An Evolving Fuzzy-neural Rule with Slack Diversification for Enhancing Job Dispatching Performance in Wafer Fabrication

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Abstract

An evolving fuzzy-neural rule with slack diversification is proposed in the present work to improve the performance of job dispatching in a wafer fabrication factory. The evolving fuzzy-neural rule is a modification from the two-factor tailored nonlinear fluctuation smoothing rule for mean cycle time (2f-TNFSMCT) by diversifying the slack values of jobs to be dispatched dynamically, which has been shown to be conducive to the performance in several previous studies. After evaluation of the proposed rule, some evidence was gained to support its effectiveness. Based on the findings in this research we also derived several directions that can be exploited in the future.

Keywords: *Job dispatching, Wafer fabrication, Fuzzy, Neural, Slack diversification*

1. Introduction

Semiconductor manufacturing is undoubtedly one of the most noticeable high-technology industries today because of the widespread applications of semiconductor products. Semiconductor manufacturing can be divided into four stages: wafer fabrication, wafer probing, packaging, and final testing. The most important stage is wafer fabrication; about 25 wafers are grouped as a job/lot and pass through hundreds of operations to build up the layers and patterns of metal and wafer materials to produce the required circuitry. In this study, we investigate job dispatching for this stage. Shortening the production cycle time through effective job dispatching is an important task [1]. Chen [2-4] noted that for a semiconductor manufacturing factory, job dispatching is very difficult. Theoretically, this is an NP-hard problem. Among the various categories of methods (including dispatching rules, heuristics, data mining-based approaches [5, 6], agent technologies [6-9], and simulation) in this field, dispatching rules (i.e., first-in first out (FIFO), earliest due date (EDD), least slack (LS), shortest processing time (SPT), shortest remaining processing time (SRPT), critical ratio (CR), the fluctuation smoothing rule for the mean cycle time (FSMCT), the fluctuation smoothing rule for cycle time variation (FSVCT), least total work (LTWK), modified due date (MDD), operation due date (ODD), cost over time (COVERT), FIFO+, SRPT+, and SRPT++) have received a lot of attention in recent years [5, 6, 8] and are also the most prevalent method in practical applications. For details on the traditional dispatching rules, refer to Lu et al. [10]. A recent simulation comparison is presented in Chiang and Fu [11].

Some advances in this field are introduced below. Altendorfer, et. al., [12] proposed the work in parallel queue (WIPQ) rule targeted at maximizing throughput at a low level of work in process (WIP). Zhang, et. al., [13] proposed the dynamic bottleneck detection (DBD) approach by classifying workstations into several categories and then applying different dispatching rules to these categories. Depending on the current conditions in the wafer fabrication factory, Hsieh, et. al., [5] chose one approach from FSMCT, FSVCT, largest deviation first (LDF), one step ahead (OSA), and FIFO. Chen [14] modified FSMCT and

proposed the nonlinear FSMCT (NFSMCT) rule, in which the fluctuation in the estimated remaining cycle times was smoothed and then balanced with that of the release time or the mean release rate. To diversify the slack, the 'division' operator was applied instead. Chen [15] later proposed the one-factor tailored NFSMCT (1f-TNFSMCT) rule and the one-factor tailored nonlinear FSVCT (1f-TNFSVCT) rule. Two-factor TNFSMCT (2f-TNFSMCT) and TNFSVCT (2f-TNFSVCT) were subsequently presented in Chen, et. al., [16] and Chen [2], respectively.

Chen [14] mentioned that a nonlinear fluctuation smoothing rule uses the divisor operator instead of the subtraction operator, the use of which diversifies the slack and makes the nonlinear fluctuation smoothing rule more responsive to changes in the parameters. Chen, et. al., [17] also proved that the effects of parameters are better balanced in a nonlinear fluctuation smoothing rule than in a traditional one if the variation in the parameters is large. In a fluctuation smoothing rule, jobs that are expected to have longer remaining cycle times will be assigned lower slack values, which gives them higher priorities of processing and speeds up their progresses. Two cases are considered. The first is that these jobs are only at their initial stages, and there are many stages to undergo. It is not necessary to deal with such a situation. The other is that because these jobs are delayed, they underwent fewer stages during the same time interval. The latter situation should be resolved in some way. However, despite these jobs having high slack values based on a fluctuation smoothing rule, they may not have sufficient priorities; sometimes a lot of jobs have high slack values at the same time, and we cannot determine an absolute sorting of them. To solve this problem, we need a rule that can diversify the slack values as much as possible. Hence, we propose the evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule.

