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Multiple generation product life cycle predictions using a novel two-stage fuzzy piecewise regression analysis method

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Abstract

Product life cycle (PLC) prediction plays a crucial role in strategic planning and policy definition for high-technology products. Forecast methodologies which can predict PLCs accurately can help to achieve successful strategic decision-making, forecasting, and foresight activities in high-technology firms, research institutes, governments, and universities. Over the past few decades, even though analytic framework strategies have been proposed for production, marketing, R&D (research and development), and finance, aiming at each stage of PLCs, forecast methodologies with which to predict PLCs are few. The purpose of this research is to develop a novel forecast methodology to allow for predictions of product life time (PLT) and the annual shipment of products during the entire PLC of multiple generation products. A novel two-stage fuzzy piecewise regression analysis method is proposed in this paper. In the first stage, the product life-time of the specific generation to be analyzed will be predicted by the fuzzy piecewise regression line that is derived based upon the product life-time of earlier generations. In the second stage of the forecast methodology, the annual shipment of products of the specified generation will be predicted by deriving annual fuzzy regression lines for each generation, based upon the historical data on the earlier generations' products. An empirical study predicting the life-time and the annual shipment of the 16 Mb (Mega bit) DRAM (Dynamic Random Access Memory) PLC is illustrated to validate the analytical process. The results demonstrate that two-stage fuzzy piecewise regression analysis can predict multiple

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generation PLT and PLC precisely, thereby serving as a foundation for future strategic planning, policy definitions and foresights.

Keywords: Product life cycle; Product life time; Forecasting; Piecewise regression; Fuzzy regression; DRAM; Semiconductor

1. Introduction

The probable course of industry evolution originated from the product life cycle (PLC) [1] — a foundation for strategic planning, policy definitions, resource allocation, human resource management, inventory control, etc. One of the major features of recent market evolution is that its products, especially high-tech products, become differentiated into multiple generations, with path dependency in the advancement of their technological performance [2]. A firm that is evaluating a new product should predict the PLC [3] in advance. The potential for forecasting key parameters – including the magnitude of sales, duration of stages, and the shape of the PLC curve – is one of the most important issues that must be faced in any meaningful application of the PLC concept [4].

Although strategic planning frameworks that aim at production, marketing, R&D (research and development), and finance for each stage of the PLCs have been proposed during recent decades, proposals for technological forecasting methodologies with which to predict PLCs have been rare. Meanwhile, most existing forecasting methodologies have focused on single-generation PLC prediction. For example, Solomon et al. [5] predicted both the number of years to obsolescence and the life cycle stages of electronic parts, using curve fitting of 16 Mb Dynamic Random Access Memory (DRAM) sales data by Gaussian distribution. Tsaur [6] predicted product sales in the next stage of a PLC, based upon a hybrid forecast model using AHP, trend analysis and fuzzy regression. Chang [7] predicted the stages of the PLC using fuzzy regression analysis. Very few studies (e.g. the researches by Norton and Bass [8] and Kim et al. [2]), have focused on multiple-generation PLC predictions. However, multiple generation products are common in high-technology industries. Semiconductor memories – like DRAM, Static Random Access Memory (SRAM), and Personal Computers (PC) – are typical examples.

In practical circumstances, it is difficult to grasp rules for predicting the non-traditional multiple generation product life time (PLT), based upon the non-linear annual shipments of earlier generations with historical data on fewer than five generations. Meanwhile, market research institutes always have difficulty in collecting exact historical market statistics, since firms seldom release actual shipment information. Therefore, the purpose of this paper is to develop a reliable model to allow for prediction of both the PLT and the annual shipments of a specific generation of a multiple-generation product. To accomplish this, we propose a new approach, comprised of two-stage fuzzy piecewise regression analysis, to predict the nonlinear time-series of PLCs. Fuzzy piecewise regression analysis was developed and validated by Yu et al. [9,10]. Meanwhile, the novel two-stage fuzzy regression method can grasp the dynamics of nonlinear time-series of PLCs. Thus, the observed PLC information can be reconstructed in a piece-wise manner. In order to show the practicality of this newly-proposed model, empirical studies on DRAM, a typical multiple-generation product, were validated by subjectively taking ten sampling points from the time-series experimental data in each DRAM generation. Here, DRAM was chosen as an empirical test of the proposed method, due to its long history, from 1970 to the present. Versus other multiple-generation products, the relatively larger numbers of DRAM generations and distinct features, and its clear path dependency in terms of product characteristics [2], makes DRAM an ideal test product for use when validating forecast methodology. Based on this empirical study, the results of the proposed novel forecast methodology can be demonstrated as appropriate for predicting multiple-generation PLC in fuzzy environments.

This paper is organized as follows. In Section 2, the concept of developing a new approach for solving nonlinear time-series in PLCs is introduced. In Section 3, conventional fuzzy regression analysis is reviewed, and a novel fuzzy piecewise regression analysis method for predicting non-linear time series is proposed. In Section 4, the proposed method using fuzzy piecewise regression on earlier generation data is tested with respect to predicting PLT and annual shipments in the case of 16 Mb DRAM PLC. In Section 5, the predicted results are discussed. Final conclusions are presented in Section 6.

2. Developing the methods for PLC predictions

Possibility theory as a tool to explain possibility distributions was proposed by Zadeh [11] and advanced by Dubois and Prade [12]. Tanaka et al. [13] introduced a linear programming (LP)-based regression method using a linear model with symmetrical triangular fuzzy parameters, and then defined the possibility and necessity regression analyses [14]. Sakawa and Yano [15,16] recently generalized the minimization, maximization and conjunction formulations developed by Tanaka and coworkers [14,17]. However, two weaknesses involving fuzzy regression models have arisen. First, Redden and Woodall [18] demonstrated that Tanaka's methodologies were extremely sensitive to outliers in possibility analysis. Furthermore, the fuzzy predictive interval tends to become fuzzier as more data are collected, and has no operational definition or interpretation. Second, in necessity analysis, the necessity area could not be obtained, owing to large variations in data [9,10,13,19]. Tanaka et al. [20] suggested a polynomial or nonlinear model to deal with the above problems. Since the distribution of data is probably segmented, Yu et al. [9,10] proposed two practical ways to avoid these problems: one is to use a piecewise model to address the necessity problem; and the other is to use fuzzy piecewise regression to address the issue of automatic change-point detection of nonlinear observations. They proposed a general piecewise necessity regression method in which, according to data distribution, even if the data are irregular, practitioners must specify the number and the positions of change-points in nonlinear observations [21].

Continuing earlier efforts in developing technological forecasting methods [22–26], we try to adopt the piecewise concept to implement a novel two-stage fuzzy piecewise regression method for solving nonlinear multiple generation PLCs, by applying the above-mentioned general fuzzy piecewise regression analysis by Yu et al. [9].

