dynamics of interbay material handling and storage systems. Fu and Liao [12] proposed an effective OHT dispatch policy, modified nearest job first (MNJF), to achieve high throughputs while reducing the carrier delivery times in a single OHT loop. Kuo [13] developed a modular-based colored time Petri net (CTPN) to model the dynamic behavior of the OHT. An object-based simulation technique was used to determine the number of OHT vehicles in the planning stage and to control the dispatching in the operational stage. Lin et al. [14] explored wafer movements by using different types of vehicles between and within bays. Various combinations among four types of vehicles were discussed. They developed a mathematical model to determine the minimum number of vehicles for connecting transports. None of the above researches deal with transport problems of priority lots.

It is well known that lots of high priority have a significant impact on cycle time and throughput of regular production [15]. Ehteshami et al. [16] conducted object-oriented simulation experiments of a wafer fabrication model to investigate the impact of hot lots on cycle time of other lots in the system. Their simulation results show that as the proportion of hot lots in the wafer-in-process (WIP) increases, both the average cycle time and the corresponding standard deviation for all other lots increase. They concluded that hot lots induce either deterioration in the services for regular lots or an increase in inventory costs. Fronckowiak et al. [17] used a simulation tool, ManSim/X, to analyze the impact for different hot lot distributions for two different products. Narahari and Khan [15] modeled semiconductor manufacturing systems as re-entrant lines and studied the effect of hot lots through an approximation analysis of the re-entrant line model using mean value analysis (MVA). The results indicate that hot lots impose significant effects on the mean and variance of cycle times, as well as the throughput rate of regular lots. The MVA approximation is under the assumption of steady-state conditions. All of these researches focus on the wafer processing operations only, and none of them discuss the problems of hot lot effects on transport operations.

This paper proposes a modular-like approach, modularized simulation method (MSM), for OHT delivery time forecast to lots of various priorities in 300 mm AMHS. Lot delivery time within an OHT loop is estimated by simulation and statistical techniques. We then estimate the loop-to-loop delivery time by adding all the forecast delivery times of each OHT loop, along the transport path.

The remaining of this paper is organized as follows. Section 2 formulates the OHT delivery problem. Section 3 details the MSM method. Experiment designs and simulation studies based on realistic data from a local 300 mm production fab are described in Sect. 4. Section 5 analyzes the experiment results. Final, in Sect. 6, concluding remarks are made with some future research directions.

2 Problem formulation

Define a transport job as a macro of transfer operations including (1) a request for transport to an empty OHT for a lot from its departure (current location) to the destination (location for the next process step), (2) an empty OHT arrives and picks up the lot at the departure, (3) the OHT moves the lot from the departure to the destination, and (4) the OHT delivers the lot at the destination. Define lot delivery time as the time to complete a transport job. Lot delivery time is composed of theoretical transport time, waiting time, OHT hoisting time, blocking time, and loop switching time.

We defined the notations used in formulating the delivery time forecast problems in 300 mm OHT systems at the beginning of the article.

Some assumptions are made as follows. Lots move from one loop to the other via a loop switch mechanism in a stocker. All vehicles in a loop reside in the same loop during the time horizon. Loop loading is assumed to be unchanged during the time horizon. Since the acceleration and deceleration of each OHT operation are relatively small, they are thus neglected. There are no failures and maintenance activities on all the entities during the simulation horizon. The inter-arrival time of transport jobs is assumed to be of exponential distribution. Furthermore, as the stocker serves as the only gateway between this loop and others, infinite capacity of each stocker is assumed.

Our objective is to estimate the total delivery time (D_x) with a 1-α% confidence level. The total delivery time (D_x) of job x includes waiting time, theoretical time, blocking time in all the loops it passes, twice hoisting time for loading and unloading, and loop switching time (η). Assume that transport operations are loop-independent. That is, transport operations in one loop are independent of those in the other loops. Based on this assumption on loop independence, we can add all the transport time in each individual loop to calculate D_x. That is, D_x

$$D_x = \sum_{l=i}^{j} (w_{xl} + b_{xl} + U_{xl}) + 2\tau + (j-i)\eta\,, \tag{1}$$

where the departure of job x is in loop i and the destination is in loop j.

