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Applying the hybrid fuzzy c-means-back propagation network approach to forecast the effective cost per die of a semiconductor product

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A R T I C L E I N F O

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A B S T R A C T

Forecasting the unit cost of every product type in a factory is an important task to the factory. After the unit cost of every product type in a factory is accurately forecasted, several managerial goals (including pricing, cost down projecting, capacity planning, ordering decision support, and guiding subsequent operations) can be simultaneously achieved. However, it is not easy to deal with the uncertainty in the unit cost. In addition, most references in this field were focused on costing and seldom investigated the forecasting of the unit cost. To tackle these problems, the hybrid fuzzy linear regression (FLR) and back propagation network (BPN) approach is applied to forecast the unit cost of every product type in a wafer fabrication plant, which is usually referred to as the determination of the effective cost per die. In practical situations the long-term effective cost per die of a product type is usually approximated with a linear regression (LR) equation, according to the "continuous cost down" philosophy, which is prone to error. Conversely, the proposed FLR–BPN approach is more accurate and be able to deal with the uncertainty in the unit cost in a simple and intuitive way. For evaluating the effectiveness of the proposed methodology, a demonstrative case was used. Experimental results showed that the hybrid FLR–BPN approach was superior to some existing approaches in forecasting accuracy and precision.

1. Introduction

Forecasting the unit cost of every product type in a factory is an important task to the factory because of the following reasons:

(1) If the future cost is over-forecasted, then the efforts and investment on cost reduction might be wasted.
(2) Conversely, if the future cost is under-forecasted, then the profitability of the product will be over-forecasted, which leads to incorrect investment and production decisions.

After the unit cost of every product type in a factory is accurately forecasted, several managerial goals (including pricing, cost down projecting, capacity planning, ordering decision support, and guiding subsequent operations) can be simultaneously achieved. However, it is not easy to deal with the uncertainty in the unit cost of a product type, especially in a wafer fabrication factory which is known a very complicated production system. In addition, most references in this field were focused on costing (i.e. to reasonably distribute all related expenses among all product types) and seldom investigated the forecasting of the unit cost. Carnes (1991) established the basic equation for calculating the unit cost of a wafer. Carnes also compared the long-term costs of owning two alternative machines, but did not distribute the costs among the product types made on these two machines. Wood (1997) defined the minimum wafer cost as the minimum costs of all operations by the same machine. In Pfitzner et al.'s viewpoint, reclaiming wafers becomes more and more important in reducing the unit cost as the size of wafer grows (Pfitzner et al., 2001).

There are two unit costs in a wafer fabrication factory, i.e. the unit costs of a wafer or a die. To calculate or forecast the unit cost of a wafer, many factors including factory capacity, factory utilization, the depreciation approach, technology (line width, number of mask layers) have to be taken into account (icknowledge.com, 2003). When these factors are stable, the fluctuation in the unit cost of a wafer can be controlled. There are three parts constituting the unit cost of a wafer: material costs, labor costs, and overhead costs. The unit cost can also be further broken down into the following items: depreciation, tool maintenance, direct labor, indirect labor, facilities, material, consumables, and monitors. In other words, to forecast the future unit cost of a wafer, you need to foresee the possible changes in these items, which is really a tough task. On the other hand, the unit cost of a die is dependent on the die yield (or the defect density) of the product type which is stochastic and difficult to forecast. Nevertheless, the unit cost of a die basically follows a learning process, which provides an opportunity of grasping the future trend of the unit cost. There are four types of learning processes: negative acceleration, positive

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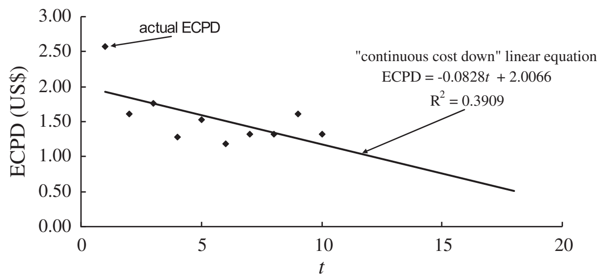

Fig. 1. Linear model of the ECPD.

acceleration, plateaus, and ogive (Bills, 1934). Describing the cost improvement process as a learning process belongs to the "negative acceleration" category and dated back to Wright (1936), in which a learning curve was used to denote the relationship between the unit cost and the cumulative output in a stable process. It also denoted the relationship between the unit defect rate and the cumulative output in the stable process. In the practice, the unit cost per die is often derived from the estimated yield. This study is also based on the same concepts.

There are several ways of representing the unit cost of a die. Among them, the effective cost per die (ECPD) is the most commonly used one. The ECPD is calculated by dividing the unit wafer cost by the average number of good dies on a wafer. The ECPD is important because it can be compared with the price of the product type in evaluating the profitability. In practical situations the trend in the ECPD is usually approximated with a linear equation (see Fig. 1), according to the management philosophy of "continuous cost down". The linear model is subjective and might be prone to error. Considering the example in Fig. 1, the coefficient of determination (R^2) of the linear model is only 0.3909.

