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A Hybrid SOM-FBPN Approach for Output Time Prediction in a Wafer Fab

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Abstract: - Output time prediction is a critical task to a wafer fab (fabrication plant). To further enhance the accuracy of wafer lot output time prediction, the concept of input classification is applied to Chen's fuzzy back propagation network (FBPN) in this study by pre-classifying input examples with the self-organization map (SOM) classifier before they are fed into the FBPN. Examples belonging to different categories are then learned with the same FBPN but with different parameter values. Production simulation is also applied in this study to generate test examples. According to experimental results, the prediction accuracy of the proposed methodology was significantly better than those of two existing approaches, FBPN without example classification, and evolving fuzzy rules (EFR), in most cases by achieving a 15%~45% (and an average of 31%) reduction in the root-mean-squared-error (RMSE).

Key-Words: - Output time prediction; Fuzzy back propagation network; Self-organization map; Wafer fab

1 Introduction

Predicting the output time for every lot in a wafer fab is a critical task not only to the fab itself, but also to its customers. After the output time of each lot in a wafer fab is accurately predicted, several managerial goals can be simultaneously achieved [5]. Predicting the output time of a wafer lot is equivalent to estimating the cycle (flow) time of the lot, because the former can be easily derived by adding the release time (a constant) to the latter. There are six major approaches commonly applied to predicting the output/cycle time of a wafer lot: multiple-factor linear combination (MFLC), production simulation (PS), back propagation networks (BPN), case based reasoning (CBR), fuzzy modelling methods, and hybrid approaches. Among the six approaches, MFLC is the easiest, quickest, and most prevalent in practical applications. The major disadvantage of MFLC is the lack of forecasting accuracy [5]. Conversely, huge amount of data and lengthy simulation time are two shortages of PS. Nevertheless, PS is the most accurate output time prediction approach if the related databases are continuingly updated to maintain enough validity, and often serves as a benchmark for evaluating the effectiveness of another method. PS also tends to be preferred because it allows for computational experiments and subsequent analyses without any actual execution [3]. Considering both effectiveness and efficiency, Chang et al. [4] and Chang and Hsieh [2] both forecasted the output/cycle time of a wafer lot with a BPN having a single hidden layer. Compared with MFLC approaches, the average prediction accuracy measured with the root mean squared error (RMSE) was considerably improved with these BPNs. For example, an improvement of about 40% in the RMSE was achieved in Chang et al. [4]. On the other hand, much less time and fewer data are required to generate an output time forecast with a BPN than with PS. More recently, Chang et al. [3] proposed a *k*-nearest-neighbours based case-based reasoning (CBR) approach which outperformed the BPN approach in forecasting accuracy. In one case, the advantage was up to 27%. Chang et al. [4] modified the first step (i.e. partitioning the range of each input variable into several fuzzy intervals) of the fuzzy modelling method proposed by Wang and Mendel [15], called the WM method, with a simple genetic algorithm (GA) and proposed the evolving fuzzy rule (EFR) approach to predict the cycle time of a wafer lot. Their EFR approach outperformed CBR and BPN in prediction accuracy. Chen [5] constructed a fuzzy BPN (FBPN) that incorporated expert opinions in forming inputs to the FBPN. Chen's FBPN was a hybrid approach (fuzzy modelling and BPN) and surpassed the crisp BPN especially in the efficiency respect.

According to these results, the concept of classifying inputs, which has been adopted in CBR

and EFR, can indeed improve the effectiveness (prediction accuracy) of wafer lot output time prediction. This fact motivates us to propose a similar hybrid approach – a self-organization map (SOM) classifier and then a FBPN regression for the same purpose.

To further enhance the effectiveness of wafer lot output time prediction, the concept of input classification is applied to Chen's FBPN by pre-classifying input examples into different categories before they are fed into the network. The classification mechanism is SOM. SOM can serve as a clustering tool for high dimensional data (e.g. production data in a wafer fab), which constructs a topology that the high-dimensional space is mapped onto the lattice of neurons in such a way that relative topology distances between input vectors are preserved [10]. In this way, similar examples are clustered in the same category. Examples of different categories are then learned with the same FBPN but with different parameter values. PS is also applied in this study to generate test examples. Using simulated data, the effectiveness of the proposed methodology is shown and compared with those of two existing approaches, EFR, and FBPN without example classification.