Assume that delivery times in each loop are independent and of normal distribution. For a job, the variance of its delivery time is equal to the sum of all the variances in each loop along its moving path. If we take the α risk level, the upper bound of the confidence value can be calculated as following:

$$D_x + z_{1-\alpha}\sqrt{\sum_{l=i}^{j} s_l^2}\,, \tag{2}$$

where the probability $\Pr(Z \geqslant z_{1-\alpha}) = \alpha$, $\alpha \in R$, and s_l^2 is the variance of delivery time in loop l.

3 Modularized simulaton method (MSM)

Due to the complicated fab dynamics, it is almost impossible to solve for the exact solution of D_x in Eq. 1. In practical applications, people are most interested in determining the average and variances of delivery time of a job. Instead, we adopt computer simulation techniques to obtain these statistics. However, it is either too complex to model the sophisticated fab operations as well as the whole AMHS, or too time-consuming to simulate with a full-scaled fab model. We, therefore, propose a heuristic approach to decompose the complicated problem into small ones. Ideas of our modularized simulation method (MSM) are described as follows.

Rather than building the sophisticated model of a 300 mm fab, we utilize the features of loop configuration in 300 mm OHT systems. We then decompose the whole 300 mm AMHS into several independent loops, from which we develop simulation models for each loop. As the operations of each loop are independent, the average loop waiting times can be additive, so can the blocking times. The average delivery time of a job can be estimated by adding all the waiting and blocking times in each loop along its transport path, as described in Eq. 3.

$$E\left[D_x\right] = \sum_{l=i}^{j} \left(\overline{W_l} + \overline{B_l} + U_{xl}\right) + 2\tau + (j-i)\eta\,, \tag{3}$$

where $\overline{W_l}$ and $\overline{B_l}$ are statistics calculated with simulation results.

Observing the dynamics of the OHT system, system loading is one of the factors to cause resource contention. The increased population of high priority lots will impose long time delays on the regular jobs. As the number of OHTs increase, system performance usually improves due to the increased resources. We, therefore, consider three dominating control variables for discrete simulation method for an OHT loop: loading ratio (ρ), population of priority jobs (Ω), and the number of OHTs (υ) in the loop. The models of each individual OHT loop are simulated for various combinations of OHT vehicles, loop loading, and percentage of priority jobs. For each OHT loop, its loop statistics are collected from which the average and variance of its lot waiting time and blocking time can be calculated. Nonlinear multiple regression technique is then used to estimate these variables.

The loop variance can be estimated by the sum of mean square errors due to waiting and blocking. That is, the standard deviation s_l is equal to $\sqrt{\sum_{l-i}^{j}\left(MSEW_l^2 + MSEB_l^2\right)}$.

4 Experiment design

To convey our idea in estimating lot transport times in 300 mm AMHS, simulation experiments are conducted based on realistic data from a local 300 mm fab. Our simulation models are implemented with the discrete-event simulation package – eM-Plant from Tecnomatix Technologies Ltd. All the experiments are executed in a Pentium-III personal computer with Microsoft Windows XP. The eM-Plant is an object-oriented simulation system with characteristics of hierarchy, inheritance, and concurrency. There are some built-in objects for easy development. Users can easily modify them into user-defined objects for their specific purposes. Some of the objects defined in our simulation models are depicted in Table 1.

The only performance measure in our simulation model is the lot delivery time. Inputs to the simulation system include loop loading, percentage of prioritized jobs, and number of vehicles in each loop. Without loss of generality, we build an OHT system with three loops as the control scenario, which represents the tool-to-tool transportation through several loops. Assume that all the lots in the simulation start from loop 1, and transit to loop 2, and then move to loop 3, and finally leave the system. Figure 2 shows the conceptual simulation model. The simulation horizon is set to one day with time units in seconds after a warm-up of 6 h.

