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LEARNING-BASED RELEASE CONTROL OF SEMICONDUCTOR WAFER FABRICATION FACILITIES

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ABSTRACT

Release control plays an important role in the performance of a semiconductor wafer fabrication facility. A new release control policy based on extreme learning machine (abbreviated as RPELM) is proposed. Its main idea is to regulate the release sequence of the lots in a daily release plan subject to the attributes of the lots and running states of the fab. Firstly, the workflow of RPELM is introduced. Secondly, correlation coefficient method is used to select running states of the fab closely related to its performance. Finally, RPELM is validated and verified by a benchmark model (fab6 of MIMAC) and an actual 6 inch fab model (called BL), respectively. The simulation results show that RPELM performs better than common release policy with higher on-time delivery rate, especially for that of hot lots, without sacrificing the throughput and cycle time performance.

1 INTRODUCTION

Semiconductor wafer fabrication facility (abbreviated as fab) is a typical multi-reentrant system, which has many special and complex characteristics like large-scale, multi-objective, unbalanced workload, mix-processing of multiple types of products and high degree of uncertainty. These features bring difficulties to its operational performance optimization. As an effective way to improve the performance of a fab, release control increasingly attracts researchers' attention in recent years.

Generally, release control is dedicated to determine when, which and how lots should be released into a fab. The existing research results on release control can be traced to late 1980s. Wein (Wein 1988) and Glassey (Glassey and Resende 1988) proved that release control played more important role on improving the performance of a fab comparing to scheduling. Since then, considerable achievements in release control field have been obtained that can be classified into open-loop and close-loop ones. The open-loop release control policies release the lots every special time interval (such as Uniform, Poisson, and fix time interval), and the release order of the lots is determined according to the experiences of managers or requirements of customers, while not considering the running state of a fab, such as first in first out policy (FIFO) and earliest due date policy (EDD). FIFO and EDD determine the release order of the lots in a release plan according to their order in the release plan and their due dates, respectively. They don't consider the running states of the fab, such as WIP number, workload of the fab, the distribution of WIP on different workstations and so on. The close-loop ones determine the release time of the lots according to the running states of a fab, such as constant work in process (CONWIP) (Spearman et al.

1990; Rose 2001), starvation avoidance (SA) policy (Lozinski et al. 1990), workload regulating rule (Chao and Sivakumar, 2006; Rose 1999) and etc. The latest successful examples improves existing release control policies, such as the pull VPLs-based effective-workload control (EWL-n-Ctrl) policy (Li et al. 2014) and the WIP load control (WIPLCTRL) (Qi et al. 2009), or integrate release control with dispatching, such as integration of lot sizing and dispatch-related decisions (Chen et al. 2010), dynamic classified work-in-process rule (DC-WIP) (Sun and Wang, 2008), and ean integrated release and dispatch policy for semiconductor wafer fabrication (Li et al. 2014), or introduce optimization methods to release control decisions, such as the Lagrangian heuristic for solving the model (Lima et al. 2014) and simulation-optimization method for the release control (Peng et al. 2012).

This work aims at proposing a new dynamic release control policy based on extreme learning machine (RPELM) to increase on-time delivery rate (ODR) of ordinary lots and that of hot-lots (HLODR), achieve high throughput (TH) and shorten cycle times (CT). The remainder of the paper is organized as follows: in Section 2, the workflow of RPELM is discussed in detail, and the correlation coefficient based feature selection method is introduced. Validation and verification of RPELM based on a benchmark model (fab6 of MIMAC) and an actual module (called BL) are presented in detail in Section 3. Section 4 includes the research work and makes conclusions finally.

2 ELM BASED RELEASE CONTROL POLICY (RPELM)

2.1 Workflow of RPELM

Release policies are dedicated to determine when, which, and how lots should be released into a fab. RPELM concerns the release sequence of the lots in a given daily release plan. Then the lots will be released to the fab once at specified time in this order.

Common release polices (such as FIFO and EDD) determine the release sequence of the lots in a daily release plan according to their attributes (such as their given order or due dates). However, they seldom take the real-time status information of the fab into account. RPELM determines the release priority of the lots according to their attributes and fab-wide real-time status information simultaneously.