2 Methodology

2.1 Example Classification with SOM

In this study, a hybrid SOM-FBPN approach is proposed to predict the output time of a wafer lot. In other words, we use a SOM classifier and then a FBPN regression. The reasons for adopting a SOM classifier instead of the others include:

(1) SOM has been proven useful in many applications including clustering, classification, monitoring, data visualization, etc., and is one of the most popular neural networks used in unsupervised learning.

(2) SOM can serve as a clustering tool for high dimensional data (e.g. production data in a wafer fab).

(3) There is potential for combination between SOM and another artificial neural network.

Every lot fed into the FBPN is called an example. Examples are pre-classified into different categories before they are fed into the FBPN with SOM. Let $X=\{x_1, x_2, \ldots, x_n\}$ denote the set of feature vectors corresponding to the examples. Each item x_i is a six-dimensional feature vector whose elements are the U_n, Q_n, BQ_n, FQ_n, WIP_n, and $D_n^{(i)}$ of the corresponding example. These feature vectors are fed into an SOM network. After the training is accomplished, input vectors that are topologically close are mapped to the same category, which means the input space is divided into k categories, and each example is associated with a certain category. Then, the classification result is post-processed, including eliminating isolated examples, merging small blocks, etc. Finally, the classification is finished.

After classification, examples of different categories are then learned with the same FBPN but with different parameter values.

2.2 FBPN for Output Time Prediction within Each Category

The configuration of the FBPN is established as follows:

(1) Inputs: six parameters associated with the n-th example/lot including the average fab utilization (U_n), the total queue length on the lot's processing route (Q_n) or before bottlenecks (BQ_n) or in the whole fab (FQ_n), the fab WIP (WIP_n), and the latenesses ($D_n^{(i)}$) of the i-th recently completed lots. These parameters have to be normalized so that their values fall within [0, 1]. Then some production execution/control experts are requested to express their beliefs (in linguistic terms) about the importance of each input parameter in predicting the cycle (output) time of a wafer lot. Linguistic assessments for an input parameter are converted into several pre-specified fuzzy numbers. The subjective importance of an input parameter is then obtained by averaging the corresponding fuzzy numbers of the linguistic replies for the input parameter by all experts. The subjective importance obtained for an input parameter is multiplied to the normalized value of the input parameter. After such a treatment, all inputs to the FBPN become triangular fuzzy numbers, and the fuzzy arithmetic for triangular fuzzy numbers is applied to deal with all calculations involved in training the FBPN.

(2) Single hidden layer: Generally one or two hidden layers are more beneficial for the convergence property of the network.

(3) Number of neurons in the hidden layer: the same as that in the input layer. Such a treatment has been adopted by many studies (e.g. [3]).

(4) Output: the (normalized) cycle time forecast of the example.

(5) Network learning rule: Delta rule.

(6) Transformation function: Sigmoid function,

$$f(x) = \frac{1}{1+e^{-x}}. \quad (1)$$

(7) Learning rate (η): 0.01~1.0.

(8) Batch learning.

The procedure for determining the parameter values is now described. After pre-classification, a portion of the adopted examples in each category is fed as "training examples" into the FBPN to determine the parameter values for the category. Two phases are involved at the training stage. At first, in the forward phase, inputs are multiplied with weights, summated, and transferred to the hidden layer. Then activated signals are outputted from the hidden layer as:

$$\begin{aligned}\tilde{h}_j &= (h_{j1},\ h_{j2},\ h_{j3}) = \frac{1}{1+e^{-\tilde{n}_j^h}} \\ &= \left(\frac{1}{1+e^{-n_{j1}^h}},\ \frac{1}{1+e^{-n_{j2}^h}},\ \frac{1}{1+e^{-n_{j3}^h}}\right)\end{aligned} \tag{2}$$