Table 1. Objects in the eM-plant simulation model

Items	Functions	Defined Object Name
Event Controller	Start system	EventControler
Source	Start of line	Sources
Stocker output port	End of line	Stk1Out, Stk2Out
Frame	Loop structure	Loop1, loop2, loop3
Special control method	Execution of special actions	IO, and so on
Raw spec. data & output	Table for spec. data & record output	Performance, and so on
Products	Entity of products	Normal lot, Hot lot
Loadport	Basic units of loadport	EQ011, EQ012 ~ EQ223
Stocker Input port	Stock in a lot	Stk1In, Stk2In
Delivery time record	Record deliver time	Deliver trend
OHT	Deliver lot	OHT
Track	Track	Track

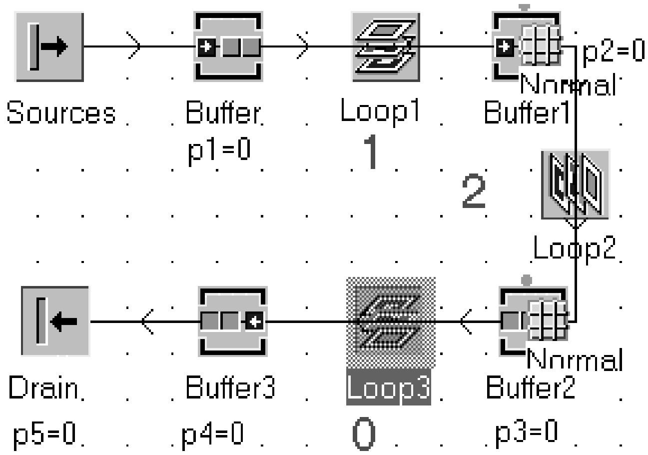

Fig. 2. A 3-OHT-loops model

Figure 3 demonstrates the simulation model of loop 1. In our simulation, each subsystem has a similar structure, but with different parameter settings for process tools. Each OHT loop is 79.4 m long, where there are two stockers and 23 pieces of equipment. All loops are designated with the same tool configurations. Loops 1 and 2 have the same processing capacity of 97.2 lots/h, and loop 3, 94.2 lots/h. The running speed of each OHT vehicle is 2 m/s. The hoisting time is 16 s. The loop switching time is set to 16 s. According to Wang and Liao's study [18], the preemptive highest priority job first (PHP) policy performs well for dispatching of prioritized lots. Here, we adopt the PHP policy as the OHT dispatching rule for all loops in our simulation experiments. The PHP policy dispatched an empty OHT to a job with the highest