The remainder of this paper is arranged as follows. Section 2 provides the details of the proposed methodology. In section 3, a simulated case is used to validate the effectiveness of the slack-diversifying fuzzy-neural rule. The performances of some of the existing rules in this field are also examined using the simulated data. Finally, we draw our conclusions in section 4 and provide some worthwhile topics for future work.

2. Methodology

The variables used in the proposed methodology are defined as follows:

(1) R_j: the release time of job j, $j = 1 \sim n$.

(2) $RCTE_{jk}$:the estimated remaining cycle times of job j since step k.

(3) SK_{jk}:the slack of job j at step k.

(4) α: $\max(R_j)$-$\min(R_j)$

(5) β: $\max(RCTE_{jk})$-$\min(RCTE_{jk})$

(6) γ: $n - 1$.

(7) λ: the mean release rate.

Before applying the evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule, the remaining cycle times required for each job needs to be estimated in advance. In this study we apply the FCM-GA-FBPN approach by Chen et al. [18] because of its effectiveness [19-22]. Then, we derive the evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule by diversifying the slack value in the 2f-TNFSMCT rule:

$$SK_{jk} = \left(\frac{\beta}{\alpha(RCTE_{jk} - \min(RCTE_{jk}))}\right)^{\xi} \cdot (j/\lambda - RCTE_{jk} + (RCTE_{jk} - 1/\lambda)\xi) \\ = a_{jk}^{\xi}(b_{jk} + c_{jk}\xi) = b_{jk}a_{jk}^{\xi} + c_{jk}\xi a_{jk}^{\xi} \quad (1)$$

where

$$a_{jk} = \frac{\beta}{\alpha(RCTE_{jk} - \min(RCTE_{jk}))} \quad (2)$$

$$b_{jk} = j/\lambda - RCTE_{jk} \quad (3)$$

$$c_{jk} = RCTE_{jk} - 1/\lambda \quad (4)$$

ξ and ζ are positive real numbers satisfying the following constraints [15]:

$$\xi = 0 \leftrightarrow \zeta = 0 \quad (5)$$

$$\xi = 1 \leftrightarrow \zeta = 1 \quad (6)$$

There are many possible models to form the combination of ξ and ζ. For example,

$$\text{(Linear model) } \xi = \zeta \quad (7)$$

$$\text{(Nonlinear model) } \xi = \zeta^{k}, k \geq 0 \quad (8)$$

$$\text{(Logarithmic model) } \xi = \ln(1 + \zeta) / \ln 2 \quad (9)$$

In the proposed methodology, some possible combinations of parameters were enumerated based on the three models of 2f-TNFSMCT to construct the feasible solution region. The results are shown in Figure 1.

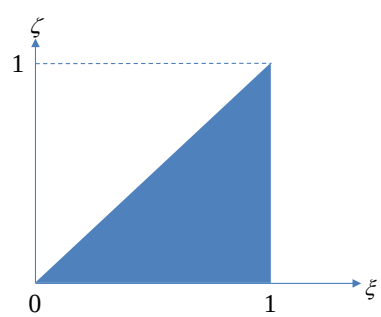

Figure 1. The Feasible Region

The traditional fluctuation smoothing rules are, in fact, special cases of these rules. However, Eq. (1) is difficult to cope with. For this reason, the following polynomial fitting technique is used to convert it into a more manageable form:

$$x^{\xi} \cong (1.15 - 0.11\xi) + (-0.07 + 0.57\xi)x \quad (10)$$

The mean absolute percentage error (MAPE) of Eq. (10) is less than 9% when $x \le 10$. The MAPE will not be a serious problem, because we are looking for ξ and ζ leading to the smallest value of $\sigma_{SK_{jk}}$, not SK_{jk}. Applying (10) to (1) yields

