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Adaptive Lot/Equipment Matching Strategy and GA Based Approach for Optimized Dispatching and Scheduling in a Wafer Probe Center

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Abstract – In this paper, we use a graphical and mathematical modeling tool – Colored-Timed Petri Nets (CTPN) to model the testing flow in the wafer probe center. With this CTPN model, we can simulate the production processes, and keep track of the equipment status and the lot conditions efficiently and precisely.

In the dispatching phase, we present the lot-based and the equipment-based selection schemes. Each of these two schemes has its own advantages, but also some drawbacks. Therefore, we propose a new approach – Pair Generation Mechanism and Adaptive Lot/Equipment Matching Strategy, which can promise a dispatching strategy that can be more optimal in the sense that both the lot-based and equipment-based viewpoints will be taken into account simultaneously. In this paper, we further adopt an efficient algorithm – Auction Algorithm to help us to find out the optimal solution to the internally generated lot/equipment matching problem. Besides, some adaptive factors will also be applied in.

At last in the scheduling phase, we apply the genetic algorithm (GA) based approach to obtain a near-optimal solution to our scheduling problem. From our experiment results, the developed CTPN based Genetic Algorithm will yield a more efficient solution than several other schedulers.

I. INTRODUCTION

This paper addresses the problem in dispatching and scheduling for wafer probing in the wafer probe center. If we want to meet customers' requirements, we have to precisely estimate the cycle time of all orders as well as other performance measures (total makespan, meet due date rate, penalty, etc.) first. In order to accomplish the task, a wafer probe center model based on CTPN (Colored Timed Petri Nets) is created. This model not only helps us to evaluate these performance measures, but also helps us to develop and evaluate our scheduler easily.

An effective scheduling can be a major means to reduce the cycle time, to increase machine utilization, throughput rate, and meet-due-date rate, and to obtain greater customer satisfaction. Since it is known that the general job shop scheduling problem is NP-hard, there is no efficient algorithm so far for solving the scheduling problems optimally in polynomial time. This is the reason why we use the Genetic Algorithm (GA) based scheduler to solve the scheduling problem in a wafer probe center.

Many researchers have worked in this field for a long period. Imed Kacem *et al.* [1] proposed a Pareto approach based on the hybridization of Fuzzy Logic (FL) and Evolutionary Algorithms (EAs) to solve the Flexible Job-shop Scheduling Problem (FJSP). B.W. Hsieh, S.C. Chang and C.H. Chen exploit the speed of an ordinal optimization-based simulation tool to investigate dynamic selection of scheduling rules. Besides, Brucker proposed the branch and bound algorithm for the Job-shop scheduling problems.

The remainder of this paper is organized as follows. In Section II we list the modeling of the wafer probe center. Section III gives the details about how we design our ALEMS in the dispatching phase. Section IV shows the scheduling phase of wafer probe center. Experiment results are shown in Section V. Finally we have a conclusion in Section VI.

II. MODELING OF THE WAFER PROBE CENTER

Some features are frequently encountered in the real setting of a wafer probe center. The modeling features mentioned include unscheduled maintenance (breakdown), setup and testing time, the overlapping phenomenon between capability groups and the hold phenomenon. In this paper, we handle these features, and construct a model for the wafer probe center based on Petri Nets.

Carl Adan Petri (1962) developed a net-theoretic approach called Petri Nets (PN) to model and to analyze a communication system. In the last three decades, Petri Nets were developed to meet the needs in specifying process synchronization, concurrent operations, conflicts or resource sharing, and asynchronous events for a variety of industrial automated systems at the discrete-event level.

The Colored-Timed Petri Nets (CTPN) extends the framework of the original PN by adding color and time attributes to the nets. In a complex system like the manufacturing system, there can be several similar elements, and a Colored PN can prevent from using a distinct net to represent each element. Even in simple systems, a complete and detailed model may form a quite large net. This is the reason for adding color attributes into the original PN.

They are many lots flowing on their own routes in a wafer probe center. When a lot is released into the probe center, its route and starting stage will be determined. Afterwards, the lot will be put into a queue and wait for an appropriate equipment with required capability to process it. After processing, it will be pulled out from the equipment and pushed into the next stage and repeat the above procedure.