Fuzzy piecewise possibility and necessity regression models are used when the function behaves differently in different parts of the range of crisp input variables. This means that the above-mentioned problem can be formulated as a mixed-integer programming problem for solving fuzzy piecewise regression. The proposed fuzzy piecewise regression method for solving nonlinear time-series has four advantages: (1) it can be used to predict nonlinear time-series data; (2) if the number of change-points is pre-specified, then the positions of change-points and the fuzzy piecewise regression model are obtained simultaneously; (3) by using mixed-integer programming, the solution is global optimal rather than local optimal; and (4) it is more robust than conventional fuzzy regression. Conventional regression models are sensitive to outliers. In contrast, based on a piecewise concept, the proposed method can deal with outliers by segmenting the data automatically. Therefore, in this work, we focus on building an appropriate model that can be used easily to predict the nonlinear trends of turbulent time-series. The details of general fuzzy piecewise regression analysis are provided in Yu et al. [9].

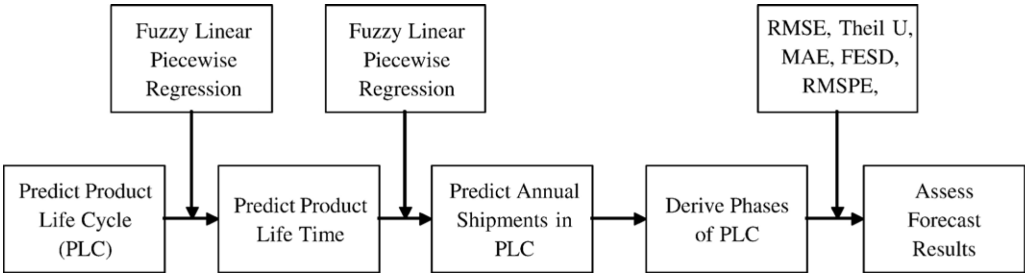

Fig. 1. An analytic framework for PLC prediction.

2.1. Analytic framework and methods for multiple generation PLC prediction

In this subsection, we will build a forecast methodology for predicting PLC, based on a fuzzy linear piecewise regression model. This forecast method (Fig. 1) consists of four main phases: (1) predicting the length of a PLC by fuzzy linear piecewise regression analysis; (2) predicting the annual shipment of the specified generation of product, by fuzzy piecewise regression analysis; (3) deriving the phases of the PLC that need to be predicted; and (4) measuring the errors of forecast results in order to validate the two-stage fuzzy piecewise regression analysis method.

In the following subsection, the concept of interval arithmetic is introduced as a foundation for fuzzy piecewise regression. A fuzzy piecewise regression model that can be applied to nonlinear times-series predictions will be reviewed in Section 2.3. Forecast model efficiency will be introduced in Section 4.

2.2. The concept of interval arithmetic

A linear interval model with independent variables is presented using interval parameters A_i (i=0, 1, 2,…, q) as

$$Y(\boldsymbol{x}_t) = A_0 + A_1 x_{1t} + \cdots + A_q x_{qt} \tag{1}$$

where $Y(\boldsymbol{x}_t)$ is the predicted interval corresponding to the input vector x_t, and t is the time datum (t=1, 2,…, n) and $\boldsymbol{x}_t$=(x_{1t}, x_{2t},…, x_{qt}). In short, $\boldsymbol{x}$=(x_1,x_2,…,x_q) is a q-dimensional input vector. Throughout this work, closed intervals are denoted by capital letters A and B. An interval is defined by an ordered pair in brackets, as

$$A = [a_{\mathrm{L}}, a_{\mathrm{R}}] = [a : a_{\mathrm{L}} < a < a_{\mathrm{R}}], \tag{2}$$

where a_{L} denotes the left limit and a_{R} denotes the right limit of A. Interval A also is denoted by its center and width (radius) as

$$A = (a_{\mathrm{c}}, a_{\mathrm{w}}) = \{a : a_{\mathrm{c}} - a_{\mathrm{w}} \le a \le a_{\mathrm{c}} + a_{\mathrm{w}}\}, \tag{3}$$

where a_{c} denotes the center and a_{w} denotes the width (radius, $a_{\mathrm{w}} \ge 0$); i.e., half of the width of A. From Eqs. (2) and (3), the center and radius of interval A can be calculated as

$$a_{\mathrm{c}} = (a_{\mathrm{R}} + a_{\mathrm{L}})/2, \tag{4}$$

$$a_{\mathrm{w}} = (a_{\mathrm{R}} - a_{\mathrm{L}})/2. \tag{5}$$

The following additions and multiplications are used hereafter:

$$A + B = (a_c, a_w) + (b_c, b_w) = (a_c + b_c, a_w + b_w)\ \text{, and} \tag{6}$$

$$rA = r(a_c, a_w) = \{ra_c, |r|a_w\}, \tag{7}$$

where r is a real number.

2.2.1. Linear interval model

The linear model of Eq. (1) is represented in detail:

$$\begin{aligned} Y(\boldsymbol{x}_t) &= A_0 + A_1 x_{1t} + \cdots + A_q x_{qt} = (a_{0c}, a_{0w}) + (a_{1c}, a_{1w}) x_{1t} + \cdots + (a_{qc}, a_{qw}) x_{qt} \\ &= (Y_c(x_t), Y_w(x_t)), \end{aligned} \tag{8}$$

$$Y_c(\boldsymbol{x}_t) = a_{0c} + a_{1c} x_{1t} + \cdots + a_{qc} x_{qt} \tag{9}$$

$$Y_w(\boldsymbol{x}_t) = a_{0w} + a_{1w} |x_{1t}| + \cdots + a_{qw} |x_{qt}| \tag{10}$$

where $Y_c(\boldsymbol{x}_t)$ represents the center; $Y_w(\boldsymbol{x}_t)$ is the width of the predicted interval $Y(\boldsymbol{x}_t)$; and $\boldsymbol{x}_t$ is a vector of variables, where $\boldsymbol{x}_t = (x_{1t}, x_{2t}, \ldots, x_{qt})$.

2.2.2. Possibility and necessity estimation models

For the input–output data $(\boldsymbol{x}_t, Y(\boldsymbol{x}_t))$, we can consider two estimation models, i.e. the possibility and necessity models [27].

The possibility estimation model can be denoted as

$$\begin{aligned} Y^*(\boldsymbol{x}_t) &= A_0^* + A_1^* x_{1t} + \cdots + A_q^* x_{qt} = (a_{0c}^*, a_{0w}^*) + (a_{1c}^*, a_{1w}^*) x_{1t} + \cdots + (a_{qc}^*, a_{qw}^*) x_{qt} \\ &= (Y_c^*(\boldsymbol{x}_t), Y_w^*(\boldsymbol{x}_t)), \end{aligned} \tag{11}$$

which satisfies the following conditions:

$$Y_t \subseteq Y^*(\boldsymbol{x}_t),\ \ t = 1, 2, \cdots, n. \tag{12}$$

Here, A_t^* is the interval of the possibility estimation model and Y_t is the observed interval at the tth observation time. The estimated interval $Y^*(\boldsymbol{x}_t)$ by the possibility model always includes the observed interval Y_t [27]. In the possibility regression analysis, the width of the predicted interval $Y^*(\boldsymbol{x}_t)$ is minimized and includes all observed data. (See Eqs. (15), (16) and (17) in Section 2.2.3.)

