Determining Vehicle Allocation for Automated Materials Handling System: New Formulation and Solution Methodology

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Abstract - Semiconductor manufacturing is one of the most complicated manufacturing systems in the world. Automated material handling system (AMHS) is an important contributor that makes the transportation between work stations more efficient and fewer human errors, particularly in the highly automatic semiconductor manufacturing facilities. In this research, we use simulation optimization approach to find optimal vehicle allocation for AMHS, with the intention to improve transportation efficiency while minimize vehicle cost. To determine the number of vehicle for each bay, we propose a random programming (RP) model based on minimal vehicle cost as the objective function and requiring transportation times between initial and destination stations being less than a prespecified constant as constraints. A new methodology, called sequential sampling method, is developed to solve the RP problem. An empirical study based on real data is conducted to verify the viability of the proposed method.

Keywords - AMHS, random programming, sequential sampling, regression, simulation optimization

I. INTRODUCTION

To increase the efficiency of semiconductor manufacturing processing, the automation and flexibility have become crucial factors in material handling system (MHS). Over the decades, automated material handling system (AMHS) plays an important role in semiconductor manufacturing, which reduce manufacturing cycle time and labor cost, increase facility use, equipment utilization and yield [1].

One of the crucial equipment in AMHS is automated guided vehicle (AGV), which includes unnamed vehicle transporting goods and materials throughout facility. For green manufacturing, the equipments and facilities have to been with eco-friendly design. Many researches have been focused on the performance evaluation with different track layouts (spine, perimeter, flexible and track options), number of vehicles, scheduling strategies, production management, etc. [2].

Among these researches, several studies have been made on vehicle requirement and fleet sizing determination: Arifin and Egbelu [3] showed a regression model to estimate vehicle requirements for an AGVs when design system. Lin, Wang and Yen. [2] used simulation model to investigate the optimal combination of vehicle number and material flow rate. Hung and Liu [4] also used simulation to obtain fleet size under different vehicle dispatching rules. Koo, Jang and Suh [5] utilized queueing model and computational experiment to minimize number of vehicle which satisfied waiting time upper bound and delivery request rate of each location. Rajotia, Shanker and Batra [6] used mixed integer programming model to minimize the empty trips with optimal fleet size, which subjected with the lower and upper bound of pick-up and unload unit. Huang, Chang and Lin [7] use COMPASS method based on simulation optimization to allocate vehicles. However, little attention has been given to the topic related to vehicle allocation with programming problem.

In this research, we allocate vehicle number for each bay with minimal vehicle cost and constrained wafer transport time. This is barely addressed in the literature.

The rest of this paper is organized as follows. In Section 2, we propose a random programming (RP) model to determine the optimal vehicle number of each bay. In Section 3, we discuss the methodology that can be used to solve for the optimal solution for proposed model. In Section 4, we conduct an empirical study to verify the viability of the proposed method. We conclude with future research in Section 5.

II. PROBLEM DEFINITION

This section we present a random programming (RP) model to minimize the vehicle total cost subject to the upper bound of transport time. The assumptions, notations and model are as follows:

A. Assumptions

No set-up time and repair time in the system.

B. Notation

1) x_i *:* the number of vehicle in bay i.

2) d_{ij}*:* the upper bound of transport time from intrabay i to intrabay j.

3) c_k *:* the cost of vehicle of bay k .

C. Mathematical Formulation

In this research, we use programming problem to find the optimal number of vehicles. The objective is to minimize the vehicle cost, transport time between stations as constraints so as to ensure transportation efficiency. We give the upper bound of each route transport time as right-hand-side (RHS) for each constraint (As "d_{ij}" in mathematical formulation):

$$\min_{x\in X} \sum_{k=1}^{n} c_k x_k$$
$$\text{s.t.} \tag{1}$$
$$g_i(x_i)+h(x_n)+g_j(x_j)\le d_{ij}$$
$$i=1,\dots,n-1;\ j=1,\dots,n-1; i\ne j$$
$$x_1,x_2,\dots,x_n \ge 0$$

Some notations are as follows:

1) $g_i(x_i)=\mathrm{E}_\omega[G(x_i,\omega)]$: the transport time in intrabay *i*.