$$\begin{aligned} SK_{jk} &\cong b_{jk}(1.15-0.11\xi+(-0.07+0.57\xi)a_{jk}) + c_{jk}\zeta(1.15-0.11\xi+(-0.07+0.57\xi)a_{jk}) \\ &= (-0.07a_{jk}b_{jk}+1.15b_{jk})+(-0.07a_{jk}c_{jk}+1.15c_{jk})\zeta \\ &+(0.57a_{jk}b_{jk}-0.11b_{jk})\xi+(0.57a_{jk}c_{jk}-0.07c_{jk})\zeta\xi \\ &= d_{jk}+e_{jk}\zeta+f_{jk}\xi+g_{jk}\zeta\xi \end{aligned} \tag{11}$$

where

$$d_{jk} = -0.07a_{jk}b_{jk}+1.15b_{jk} \tag{12}$$

$$e_{jk} = -0.07a_{jk}c_{jk}+1.15c_{jk} \tag{13}$$

$$f_{jk} = 0.57a_{jk}b_{jk}-0.11b_{jk} \tag{14}$$

$$g_{jk} = 0.57a_{jk}c_{jk}-0.07c_{jk} \tag{15}$$

To diversify the slack, the standard deviation of the slack is to be maximized:

$$\sigma_{SK_{ij}} = \sqrt{\frac{\sum_{j=1}^{n}(SK_{jk}-\overline{SK_k})^2}{n-1}} = \sqrt{\frac{1}{\gamma}}\sqrt{\sum_{j=1}^{n}SK_{jk}^2-\frac{1}{n}(\sum_{i=1}^{n}SK_{jk})^2} \tag{16}$$

Objective (16) is equivalent to maximizing the following term,

$$\begin{aligned} &\sum_{j=1}^{n}SK_{jk}^2-\frac{1}{n}(\sum_{j=1}^{n}SK_{jk})^2 \\ &= \sum_{j=1}^{n}(d_{jk}+e_{jk}\zeta+f_{jk}\xi+g_{jk}\zeta\xi)^2-\frac{1}{n}(\sum_{j=1}^{n}(d_{jk}+e_{jk}\zeta+f_{jk}\xi+g_{jk}\zeta\xi))^2 \\ &= \sum_{j=1}^{n}(d_{jk}^2+e_{jk}^2\zeta^2+f_{jk}^2\xi^2+g_{jk}^2\zeta^2\xi^2+2d_{jk}e_{jk}\zeta+2d_{jk}f_{jk}\xi+2d_{jk}g_{jk}\zeta\xi \\ &+2e_{jk}f_{jk}\zeta\xi+2e_{jk}g_{jk}\zeta^2\xi+2f_{jk}g_{jk}\zeta\xi^2)-\frac{1}{n}((\sum_{j=1}^{n}d_{jk})^2+(\sum_{j=1}^{n}e_{jk})^2\zeta^2 \\ &+(\sum_{j=1}^{n}f_{jk})^2\xi^2+(\sum_{j=1}^{n}g_{jk})^2\zeta^2\xi^2+2\sum_{j=1}^{n}d_{jk}\sum_{j=1}^{n}e_{jk}\zeta+2\sum_{j=1}^{n}d_{jk}\sum_{j=1}^{n}f_{jk}\xi \\ &+2\sum_{j=1}^{n}d_{jk}\sum_{j=1}^{n}g_{jk}\zeta\xi+2\sum_{j=1}^{n}e_{jk}\sum_{j=1}^{n}f_{jk}\zeta\xi+2\sum_{j=1}^{n}e_{jk}\sum_{j=1}^{n}g_{jk}\zeta^2\xi+2\sum_{j=1}^{n}f_{jk}\sum_{j=1}^{n}g_{jk}\zeta\xi^2) \\ &= w_1+w_2\zeta+w_3\xi+w_4\zeta^2+w_5\xi^2+w_6\zeta\xi+w_7\zeta\xi^2+w_8\zeta^2\xi \end{aligned} \tag{17}$$

Taking the partial derivative of (17) with respect to ζ, and forcing it to zero, we obtain

$$w_2+2w_4\zeta+w_6\xi+w_7\xi^2+2w_8\zeta\xi=0 \tag{18}$$

Similarly, we obtain the partial derivative of (17) with respect to ξ and force it to zero,

$$w_3 + 2w_5\xi + w_6\xi + 2w_7\zeta\xi + w_8\zeta^2 = 0 \tag{19}$$

Besides, ζ and ξ have to follow some model, e.g. Eq. (7), (8), or (9). In addition, to guarantee it is a maximum, the second-order derivative has to be negative,

$$2w_4 + 2w_8\xi \le 0 \tag{20}$$

$$2w_5 + w_6 + 2w_7\zeta \le 0 \tag{21}$$

Finally, the same treatment can also be applied to 2f-TNFSVCT to make it slack-diversifying.