The relationship between the release priority of a lot and its attributes is defined as

$$P_i = a * \frac{CT_i}{\max(CT_i)} + b * \frac{T_i}{\max(T_i)} + c * \frac{Steps_i}{\max(\mathrm{Steps}_i)} + IsHotLot(i) \tag{1}$$

where $P_i, CT_i, T_i, Steps_i$ and $IsHotLot(\mathrm{i})$ denote the release priority, cycle time (CT), pure processing time, number of steps and priority attribute of Lot_i, respectively; $IsHotLot(\mathrm{i})$ is determined by whether Lot_i is a hot-lot. If Lot_i is a hot-lot, $IsHotLot(\mathrm{i})$ equals 1, else $IsHotLot(\mathrm{i})$ equals 0; a , b and c represent the weights of CT, pure processing time and number of steps of Lot_i . The weights are gained according to the real-time status information by a learning machine based ELM. So RPELM contains both the attributes of the lots and the real-time status information of the fab.

ELM is a new popular neural network developed in recent years. ELM learns fast and can be implemented simply to obtain global optimal solutions. So we adopt it as the learning mechanism here.

In order to establish the learning mechanism, we need to obtain plenty of samples and select the excellent samples as the inputs and outputs of ELM. The specific steps are as follows.

Step1: Select the values of a , b and c randomly. With their attributes information (such as CT, pure processing time and number of steps), we can gain the release priority of the lots. Then release the lots into the fab according to their release priority. The lot with the highest priority will be released first into the fab

Step2: Record real-time status information and short-term performance indicators. The real-time status information includes the number of different kinds of products in front, middle and behind stage, respectively. Here front, middle and behind stage of a product are defined as its first one third steps, one third to second thirds steps and the last one third steps, respectively. The short-term performance indicators include utilization of bottlenecks, the movements of lots per day and throughput per day. These short-term performance will reflect the long-term performance including throughput (TH), CT and ODR.

Step3: Choose the inputs and outputs of ELM. Select those real-time status information and corresponding attributes' weights with excellent short-term performance from statistical results as the inputs and outputs of EML, respectively. After these steps, ELM, i.e., the learning mechanism is established.

Step4: Testing set is then applied into ELM to judge the accuracy of the learning mechanism.

Then the priority P_i will be changing according to the attributes of the lots and the real-time status information of the fab.

2.2 Feature Selection

We only consider the number of different products in different stages as the real-time status information above according to the experience of the real fab. In fact, there are many running status information affecting the release sequence. It is necessary to find the exact ones to improve the release decisions.

The correlation coefficient, expressed by (2), reflects the correlation degree of the relationship between two variables, where $Cov(X,Y)$ represents the covariance between X and Y, $D(X)$ and $D(Y)$ denote the variance of X and Y, respectively. We adopt this method to select the running states of the fab closely related to the performance.

$$\rho_{XY} = \frac{Cov(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}} \tag{2}$$

Firstly, simulations are run to gain running status features. Here we consider the features including the different kinds of products in front, middle and behind stage; moves of the lots in production line per day, processing time of the lots per day, moves in the bottlenecks of the fab per day, queue length of the lots before the bottlenecks of the fab per day and the number of lots (i.e., WIP) per day.

Then select the running states closely related to the performance according to the correlation coefficient evaluation.

3 SIMULATIONS

In order to compare RPELM with common release control methods such as FIFO and EDD, we run simulations on a benchmark simulation model (fab6 of MIMAC) and an actual 6 inch fab model (called BL), respectively.

3.1 Simulations on MIMAC

MIMAC is a benchmark fab model set including six different fab models. Here we use fab6 as the simulation model. It has 104 workstations, 228 machines and 9 kinds of products. The dispatching rule is set to first-in-first-out (FIFO).

We firstly run the simulations with FIFO and EDD as release control policies and record the simulation results for 300 times. Then, in order to use RPELM, we select the number of the 9 kinds of products in front, middle and behind stage as the running states. The short-term performance is selected as Section 2.

Every simulation has been done with 90 days (including 30 days warm-up period). To facilitate analysis on the performance of RPELM, we set different number of WIP as 2500, 3500, 4500 and 5500, respectively. The simulation results are shown as Table I, where TH, CT, ODR and hot-lot ODR (HLODR) as the performance indicators.

In order to describe the comparison more clearly, the results are also expressed in Figure 1-4.

From Table 1 and Fig.1-4, we can obtain following conclusions.

(1) TH is almost not changing with the release policy because of the limit of workloads of the production line.

(2) Performance CT of RPELM gets a little improvement comparing to that of FIFO and EDD, but it is not obviously.

Table 1: Results of simulations with different number of WIP.

