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A collaborative and artificial intelligence approach for semiconductor cost forecasting

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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 a semiconductor product is an important task to the manufacturer. However, it is not easy to deal with the uncertainty in the unit cost. In order to effectively forecast the semiconductor unit cost, a collaborative and artificial intelligence approach is proposed in this study. In the proposed methodology, a group of domain experts is formed. These domain experts are asked to configure their own fuzzy neural networks to forecast the semiconductor unit cost based on their viewpoints. A collaboration mechanism is therefore established. To facilitate the collaboration process and to derive a single representative value from these forecasts, a radial basis function (RBF) network is used. The effectiveness of the proposed methodology is shown with a case study.

1. Introduction

Cost estimation has been studied extensively in various fields, such as product design (Bakker, Parameswariah, & Rajagopal, 2008), construction cost estimates (Dukic, Maric, & Babic, 2007; Moon, Kim, & Kwon, 2007), project management (Dukic et al., 2007), process design (Gudmundsson, Andersson, Durgut, Levik, & Mork, 1999), and so on. Forecasting the unit cost of a semiconductor product is an important task to the manufacturer. The unit cost, taking into account factory capacity, factory utilization, the depreciation approach, and technology (line width, number of mask layers), is considered to be one of the most important measures of operational and financial performance, and should be closely monitored, effectively forecasted, and controlled. A product's profitability is inversely proportional to the unit cost. For this reason, reducing the unit cost of each product type is a very important task to the factory. To this end, effectively forecasting the unit cost is a prerequisite However, forecasting the unit cost is not easy, because it is not easy to deal with the uncertainty in the unit cost. In addition, the range of the unit cost is also important, and the narrowest range should be determined so that the unit cost is neither over-estimated or under-estimated.

Cost forecasting means different things at different stages of the product life cycle. In product design, designers need to know whether the product can be economically produced. Sometimes we forecast the cost of a product in order to set up a budget ceiling for subsequent operations. After a product goes into mass production, the predicted unit cost is the basis of financial and production planning activities. After the unit cost of a semiconductor product is effectively 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; few investigated the forecasting of the unit cost (Chen & Lin, 2008). Carnes (1991) established the basic formula for calculating the unit cost of a wafer. Carnes also compared the long-term costs of two alternative machines, but did not allocate the costs among the products made on these two machines. In Wood (1997), the lowest wafer cost is defined as the lowest costs of all operations by the same machine. To calculate this, a lot of statistics are to be collected (Yager, 2011).

There are two viewpoints to forecasting the semiconductor unit cost. The input–output relationship viewpoint, is to determine the economic, technological, and managerial factors (e.g. technology, equipment investment, government support, bottleneck capacity consumption, etc.) that influence the unit cost, and then apply different approaches (e.g. multiple linear regression (MLR), artificial neural network (ANN), etc.) to model the relationship between the unit cost and these factors, and so forecast the unit cost. The time-series viewpoint, is to treat the fluctuation in the unit cost as a type of time series. Theoretically there are many approaches, e.g. moving average (MA), weighted moving average (WMA),

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exponential smoothing (ES), MLR, ANN, auto-regressive integrated moving average (ARIMA), and others that can be applied to forecast the unit cost. Generally, an ANN is suitable for modeling a short-term nonlinear pattern of the unit cost, while traditional approaches such as MA, WMA and ES provide good performances when the trend in the unit cost is stable. This study belongs to the second category. Chen (in press-b) proposed the hybrid fuzzy linear regression (FLR) and back propagation network (BPN) approach to forecast the unit cost per die in a wafer fabrication plant, which was thought to follow a learning process.

In order to effectively forecast the semiconductor unit cost, a collaborative and artificial intelligence approach is proposed in this study. In the proposed methodology, a group of domain experts is used. These domain experts are asked to configure their own FBPNs to forecast the semiconductor unit cost based on their viewpoints. A collaboration mechanism is therefore established. In Yan, Zheng, and Lin (2009), it was found that opportunistic collaboration can reach better performance than direct transmission. This also affects the design of our mechanisms for collaboration. To facilitate the collaboration process and to derive a single representative value from these forecasts, a radial basis function (RBF) network is used.