The necessity estimate model can be denoted as

$$\begin{aligned} Y_*(\boldsymbol{x}_t) &= A_{0^*} + A_{1^*} x_{1t} + \cdots + A_{q^*} x_{qt} = (a_{0c^*}, a_{0w^*}) + (a_{1c^*}, a_{1w^*}) x_{1t} + \cdots + (a_{qc^*}, a_{qw^*}) x_{qt} \\ &= (Y_{c^*}(\boldsymbol{x}_t), Y_{w^*}(\boldsymbol{x}_t)), \end{aligned} \tag{13}$$

which satisfies the following conditions:

$$Y_*(\boldsymbol{x}_t) \subseteq Y_t,\ \ t = 1, 2, \cdots, n. \tag{14}$$

Here, A_{t^*} is the interval of the necessity estimation model and Y_t is the observed interval at the tth observation time. The estimated interval $Y_*(\boldsymbol{x}_t)$ by the necessity model should be included in the observed

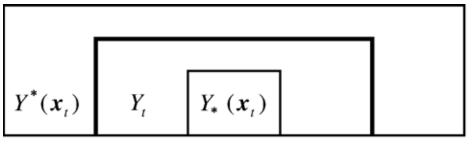

Fig. 2. Relations among the possibility model $Y^*(\boldsymbol{x}_t)$, the necessity model $Y_*(\boldsymbol{x}_t)$, and the given interval Y_t. Source: Tanaka and Lee [27].

interval Y_t. In the necessity regression analysis, the width of the predicted interval $Y_*(\boldsymbol{x}_t)$ is maximized and is included by all the observed data. (See Eqs. (22), (23) and (24) in Section 2.2.4.).

In summary, these relations can be expressed as $Y_*(\boldsymbol{x}_t) \subseteq Y_t \subseteq Y^*(\boldsymbol{x}_t)$ and illustrated by Fig. 2.

2.2.3. Predictions based on the interval-valued data and the associated problem

To make a prediction based on the interval-valued data, the basic formulation of the interval regression can be expressed by Eqs. (15), (16) and (17) as

$$\text{Minimize } Y_{\text{w}}(\boldsymbol{x}_1) + Y_{\text{w}}(\boldsymbol{x}_2) + \cdots + Y_{\text{w}}(\boldsymbol{x}_n). \tag{15}$$

Subject to

$$Y_t \subseteq Y^*(\boldsymbol{x}_t), \; t = 1, 2, \cdots, n, \tag{16}$$

$$a^*_{iw} \geq 0; i = 1, 2, \cdots, q. \tag{17}$$

This LP problem is written as follows:

$$\text{Minimize } \sum_{t=1}^{n} (a^*_{0\text{w}} + a^*_{1\text{w}}|x_{1t}| + \cdots + a^*_{q\text{w}}|x_{qt}|) \tag{18}$$

$$\text{Subject to} \quad (a^*_{0\text{c}} + \sum_{i=1}^{q} a^*_{i\text{c}} x_{it}) - (a^*_{0\text{w}} + \sum_{i=1}^{q} a^*_{i\text{w}} x_{it}) \leq Y_{tL}, \quad t = 1, 2, \cdots, n; \tag{19}$$

$$(a^*_{0\text{c}} + \sum_{i=1}^{q} a^*_{i\text{c}} x_{it}) + (a^*_{0\text{w}} + \sum_{i=1}^{q} a^*_{i\text{w}} x_{it}) \geq Y_{tR}, \quad t = 1, 2, \cdots, n; \tag{20}$$

$$a^*_{0\text{w}}, a^*_{i\text{w}} \geq 0, \; i = 1, 2, \cdots, q. \tag{21}$$

The weakness in the above model is that it is sensitive to outliers. The model used to have larger possibilities than the system should have and used to be warped and bent too much by various fluctuating data. The fuzzy predictive model from Eqs. (15)–(21) tends to become fuzzier as more data are collected, and has no operational definition or interpretation (see Appendix for further explanations and illustrations).

2.2.4. Necessity regression analysis and the associated problem

The necessity regression analysis problem being introduced in Eqs. (13) and (14) can be written as:

$$\text{Maximize } Y_{\mathrm{w}^*}(\boldsymbol{x}_1) + Y_{\mathrm{w}^*}(\boldsymbol{x}_2) + \cdots + Y_{\mathrm{w}^*}(\boldsymbol{x}_n) \tag{22}$$

Subject to

$$Y_*(\boldsymbol{x}_t) \subseteq Y_t, \;\; t = 1, 2, \cdots, n; \tag{23}$$

$$a_{i\mathrm{w}^*} \geq 0; i = 1, 2, \cdots, q; \tag{24}$$

where the LP problem can be expressed as follows:

$$\text{Maxmize } \sum_{t=1}^{n} (a_{0\mathrm{w}^*} + a_{1\mathrm{w}^*}|x_{1t}| + \cdots + a_{q\mathrm{w}^*}|x_{qt}|) \tag{25}$$

Subject to

$$(a_{0\mathrm{c}^*} + \sum_{i=1}^{q} a_{i\mathrm{c}^*}x_{it}) - (a_{0\mathrm{w}^*} + \sum_{i=1}^{q} a_{i\mathrm{w}^*}x_{it}) \geq Y_{tL}, \qquad t = 1, 2, \cdots, n; \tag{26}$$

$$(a_{0\mathrm{c}^*} + \sum_{i=1}^{q} a_{i\mathrm{c}^*}x_{it}) + (a_{0\mathrm{w}^*} + \sum_{i=1}^{q} a_{i\mathrm{w}^*}x_{it}) \leq Y_{tR}, \qquad t = 1, 2, \cdots, n; \tag{27}$$

$$a_{0w^*}, a_{1\mathrm{w}^*} \geq 0, \;\; i = 1, 2, \cdots, q. \tag{28}$$

The above LP formulation of necessity has no feasible solution, owing to large fluctuations in the given data (see Appendix for further explanations and illustrations). Fuzzy piecewise regression was proposed by [9] as a means to handle such a problem. In [9], the change-points are given before employing the necessity regression method.

2.3. The concept of fuzzy piecewise regression analysis

To determine the necessity area by the piecewise linear interval model, an LP formulation is presented in this subsection for the univariate linear piecewise regression analysis, which commonly is observed in forecast problems.

$$\begin{aligned} &Y_*(x_j) = h(x_j) + \sum_{t=1}^{k-1} B_{t^*}(|x_j - P_t| + x_j - P_t)/2, \\ &h(x_j) = A_{0^*} + A_{1^*}x_j \end{aligned} \tag{29}$$

If P is a change-point, then

$$(|x_j - P| + x_j - P)/2 = \begin{cases} x_j - P & \text{if } x_j \geq P, \\ 0 & \text{if } x_j < P. \end{cases}$$

$P = \{P_1, P_1, \ldots, P_k\}$ are the values of variable $x_j (j = 1, 2, \ldots, n)$ and are subject to an ordering constraint $P_1 < P_2 < \ldots < P_k$, $k \leq n$.

For easy illustration, the following formulation assumes that every datum is a change-point, except P_k. Therefore, $k-1$ change points in the initial necessity regression model are available.

