INTRODUCTION

Semiconductor manufacturing is a highly competitive industry. To become an agile supplier, shorting the cycle time of every operation is the most critical step. For this purpose, a number of strategies are applicable, such as downsizing, lean production, better scheduling, and others. In order to allocate limited resources in these strategies, precisely estimating their benefits is a pre-requisite, which relies on the accurate cycle time estimates.

A number of studies (Chen, 2003, 2008a; Pai et al., 2004) have stressed the importance of cycle time estimation to the management of a semiconductor manufacturing factory.

However, in a reentrant production system such as a semiconductor manufacturing factory, the cycle time of a job depends not only on the progresses of jobs that have been released, but also on jobs that will be released in the future, which constitutes a complex issue involving much uncertainty.

Semiconductor manufacturing is generally split into four main phases: wafer fabrication, wafer probe, packaging, and final test. This study is focused on the wafer fabrication phase, which usually takes several months and is the top priority for improvement.

The existing approaches to estimate the cycle time of a job in a wafer fabrication factory can be classified into the following categories (Chen, 2006): statistical analysis (Raddon & Grigsby, 1997; Hung & Chang, 2002), simula-
tion, artificial neural networks (ANN) (Chang & Hsieh, 2003; Haller et al., 2003; Chang et al., 2005; Chen, 2009; Kuo et al., 2010), case-based reasoning (CBR) (Chang et al., 2001), fuzzy theory (Haller et al., 2003; Chen, 2006; Hsiao et al., 2005; Chen et al., 2010), and hybrid approaches (Chen, 2006). A comprehensive comparison of these approaches can be found in reference (Chen, 2007a). In addition, Chen et al. (2009) considered a special case in which the cycle time of a job in a ramping-up wafer fabrication factory is to be estimated. Chung and Huang (2002) considered the special condition in a wafer fabrication factory with engineering lots. Moreover, an internal due date is usually based on the estimated cycle time. Therefore, research on internal due date assignment should also be investigated (e.g., Wilamowsky et al., 1996; Behnamian et al., 2009).

Recently, various research work has been dedicated to estimate the cycle time using hybrid approaches. Some approaches classified jobs before estimating the cycle times, i.e., the pre-classifying approaches. For example, Chang et al. (2005) modified the first step (i.e., partitioning the range of each input variable into several fuzzy intervals) of the fuzzy modeling method proposed by Wang and Mendel (1992), known as the WM method, with a simple genetic algorithm (GA) and proposed the evolving fuzzy rule (EFR) approach to estimate the cycle time of a job in a wafer fabrication factory. Their EFR approach was superior to CBR and ANN in terms of estimating accuracy. Another pre-classifying fuzzy-neural approach was proposed in Chang and Liao (2006) by combining self-organization map (SOM) and WM, in which a job was classified using SOM before estimating the cycle time of the job with WM. Chen (2007a) constructed a look-ahead k-means (kM)-fuzzy back propagation network (FBPN) for the same purpose, and provided a detailed discussion of the effects of using different look-ahead function. Subsequently, Chang and Liao (2006) proposed a hybrid method of SOM and CBR. Simulated data were used to validate the effectiveness of the proposed methodology. Chen (2007b) proposed the look-ahead SOM-FBPN approach. A set of fuzzy inference rules were also developed to evaluate the achievability of a cycle time forecast. Chen et al. (2008b) then added a selective allowance to the cycle time estimated using the look-ahead SOM-FBPN approach to determine the internal due date. For the same purpose, Chen and Wang (2010) constructed a nonlinear programming model to modify the cycle time estimated using the hybrid fuzzy c-means (FCM) and BPN approach (Chen, 2007c). Chen et al. (2009) applied the FCM-FBPN approach to estimate the remaining cycle time at a processing step. Chen and Lin (2010) proposed the concept of an inclusion interval that was added to the cycle time forecast to improve the performance of on-time delivery. Large amount of data and difficulty of use are the shortcoming of hybrid approaches. However, hybrid approaches are one of the most accurate cycle time estimation approaches.

The performance of an artificial neural network depends largely on the correct choice of input variables. However, few attempts have been made by the existing approaches to improve the forecasting performance with variable replacement, which is already a well-known technique in other application fields. For example, Li et al. (2009) combined principal component analysis (PCA) and support vector machine (SVM) for long-term load forecasting. In this field, Chen (2003) formed a group of domain experts, which was asked to assess the importance of each variable to the estimation of the job cycle time. The original value of a variable is then multiplied by its weight. The result replaces the original variable and becomes a new input to the FBPN. In this study, we apply principal component analysis (PCA), which is a multivariate statistical analysis method. This method constructs a series of linear combinations of the original variables to form a new variable, so that these new variables are unrelated to each other as much as possible to reflect information in a better way.

To further improve the performance of cycle time estimation in a wafer fabrication factory, a hybrid PCA and FBPN approach is presented in this study. Instead of using the
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