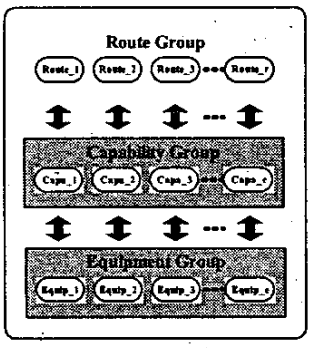

Fig. 1 The relationship among the three modules

Therefore, we can classify the environment into three parts. There are the Route Module, the Capability Module, and the Equipment Module. The general relationship between these three kinds of module is showed in Figure 1. In this diagram, r, c, and e mean the number of routes, capabilities, and equipment, respectively. The detailed model can be found in [5].

III. DISPATCHING IN THE WAFER PROBE CENTER

We can stand from two different viewpoints when making decisions in the dispatching process. From the perspective of the equipment, it needs to select a suitable lot to process based on lot information like due date, whereas from the perspective of the lot, it needs to select a suitable equipment to be processed based on equipment information like processing time. Inappropriate matching of lots and equipment will lead to longer cycle time, poorer commit-due-date rate, and higher WIP. Therefore, making the fittest matching of lots and equipment is the main objective in this phase.

Lot Based Selection

In the wafer probe center, when the lot moves out from a stage, it needs to determine which equipment will process its next stage. At first, we collect the set of all possible idle equipment with the currently required capability and put them into a candidate pool. Right after that, we calculate a score for each piece of equipment in the pool depends on some criteria. Choosing the suitable equipment from the candidate pool is a key to the performance of the scheduling system. In this paper, we compute the score for each piece of equipment by rules MST (Minimum Setup Time), MPT (Minimum Processing Time) and LMBR (Lowest Machine Breakdown Rate).

Equipment Based Selection

When the equipment finishes a testing process, it must choose a lot that it is capable to process from the waiting pool. But how does it choose? The equipment based selection rules provide the guideline to achieve that. This selection should take considerations from the viewpoint of equipment and consider the status of the lots in the waiting pool. Which waiting lot can be tested on this equipment without changeover of the accessories? Which one requires the shortest testing time or setup time? Which one has the longest waiting time? Which one has higher penalty? How to choose the lot from the waiting pool is also critical to the performance of the scheduling system.

In this paper, we have picked several important rules, EDD (Earliest Due Date), MQT (Maximum Queuing Time), Penalty, and RHLD (Run Hold First), and applied them to our scheduling system.

After introducing the lot-based selection and equipment-based selection, we conclude two disadvantages:

- We may obtain inappropriate assignments with one-side biased information.
- The assignment will be improper without considering in-process lots and busy equipment.

According to the above reasons, we need to find a way to solve these potential problems. In this paper, we propose a new approach, called "Pair Generation Mechanism" (PGM). The goal of the PGM is to integrate the lot based selection and the equipment based selection. Moreover, we can eliminate the drawbacks of these two selection methods. After we apply the PGM, we can get the scores of all pairs of candidate lot and equipment. Then, we can use the Lot/Equipment Matching Strategy (LEMS) that will be described later to match these lots and equipment based on the PGM result.

Pair Generation Mechanism

At beginning, when a lot tracks into a stage, we collect all lots waiting at this stage and a set of equipment capable to process these lots to the lot/equipment candidate pool. We call this phase "Collection". Next, we prepare to put some lots that are coming to arrive at this stage to the candidate pool by a filtering procedure. We calculate the remaining processing times of all these lots, and then compare them with a predefined threshold. If the remaining processing time of a lot is not greater than the threshold, we will collect it. Here, we call this phase "Fillter1"

After the lot candidate pool is formed, we also establish the equipment candidate pool. For each lot in the lot candidate pool, we find the set of all capable equipment (i.e., each of them possesses the required capability for that lot), and add them into the equipment candidate pool. Considering the status of the equipment, running or idle but not down, they will be chosen in our mechanism. Similarly, we compute the remaining processing time of every piece of equipment in the pool. After that, we compare it with another predefined threshold. Only those pieces of equipment with remaining processing time not greater than the threshold will be collected. This operation is called "Filter2".