The difference between Eqs. (29) and (22) is Eq. (30); i.e., the piecewise expression for the given data.

$$\begin{aligned} \sum_{t=1}^{k-1} B_{t^*}(|x_j - P_t| + x_j - P_t)/2 &= \sum_{t=1}^{k-1} B_{tc^*}(|x_j - P_t| + x_j - P_t)/2 \\ &\quad + \sum_{t=1}^{k-1} B_{tw^*}(|x_j - P_t| + x_j - P_t)/2 \\ &\quad t = 1, 2, \cdots, n. \end{aligned} \tag{30}$$

The piecewise LP formulation for the necessity analysis is as follows:
Maximize

$$z = \sum_{t=1}^{n} \left[A_{0w^*} + A_{1w^*} x_j + \sum_{t=1}^{k-1} B_{t^*}(|x_j - P_1| + x_j - P_1)/2\right]$$

Subject to

$$\begin{aligned} & A_{0c^*} + A_{1c^*} x_j + \sum_{t=1}^{k-1} B_{tc^*}(|x_j - P| + x_j - P_1)/2 \\ & \quad - \left[A_{0w^*} + A_{1w^*} x_j + \sum_{t=1}^{k-1} B_{tw^*}(|x_j - P_1| + x_j - P_1)/2\right] \geq Y_{jL}, \\ & A_{0c^*} + A_{1c^*} x_j + \sum_{t=1}^{k-1} B_{tc^*}(|x_j - P_1| + x_j - P_1)/2 \\ & \quad + \left[A_{0w^*} + A_{1w^*} x_j + \sum_{t=1}^{k-1} B_{tw^*}(|x_j - P_1| + x_j - P_1)/2\right] \leq Y_{jR}, \quad j = 1, 2, \cdots, n. \end{aligned} \tag{31}$$

The formulation can be extended as a multivariate piecewise linear regression model, as long as the number of independent variables is increased.

2.4. Measurement of forecast model efficiency

To measure forecast efficiency, the residual error test method will be applied as

$$\mathrm{err}(\boldsymbol{x}_t) = \left| \frac{y(\boldsymbol{x}_t) - \hat{y}(\boldsymbol{x}_t)}{y(\boldsymbol{x}_t)} \right| \times 100\% \tag{32}$$

where err($\boldsymbol{x}_t$) stands for residual percentage between actual value, $y(\boldsymbol{x}_t)$, and the forecast value, $\hat{y}(\boldsymbol{x}_t)$, of the annual product shipment of the specific generation in the tth year of the PLC. The forecast error of the whole period of PLC can be evaluated by

$$\mathrm{err} = \frac{1}{n}\sum_{j=1}^{t} \mathrm{err}(j) \tag{33}$$

3. PLC and DRAM industry background

The concept of PLC indicates that an industry passes through a number of phases, or stages, which are introduction, growth, maturity and decline [28]. These stages are defined by inflection points in the rate of growth of industry sales. Industry growth follows an S-shaped curve, because of the innovation and diffusion of new products [1]. PLCs have been of prominent concern with DRAM, because the life cycle is short for a single generation of DRAM. This has had a significant impact on the planning and capital investment levels of both memory and system manufacturers [28,29].

The first commercial DRAM, a 1 Kb chip, was released by Intel in 1970. After that, the advantages of cost per bit and high density have made DRAMs the most widely-used semiconductor memories in commercial applications [31]. Currently, DRAM has become one of the major integrated circuit (IC) components, due to its serving as the main memory of most computers, telecommunications equipment, and consumer electronic products. DRAM holds one fifth of the worldwide IC market.

Even though DRAM has played such an important role in the IC industry, surviving in the DRAM industry is not easy. The DRAM market is full of uncertainties, which are caused by the highly-fluctuating demand versus supply relationship. Usually, DRAM vendors must accept high risks for big losses, and thus, risk being forced out of the market, due to improper strategic maneuvering, which could be manifest as late product development, improper roadmap definitions or technology transfer partners, over-aggressive fab expansion plans, or late investments in next generation products and technologies.

Over the past three decades, DRAMs consistently have quadrupled in size every three to four years. Meanwhile, as observed by Prince [30], the entire DRAM cycle, between the introduction of one generation and the next, is in the range of three to four years, as shown in Fig. 3. 1 Mb, 4 Mb, 16 Mb, and 64 Mb, all released by 1998, were typical examples. The 128 Mb generation has been the only exception, and this was caused because of an extreme oversupply situation which, in turn, was caused by DRAM vendors' overly aggressive expansion plan after the severe shortage of 1993–1994 and the entrance of Taiwanese vendors – Powerchip, Winbond, and ProMos – into the DRAM market in around 1995.

In terms of technology and product optimization, development of a new generation of DRAM begins about three years before production and introduction into the market. Once in production, engineering efforts shift to cost reduction and yield enhancement, in order to minimize the cost and maximize the production volume of a given manufacturing line [30]. DRAM costs decline dramatically as the DRAM matures [32]. Volume increases and costs fall until higher cost suppliers begin to leave the market, about four years into the cycle. Volume then declines, as suppliers

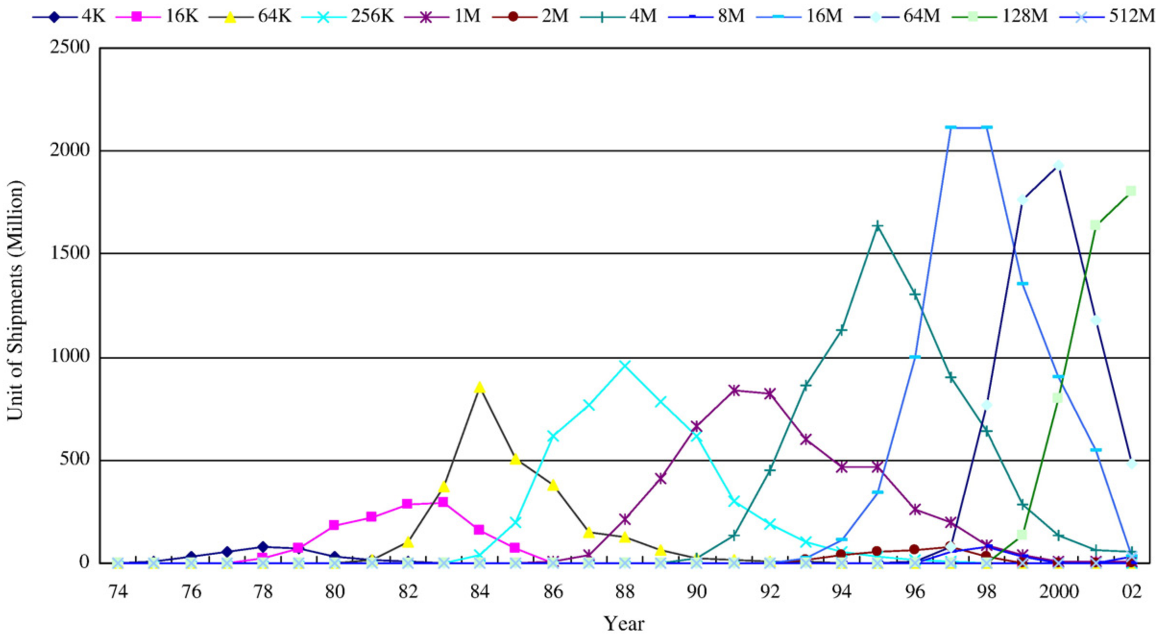

Fig. 3. Illustrating the PLCs of twelve generations of DRAMs in [millions] of units. Source: Dataquest [34].

leave the market [30]. Often, the cost of producing a DRAM at the end of its life cycle is less than one-tenth its cost in the first year of production. Because costs drop steeply as the cumulative volume shipped increases, DRAM vendors need to jump into each new generation as quickly as their R&D resources permit [32]. Commodity DRAM products tend to have approximately 10-year life cycles.

