Estimating the Job Cycle Time in Wafer Fabrication with Distributed Sensors

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Abstract

Estimating the job cycle time is very important for the control of a factory. However, the uncertainty in the job cycle time is not easy to deal with. In order to effectively estimate the job cycle time in a wafer fabrication factory, a group of distributed sensors are used in this study. In the proposed methodology, each sensor monitors the factory conditions, and uses a fuzzy neural network to estimate the job cycle time, based on its local observation. Each sensor communicates its view and estimates to other sensors with the aid of the central control unit. According to the experimental results, the aggregate estimation performance was considerably improved through the sensors' collaboration.

Keywords: Distributed sensor, Fuzzy neural network, Cycle time, Wafer fabrication.

1. Introduction

A group of distributed sensors is used in this study for estimating the job cycle time in a wafer fabrication factory, which is an important topic and has received a lot of attention [1]. Distributed sensor network is remarkable for its promising use on human-unattended information collection [2]. Wang et al. [2] mentioned that there are two performance measures in evaluating the optimal routing performance of a distributed sensor network – the network lifetime finally acquired and the total information finally collected. However, in different circumstances, the targets may not be the same. In Yan et al. [3], it was found that opportunistic collaboration can reach better performance than direct transmission. This also affects the design of our mechanisms for collaboration. Sang et al. [4] developed a sensor network testbed. A good literature review of sensor networks can be found in Yick et al. [5]. Network based sensing has become an important field of research, and new applications of remote sensing are expected to appear. A synchronized sensor network is system was developed in Uchimura et al. [4] for vibration measurement. It is now possible to obtain environment information from difficult to reach places [6]. In Morreale's opinions [7], sensor networks have potential applications in urban telehealth.

The existing approaches to estimate the cycle time of a job in a wafer fabrication factory can be classified into the following categories [8]: statistical analysis, simulation, artificial neural networks (ANN), case-based reasoning (CBR), fuzzy theory, and hybrid approaches. A comprehensive comparison of these approaches can be found in reference [9]. Recently, various research works has been dedicated to estimate the cycle time using hybrid approaches. Some approaches classified jobs before estimating the cycle times, i.e., the preclassifying approaches. However, there are so many classification methods. Which one is most suitable for our purpose? In addition, can we develop a new classification method that can help to further improve the performance of cycle time estimation? To solve these problems, some

actions have been taken in the literature. For example, a postclassification fuzzy–neural approach can be used in which a job was not preclassified but rather postclassified after estimating the cycle time. In preclassifying approaches, jobs with similar attributes are classified into the same category according to various attributes. However, there is no absolute measure of the similarity between the jobs. On the contrary, in postclassification approaches, jobs with the same cycle time estimating accuracy will be gathered in the same category and the classification algorithm is to be tailored to the estimation approach. However, the classification of a job takes only the estimation error into account, not all the attributes is difficult. In order to effectively estimate the job cycle time, a group of distributed sensors are used in this study. Why a system that seems complex, time consuming, and requires the collaboration of a number of sensors is used in this study? Although the existing methods can provide the same job cycle time estimate in a more realistic manner and in a shorter time, the estimation accuracy is often far from perfect, mainly due to unpredictable changes in the factory conditions. On the contrary, a collaborative intelligence approach has a rich potential to improve the accuracy of estimation [10, 11]. In addition, seeing a problem from various perspectives ensures that no parts are ignored when solving the problem.
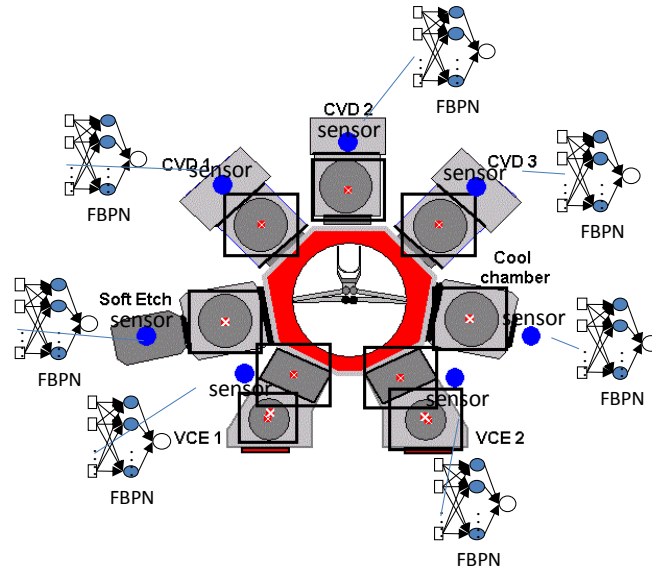
In the proposed methodology, a group of distributed sensors is used. These sensors are programmed to monitor factory conditions based on their local observations, and may not share the raw data they own with each other. A collaboration mechanism is therefore established. For each sensor, a fuzzy back propagation network (FBPN) reasoning module is equipped to estimate the job cycle time, based on the administrator's point of view. To facilitate the collaboration process and to aggregate these observations, the central control unit is equipped with a radial basis function network (RBF) reasoning module. Therefore, the whole system is built on a centralized point-to-point (P2P) communication architecture.