where

$$\begin{aligned}\tilde{n}_j^h &= (n_{j1}^h,\ n_{j2}^h,\ n_{j3}^h) = \tilde{I}_j^h (-) \tilde{\theta}_j^h \\ &= (I_{j1}^h - \theta_{j3}^h,\ I_{j2}^h - \theta_{j2}^h,\ I_{j3}^h - \theta_{j1}^h)\end{aligned} \tag{3}$$

$$\begin{aligned}\tilde{I}_j^h &= (I_{j1}^h,\ I_{j2}^h,\ I_{j3}^h) = \sum_{all\ i} \tilde{w}_{ij}^h (\times) \tilde{x}_{(i)} \\ &\cong \Big(\sum_{all\ i} \min(w_{ij1}^h x_{(i)1},\ w_{ij3}^h x_{(i)3}),\ \sum_{all\ i} w_{ij2}^h x_{(i)2}, \\ &\quad \sum_{all\ i} \max(w_{ij1}^h x_{(i)1},\ w_{ij3}^h x_{(i)3})\Big)\end{aligned} \tag{4}$$

and $(-)$ and $(\times)$ denote fuzzy subtraction and multiplication, respectively; $\tilde{h}_j$'s are also transferred to the output layer with the same procedure. Finally, the output of the FBPN is generated as:

$$\begin{aligned}\tilde{o} &= (o_1,\ o_2,\ o_3) = \frac{1}{1+e^{-\tilde{n}^o}} \\ &= \left(\frac{1}{1+e^{-n_1^o}},\ \frac{1}{1+e^{-n_2^o}},\ \frac{1}{1+e^{-n_3^o}}\right)\end{aligned} \tag{5}$$

where

$$\begin{aligned}\tilde{n}^o &= (n_1^o,\ n_2^o,\ n_3^o) = \tilde{I}^o (-) \tilde{\theta}^o \\ &= (I_1^o - \theta_3^o,\ I_2^o - \theta_2^o,\ I_3^o - \theta_1^o)\end{aligned} \tag{6}$$

$$\begin{aligned}\tilde{I}^o &= (I_1^o,\ I_2^o,\ I_3^o) = \sum_{all\ j} \tilde{w}_j^o (\times) \tilde{h}_j \\ &\cong \Big(\sum_{all\ j} \min(w_{j1}^o h_{j1},\ w_{j3}^o h_{j3}),\ \sum_{all\ j} w_{j2}^o h_{j2}, \\ &\quad \sum_{all\ j} \max(w_{j1}^o h_{j1},\ w_{j3}^o h_{j3})\Big)\end{aligned} \tag{7}$$

To improve the practical applicability of the FBPN and to facilitate the comparisons with conventional techniques, the fuzzy-valued output $\tilde{o}$ is defuzzified according to the centroid-of-area (COA) formula:

$$o = \mathrm{COA}(\tilde{o}) = \frac{o_1 + 2o_2 + o_3}{4} \tag{8}$$

Then the defuzzified output o is applied to predict the actual cycle time a, for which the RMSE is calculated:

$$RMSE = \sqrt{\frac{\sum_{\text{all examples}} (o-a)^2}{\text{number of examples}}} \tag{9}$$

Subsequently in the backward phase, the deviation between o and a is propagated backward, and the error terms of neurons in the output and hidden layers can be calculated, respectively, as

$$\delta^o = o(1-o)(a-o) \tag{10}$$

$$\begin{aligned}\tilde{\delta}_j^h &= (\delta_{j1}^h,\ \delta_{j2}^h,\ \delta_{j3}^h) = \tilde{h}_j (\times)(1-\tilde{h}_j)(\times)\tilde{w}_j^o \delta^o \\ &\cong (\min(\min(h_{j1}(1-h_{j3})w_{j1}^o,\ h_{j3}(1-h_{j1})w_{j1}^o)\delta^o, \\ &\quad \max(h_{j3}(1-h_{j1})w_{j3}^o,\ h_{j1}(1-h_{j3})w_{j3}^o)\delta^o), \\ &\quad h_{j2}(1-h_{j2})w_{j2}^o\delta^o,\ \max(\min(h_{j1}(1-h_{j3})w_{j1}^o, \\ &\quad h_{j3}(1-h_{j1})w_{j1}^o)\delta^o,\ \max(h_{j3}(1-h_{j1})w_{j3}^o, \\ &\quad h_{j1}(1-h_{j3})w_{j3}^o)\delta^o))\end{aligned} \tag{11}$$