WIP	FIFO				EDD				RPELM			
	TH (lot)	CT (hour)	ODR	HLODR	TH (lot)	CT (hour)	ODR	HLODR	TH (lot)	CT (hour)	ODR	HLODR
2500	582	356	48.77%	90.70%	581	354	48.76%	100%	582	356	52.41%	100%
3500	674	408	49.53%	75%	671	409	48.91%	71.43%	671	408	52.85%	78.57%
4500	646	635	48.79%	76.67%	644	654	48.74%	76.67%	646	634	52.51%	78.58%
5500	704	831	47.62%	54.16%	698	842	48.01%	54.16%	705	829	49.79%	54.16%

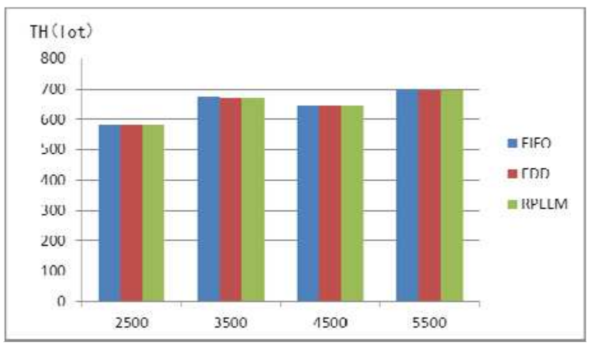

Figure 1: TH performance comparison.

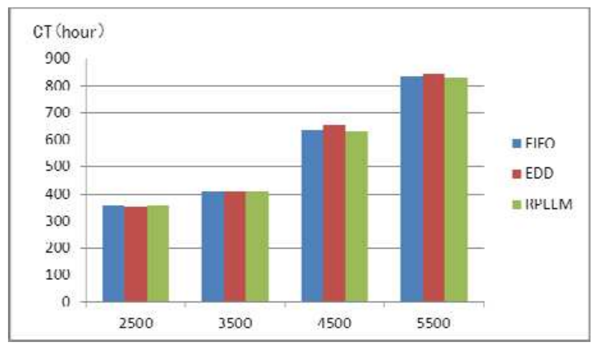

Figure 2: CT performance comparison.

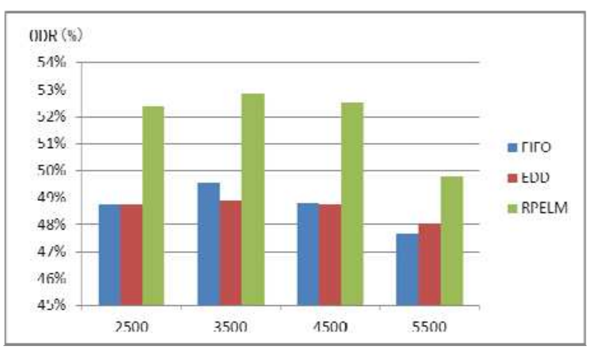

Figure 3: ODR performance comparison.

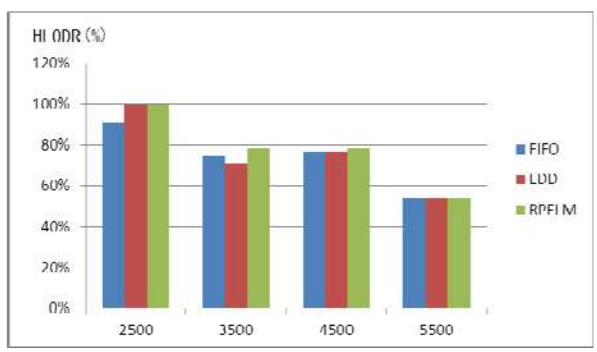

Figure 4: HLODR performance comparison.

(3) ODR has been improved obviously with RPELM. The improvements of different number of WIP are 3.64%, 3.32%, 3.72% and 2.17%, respectively, comparing to FIFO. Comparing to EDD, the improvements are 3.65%, 3.94%, 3.77% and 1.78%, respectively.

(4) When workload in production is light, the improvements are obviously, but the improvements become smaller with the number of WIP becomes bigger.

In conclusion, RPELM are effective to improve ODR and HLODR.

Then we further implement simulations with RPELM using feature selection (RPELM_FS). Besides the number of the 9 kinds of products in front, middle and behind stage, we consider more running states, such as WIP per day, moves of WIP per day, throughput per day, process time of the fab per day, the moves in bottlenecks per day, the queue lengths before bottlenecks per day and utilization of bottlenecks per day. In fab6 of MIMAC, there are 8 bottlenecks, so the number of the features is 55. We select 25 features closely related to TH per day. The simulations have been done for 300 days with 30 days warm-up period and the simulation results are shown as Table 2. There are 3 simulation scenarios in Table II, i.e., FIFO, EDD, and RPELM_FS, respectively.