Since DRAM PLCs serve as such an important index for manipulating R&D, production, marketing, finance, and other strategies, an efficient DRAM PLC prediction methodology is essential for DRAM vendors' developing competitive advantage, thereby becoming profitable in the highly uncertain and competitive environment that exists.

4. Forecast results

The 16 Mb DRAM was chosen as a test product to validate the proposed two-stage fuzzy regression forecast methodology, since 16 Mb DRAM is the final generation DRAM which just finished its lifetime in 2002. Other newer generation DRAMs still are alive and unsuitable to serve as the target for life-time predictions, because we are not able to validate the effectiveness of the forecast methodology. Based upon the historical PLC information of six generations of main stream DRAMs, 4 K, 16 K, 64 K, 256 K, 1 M, and 4 M provided by Dataquest [34], we predict the 16 Mb DRAM life time in Section 4.1; the annual shipment volumes of 16 Mb DRAM and change points of the different phases of the 16 Mb DRAM PLC in Section 4.2; and, finally, measurement of forecast model efficiency in Section 4.3.

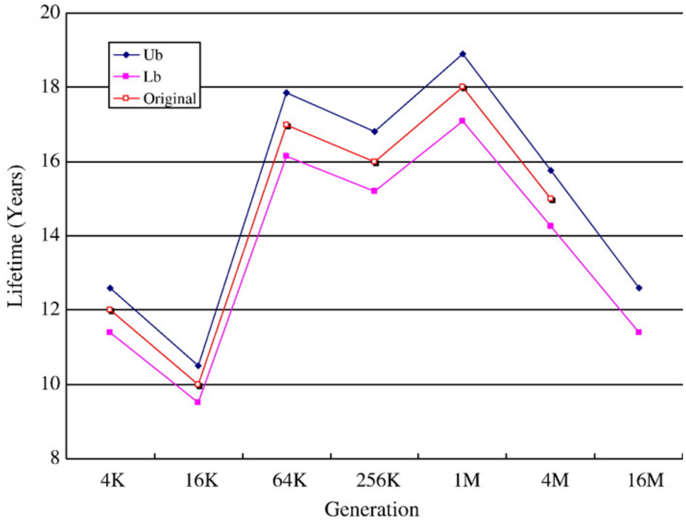

Fig. 4. Predictions of the 16 Mb DRAM life cycle.

4.1. Prediction of the PLT

First, we predict the PLT of 16 Mb DRAM as the basis for the prediction of annual shipments. The life-time for 4 Kb, 16 Kb, 64 Kb, 256 Kb, 1 Mb, and 4 Mb DRAMs have been 12, 10 , 17, 16, 18, and 15 years, respectively. To predict the PLT for the next generation 16 Mb DRAM, we choose the life time of the above-mentioned six generation DRAMs as the change points for the fuzzy piecewise regression analysis. By applying Eq. (31), we may derive the parameters of Eq. (29), using LP easily. Thus, the necessity area can be derived easily, via Eq. (29), as

$$\begin{aligned} Y_*(x_j) = {} & (-172.08, -323.41) + (184.08, 322.81) \times x_j + (-186.08, -322.71) \\ & \times(|x_j - 1| + x_j - 1) + (9.00, -0.45) \times (|x_j - 2| + x_j - 2) + (-8.00, 0.40) \\ & \times(|x_j - 3| + x_j - 3) + (3.00, -0.15) \times (|x_j - 4| + x_j - 4) + (-5.00, 0.25) \\ & \times(|x_j - 5| + x_j - 5); \\ Y_*(x_j) \geq {} & 0. \end{aligned}$$

By applying Eq. (34), we may predict the life-time of the next generation 16 Mb DRAM, by setting x_j as 7. The projected center life-time for the 16 Mb DRAM is twelve years; the upper limit is 12.6 years; and the lower limit is 11.4 years (Fig. 4). Versus the real life-time for the 16 Mb DRAM, which was 12 years, we precisely predicted the 16 Mb DRAM life-time.

4.2. Prediction of the annual shipment of products

After our successful prediction of the 16 Mb PLT, annual 16 Mb DRAM shipments were predicted, based upon the annual shipment of the earlier generations of 4 Kb, 16 Kb, 64 Kb, 256 Kb, 1 Mb, and 4 Mb DRAMs.

We may derive the parameters of the fuzzy regression equations, $Y_{k^*}(x_j)$, in order to calculate the kth year annual shipments, based on Eq. (31). The derived equations for the 1st to the 12th year are listed below, as a basis for further calculation of the annual shipments and change points in the PLC.