After the former two steps, we have successfully obtained the lot and equipment candidate pools. Soon afterwards, we calculate the scores of each reasonable pair of lot and equipment by those rules we listed earlier. We call this phase "Ranking". For example, we take a pair of a lot and a piece of equipment, say, Lot_A and Eqpipment_1. First we compute the lot score from the viewpoint of Lot_A using all the lot-based selection rules (we calculate the scores rule by rule and then sum them up), and then the equipment score from the viewpoint of Equipment_1 using all the equipment-based selection rules (by the same method). Finally, we sum these two scores to obtain a value that represents the gain of matching this lot and equipment (i.e., the gain if we let Equipment_1 process Lot_A.). By this way, we can compute the values of all reasonable pairs of lot and equipment.

The foregoing method is the Pair Generation Mechanism. It successfully generates an assignment problem that contains the nature of both lot selection and equipment selection. Our next step is to apply the Lot/Equipment Matching Strategy to match these lots and the associated set of equipment.

Basic Lot/Equipment Matching Strategy

For reducing the size of the assignment problem generated by PGM, we will use another process to eliminate the unlikely candidate pairs of lots and equipment, which called phase "*Filter3*". In this phase, we check the status of lots in all pairs first. If the status is running, it means the lot is being processed at the former stage now. Following that, we compute the ratio of the score against the remaining processing time of this lot. Then, we compare this ratio with a threshold. If the ratio is not less than the threshold, it means that it is advisable for the equipment to remain idle for a while and wait for this lot, and this pair of lot and equipment will still be kept in the candidate pool. Otherwise, we will remove this lot and equipment pair from the pool. With this reduction of problem size, we can save the time to solve the assignment problem and thus improve the performance of our scheduling system.

In the case of equipment, we will also take account of each pair. If the status of the equipment is running, by the similar procedure, we calculate the ratio of the score against the remaining processing time of this equipment first. Then, we also compare this ratio with another threshold. If the ratio is greater than or equal to the threshold, it means that it is advisable to keep the lot idle to wait for the job completion of the equipment. Otherwise, we can remove this pair of lot and equipment from the pair set.

After taking all these measures, we have the considerable number of pairs of these lots and equipment. Moreover, each pair has a value that represents the gain of its being selected (Figure 2).

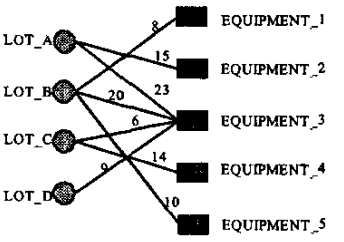

Fig. 2 The relationship between LOT and EQUIPMENT

Adaptive Lot/Equipment Matching Strategy

In a probe center, managers usually have concluded a suite of guidelines following which we can get satisfactory performance in most cases. With this invaluable experience, we can effectively reduce the number of potential matching pairs without sacrificing the quality of the scheduler.

Let us take an example as illustrated in Fig. 3. Suppose the manager finds that it is good for lots belonging to PART_B to be processed by the equipment with type EquipmentType_A. In this case, we can directly assign the lot LOT_A to the equipment EQUIPMENT_2 after we assure that they are the favorite mate of each other. After this operation, we not only reduce the size of the assignment problem by disregarding three pairs but also obtain a successful assignment by adopting the expert knowledge.

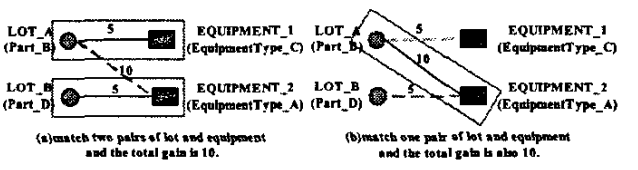

Fig. 3 Two kinds of possible matchings

Two problems should be addressed here. How can we know what rules should be applied and which equipment has the property mentioned in the above paragraph (here we say this kind of equipment is "adaptive")? We resort to the genetic algorithm to solve them (The Genetic Algorithm will be introduced in next section.). We use GA to find out these rules, therefore the GA-equipped LEMS can learn by itself. That is why we call this method Adaptive Lot/Equipment Matching Strategy (ALEMS)

The goal of our ALEMS now is to figure out a set of matching pairs with the maximal sum of scores under the constraint that any lot and any piece of equipment can appear at more once in the consequent matching pairs. Then we can apply these matching results to the model and proceed the simulation. Here we employ a concise and excellent algorithm *Auction Algorithm* [2] to help us find out the perfect matching very efficiently.