2*)* $h(x_n)=\mathrm{E}_\omega[H(x_n,\omega)]$: the transport time in interbay.

And the decision variables x_i, x_n and x_j, represent the number of vehicles in *i*th , *n*th and *j*th bays. X is the decision space that the decision variables we simulate based on this region. ω is the randomness in the simulation model. From *i*th to *j*th intrabay, supposed simulate *N* times, the sample average of transport time is defined as:

$$\overline{G_i}(x_i)+\overline{H}(x_n)+\overline{G_j}(x_j)= \frac{1}{N}\sum_{k=1}^{N}\left(G_i(x_i,\omega_k)+H(x_n,\omega_k)+G_j(x_j,\omega_k)\right) \tag{2}$$

According to the law of large number, as *N* is sufficiently large, the sample average of transport time between *i*th and *j*th intrabay approximates to $g(x_i)+h(x_n)+g(x_j)$, that is:

$$\mathrm{E}_\omega[G_i(x_i,\omega)]\approx \overline{G}_i(x_i)=\frac{1}{N}\sum_{k=1}^{N}G_i(x_i,\omega_k) \tag{3}$$

$$\mathrm{E}_\omega[H(x_n,\omega)]\approx \overline{H}(x_n)=\frac{1}{N}\sum_{k=1}^{N}H(x_n,\omega_k) \tag{4}$$

$$\mathrm{E}_\omega[G_j(x_j,\omega)]\approx \overline{G}_j(x_j)=\frac{1}{N}\sum_{k=1}^{N}G_j(x_j,\omega_k) \tag{5}$$

About the simulation model, we have to optimize through stochastic optimization. It is hard to solve this problem if not having an efficient methodology. So how to estimate constraints based on efficient simulation runs is crucial. In this study, we present a methodology which can satisfy these conditions. The details are listed in next section.

III. METHOD

As the model described in Section 2, this research focuses on RP problem. Solving RP model is more difficult than the classic nonlinear programs because the coefficients of constraints in RP are stochastic and requires estimation. However, it is known that estimation can contain noise and consequently the solution based on the estimation model may quite different from the true optimal solution. In this research, we propose a new framework that attempts to bridge the gap. We use simulation to collect data and use simulation optimization to estimate. However, the question is how many runs need to estimate. About this topic, some researchers have presented methods to determine sample size and solve the model.

Prékopa and Hou [8] proposed a nonlinear programming problem to decide the sample size in coefficient estimation, which considers the cost of sampling in each coefficient. The objective function is to minimize the sampling cost. The constraints are two chance-constraints that promise the accuracy of optimal value estimation. Thus, by means of solving this sample size determination problem we can know the number of samples we need to take that promise the estimate accuracy. In Chang [9], we also guaranteed the solution's quality but utilized an algorithm to estimate each coefficient and the solution asymptotically close to true coefficients in each problem solving. Also, it focused on influential constraints and sensitive coefficients. This prevents choosing unhelpful coefficients to take sample so as to save the cost of sampling.

The most challenge task to solve this problem is to estimate the constraints in the model. Since we cannot directly have explicit function to express the relation between number of vehicles and transport time, we use metamodeling to fit the model.

A. Metamodeling

Here we assume that the relationship between vehicle number and transport time is based on quadratic function. We fit regression model to depict this relationship. The number of vehicles (x_i, x_n and x_j) and the corresponding transport time ($g_i(x_i)$, $h(x_n)$ and $g_j(x_j)$) is independent and dependent variable respectively. About data collection, by means of simulation we collect some transport time data which is based on different scenarios (different number of vehicle for each bay). For example, for the transport time in the *i*th (*i*=1,…, *n*) intrabay, the regression model is as equation (6):

$$\hat{g}(x_i)=b_0+b_1x_i+b_2x_i^2 \tag{6}$$

After fitting the regression model for each bay, the Random Programming (RP) is as follows:

$$\min_{x\in X} \sum_{k=1}^{n} c_k x_k$$
$$\text{s.t.} \tag{7}$$
$$\hat{g}_i(x_i)+\hat{h}(x_n)+\hat{g}_j(x_j)\le d_{ij}$$
$$i=1,\dots,n-1;\ j=1,\dots,n-1; i\ne j$$
$$x_1,x_2,\dots,x_n \ge 0$$

As the simulation runs increases, the coefficient estimates of metamodel converges to real parameter then the solution of RP model also being more accurate. However, too many simulation runs is impossible in practice, we use an algorithm to estimate the transport time based on required simulation runs. Moreover, this method also considers the cost of simulation run and ensures the solution quality.