$$\begin{aligned}
Y_{1^*}(x_j) &= (485.2042, -240.2646) + (129.7958, 209.5146) \times x_j + (-690.7958, -181.4646) \times (|x_j-1| + x_j - 1) \\
&\quad + (543, -27.15) \times (|x_j-2| + x_j - 2) + (-8, 0.4) \times (|x_j-3| + x_j - 3) + (182, -9.1) \\
&\quad \times (|x_j-4| + x_j - 4) + (-303, 15.15) \times (|x_j-5| + x_j - 5) \\
Y_{2^*}(x_j) &= (-16,462, -21,332) + (21,752,\ 21,068) \times x_j + (-25,034, -20,904) \times (|x_j-1| + x_j - 1) \\
&\quad + (1715, -85.75) \times (|x_j-2| + x_j - 2) + (2826, -141.3) \times (|x_j-3| + x_j - 3) + (1360, -68) \\
&\quad \times (|x_j-4| + x_j - 4) + (-5626, 281.3) \times (|x_j-5| + x_j - 5) \\
Y_{3^*}(x_j) &= (-224,090, -241,930) + (252,100,\ 240,530) \times x_j + (-259,330, -240,170) \times (|x_j-1| + x_j - 1) \\
&\quad + (-929,\ 46.45) \times (|x_j-2| + x_j - 2) + (33,503, -1675.1) \times (|x_j-3| + x_j - 3) \\
&\quad + (-20,748,\ 1037.4) \times (|x_j-4| + x_j - 4) + (-22,777,\ 1138.8) \times (|x_j-5| + x_j - 5) \\
Y_{4^*}(x_j) &= (-2,523,000, -2,448,000) + (2,580,500,\ 2,445,100) \times x_j \\
&\quad + (-2,567,900, -2,445,700) \times (|x_j-1| + x_j - 1) + (21,344, -1067.2) \\
&\quad \times (|x_j-2| + x_j - 2) + (63,633, -3181.6) \times (|x_j-3| + x_j - 3) + (-86,431,\ 4321.6) \\
&\quad \times (|x_j-4| + x_j - 4) + (-86,172,\ 4308.6) \times (|x_j-5| + x_j - 5) \\
Y_{5^*}(x_j) &= (-2,137,600, -2,008,300) + (2,214,800,\ 2,004,500) \times x_j \\
&\quad + (-2,108,000, -2,009,800) \times (|x_j-1| + x_j - 1) + (80,490, -4024.5) \\
&\quad \times (|x_j-2| + x_j - 2) + (59,351, -2967.5) \times (|x_j-3| + x_j - 3) + (-457,130,\ 22,857) \\
&\quad \times (|x_j-4| + x_j - 4) + (252,270, -12,614) \times (|x_j-5| + x_j - 5) \\
Y_{6^*}(x_j) &= (-2,288,900, -2,121,100) + (2,358,900,\ 2,117,600) \times x_j \\
&\quad + (-2,207,400, -2,125,200) \times (|x_j-1| + x_j - 1) + (478,660, -23,933) \\
&\quad \times (|x_j-2| + x_j - 2) + (-715,400,\ 35,770) \times (|x_j-3| + x_j - 3) \\
&\quad + (-16,017,\ 800.85) \times (|x_j-4| + x_j - 4) + (295,450, -14,773) \times (|x_j-5| + x_j - 5) \\
Y_{7^*}(x_j) &= (-2,288,900, -2,121,100) + (2,358,900,\ 2,117,600) \times x_j \\
&\quad + (-2,207,400, -2,125,200) \times (|x_j-1| + x_j - 1) + (478,660, -23,933) \\
&\quad \times (|x_j-2| + x_j - 2) + (-715,400,\ 35,770) \times (|x_j-3| + x_j - 3) + (-16,017,\ 800.85) \\
&\quad \times (|x_j-4| + x_j - 4) + (295,450, -14,773) \times (|x_j-5| + x_j - 5) \\
Y_{8^*}(x_j) &= (-2,132,200, -1,872,100) + (2,145,200,\ 1,871,500) \times x_j \\
&\quad + (-1,861,700, -1,885,700) \times (|x_j-1| + x_j - 1) + (-198,120,\ 9906.2) \\
&\quad \times (|x_j-2| + x_j - 2) + (313,040, -15,652) \times (|x_j-3| + x_j - 3) + (-357,760,\ 17,888) \\
&\quad \times (|x_j-4| + x_j - 4) + (777,530, -38,876) \times (|x_j-5| + x_j - 5)| + xj - 5) \\
Y_{9^*}(x_j) &= (-2,079,300, -1,835,800) + (2,083,900,\ 1,835,600) \times x_j \\
&\quad + (-1,927,300, -1,843,400) \times (|x_j-1| + x_j - 1) + (-165,360,\ 8268.2) \\
&\quad \times (|x_j-2| + x_j - 2) + (476,600, -23,830) \times (|x_j-3| + x_j - 3) + (-486,890,\ 24,344) \\
&\quad \times (|x_j-4| + x_j - 4) + (720,670, -36,034) \times (|x_j-5| + x_j - 5)| + xj - 5) \\
Y_{10^*}(x_j) &= (-2,499,700, -2,322,500) + (2,502,100,\ 2,322,400) \times x_j \\
&\quad + (-2,433,600, -2,325,800) \times (|x_j-1| + x_j - 1) + (-12,338,\ 616.9) \\
&\quad \times (|x_j-2| + x_j - 2) + (115,850, -5792.5) \times (|x_j-3| + x_j - 3) + (-2386,\ 119.3) \\
&\quad \times (|x_j-4| + x_j - 4) + (260,640, -13,032) \times (|x_j-5| + x_j - 5)| + xj - 5) \\
Y_{11^*}(x_j) &= (-2,484,300, -2,473,100) + (2,486,600,\ 2,473,000) \times x_j + (-2,488,800, -2,472,900) \\
&\quad \times (|x_j-1| + x_j - 1) + (67,584, -3379.2) \times (|x_j-2| + x_j - 2) + (62,655, -3132.8) \\
&\quad \times (|x_j-3| + x_j - 3) + (145,810, -7290.7) \times (|x_j-4| + x_j - 4) + (-103,200,\ 5159.9) \\
&\quad \times (|x_j-5| + x_j - 5)| + xj - 5) \\
Y_{12^*}(x_j) &= (-2,480,000, -2,444,300) + (2,482,400,\ 2,444,100) \times x_j + (-2,484,700, -2,444,000) \\
&\quad \times (|x_j-1| + x_j - 1) + (28,087, -1404.4) \times (|x_j-2| + x_j - 2) + (53,410, -2670.5) \\
&\quad \times (|x_j-3| + x_j - 3) + (75,071, -3753.6) \times (|x_j-4| + x_j - 4) + (-127,020,\ 6350.8) \\
&\quad \times (|x_j-5| + x_j - 5)| + xj - 5)
\end{aligned}$$

$$Y_{1^*}(x_j), Y_{2^*}(x_j), Y_{3^*}(x_j), Y_{4^*}(x_j), Y_{5^*}(x_j), Y_{6^*}(x_j), Y_{7^*}(x_j), Y_{8^*}(x_j), Y_{9^*}(x_j), Y_{10^*}(x_j), Y_{11^*}(x_j), Y_{12^*}(x_j) \geq 0.$$

The annual shipments of the 16 Mb DRAM can be calculated by means of the above twelve equations, where the results are shown in Table 1 and Fig. 5.

Table 1
Actual versus predicted annual shipments of 16 Mb DRAMs (unit: million pieces)

Years	1 (1991)	2 (1992)	3 (1993)	4 (1994)	5 (1995)	6 (1996)
Forecast center	0.000	0.000	6.199	62.715	491.004	1053.549
Forecast low	0.000	0.000	5.881	59.735	466.755	1000.721
Forecast high	0.000	0.000	6.517	65.695	515.254	1106.377
Actual	0.133	1.808	21.555	108.116	337.005	996.316
Years	7 (1997)	8 (1998)	9 (1999)	10 (2000)	11 (2001)	12 (2002)
Forecast center	1434.895	2457.340	2004.470	1329.232	808.670	313.848
Forecast low	1363.535	2334.375	1904.455	1262.940	768.191	297.985
Forecast high	1506.255	2580.305	2104.485	1395.524	849.150	329.711
Actual	2116.025	2116.140	1353.059	902.000	548.170	33.330

According to Porter's [1] PLC definitions, the stages of the PLC are inflection points in the rate of growth of industry sales. Thus, the PLC of 16 Mb DRAM changed from the growth stage to the maturity stage in the 8th year, and changed from the maturity stage to the decline stage in the 9th year (Fig. 6). For our forecast data, the PLC of 16 Mb DRAM changed from the growth stage to the maturity stage in the 9th year, and changed from the maturity stage to the decline stage in the 10th year (Fig. 7).