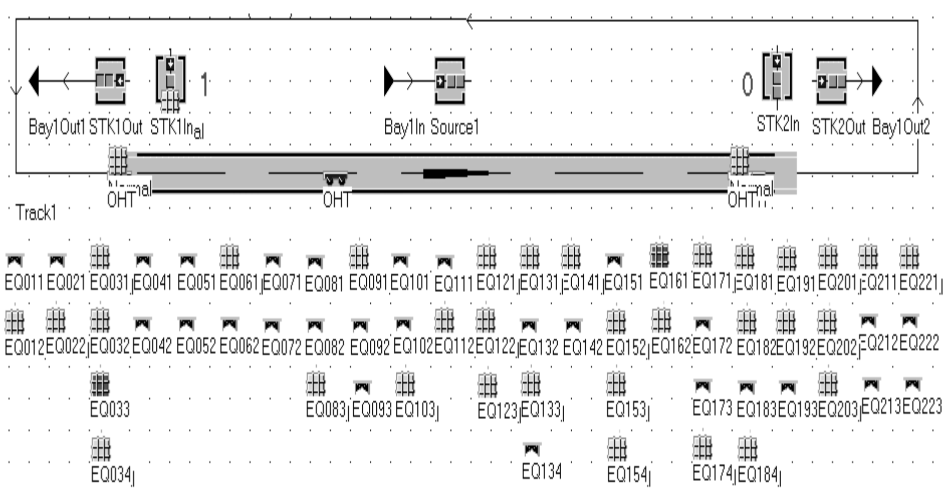

Fig. 3. OHT loop simulation model

priority. The dispatched OHT is reserved to the job once after it is dispatched and becomes empty again after completing this job. Our objective of OHT dispatching is to minimize the mean and variance of carrier delivery times. For each OHT loop, the OHT dispatching rule deployed for this loop remains unchanged.

The models of each individual OHT loop are simulated for various combinations of OHT vehicles, loop loading, and percentage of priority jobs to collect the statistics of waiting time and blocking time for each loop. Seven loop loading ratios (ρ), 90, 92.5, 95, 97.5, 100, 102.5, and 105% of the design specifications, are used in the simulation. Five configurations of priority job percentage (Ω), 2, 4, 6, 8 and 10%, are designed for the high-priority population tests. In the simulation study, we consider three configurations of the number of OHT vehicles (υ), 3, 4 and 5 OHTs in the loop, respectively. One hundred five simulation experiments (ρ: 7, Ω: 5, υ: 3, $7 \times 5 \times 3 = 105$) are then conducted based on the scenarios for these three control factors.

5 Simulation results

We first check the correlation of variables in each loop, which are number of vehicles, percentage of priority jobs, and loop loading of the loop. Since loops 1 and 2 have the same processing capacity, the correlation results of these two loops are listed in Table 2. For loop 3, its correlation results are showed in Table 3. Note that all correlation coefficients are less than 0.05, which implies that these variables are almost independent. Thus, the multicollinearity effect in regression modeling is not considered.

In order to satisfy the assumptions of normality and homoscedasticity of variables, all the data in the simulation model are first standardized before regression. The nonlinear multiple regression technique is then used to determine the characteristics among the variables.

As some of the values are fixed and mandatory for both regular and priority transports, only the non-value-added ones are considered in our numerical analysis to concentrate on the comparisons. Here, define job non-value-added time to be the sum of job waiting time and carrying blocking time along the loops.

Table 2. Variables correlation table of loops 1 and 2

	ρ	Ω	υ
ρ	1.00000	−0.03197	−0.02973
Ω	−0.03197	1.00000	−0.00820
υ	−0.02973	−0.00820	1.00000

Pearson correlation coefficients, $N = 105$

Table 3. Variables correlation table of loop 3

	ρ	Ω	υ
ρ	1.00000	0.00084	−0.04079
Ω	0.00084	1.00000	0.01098
υ	−0.04079	0.01098	1.00000

Pearson correlation coefficients, $N = 105$

Table 4. Prioritized lots regression equation models

	Loop 1&2 Waiting time	Loop 1&2 Blocking time	Loop 3 Waiting time	Loop 3 Blocking time
Intercept	21.50159	0.6337154	20.2206	0.3778069
ρ	– 1.48846	0.1269775	–	–
Ω	1.05056	–	1.58692	0.1023634
υ	–	–	– 3.76146	–
ρ^2	–	–	0.47758	0.1164286
Ω^2	–	– 0.066419	–	–
υ^2	1.1691	0.2898994	1.45006	0.3488951
ρ^3	1.07716	–	–	–
υ^3	– 2.88357	– 0.1551079	–	–
$\rho\upsilon$	–	–	– 0.28075	–
$\rho\Omega^2$	1.61559	–	–	–
$\rho\upsilon^2$	–	0.1386985	–	0.2285595
$\rho\Omega^3$	–	–	– 0.18441	–
$\rho\upsilon^3$	–	– 0.0793121	0.25466	– 0.3313136
$\rho^2\Omega$	–	–	– 0.32692	–
$\rho^2\upsilon$	0.3853	0.132838	–	0.0539166
$\rho^2\Omega^3$	–	0.0480561	–	–
$\rho^3\upsilon$	– 0.20039	–	–	–
$\rho^3\Omega^2$	– 0.73747	–	–	–
$\rho^3\upsilon^3$	–	–		0.1105681
$\Omega\upsilon$	–	–	– 0.63611	–
$\Omega^2\upsilon$	– 0.28723	–	–	–
$\Omega^3\upsilon$	– 0.18302	–	–	0.026031169
$\rho\Omega\upsilon^2$	–	– 0.0543073	–	–
$\rho\Omega\upsilon^3$	–	–	–	0.037815072
$\rho\Omega\upsilon$	–	0.1043169	–	–