B. The Sequential Sampling Algorithm

Chang [9] proposed an algorithm, called Sequential Sampling Method, which estimates coefficient in constraint of random programming problem using sequential sampling. In iterations, take sample average as the estimate. To decrease sampling cost, only increase samples on the coefficients of important constraints, that is, the constraint that the gap between solution and RHS is smaller or even zero (the binding constraints). Further, the sample size of coefficients in each chosen constraints depends on the sampling error and the corresponding decision variable's value. In this case, we take more samples on the route which having larger transport time and sampling error. Then the solution converges to the optimal solution of original problem as sample (simulation run) increases. Moreover, through a random nonlinear programming, termed "sub-problem", the solution algorithm performs is more promising of feasibility achieving.

However, since we do not have an explicit form for the constraints, and the constraints here are not linear function. In this research, the algorithm flow is altered as Figure 1.

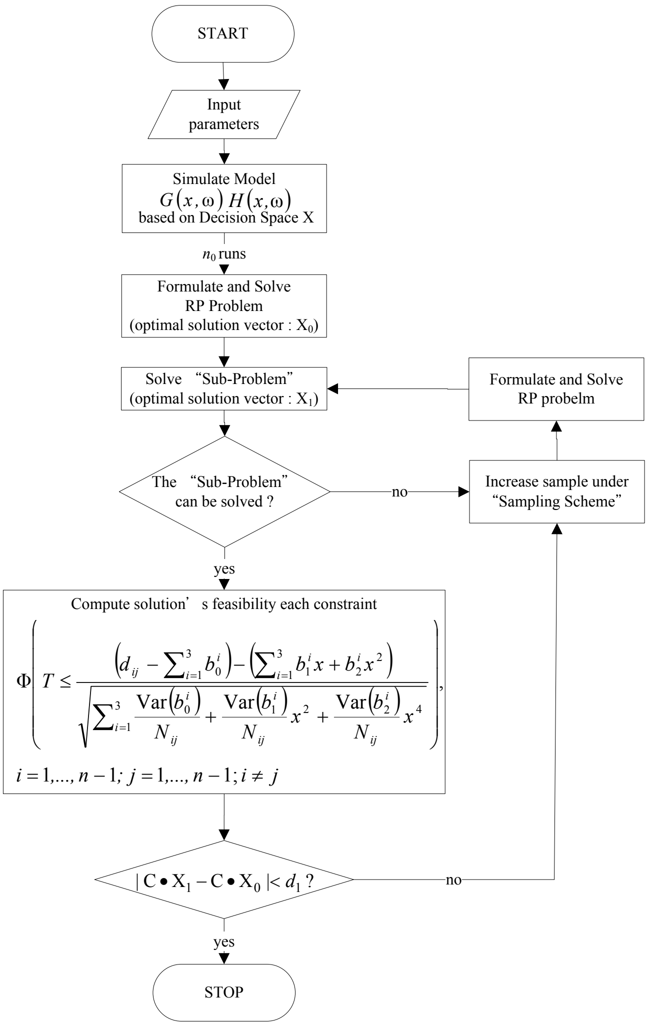

Fig. 1 Sequential sampling method flow

Before executing the algorithm, it needs to input parameters and declare variables, which includes:

1) $1-\alpha$ *:* the confidence level that the random optimal solution satisfies the constraints.

2) n_0 : the runs for each element of X in each bay respectively.

3) N_{ij} *:* the number of simulation runs from ith to jth intrabay. The initial number is n_0, when simulation run increases in each replication, new number of sample replace original ones.

4) d_1 *:* the upper bound of the distance between optimal value based on X_0 and X_1.