4.3. Errors in the forecasts

By using Eqs. (32) and (33) and the forecast results of 16 Mb DRAM PLT, which was 12 years, as shown in Section 4.1, forecast efficiency can be calculated. First, the residual error for the PLT is 0%, which implies perfect prediction of the PLT. Second, to observe whether the forecast predicts the trends

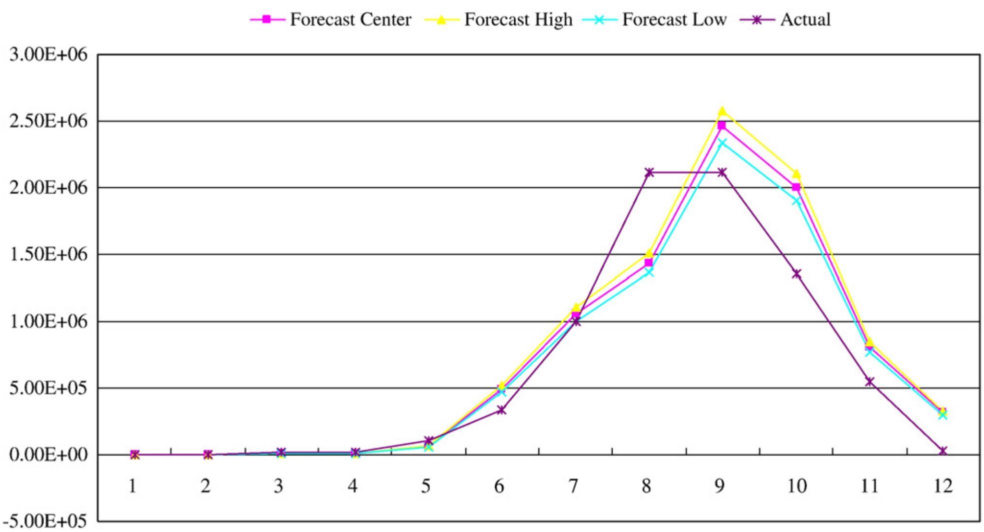

Fig. 5. Actual versus predicted annual shipments of 16 Mb DRAMs.

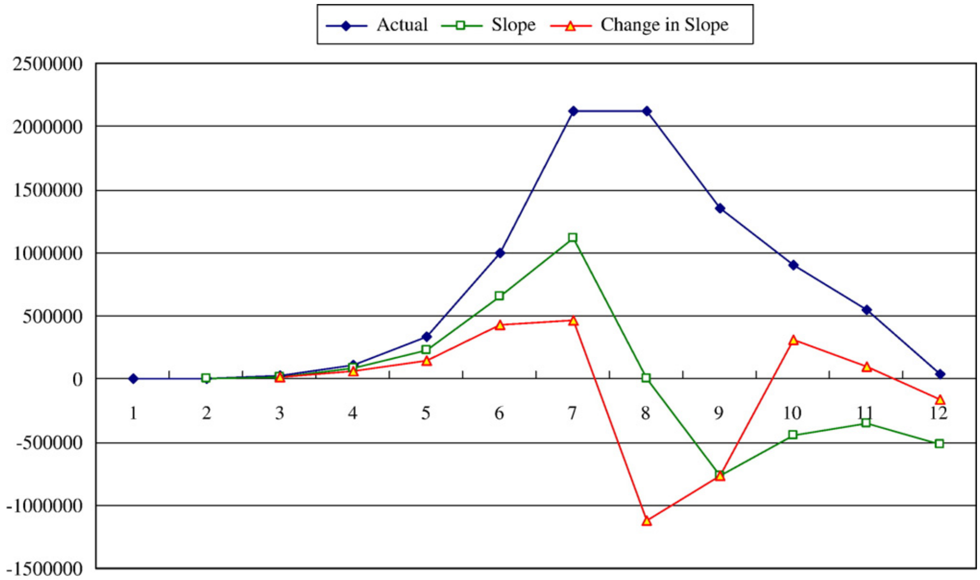

Fig. 6. Change points of the 16 Mb PLC, calculated by differentiation of slopes.

perfectly, we take the logarithms of the projected annual shipment and calculate the residual errors, using Eq. (32). The results are shown in Table 2 and Fig. 8. Using Eq. (33), the forecast error of the whole period of PLC is 20.648%. Meanwhile, by neglecting the forecast errors in the 1st, 2nd and 12th year, wherein the annual shipments of the specified years are comparatively smaller than the peak

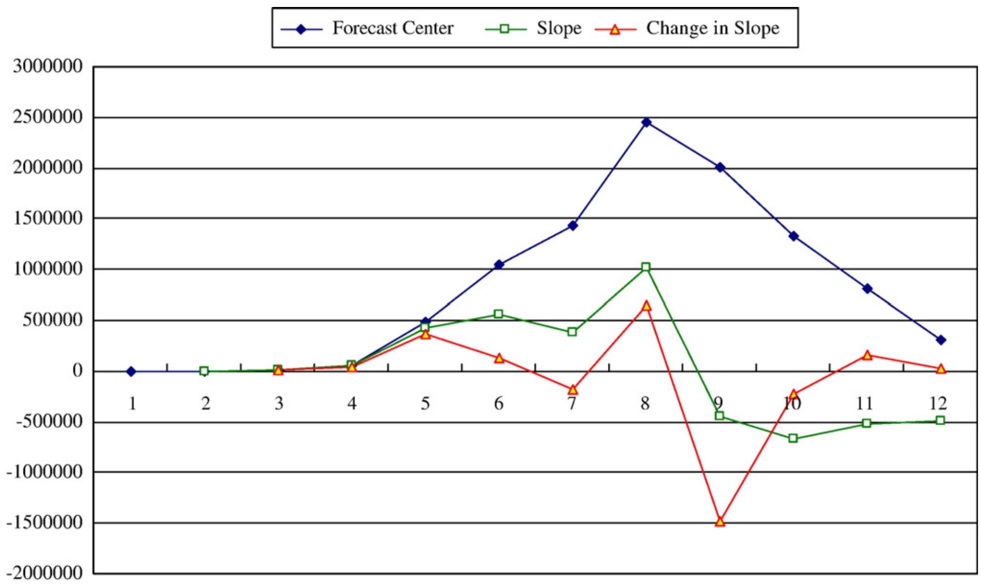

Fig. 7. Change points of the predicted PLCs, calculated by differentiation of slopes.

Table 2
Logarithmic values of the actual and predicted annual shipments of 16 Mb DRAMs

Years	1 (1991)	2 (1992)	3 (1993)	4 (1994)	5 (1995)	6 (1996)	7 (1997)	8 (1998)	9 (1999)	10 (2000)	11 (2001)	12 (2002)
Forecast center	0.000	0.000	0.792	1.797	2.691	3.023	3.157	3.390	3.302	3.124	2.908	2.497
Forecast low	0.000	0.000	0.769	1.776	2.669	3.000	3.135	3.368	3.280	3.101	2.885	2.474
Forecast high	0.000	0.000	0.814	1.818	2.712	3.044	3.178	3.412	3.323	3.145	2.929	2.518
Actual	0.000	0.257	1.334	2.034	2.528	2.998	3.326	3.326	3.131	2.955	2.739	1.523
Error (%)	0.000	100.000	40.585	11.629	6.466	0.809	5.073	1.952	5.451	5.698	6.165	63.952

values of the annual shipments in the PLC, the forecast errors of the whole PLC can be minimized further to 6.986%.