Table 5. Regular lots regression equation models

	Loop 1&2 Waiting time	Loop 1&2 Blocking time	Loop 3 Waiting time	Loop 3 Blocking time
Intercept	81.32562	5.8673664	51.67604	5.724393
Ω	–	0.8280088	– 39.83946	0.7978134
υ^2	145.62597	– 0.6955856	57.11975	– 0.6210066
υ^3	– 153.42675	1.0888534	– 61.0485	0.8614784
$\rho\upsilon$	– 357.54335	–	–	0.5169598
$\rho\upsilon^2$	294.37959	–	75.74651	– 0.1971796
$\rho\Omega^3$	–	–	–	0.0771256
$\rho\upsilon^3$	–	0.1808086	– 79.46953	–
$\rho^2\Omega$	–	–	41.34817	–
$\rho^2\Omega^2$	– 21.34325	–	–	–
$\rho^2\upsilon^2$	132.74628	–	86.29826	–
$\rho^2\upsilon^3$	– 96.62153	– 0.09095	– 66.96296	–
$\rho^3\upsilon^2$	–	–	38.70043	–
$\rho^3\upsilon^3$	–	–	– 27.07322	– 0.1015002
$\Omega\upsilon^2$	147.91911	–	99.83647	–
$\Omega\upsilon^3$	– 119.36141	0.1575254	– 75.86935	0.212823
$\Omega^2\upsilon^2$	45.00707	–	25.43009	–
$\Omega^2\upsilon^3$	– 26.90771	–	– 16.64411	–
$\rho\Omega\upsilon^2$	111.16575	–	92.69853	–
$\rho\Omega\upsilon^3$	– 90.88981	–	– 66.18869	–
$\rho\Omega^2\upsilon^2$	–	–	15.72335	–
$\rho\Omega^3\upsilon$	–	– 0.09095	–	–

The regression model of each loop is estimated. Tables 4 and 5 demonstrate the regression equation models of prioritized and regular transports, perspective. For prioritized jobs, the r squares of the estimated waiting time of loops 1, 2 and 3 are 0.9240, 0.9240, and 0.9359, respectively. The r squares of the estimated blocking time of loops 1, 2 and 3 are 0.7085, 0.7085, and 0.7664, respectively. Among the cases of regular jobs, 19 scenarios are diverged and thus excluded. The r squares of estimated waiting time for loop 1, 2, and 3 are 0.9962, 0.9962, and 0.9464, respectively. The r squares of estimated blocking time for loops 1, 2, and 3 are 0.9926, 0.9926, and, 0.8952, respectively. From the above data, we find that the r squares of waiting time perform well. All of them are larger than 0.9. The r squares of the blocking time are not as good as those for the waiting time. However, its minimum value is 0.7085. We therefore conclude that the estimation results are sound for realistic data.