3. A Simulation Study

To evaluate the effectiveness of the proposed evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule, we used simulated data to avoid disturbing the regular operations of the wafer fabrication factory. A real wafer fabrication factory located in Taichung Scientific Park of Taiwan with a monthly production capacity of about 32,000 wafers was simulated using Visual C++. Jobs released into the factory are assigned three types of priorities, i.e. “normal”, “hot”, and “super hot”. Jobs with the highest priorities will be processed first. Currently, the release policy adopted by the wafer fabrication factory is the uniform release policy, namely jobs are released into it every fixed interval. FIFO is employed to sequence jobs on most of the workstations. As a result, the longest average cycle time exceeds three months with a variation of more than 300 hours. Only five major cases occupying most of the factory capacity were considered, indicated with I~V. Each case is represented with (product type, priority). Nine existing approaches, FIFO, EDD, SRPT, CR, Justice [23], FSVCT, FSMCT, 1f-TNFSMCT, and 2f-TNFSMCT were also applied to job dispatching in the simulated wafer fabrication factory. The value of ξ in 1f-TNFSMCT was set to 1.4. The values of ξ and ζ in 2f-TNFSMCT were set to (0.585, 0.5). In addition to the average cycle time, cycle time standard deviation of each case was also examined. The complete results were summarized in Table 1 and Table 2, respectively.

Firstly, all the compared approaches were dominated by the evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule because in most of the cases they were inferior to the evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule [24-28]. Secondly, cycle time standard deviation also reduced with the evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule. Last, compared with the original rule, 2f-TNFSMCT, the performance of the proposed methodology was also better, by dominating 2f-TNFSMCT in most cases. The advantages of the proposed methodology over 2f-TNFSMCT in the average cycle time and cycle time standard deviations were 3% and 14% on average, respectively, which confirmed the effectiveness of slack diversification to a TNFS rule like 2f-TNFSMCT.

Table 1: The Performances of Various Approaches in the Average Cycle Time

Avg. cycle time (hrs)	Case I (A, normal)	Case II (A, hot)	Case III (A, super hot)	Case IV (B, normal)	Case V (B, hot)
FIFO	1226	388	333	1233	459
EDD	1057	343	299	1458	459
SRPT	963	359	310	1724	462
CR	1144	365	290	1456	479
FSMCT	1423	401	308	1449	444
FSVCT	1089	366	325	1718	520
1f-TNFSMCT	1297	374	303	1249	416
2f-TNFSMCT	1246	355	297	1203	398
Justice	1136	394	333	1561	499
The proposed methodology	1207	344	286	1160	399

Table 2: The Performances of Various Approaches in Cycle Time Variation

Cycle time std. dev. (hrs)	Case I (A, normal)	Case II (A, hot)	Case III (A, super hot)	Case IV (B, normal)	Case V (B, hot)
FIFO	58	24	23	84	42
EDD	125	25	22	49	41
SRPT	248	33	22	107	31
CR	70	30	20	56	36
FSMCT	43	44	23	35	28
FSVCT	304	35	29	211	55
1f-TNFSMCT	84	43	21	49	24
2f-TNFSMCT	80	41	20	58	22
Justice	122	25	19	65	33
The proposed methodology	76	38	22	45	12

4. Conclusions and Directions for Future Research

In this paper, we have presented an evolving fuzzy-neural slack-diversifying nonlinear fluctuation smoothing rule to enhance the performance of job dispatching in a wafer fabrication factory. 2f-TNFSMCT is modified to produce a slack-diversifying nonlinear fluctuation smoothing rule that adjusts its content dynamically by diversifying the slack values, which was considered to be conducive to the performance of job dispatching in many preceding studies about similar rules. The same concept can be applied to optimize other rules to pursue better performance of job dispatching in future studies. In addition, to further assess the effectiveness and efficiency of the proposed methodology, the only way is to apply it an actual wafer fabrication factory.

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