To further enhance the performance of forecasting the ECPD of every product type in a wafer fabrication factory, Chen and Lin's hybrid fuzzy linear regression (FLR)–back propagation network (BPN) approach (Chen & Lin, 2008) is applied in this study. The hybrid FLR–BPN approach has been applied to various fields other than unit cost forecasting. In the proposed methodology, multiple experts (or decision makers) construct their own FLR equations from various viewpoints to forecast the ECPD of a product type. Compared with the existing LR approach, the FLR approach has the following advantages:

(1) An FLR model is more flexible than LR and be able consider the variation in the ECPD.
(2) It is easier to incorporate subjective judgments into an FLR model (Chen & Wang, 1999).
(3) An FLR model might be more precise than LR (Chen & Lin, 2008).

Each FLR model is usually converted into an equivalent linear programming (LP) model (Tanaka & Watada, 1988; Peters, 1994) to be solved, but in Chen and Lin's approach is replaced with two equivalent nonlinear programming (NP) problems (Chen & Lin, 2008) because the incorporation of expert opinions about the effects of outliers changed the objective function to a nonlinear one. The ECPD forecasted with an FLP model is a fuzzy value that contains the actual value. In addition, the ECPD forecasted by different experts might not be equal and therefore need to be aggregated in some way. Further, these expert opinions can also be considered as unequally important. In the hybrid FLR–BPN approach, a two-step aggregation mechanism is applied. At first, fuzzy intersection (FI) is applied to aggregate the fuzzy ECPDs forecasted by different experts into a polygon-shaped fuzzy number, in order to improve the forecasting precision. After that, since the shape of the polygon-shaped fuzzy number is so special, a BPN is constructed to defuzzify the polygon-shaped fuzzy number and to generate a representative/crisp value, so as to enhance the forecasting accuracy.

The rest of this paper is organized as follows. Section 2 introduces the hybrid FLR–BPN which is composed of three steps. A demonstrative example is used to demonstrate the applicability of the proposed methodology. The forecasting accuracy and precision of the proposed methodology are evaluated and compared with those of some existing approaches in Section 3. The advantage of the proposed methodology over the existing approaches is also examined with statistical analyses. Based on analysis results, some points are made. Finally, the concluding remarks and some directions for future research are given in Section 4.

2. The hybrid FLR–BPN approach

Parameters that will be used in this study are defined as follows:

(1) C: the unit wafer cost.
(2) $\tilde{c}_t$: the fuzzy ECPD forecast at period t. $\tilde{c}_t = (c_{t1}, c_{t2}, c_{t3})$ if represented with a triangular fuzzy number (TFN). There are various types of fuzzy numbers with different shapes (see Fig. 2). Among them, a TFN is easily implemented and has been universally applied to numerous applications (e.g. Chen & Wang, 1999; Huang, Chen, & Wang, 2001; Chen, 2003). Further, since at the aggregation stage the focus is on the corners of the FI of fuzzy forecasts, the shapes of the fuzzy forecasts become not that important. Further, a Gaussian or bell-shaped fuzzy number is symmetric, while a TFN is the simplest fuzzy number that can be asymmetric.
(3) c_t: the actual ECPD at time period t.
(4) G: gross die.
(5) T: the current time.
(6) Y_t: the yield at time period t.
(7) Y_0: the asymptotic/final yield.

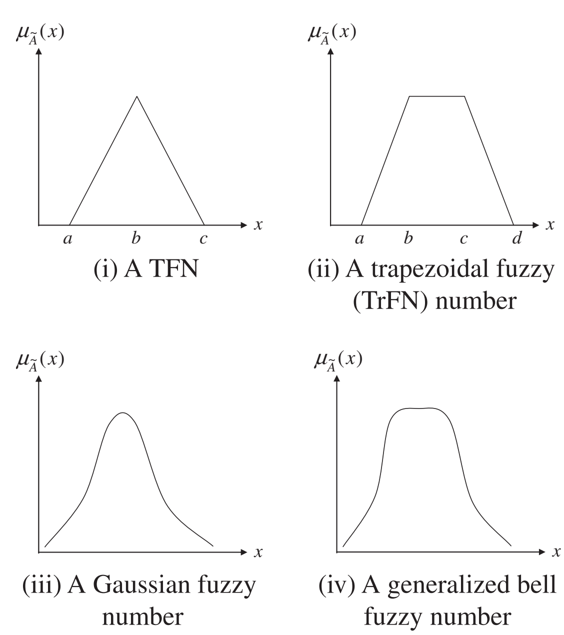

Fig. 2. Some types of fuzzy numbers.