The remainder of this paper is organized as follows. Section 2 introduces the proposed methodology. In section 3, the case of a real wafer fabrication factory is used to demonstrate the application of the proposed methodology. The performance of the proposed methodology is evaluated and compared with those of some existing approaches. Based on the results of the analysis, some points are made. Finally, the concluding remarks and some directions for future research are given in Section 4.

2. Methodology

The proposed methodology (see Figure 1) consists of several steps:

(1) The proposed methodology starts from the deployment of a group of sensors.

(2) The administrators of these sensors are asked to put forward their settings that are incorporated into the sensors' FBPN reasoning modules.

(3) Each sensor estimates the job cycle time using the FBPN.

(4) Each sensor communicates its setting and estimates to other sensors with the aid of the central control unit. After receiving the setting and estimates of others, a sensor may be affected to modify its setting.

(5) To aggregate the estimates, a RBF network is employed.

Figure 1. The Group of Distributed Sensors

In the proposed methodology, each sensor detects the following information of the factory:

(1) The equipment utilization information.

(2) The job queuing information on the processing route.

(3) The job queuing information before bottlenecks.

(4) The factory workload information.

(5) The delay status of some recently completed jobs.

and uses a FBPN to aggregate these information. Although there have been some more advanced artificial neural networks, such as ccompositional pattern-producing network, cascading neural network, and ddynamic neural network, a well-trained FBPN with an optimized structure can still produce very good results [13]. That is why it is selected in this study:

(1) Inputs: the five types of information detected by the sensor. To facilitate the search for solutions, it is strongly recommended to normalize the inputs to a range narrower than [0 1] [12]:

$$N(x) = N_L + \frac{x - x_{min}}{x_{max-}x_{min}} \cdot (N_U - N_L), \qquad (1)$$

where $N(x)$ is the normalized value of x; N_L and N_U indicate the lower and upper bounds of the range of the normalized value, respectively. x_{min} and x_{max} are the minimum and maximum of x, respectively. The formula can be written as

$$x = \frac{N(x) - N_L}{N_U - N_L} \cdot (x_{max-}x_{min}) + x_{min}, \qquad (2)$$

if the un-normalized value is to be obtained instead.

(2) The FBPN has only one hidden layer. Two or more hidden layers slow down the convergence speed, and may not lead to any better solution. The number of nodes in the hidden layer is chosen from 1 to $2K$ after trying each of them.

(3) The output from the FBPN is the job cycle time estimate by the sensor.

(4) The activation function used for the hidden layer is the hyperbolic tangent sigmoid function, and for the others is the linear activation function.

(5) 70000 epochs will be run each time. The start conditions will be randomized to reduce the possibility of being stuck on local optima.