Based on them, adjustments that should be made to the connection weights and thresholds can be obtained as

$$\begin{aligned}\Delta\tilde{w}_j^o &= (\Delta w_{j1}^o,\ \Delta w_{j2}^o,\ \Delta w_{j3}^o) = \eta\delta^o \tilde{h}_j \\ &= \eta\delta^o(\min(h_{j1},\ h_{j3}), h_{j2}, \max(h_{j1},\ h_{j3}))\end{aligned} \tag{12}$$

$$\begin{aligned}\Delta\tilde{w}_{ij}^h &= (\Delta w_{ij1}^h,\ \Delta w_{ij2}^h,\ \Delta w_{ij3}^h) = \eta\tilde{\delta}_j^h (\times)\tilde{x}_i \\ &\cong \eta(\min(\delta_{j1}^h x_{i1},\ \delta_{j1}^h x_{i3},\ \delta_{j3}^h x_{i1},\ \delta_{j3}^h x_{i3}),\ \delta_{j2}^h x_{i2}, \\ &\quad \max(\delta_{j1}^h x_{i1},\ \delta_{j1}^h x_{i3},\ \delta_{j3}^h x_{i1},\ \delta_{j3}^h x_{i3}))\end{aligned} \tag{13}$$

$$\Delta\theta^o = -\eta\delta^o \tag{14}$$

$$\begin{aligned}\Delta\tilde{\theta}_j^h &= (\Delta\theta_{j1}^h,\ \Delta\theta_{j2}^h,\ \Delta\theta_{j3}^h) = -\eta\tilde{\delta}_j^h \\ &= (-\eta\delta_{j3}^h,\ -\eta\delta_{j2}^h,\ -\eta\delta_{j1}^h)\end{aligned} \tag{15}$$

Theoretically, network-learning stops when the RMSE falls below a pre-specified level, or the improvement in the RMSE becomes negligible with more epochs, or a large number of epochs have already been run. Then test examples are fed into the FBPN to evaluate the accuracy of the network that is also measured with the RMSE. However, the accumulation of fuzziness during the training process continuously increases the lower bound, the upper bound, and the spread of the fuzzy-valued output $\tilde{o}$ (and those of many other fuzzy parameters), and might prevent the RMSE (calculated with the defuzzified output o) from converging to its minimal value. Conversely, the centers of some fuzzy parameters are becoming smaller and smaller because of network learning. It is possible that a fuzzy parameter becomes invalid in the sense that the lower bound higher than the center. To deal with this problem, the lower and upper bounds of all fuzzy numbers in the FBPN will no longer be modified if the following index converges to a minimal value

$$\alpha\sqrt{\frac{\sum_{\text{all examples}} \min((o_1-a)^2,\ (o_3-a)^2)}{\text{number of examples}}} + (1-\alpha)$$

$$\sqrt{\frac{\sum_{\text{all examples}} \max((o_1 - a)^2,\ (o_3 - a)^2)}{\text{number of examples}}}$$

$0<\alpha<1$ (16)

Finally, the FBPN can be applied to predicting the cycle time of a new lot. When a new lot is released into the fab, the six parameters associated with the new lot are recorded and compared with those of each category center. Then the FBPN with the parameters of the nearest category center is applied to forecasting the cycle time of the new lot. In this study, the SOM was implemented on the software "NeuroSolutions 4.0", while a VB.NET program has been constructed to implement the FBPN.