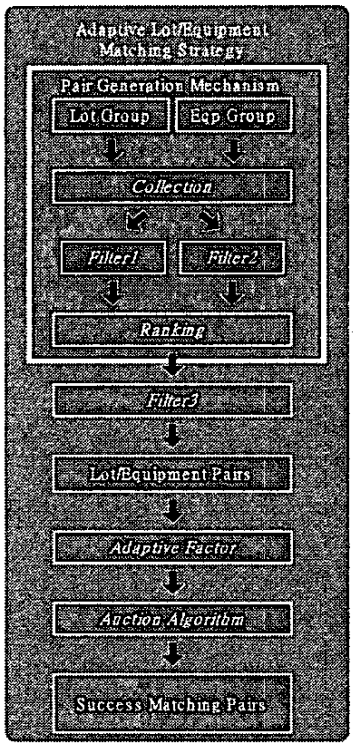

Fig. 4 The illustration of the Adaptive Lot/Equipment Matching Strategy

IV. SCHEDULING IN THE WAFER PROBE CENTER

Genetic Algorithms were proposed by Holland. Holland's colleagues and students at the University of Michigan in 1975, who used it as a new learning paradigm to model a natural evolution mechanism. Although GAs were not well known at the beginning, after the publication of Goldberg's book [3], GAs have recently attracted considerable attention in a number of fields such as methodology for optimization, adaptation, learning, and job-shop scheduling.

The genetic algorithm starts with an initial set of random configurations called a population. Each individual in the population is a string of symbols known as genes, and the string made up of genes is termed a chromosome. The chromosome represents the solution to the optimization problem. During each generation the individuals in the current population are evaluated using the fitness function. Based on the fitness value, two individuals (called parents) are selected at a time from the population. The fitter the individuals are the higher the probability they will be selected as parents. Then, a number of genetic operators are applied on the selected parents to generate new individual solutions called offspring. These genetic operators will combine the features of both parents and maintain the diversity of species. Common operators are reproduction, crossover, and mutation. They are derived by the analogy from the biological evolution.

GA Based Scheduling

There are two sub-problems in the scheduling problem. First, what searching method do we apply to optimize the scheduling results? Next, how do we evaluate the performance of each scheduling policy? For the first sub-problem, we apply the genetic algorithm. For the second sub-problem, we use simulation based on our CTPN model to complete performance evaluation.

Proposed Method and Mixed Rules

Let us take an overview on the method used to mix the lot-based and equipment-based selection rules. This method first normalizes the index values obtained from lot-based and equipment-based selection rules into the same range. Then, it uses different weights to combine these index values to generate the score of each lot and equipment pair. These different combinations of weights are indexed by the equipment type and the product type.

We use MST, MPT, and LMBR rules as lot-based selection rules and EDD, MQT, Penalty, and RHLD as equipment-based selection rules in this paper (mentioned in Section III.).

Chromosome Representation

There are three types of genes in our chromosome: g_a, g_e and g_l, which are related to adaptive factors, equipment based selection rules, and lot based selection rules, respectively. The length of a chromosome is fixed and the structure of the chromosome is illustrated in Figure 5. There are three groups of genes. The first group contains genes from gene 1 to gene N, which represents the adaptive factors of each equipment type, where N is the number of equipment types. If the adaptive factor is equal to 1, the corresponding equipment will be set to adaptive. The second part of the chromosome contains gene N+1 to gene 2N, which manages the equipment-based selection rules for each equipment type. The last part of the chromosome including gene 2N+1 to 2N+M affects the lot-based selection rules for each kind of product, where M is the number of different product types. The symbol et_i means the equipment type $i = 1, \ldots, N$, and p_j means the product type of the lot $j = 1, \ldots, M$.