C. Sampling Scheme

Choose constraints and add sample size as below:

1) Constraints which

$$\Phi\left(T \le \frac{\left(d_{ij} - \sum_{i=1}^{3} b_0^i\right) - \left(\sum_{i=1}^{3} b_1^i x + b_2^i x^2\right)}{\sqrt{\sum_{i=1}^{3} \frac{\mathrm{Var}(b_0^i)}{N_{ij}} + \frac{\mathrm{Var}(b_1^i)}{N_{ij}} x^2 + \frac{\mathrm{Var}(b_2^i)}{N_{ij}} x^4}}\right), \quad (8)$$

$i = 1,\ldots,n-1;\ j = 1,\ldots,n-1;\ i \ne j$ *larger than* $1-\alpha$ *are grouped into Group* 1*, between* $1-\alpha$ *and* 0.5 *are grouped into Group* 2*, approximately equal to* 0.5 *are Group* 3*.*

2) For Group 1*, choose the kth constraint* ($k \in \max_{k\in\Theta_1} \sqrt{\sum_{i=1}^{3} \frac{\mathrm{Var}(b_0^i)}{N_{ij}} + \frac{\mathrm{Var}(b_1^i)}{N_{ij}} x^2 + \frac{\mathrm{Var}(b_2^i)}{N_{ij}} x^4}$ *,* Θ_1 *is the number of whole constraints in Group* 1)*.*

3) For Group 2*, choose the kth constraint* ($k \in \max_{k\in\Theta_2} \sqrt{\sum_{i=1}^{3} \frac{\mathrm{Var}(b_0^i)}{N_{ij}} + \frac{\mathrm{Var}(b_1^i)}{N_{ij}} x^2 + \frac{\mathrm{Var}(b_2^i)}{N_{ij}} x^4}$ *,* Θ_2 *is the number of whole constraints in Group* 2)*.*

4) For Group 3*, choose whole constraints.*

5) Combine the constraints in Step 2*,* 3 *and* 4*, of which are chosen constraints* (*routes*)*.*

6) Simulate more n_0 *runs in chosen constraints.*

In AMHS cases, if the sub-problem can be solved, replace the optimal solution X_0 of RP by solution from sub-problem (X_1). Also we check the optimal value based on X_0 and X_1. We simulate more runs until fulfill stopping criteria, that is, the gap between these two value is smaller than d_1.

IV. NUMERICAL EVALUATION

The example considers the model described in Section 2. To obtain the data for fitting regression model in RP model, constructing an AMHS system and doing simulation. We take samples from simulation and solve the RP model based on the sequential sampling algorithm at the same time. The detail is as follows:

About the simulation, use eM-Plant 8.0 software to develop a discrete event simulation model. It includes important features of typical 300mm wafer fabrication, where considering the interbay and intrabay systems simultaneously. The system layout is as following:

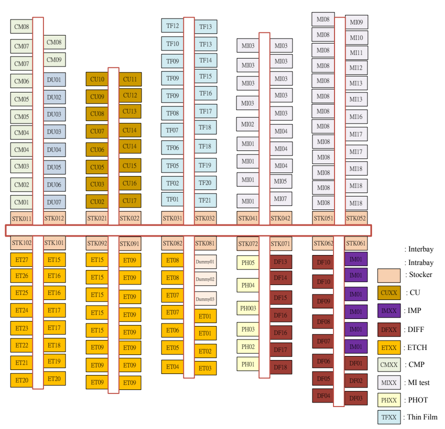

Fig. 2 The 300mm wafer fab layout [7]

To simplify the simulation model, we narrow some parameters. The system includes six intrabays and one interbay which is on the center. The detail description is given below:

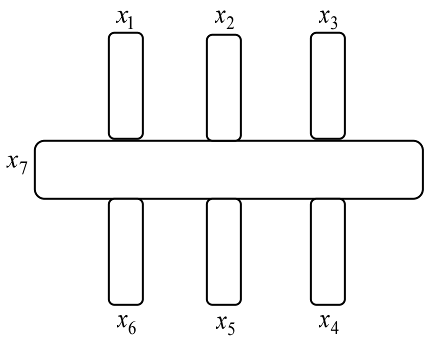

Fig. 3 The simplified wafer fabrication route layout

A. Indices

1) *i: the pick-up intrabay i* ($i = 1,2,3,4,5,6$)