3 PS for Generating Test Data

In practical situations, the history data of each lot is only partially available in the factory. Further, some information of the previous lots such as Q_n, BQ_n, and FQ_n is not easy to collect on the shop floor. Therefore, a simulation model is often built to simulate the manufacturing process of a real wafer fabrication factory [1-5, 8, 11]. Then, such information can be derived from the shop floor status collected from the simulation model [3]. To generate test data, a simulation program coded using Microsoft Visual Basic .NET is constructed to simulate a wafer fabrication environment with the following assumptions:

(1) The distributions of the interarrival times of orders are exponential.
(2) The distributions of the interarrival times of machine downs are exponential.
(3) The distribution of the time required to repair a machine is deterministic.
(4) The percentages of lots with different product types in the fab are predetermined. As a result, this study is only focused on fixed-product-mix cases. However, the product mix in the simulated fab does fluctuate and is only approximately fixed in the long term.
(5) The percentages of lots with different priorities released into the fab are controlled.
(6) The priority of a lot cannot be changed during fabrication.
(7) Lots are sequenced on each machine first by their priorities, then by the first-in-first-out (FIFO) policy. Such a sequencing policy is a common practice in many foundry fabs.
(8) A lot has equal chances to be processed on each alternative machine/head available at a step.
(9) A lot cannot proceed to the next step until the fabrication on its every wafer has been finished.
(10) No preemption is allowed.

The basic configuration of the simulated wafer fab is the same as a real-world wafer fabrication factory which is located in the Science Park of Hsin-Chu, Taiwan, R.O.C. A trace report was generated every simulation run for verifying the simulation model. The simulated average cycle times have also been compared with the actual values to validate the simulation model, and the deviations were considered small. Assumptions (1)~(3), and (7)~(9) are commonly adopted in related researches (e.g. [2-5]), while assumptions (4)~(6) are made to simplify the situation. There are five products (labeled as A~E) in the simulated fab. A fixed product mix is assumed. The percentages of these products in the fab's product mix are assumed to be 35%, 24%, 17%, 15%, and 9%, respectively. The simulated fab has a monthly capacity of 20,000 pieces of wafers and is expected to be fully utilized (utilization = 100%). POs with normally distributed sizes (mean = 300 wafers; standard deviation = 50 wafers) arrive according to a Poisson process, and then the corresponding MOs are released for these POs a fixed time after. Based on these assumptions, the mean inter-release time of MOs into the fab can be obtained as (30.5 * 24) / (20000 / 300) = 11 hours. An MO is split into lots of a standard size of 24 wafers per lot. Lots of the same MO are released one by one every 11 / (300/24) = 0.85 hours. Three types of priorities (normal lot, hot lot, and super hot lot) are randomly assigned to lots. The percentages of lots with these priorities released into the fab are restricted to be approximately 60%, 30%, and 10%, respectively. Each product has 150~200 steps and 6~9 reentrances to the most bottleneck machine. The singular production characteristic "reentry" of the semiconductor industry is clearly reflected in the example. It also shows the difficulty for the production planning and scheduling people to provide an accurate due-date for the product with such a complicated routing. Totally 102 machines (including alternative machines) are provided to process single-wafer or batch operations in the fab. Thirty replicates of the simulation are successively run. The time required for each simulation replicate is about 12 minute on a PC with 512MB RAM and Athlon™ 64 Processor 3000+ CPU. A horizon of twenty-four months is simulated. The maximal cycle time is less than three months. Therefore, four months and an initial WIP status (obtained from a pilot simulation run) seemed to be sufficient to drive the simulation into a steady state. The statistical data were collected starting at the end of the fourth month. For each replicate, data of 30 lots are collected and classified by their product types and priorities. Totally, data of 900 lots can be collected

as training and testing examples. Among them, 2/3 (600 lots, including all product types and priorities) are used to train the network, and the other 1/3 (300 lots) are reserved for testing.

The time series plot of 100 simulated cycle time data is shown in Fig. 1. As we can observe here, the pattern of the cycle time is not stable and very non-stationary. The traditional approach by human decision is very inaccurate and very prone to failure when the shop status is totally different even for the same product.