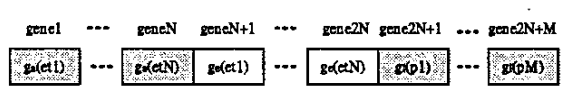

Fig. 5 Chromosome representation

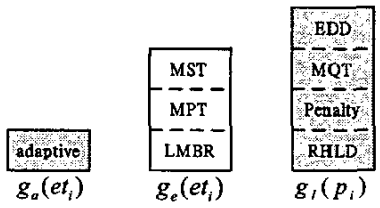

Fig. 6 Gene representation

Fitness Function

In this paper, we adopt four most representative performance criteria. In our design, we let the users select their own preferred objective functions, and they can define their associated weights. Here, we explain this function with an equation:

$$f(c) = w_1 \cdot f_1(c) + w_2 \cdot f_2(c) + w_3 \cdot f_3(c) + w_4 \cdot f_4(c)$$

where f_1 is the score of the total makespan;
f_2 is the score of the meet due date rate;
f_3 is the score of the mean cycle time;
f_4 is the score for the penalty tardy rate.

Note that the penalty tardy rate is defined as $(\sum_N (is\_tardy) * (the\ penalty\ of\ lot)) / N$, where N is the number of lots.

V. EXPERIMENT RESULTS

The model of our experiments has totally 80 machines, 20 equipment types, and 30 capabilities. For the purpose of performance evaluation and testing the proposed modeling, dispatching, and scheduling method, we developed a simulation tool named *ALEMS Sim*.

ALEMS Sim consists of two parts. The first part is a *Simulator* which is based on the CTPN model and the proposed dispatching strategy, LEMS. By conducting simulations, we can get information including the progress of each lot, the utilization of each machine group, the makespan, and so on.

The second part of *ALEMS Sim* is the *GA schedule generator*. It will generate a high-quality schedule based on the genetic parameters (generation size, population size, ...) and the importance of performance measures.

We will compare the dispatching strategy LEMS with three other strategies, Lot-Based Selection (LBS), Equipment-Based Selection (EBS), and Lin's method [4][1] (LM). LBS (EBS) means that we just take considerations from the lot's viewpoint (equipment's viewpoint) when we match lots and equipment in the dispatching phase.

[1] Lin's method uses Lot Based Selection when the lots track into a stage and Equipment Based Selection when the equipment becomes idle.

The experiments about LEMS

Here we simulate several testing cases with different number of lots and different dispatching strategies, and the experiment results will be shown with four performance measurements, makespan, meet-due-date rate, penalty tardy rate, and mean cycle time in Figure 7, respectively.

We run the *Simulator* 10 times for each testing case and the points in these figures represent the average values. In Figure 7, we can see that LEMS performs better than others. For example, in Figure 7 (a), the makespan can be reduced by 26~34 hours using the LEMS when the number of released lots is 250

The experiments about GA Schedule Generator

We run *GA schedule generator* 20 times and compare ALEMS with other dispatching strategies, and the number of released lot is 1000. The experiment results will be shown in Figures 8~11. We run 10 generations with population size 10. Figure 8 shows means and variances of makespan with four dispatching strategies. It shows that the scheduler using ALEMS can reduce the makespan by about 32~82 hours and the variance is also the minimum. It is a significant improvement, and other experiment results shown in Figure 9~11 also point out the superiority of the ALEMS. These provide strong evidence that the ALEMS performs better than other strategies.

VI. CONCLUSION

With appropriate modeling and analysis tool, we can evaluate the system performance very easily. In this paper, we created a wafer probe center model based on Colored-Timed Petri Nets (CTPN). Important features such as unscheduled maintenance (breakdown), setup and testing times, the overlapping phenomenon between capability groups, and the hold phenomenon are all considered. In the dispatching phase, our proposed pair generation mechanism (PGM) provides a close integration of two conventionally separating subtasks – lot section and equipment selection. Then our Adaptive Lot/Equipment Matching Strategy (ALEMS), an auction algorithm-embedded approach, solves the original dispatching problem by targeting the PGM-generated problem.