2) *j: the unloaded intrabay j* ($j = 1,2,3,4,5,6$)

B. Processing Time of Stations in 6 intrabays

TABLE I
AVERAGE PROCESSING TIME OF STATIONS IN EACH BAY
(unit: seconds)

Bay 1		Bay 2		Bay 3	
CM08	71.95	TF05	153.36	MI05	576
CM02	83.72	TF17	97.30	MI07	384
DU05	22.36	TF20	53.41	MI01	864.35
Bay 6		Bay 5		Bay 4	
ET24	41.47	PH05	89.48	DF05	31034.48
ET17	42.07	DF18	21356.12	IM01	22.91
ET20	32.52	PH03	35.73	DF02	24394.23

Note: CM: common message processing, TF: thin film, MI: MI test, ET: etching, PH: photolithography, DF: diffusion, IM: implant.

C. Parameters

Simulate 100 wafer cassettes processing and record the transport time of 50th cassette for each macro simulation:

1) c_k=1000 *unit dollars*

2) d_{ij} *: depends on current transport time from intrabay i to intrabay j..*

3) $1-\alpha = 0.8$

4) n_0 =3

5) d_l =450 *dollars.*

6) $X \in [1,9]$

D. Model

$$\min_{x \in X} \sum_{k=1}^{7} c_k x_k$$
$$\text{s.t.}$$
$$\hat{g}_i(x_i) + \hat{h}(x_7) + \hat{g}_j(x_j) \le d_{ij}$$
$$i = 1,\ldots 6;\ j = 1,\ldots 6;\ i \ne j$$
$$x_1, x_2, \ldots, x_7 \ge 0 \tag{9}$$

Since processing time is stochastic in nature, we collect some observations for transfer time in each run. We assume that only transport one cassette per run. For each macro simulation, we record the transport time of 50th cassette. Later, we start to execute the sequential sampling algorithm. At first, we simulate basic macro runs, and estimate the transfer time of each bay and solve the sub-problem to collect more feasible solution. Then, calculating the feasibility of each constraints (in this case, we have $P_2^n = P_2^6 = 30$ constraints.), we use this result to choose some important constraints which may be the binding constraints or having larger estimate error. We take more samples in these constraints, solve the primal problem and sub-problem, and go on the procedure from calculating feasibility until the stopping criteria of algorithm is satisfied. Figure 4 shows the gap between the optimal values from primal and sub-problem respectively get smaller as the sample size increases. The optimal vehicle number of each bay is given in Table II (in practice, we take integer number of vehicles from this result):

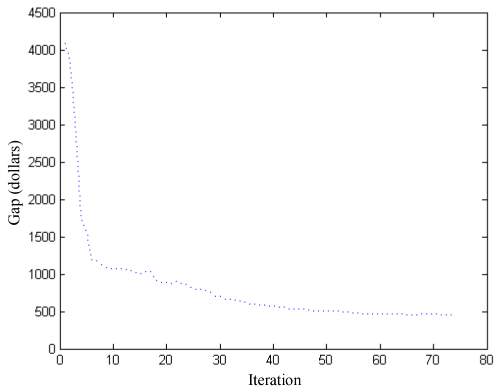

Fig. 4 Gap between optimal value of primal and sub-problem as sample increases.

TABLE II
OPTIMAL VEHICLE ALLOCATION

	intrabay	interbay
1	2.55	5.07
2	1.00	
3	1.43	
4	2.57	
5	2.76	
6	4.18	

Note: Solved by MatLab7.9.0 (R2009b) software.

The results lead us to the conclusion that for each intrabay, the processing time of bay is a factor affects the required vehicle number. As the total processing time in intrabay shorter, more vehicles required. Since the transport frequency more when the processing time of stations are shorter, we need more vehicles to delivery materials. Also, the total cost is about 20 thousand dollars. We could reference this result as the parameter used in facility.

V. CONCLUSION

In this paper, we developed a random program model to decide the optimal vehicle allocation of each bay in AMHS system. We proposed a sequential sampling method that increases samples sequentially to improve the solution quality and finally converge to the optimal solution of the model.

Empirical study shows the proposed method can work well in practical problems. Future research will extend the current framework to solve the problems where larger-scale decision variables and constraints exist.

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