Tables 6 and 7 demonstrate the simulation results for 105 scenarios for prioritized and regular lots, respectively. Observed from Tables 6 and 7, they demonstrate almost the same trends. We find that the dominating factor is the number of OHT vehicles. The effects from different combinations of loading and prioritized ratio are not significant. Even though loop loading is higher than 100%, it seems not to reach the maximum capacity of the OHT system for prioritized lots. Its OHT non-value-added time is still acceptable. However, for regular lots, when the loop loading is high and the vehicles are scarce (e.g., number of vehicles is 3), the results become diverged. This is caused by the PHP policy, from which the transport of prioritized lots are preemptive. When the numbers of OHT is not sufficient, regular lots will not receive enough resources to serve them. Their delivery times then become diverged. It also tends to have longer delivery time if the loading is high. That is, the higher the pri-

Table 6. Non-valuable times comparisons for prioritized lots

Configuration		Non-value-added time Number of vehicles					
		Modularized simulation method			Simulation results		
Loading	Priority ratio	3	4	5	3	4	5
90%	2%	70.0	57.1	53.8	74.0	57.7	53.1
	4%	73.5	60.7	55.8	76.0	62.0	53.9
	6%	77.7	62.7	57.3	72.0	62.0	57.8
	8%	81.5	65.4	58.9	83.0	66.0	58.1
	10%	83.3	68.0	60.4	80.0	64.0	59.8
92.5%	2%	74.7	57.3	49.4	71.0	57.1	50.2
	4%	81.2	63.7	56.1	80.0	63.0	55.5
	6%	85.2	66.4	59.4	83.0	64.0	57.9
	8%	88.8	68.6	59.2	85.0	66.0	81.0
	10%	91.2	67.8	57.9	95.0	69.0	62.0
95%	2%	77.0	59.1	50.8	77.0	59.3	50.2
	4%	81.6	63.4	56.0	77.0	64.0	55.2
	6%	87.7	65.7	58.4	87.0	64.0	59.2
	8%	89.3	67.4	58.9	97.0	69.0	58.3
	10%	93.4	67.4	56.7	94.0	66.0	57.3
97.5%	2%	80.9	59.8	51.2	77.0	59.7	53.0
	4%	85.0	61.6	53.9	84.0	62.0	53.1
	6%	86.9	64.6	56.6	86.0	70.0	56.9
	8%	90.7	66.9	57.6	93.0	64.0	62.0
	10%	97.6	68.8	58.7	97.0	67.0	62.0
100%	2%	85.0	61.5	53.7	86.2	64.0	52.4
	4%	85.3	61.9	53.8	87.0	60.0	57.9
	6%	87.6	64.1	55.2	92.0	67.0	59.2
	8%	90.2	68.4	57.4	88.0	73.0	59.1
	10%	98.5	70.6	61.0	92.0	72.0	65.0
102.5%	2%	88.1	63.8	56.9	91.0	59.5	53.9
	4%	88.3	63.4	56.5	86.0	66.0	58.1
	6%	89.0	64.7	56.3	89.0	70.0	56.3
	8%	93.0	67.2	59.4	92.0	71.0	62.0
	10%	101.3	73.1	61.2	99.0	74.0	61.0
105%	2%	90.5	64.2	56.5	85.0	63.0	55.8
	4%	93.7	68.2	55.9	93.0	61.0	57.0
	6%	94.2	70.5	58.0	90.0	70.0	59.8
	8%	98.3	70.9	60.6	94.0	72.0	64.0
	10%	100.1	73.3	62.2	94.0	75.0	63.0
Summary	Mean		69.9			70.1	
	Std. Deviation		13.9			13.4	