Moreover, with some features of the equipment, such as that some machines have higher priority to choose their favorite products to process, we adopted an adaptive factor to figure out these characteristics. It can speed up solving our lot and equipment matching problem.

In the scheduling phase, the proposed GA scheduler can dynamically search for an appropriate weight of each dispatching rule for each product and equipment type. Our approach can be considered as taking advantage of heuristic rules to guide the search. This approach can reduce the solution space and help us to find the superior solution quickly.

Finally, we know the proposed ALEMS can produce a more effective solution by a lot of experiments. It can reduce the makespan, penalty tardy rate, and mean cycle time, and increase the meet-due-date rate. Besides, the GA scheduler generator can get an answer with low variance.

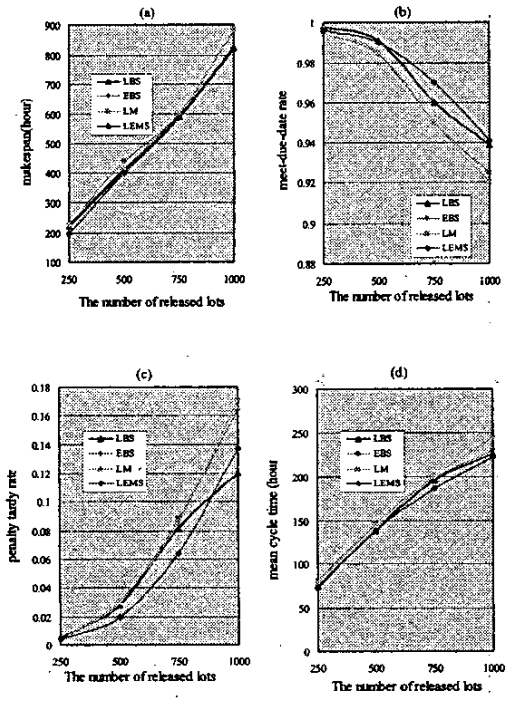

Fig. 7 The experiment about the Simulation

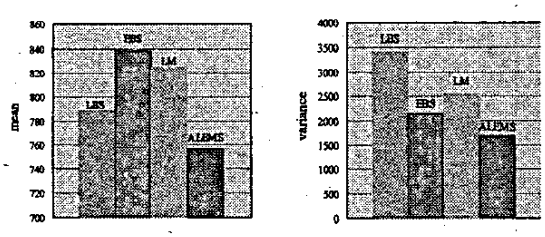

Fig. 8 The result of the scheduler (makespan)

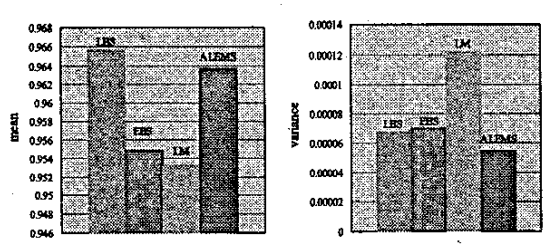

Fig. 9 The result of the scheduler (meet-due-date rate)

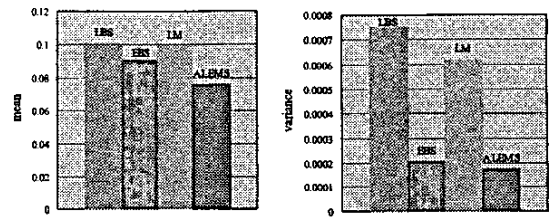

Fig. 10 The result of the scheduler (penalty tardy rate)

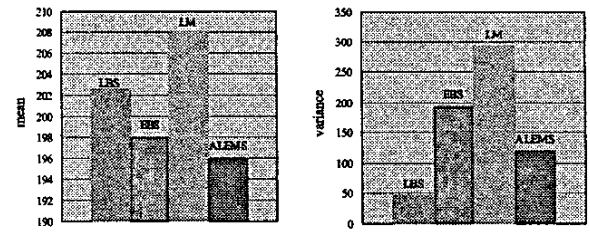

Fig. 11 The result of the scheduler (mean cycle time)

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