From Table 2, we can see the improvements of ODR with the policy RPELM_FS are 3.02%, 2.26% and 2.69% comparing to FIFO, EDD and RPELM, respectively. The improvements of HLODR with the policy RPELM_FS are 2.01%, 1.00% and 0.26% comparing to FIFO, EDD and RPELM, respectively. TH and CT are improved a little, but not obviously. So RPELM_FS is useful and meaningful.

Table 2: Comparison of RPELM, FIFO and EDD.

	FIFO	EDD	RPELM	RPELM_FS	C_FIFO	C_ EDD	C_RPELM
TH(lot)	2396	2393	2394	2398	0.08%	0.21%	0.17%
CT(hour)	352	351	351	350	0.57%	0.28%	0.28%
ODR	25.39%	26.15%	26.41%	28.41%	3.02%	2.26%	1.69%
HLODR	45.22%	46.23%	46.97%	47.23%	2.01%	1.00%	0.26%

3.2 Simulations on BL

Simulations are also carried out on a simulation model from an actual 6 inch fab. It has 19 workstations, 119 machines and 9 kinds of products in the fab. Every simulation has been done for 300 days with 30 days warm-up period. The release policies are set as FIFO, EDD and RPELM_FS, respectively. And the dispatching rules are set as FIFO, earliest due date (EDD), shortest processing time (SPT), longest processing time (LPT), shortest remaining processing time (SRPT) and least slack (LS), respectively. So we can confirm the suitable dispatching rules with RPELM_FS.

We select the number of the 9 kinds of products in front stage, in middle stage, and in behind stage, WIP per day, moves of WIP per day, process time of the fab per day, moves in bottlenecks per day and queue lengths before bottlenecks per day as the running states. There are four bottlenecks, so 38 features have been recorded. We choose 9 features according to feature selection.

We can obtain following conclusions from the simulation results (shown as Table 3-8).

(1) TH, CT, HLCT, CLCT, VAR, HLVAR and CLVAR are almost not changed with the different release policies based on different dispatching rules.

(2) When the dispatching rule is SPRT, ODR and HLODR of RPELM_FS become worse comparing to FIFO and EDD. So RPELM_FS are not suitable to the dispatching rule SRPT.

(3) ODR of RPELM_FS has been improved with the dispatching rules FIFO, EDD, SPT and LS comparing to FIFO. The improvements are ranging from 1% to 2%. Comparing to EDD, ODR with RPELM_FS are almost equal.

Table 3: Comparison with dispatching rule FIFO.

	FIFO	EDD	RPELM_FS	C_FIFO	C_EDD
TH(lot)	2065	2070	2070	0.24%	0
CT(hour)	1150	1148	1148	0.17%	0
VAR	435.62	434.08	433.42	0.51%	0.15%
HLCT(hour)	1135	1131	1131	0.35%	0
HLVAR	363.80	361.93	361.82	0.54%	0.03%
CLCT(hour)	1150	1149	1149	0.09%	0

CLVAR	443.22	441.64	440.92	0.52%	0.16%
ODR	46.79%	48.63%	48.82%	1.03%	0.19%
HLODR	20.95%	24.76%	27.62%	6.67%	2.86%

*VAR: the variance of CT; HLCT: the CT of hot-lots; HLVAR: the variance of the hot-lots' CT; CLCT: the CT of ordinary lots; CLVAR: the variance of the ordinary lots' CT

Table 4: Comparison with dispatching rule EDD.

	FIFO	EDD	RPELM_FS	C_FIFO	C_EDD
TH(lot)	2007	2001	1996	-0.55%	-0.25%
CT(hour)	865	859	860	0.58%	-0.12%
VAR	661.22	641.77	649.56	1.76%	-1.21%
HLCT(hour)	802	804	802	0	0.25%
HLVAR	537.49	535.09	531.39	1.1%	0.69%
CLCT(hour)	870	864	865	0.57%	-0.12%
CLVAR	672.35	651.52	659.89	1.85%	-1.13%
ODR	57.54%	58.91%	59.31%	1.77%	0.40%
HLODR	69.39%	68.70%	67.34%	-2.05%	-1.36%

Table 5: Comparison with dispatching rule SPT.