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:

$$\tilde{h}_l = (h_{l1},\ h_{l2},\ h_{l3}) = \frac{1}{1+e^{-\tilde{n}_l^h}} = (\frac{1}{1+e^{-n_{l1}^h}},\ \frac{1}{1+e^{-n_{l2}^h}},\ \frac{1}{1+e^{-n_{l3}^h}}),\tag{3}$$

where

$$\tilde{n}_l^h = (n_{l1}^h,\ n_{l2}^h,\ n_{l3}^h) = \tilde{I}_l^h(-)\tilde{\theta}_l^h = (I_{l1}^h - \theta_{l3}^h,\ I_{l2}^h - \theta_{l2}^h,\ I_{l3}^h - \theta_{l1}^h),\tag{4}$$

$$\tilde{I}_l^h = (I_{l1}^h,\ I_{l2}^h,\ I_{l3}^h) = \sum_{all\ k} \tilde{w}_{kl}^h \cdot x_k$$
$$= (\sum_{all\ k} \min(w_{kl1}^h x_k,\ w_{kl3}^h x_k),\ \sum_{all\ k} w_{xk2}^h x_k,\ \sum_{all\ k} \max(w_{kl1}^h x_k,\ w_{kl3}^h x_k)),\tag{5}$$

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

$$\tilde{o}_i = (o_{i1},\ o_{i2},\ o_{i3}) = \frac{1}{1+e^{-\tilde{n}^o}} = (\frac{1}{1+e^{-n_1^o}},\ \frac{1}{1+e^{-n_2^o}},\ \frac{1}{1+e^{-n_3^o}}),\tag{6}$$

where

$$\tilde{n}^o = (n_1^o,\ n_2^o,\ n_3^o) = \tilde{I}^o(-)\tilde{\theta}^o = (I_1^o - \theta_3^o,\ I_2^o - \theta_2^o,\ I_3^o - \theta_1^o),\tag{7}$$

$$\tilde{I}^o = (I_1^o, I_2^o, I_3^o) = \sum_{all\ l} \tilde{w}_l^o(\times)\tilde{h}_l$$
$$\cong (\sum_{all\ l} \min(w_{l1}^o h_{l1},\ w_{l3}^o h_{l3}),\ \sum_{all\ l} w_{l2}^o h_{l2},\ \sum_{all\ l} \max(w_{l1}^o h_{l1},\ w_{l3}^o h_{l3})).\tag{8}$$

Subsequently in the backward phase, the training of the FBPN is decomposed into three subtasks: determining the center values, upper, and lower bounds of the parameters.

First, to determine the center value of each fuzzy parameter (such as w_{kl2}^h, θ_{l2}^h, w_{l2}^o, and θ_2^o), the FBPN is treated as a crisp one. Some algorithms are applicable for training a crisp feed-forward neural network (FNN), such as the gradient descent (GD) algorithms, the conjugate gradient algorithms, and others.

Subsequently, the following goal programming (GP) problem is solved to determine the upper bound of each fuzzy parameter (e.g. w_{kl3}^h, θ_{l3}^h, w_{l3}^o, and θ_3^o), so that the actual value will be less than the upper bound of the network output:

$$\text{Min} \sum_{\text{all } i} \pi_i(g) \tag{9}$$

subject to

$$\ln(\frac{1}{o_{i3}} - 1) = \theta_3^o - \sum_{\text{all } l} w_{l3}^o h_{l3}, \tag{10}$$

$$\sum_{\text{all } l} w_{l3}^o h_{l3} - \theta_3^o = -\ln(1/\pi_i(g) - 1), \tag{11}$$

$$\sum_{\text{all } l} w_{l3}^o h_{l3} - \theta_3^o \leq -\ln(1/\Psi(g) - 1), \tag{12}$$

$$\sum_{\text{all } l} w_{l3}^o h_{l3} \leq \theta_3^o - \ln(\frac{1 - s_R(g)}{a_i - s_R(g)o_{i2}} - 1), \tag{13}$$

$$\sum_{\text{all } l} w_{l3}^o h_{l3} \geq \theta_3^o - \ln(\frac{1}{a_i} - 1), \tag{14}$$

$$\sum_{\text{all } k} w_{kl3}^h x_k - \theta_{l3}^h \geq -\ln(1/h_{l3} - 1), \tag{15}$$