The purposes of this study include:

(1) To propose a collaborative and artificial intelligence approach to effectively forecast the semiconductor unit cost, so that long-term operational or managerial planning can be based on it.
(2) To establish a precise interval of the unit cost, making it less likely for the company to raise budget on cost reduction unreasonably.
(3) Reducing the risk of overestimating or underestimating the unit cost.

A practical case of the DRAM unit cost forecasting is used to evaluate the effectiveness of the collaborative and artificial intelligence approach. In the proposed methodology, each domain expert uses a FBPN to predict the DRAM unit cost, based on his/her viewpoint. Each domain expert conveys his/her setting and forecasting results to others with the aid of the central control unit. After receiving this information, if it reveals that the forecasting performance of a domain expert is very prominent, the others may change their settings, so that their settings will move closer. In addition, if a domain expert is not satisfied with the forecast of a specific period, then he/she should reference the forecasts by others.

The remainder of this paper is organized as follows. Section 2 introduces the proposed collaborative and artificial intelligence approach. In Section 3, the case of the DRAM unit cost forecasting 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 operating procedure of the collaborative and artificial intelligence approach consists of several steps that will be described in the following sections:

(1) The collaborative and artificial intelligence approach starts from the formation of a group of domain experts, such as product managers, market researchers, and others.
(2) These domain experts are asked to put forward their settings on certain aspects of forecasting.
(3) Each domain expert predicts the semiconductor unit cost based on his/her own viewpoint.
   (i) Replacing parameters using PCA.
   (ii) Determining the center values of the parameters in FBPN.
   (iii) Determining the upper bounds of the parameters based on the expert's view.
   (iv) Determining the lower bounds of the parameters based on the expert's view.
   (v) Forecasting the unit cost using the FBPN.
(4) Each domain expert conveys his/her setting and forecasting results to others with the aid of the central control unit. After receiving the setting and forecasting results of others, a domain expert may be affected to modify his/her setting.
(5) To arrive at a representative value from the forecasting results, a RBF network is employed.
(6) The collaboration process is terminated if the improvement in the forecasting performance becomes negligible. Otherwise, return to step (4).

The system diagram of the proposed methodology is shown in Fig. 1. Before introducing the details of the collaborative and artificial intelligence approach, we first define all required parameters as follows:

(1) g: the expert number; $g = 1 \sim G$.
(2) G: the number of experts.
(3) a_t: the actual value (after normalization) at period t.
(4) $\widetilde{C}_t(g)$: the unit cost forecast at period t by expert g. $\widetilde{C}_t(g)$ is expressed with a triangular fuzzy number (TFN), i.e. $\widetilde{C}_t(g) = (C_{t1}(g), C_{t2}(g), C_{t3}(g))$.
(5) $s_U(g)$: The extent that the fuzzy forecast by expert g is satisfied with the actual value on the right-hand side (see Fig. 2a).
(6) $s_L(g)$: The extent that the fuzzy forecast by expert g is satisfied with the actual value on the left-hand side (see Fig. 2b).
(7) $t(g)$ includes the indexes of all forecasts in the part domain expert g is satisfied with the forecasts.
(8) $t^c(g)$ is the complement of $t(g)$, i.e. $t^c(g) = [1\ T] - t(g)$.
(9) $\Psi(g)$: The required range of the fuzzy forecast by expert g (see Fig. 2).
(10) $\pi_t(g)$: The range of the fuzzy forecast at period t by expert g.
(11) $x_k(t)$: inputs to the FBPN; $k = 1 \sim K$.
(12) $\tilde{h}_l(t)$: the output from hidden-layer node l; $l = 1 \sim L$.
(13) $\tilde{o}(t)$: the FBPN output, which is the normalized unit cost forecast at period t, i.e. $\tilde{o}_t = N(\widetilde{C}_t)$ where $N()$ is the normalization function.
(14) $\tilde{w}_l^o$: the weight of the connection between hidden-layer node l and the output node.
(15) $\tilde{w}_{kl}^h$: the weight of the connection between input node k and hidden-layer node l; $k = 1 \sim K$; $l = 1 \sim L$.
(16) $\tilde{\theta}_l^h$: the threshold for screening out weak signals by hidden-layer node l.
(17) $\tilde{\theta}^o$: the threshold for screening out weak signals by the output node.

2.1. Forecasting the unit cost using FBPN

First, PCA is used to replace the inputs to the FBPN. PCA 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. PCA consists of the four following steps.