	FIFO	EDD	RPELM_FS	C_FIFO	C_EDD
TH(lot)	2085	2080	2084	-0.05%	0.19%
CT(hour)	979	973	975	0.41%	-0.21%
VAR	374.15	377.71	373.0625	0.29%	1.23%
HLCT(hour)	1025	1018	1020	0.49%	-0.20%
HLVAR	459.84	448.21	452.61	1.57%	-0.98%
CLCT(hour)	973	967	969	0.41%	-0.21%
CLVAR	364.37	369.49	363.92	0.12%	1.51%
ODR	42.39%	43.51%	43.54%	1.15%	0.03%
HLODR	37.56%	40.64%	40.64%	3.08%	0.00%

Table 6: Comparison with dispatching rule LPT.

	FIFO	EDD	RPELM_FS	C_FIFO	C_EDD
TH(lot)	2048	2047	2044	-0.20%	-0.15%
CT(hour)	973	974	975	-0.21%	-0.10%
VAR	383.26	382.84	382.88	0.10%	-0.01%
HLCT(hour)	964	973	974	-1.04%	-0.10%
HLVAR	367.04	364.02	367.59	-0.15%	-0.98%
CLCT(hour)	975	974	975	0.00%	-0.10%

CLVAR	384.91	384.2	384.79	0.03%	-0.15%
ODR	48.73%	49.26%	48.80%	0.07%	-0.46%
HLODR	30.90%	31.43%	33.71%	2.81%	2.28%

(4) HLODR of RPELM_FS has been improved 6.67%, 3.08% and 2.81% with the dispatching rules FIFO, SPT and LPT comparing to FIFO, respectively.

In conclusion, RPELM_FS are adapted to the fabs with various dispatching rules except SRPT.

The proportion of hot-lots affects the performance directly. So we also do some simulations to study the fitness of RPELM_FS with different hot-lots proportions. The simulation results are shown as Table 9.

Table 7: Comparison with dispatching rule SRPT.

	FIFO	EDD	RPELM_FS	C_FIFO	C_EDD
TH(lot)	2387	2381	2387	0.00%	0.25%
CT(hour)	701	709	705	-0.57%	0.56%
VAR	285.50	307.45	288.25	-0.88%	6.24%
HLCT(hour)	583	613	611	-4.8%	0.33%
HLVAR	227.46	273.01	230.80	-1.47%	15.46%
CLCT(hour)	717	721	717	0	0.55%
CLVAR	291.6	301.64	294.44	-0.97%	2.39%
ODR	45.32%	48.78%	43.26%	-2.06%	-5.52%
HLODR	52.42%	54.2%	48.22%	-4.20%	-5.98%

Table 8: Comparison with different hot-Lot proportions.

	FIFO				EDD				RPELM			
	TH (lot)	CT (hour)	ODR	HLODR	TH (lot)	CT (hour)	ODR	HLODR	TH (lot)	CT (hour)	ODR	HLODR
1	2065	949	46.84%	18.90%	2072	948	48.53%	23.17%	2075	946	48.23%	23.17%
2	2065	949	47.39%	26.75%	2072	949	47.57%	28.93%	2073	945	47.70%	28.96%
3	2065	949	46.98%	25.56%	2072	947	48.51%	30.00%	2069	947	49.72%	32.22%
4	2065	949	42.65%	20.00%	2072	948	43.35%	24.29%	2075	946	43.14%	24.29%

We can obtain following conclusions from the simulation results.

(1) TH and CT of FIFO and EDD are equal, because they are not related with the proportions of hot-lots. RPELM_FS is related with hot-lots proportions, so the values of TH in the four simulations are not equal.

(2) In the first simulation, ODR and HLODR of RPELM_FS are better than the performance of FIFO, but there is no improvement comparing to EDD. The same conclusion can be gained from the second simulation and the fourth simulation. In the third simulation, ODR and HLODR of RPELM are better than the performance of FIFO and EDD.

So RPELM_FS is effective with different proportions of hot-lots.

4 CONCLUSION

This paper proposed a new release control policy based on extreme learning machine called RPELM. The simulations on MIMAC and BL prove that RPELM can improve ODR and HLODR effectively comparing to common release policies such as FIFO and EDD. We also improve RPELM with feature selection. The simulation results demonstrate that RPELM_FS is adapted to the fabs with various dispatching rules except SRPT and different proportion of hot-lots.

However, the bottleneck workstation here is selected empirically and does not changed according to the running states in the fabs and ELM is used without comparison with other learning machines. We will further research these problems in the future.

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