4 Results and Discussions

To evaluate the effectiveness and efficiency of the proposed methodology and to make some comparisons with two existing approaches – FBPN without example classification, and EFR, all the three methods were applied to five test cases containing the data of full-size (24 wafers per lot) lots with different product types and priorities. The minimal RMSEs achieved by applying the three approaches to different cases were recorded and compared in Table 1. The convergence condition was established as either the improvement in the RMSE becomes less than 0.001 with one more epoch, or 1000 epochs have already been run. According to experimental results, the following discussions are made:

(1) From the effectiveness viewpoint, the prediction accuracy (measured with the RMSE) of the hybrid SOM-FBPN approach was significantly better than those of the other approaches in most cases by achieving a 15%~45% (and an average of 31%) reduction in the RMSE over the comparison basis – the FBPN. There is only one exception, A (super hot lots), in which the RMSE of the hybrid SOM-FBPN approach was 5% worse than that of EFR. Overall, the prediction accuracy of the hybrid SOM-FBPN approach was still better than that of EFR. The average advantage is 3%.

(2) In the case that the lot priority was the highest (super hot lot), the hybrid approach has the greatest advantage over FBPN in forecasting accuracy. In fact, the cycle time variation of super hot lots is the smallest, which makes their cycle times easy to predict. Clustering such lots seems to provide the most significant effect on the performance of cycle time prediction.

(3) As the lot priority increases, the superiority of the hybrid SOM-FBPN approach over FBPN becomes more evident.

(4) The greatest superiority of the hybrid SOM-FBPN approach over EFR happens when the lot priority is the smallest (normal lots).

5 Conclusion

To further enhance the effectiveness of wafer lot output time prediction, the concept of classifying inputs is applied to Chen's FBPN by pre-classifying input examples into different categories before they are fed into the FBPN. The classification mechanism is SOM, which can serve as a clustering tool for high dimensional data (e.g. production data in a wafer fab). In this way, similar examples are clustered in the same category. Examples of different categories are then learned with the same FBPN but with different parameter values. For evaluating the effectiveness of the proposed hybrid SOM-FBPN approach and to make some comparisons with two existing approaches – FBPN without example classification, and EFR, production simulation is applied in this study to generate test data. Then all the three methods are applied to five cases elicited from the test data. According to experimental results, the prediction accuracy (measured with the RMSE) of the hybrid SOM-FBPN approach was significantly better than those of the other approaches in most cases by achieving a 15%~45% (and an average of 31%) reduction in the RMSE over the comparison basis – the FBPN. The average advantage of SOM-FBPN over EFR is 3%.

However, to further evaluate the effectiveness and efficiency of the proposed methodology, it has to be applied to fab models of different scales, especially a full-scale actual wafer fab. In addition, the proposed methodology can also be applied to cases with changing product mixes or loosely controlled priority combinations, under which the cycle time variation is often very large.

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Table 1. Comparisons of the RMSEs of various approaches

RMSE	FBPN	EFR	SOM-FBPN
A(normal lots)	177.1	164.29(-7%)	151.34(-15%)
A(hot lots)	102.27	66.21(-35%)	63.66(-38%)
A(super hot lots)	12.23	9.07(-26%)	9.72(-21%)
B(normal lots)	286.93	208.28(-27%)	188.55(-34%)
B(hot lots)	75.98	44.57(-41%)	41.43(-45%)

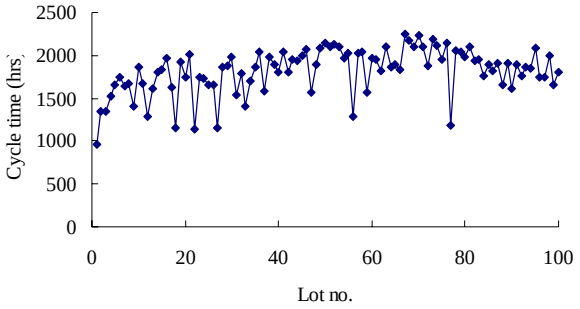

Fig. 1. Time series plot of cycle time (product A, normal lots)