Table 7. Non-valuable times comparisons for regular lots

Configuration		Non-value-added time Number of vehicles					
		Modularized simulation method			Simulation results		
Loading	Priority ratio	3	4	5	3	4	5
90%	2%	314.5	146.0	123.0	334.0	140.0	117.0
	4%	380.9	144.0	118.3	373.0	149.0	116.0
	6%	391.4	152.3	122.9	404.0	159.0	124.0
	8%	480.2	161.1	127.9	471.0	164.0	127.0
	10%	497.1	165.5	128.7	484.0	173.0	134.0
92.5%	2%	395.9	143.9	111.1	397.0	147.0	113.0
	4%	482.7	154.5	118.5	493.0	160.0	119.0
	6%	554.0	166.6	126.9	549.0	165.0	130.0
	8%	667.9	179.3	134.1	675.0	177.0	137.0
	10%	949.8	184.1	140.5	976.0	182.0	138.0
95%	2%	498.7	153.5	112.8	485.0	157.0	117.0
	4%	595.2	165.1	123.2	551.0	167.0	124.0
	6%	772.9	173.5	131.2	801.0	178.0	133.0
	8%	872.8	186.7	135.1	830.0	184.0	132.0
	10%	X	200.1	144.2	X	190.0	139.0
97.5%	2%	677.4	163.5	115.5	700.0	164.0	119.0
	4%	881.4	170.5	123.4	890.0	168.0	127.0
	6%	X	186.0	135.0	X	187.0	134.0
	8%	X	197.1	140.1	X	190.0	134.0
	10%	X	206.2	145.5	X	197.0	146.0
100%	2%	X	177.1	121.6	X	169.0	119.0
	4%	X	182.4	127.1	X	174.0	128.0
	6%	X	198.1	133.2	X	201.0	138.0
	8%	X	216.1	141.6	X	215.0	139.0
	10%	X	221.6	152.8	X	220.0	158.0
102.5%	2%	X	177.2	124.9	X	177.0	123.0
	4%	X	192.9	130.3	X	187.0	130.0
	6%	X	207.5	134.1	X	204.0	133.0
	8%	X	221.2	145.6	X	211.0	143.0
	10%	X	247.2	153.6	X	263.0	155.0
105%	2%	X	179.0	123.0	X	185.0	124.0
	4%	X	201.1	130.4	X	202.0	127.0
	6%	X	220.2	138.9	X	226.0	141.0
	8%	X	239.7	150.0	X	244.0	148.0
	10%	X	275.4	159.0	X	280.0	159.0
Summary	Mean		239.5			239.4	
	Std. Deviation		189.8			190.3	

Remark: X indicates that the case diverges.

ority ratio is, the longer delivery time incurs. In average, the means of non-value-added time of priority jobs are 69.9 s for MSM and 70.1 s for simulation results, respectively. The average difference is just 0.2 s. The standard deviations of prioritized delivery time are 13.9 and 13.4 s, respectively. After removing diverged outliers, the means of non-value-added time of regular jobs are 239.5 s for MSM and 239.4 s for simulation results, respectively. The standard deviations of regular delivery time are 189.8 and 190.3 s, respectively. Complying with our conjecture on the effect of forecasting methods in all of the scenarios tested, the MSM and system simulation results are very close. These results coincide with our expectations. These simulation experiments show that the MSM is a good method to estimate the delivery time of prioritized lots in a 300 mm OHT environment.

6 Conclusions

The more accurate the forecast of lot delivery time is, the more efficient fab scheduling performs. In the fab operations, scheduling is the major control factor of tools capacity allocation, tools utilization control, and bottleneck management. However, there is no effective method to estimate delivery time in 300 mm AMHS fab operations. This paper proposes the modularized estimation methodology for OHT delivery time forecast to differentiated lots in a 300 mm AMHS environment. According to the basic information of loop parameters of (ρ, Ω, υ), we can find out the characteristics of each loop by simulation techniques. We then use statistical regression to modularize the loop characteristic equations. Along the job transport path, we can easily sum to estimate the precisely integrated delivery time by these modularized loop characteristic equations.

We conducted simulation experiments based on realistic data from a local 300 mm manufacturing fab. Simulation results demonstrate that the MSM achieves a sound performance of delivery time estimation for differentiated lots. Using the MSM method to forecast AMHS delivery time can help streamline shop floor operations, like scheduling and dispatching, by eliminating time delays in the 300 mm automatic environment.

Future research includes developing the estimation method of the lots cycle time, combining with processing time, queuing time, delivery time, which is more complicated due to large variances in different loops, and the integration of the proposed differentiated material handling mechanism with fab shop floor control systems to provide no-wait services for lot management.

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