$$\sum_{\text{all } k} w_{kl3}^h x_k - \theta_{l3}^h \leq -\ln(1/h_{l3} - 1), \tag{16}$$

$$k = 1 \sim K, \tag{17}$$

$$l = 1 \sim L \text{ (the number of hidden-layer nodes)}, \tag{18}$$

In a similar way, another GP problem is solved to determine the lower bound of each fuzzy parameter (e.g. w_{kl1}^h, θ_{l1}^h, w_{l1}^o, and θ_1^o), so that the actual value will be greater than the lower bound of the network output. The estimates by all sensors can be communicated to each other,

so that they can modify their views, and generate more accurate monitoring results if all viewpoints are taken into account.

Subsequently, a RBF is used to aggregate the estimates. The RBF network has three layers: the input, hidden (middle) and output layers. Inputs to the RBF are the estimates by all sensors. Each input is assigned to a node in the input layer and passed directly to the hidden layer without being weighted. The transfer function used for the hidden layer is Gaussian transfer function, while the output layer uses the linear transfer function. For determining the parameter values, k-means (KM) is first used to find out the centers of the RBF units. Subsequently, the nearest-neighbor method is used to determine their widths. The weights of the connections can be obtained by linear regression.

3. Experiment

To illustrate the application of the proposed methodology, a real case containing the data of 500 jobs has been collected from a wafer fabrication factory located in Taichung City Scientific Park, Taiwan. Up to 350 sensors were deployed. Locations near the bottlenecks were first installed.

Three existing approaches, statistical analysis, CBR, and back propagation network (BPN) are also applied to the case. Performance measures including mean absolute error (MAE), mean absolute percentage error (MAPE), and the minimal root mean squared error (RMSE) are evaluated. The performances by applying the three approaches are recorded and compared and are summarized in Table 1. In the BPN approach, there was one hidden layer with 1~12 nodes, depending on the results of a preliminary analysis for establishing the best configuration. The optimal value of parameter k in the CBR approach was equal to the value that minimized the RMSE. In this experiment, $k* = 8$.

According to experimental results, the estimating accuracy in terms of three measures RMSE, MAE, and MAPE has been assessed for each method. The estimating accuracy of MFLR was clearly the worst one, which revealed the nonlinear nature of the problem. Nonlinear approaches such as BPN and the proposed methodology both achieved satisfactory performances in this regard. In particular, the proposed methodology was superior to the three existing methods, by improving MAPE up to 33%.

Table 1: Comparisons of the Performances of Various Approaches

Performance measure	Statistical analysis	CBR	BPN	The proposed methodology
RMSE	77	74	53	18.75
MAE	63	62	43	11.26
MAPE	5%	5%	4%	0.96%

4. Conclusions and Directions for Future Research

Job cycle time has the greatest impact for the factory. Data analysis and estimation in this area is extremely important. There is more and more evidence showing that there is a widespread and long-term trend toward lean production. Job cycle time estimation is considered to be one of the most important tasks to this end.

Many evidences also revealed that collaborative intelligence have potential applications in job cycle time estimation. On the other hand, network based sensing has become an important

field of research, and new applications of remote sensing are expected to appear. In order to effectively estimate the job cycle time, a group of distributed sensors are used in this study. In the proposed methodology, each sensor monitors the factory conditions, and uses the FBPN to estimate the job cycle time. Each sensor communicates its view and estimates to other sensors with the aid of the central control unit. After receiving this information, the sensors may change their settings, based on the RBF collaboration mechanism.

After applying the proposed methodology to a wafer fabrication factory, the following experimental results were obtained:

(1) The aggregate estimation performance was considerably improved through the sensors' collaboration. Especially, the MAE, MAPE, and RMSE of estimating the job cycle time by the proposed methodology was satisfactory.

(2) It is therefore possible to estimate the job cycle time very precisely and accurately using a group of sensors governed by a centralized collaboration mechanism.

More sophisticated collaboration mechanisms can be developed in similar ways in future studies. However, the computation becomes very complicated if many sensors are involved. For this reason, future studies may restrict the size of the sensor coalition.

Acknowledgements

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