5. Discussions

In this paper, we demonstrated a two-stage fuzzy linear piecewise regression analysis method which can predict PLT, annual shipments, and change points in the PLC. The new forecast methodology can serve as a foundation for such elements for use in policy foresight, strategic definitions, human resources management and inventory control.

This forecast methodology differs from traditional time-based approaches, the forecast results of which are time variant. Compared to one of the best known and widely used PLC prediction methods by Norton and Bass [8], which was fitted to DRAMs and achieved good predictive validity, there are two advantages in the proposed method. (1) The assumptions for (a) the existence of a series of advancing generations, each of which can do everything the previous generation could do, and possibly more, (b) a density function of time to adoption for each generation applying against a time-varying potential, and (c) the substitution of actual and potential sales from earlier and later generations are necessary for the method proposed by Norton and Bass [8]. However, the proposed method successfully predicted PLT and PLC based merely on

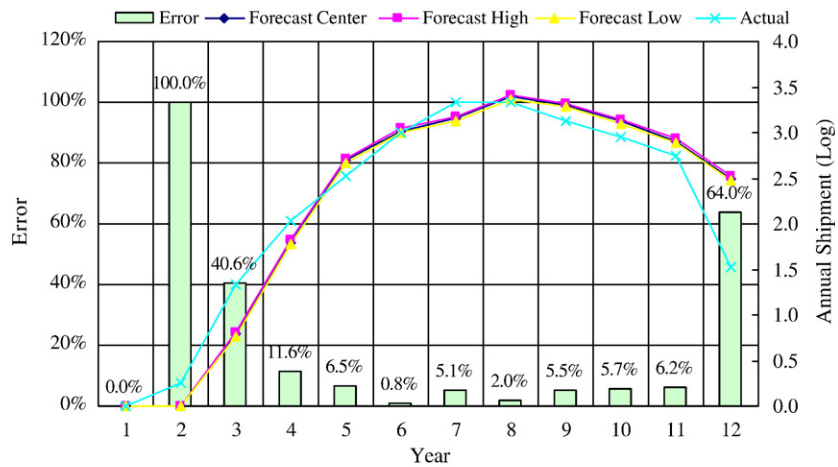

Fig. 8. Logarithm of the actual versus predicted annual shipments of 16 Mb DRAM, and forecast errors.

historical data. No assumption is required. (2) The method by Norton and Bass [8] analyzes crisp data. However, uncertainties always exist in the marketing information due to errors, biases, or purposely designed fault data. This phenomenon can be observed from DRAM historical market information being provided by leading market research institutes. The annual shipment data provided by each institute seldom was the same. The authors believe that the proposed method, which also takes into account the fuzziness of information in the forecasting method, can solve these kinds of error, bias, and uncertainty that usually found in the real market.

Meanwhile, in comparison with one of the well-known non-parametric piecewise linear regression methods proposed by Phillips [35], which used the Akaike information criterion to find the optimal piecewise linear regression model, the proposed fuzzy piecewise regression analysis method specified the change points as a priori.

In this paper, we introduced the generation-based concept, which predicts the *k*th year PLT shipment by the *k*th year annual shipments of earlier generations. Compared with traditional time-variant forecast methodology, generation-based forecast methodology accurately can predict life-time as well, as change points and trends in the PLC, without any shipment information on the specific generation to be projected. Thus, the forecast can be executed prior to the release of a new generation of multiple-generation products. This especially is helpful for marketers or policy makers who would like to define strategies or policies for a new product. Meanwhile, fuzzy linear regression analysis can resolve the non-linear problems which traditional time series problems cannot solve. Additionally, fuzzy regression analysis serves as a good forecast methodology, even when the available information is vague. Accurate market statistics rarely are readily accessible. Companies usually do not disclose actual shipment or sales information, due to security concerns. Meanwhile, accurate collections of the worldwide sales of some specific industries are difficult to attain. This situation is even more significant when market research institutes try to excavate information from private companies in the third world. Errors and biases always exist in the market statistics. Furthermore, no assumptions for the functionality of successive generation of products, a density function of time to adoption for each generation, and the substitution of actual and potential sales from earlier and later generations are required. Finally, compared with traditional regression analysis, fuzzy regression analysis does not require huge bodies of data. Apparently, fuzzy linear piecewise regression analysis serves as an effective tool for analyzing the PLC of multiple-generation products, even when the available information is vague. Consequently, this procedure provides a solution by which to address real world forecast problems.

The proposed forecast method successfully predicted the PLT of 16 Mb DRAM, based upon annual shipment information on earlier-generation DRAMs. Meanwhile, the forecast results for the change points between stages of the PLC also were correct. Here, the accuracy of predicted annual shipments should be discussed. We found that the actual annual shipment exceeded the forecast results significantly in the 7th, 8th and 9th years of the PLC, for the following reasons: (1) the release of Microsoft Windows 95 in August 1995 affected the market, which drove the PC main memory (DRAM) size up from 4 MB (Mega Bytes) to 8 MB in the low-end segment, and from 8 MB to 16 MB in the mid-range [31]; (2) new Taiwanese DRAM vendors [33], including Powerchip Semiconductor Corp., Winbond Electronics Corp., and Promos Technologies Inc. entered the DRAM market during the 1996 to 1998 period, which produced an extra five to ten million 16 Mb DRAMs per month; (3) existing DRAM vendors were forced to accelerate the pace of process shrinkage, from 0.45 um to 0.35 um or below, more aggressively than expected, to cut the cost per die, thereby increasing the profit margin and, thus, enhancing competitiveness in the existing oversupply situation; and (4) the Asian crisis started in mid 1997, forcing

Korean vendors, especially Hyundai and L.G., to dump inventory into the market, which disrupted the supply-versus-demand balance further. Meanwhile, to enhance competitiveness and profit margins, DRAM vendors advanced the release schedule for the next-generation 64 Mb DRAM, and allocated some 16 Mb DRAM capacities to niche products like 8 Mb SGRAM (Synchronous Graphics RAM) and semiconductor foundry, which caused actual shipments to fall far below the volume predicted for the ninth year of the 16 Mb PLC. Although the macro and micro-environment fluctuates, we also found that fuzzy regression predicted the trend correctly, by taking the logarithmic value of the predicted annual shipment. Meanwhile, implications related to management and possible strategies aimed at the different stages of the DRAM PLC are discussed below, which may serve as a basis for future management and strategic definitions of DRAM vendors.

During the introduction phase, product and technology development costs are high and suppliers are few. Profit margins are low, even though selling prices are high, due to the amortization of development costs and the high initial manufacturing costs [30].

For the strategies of the growth stage, from the introduction of the 16 Mb DRAM to the maturity stage in the 8th year, DRAM vendors should expand their fab capacity, so as to maximize revenue and profits and, thus, market share.

Increased competition drives the prices and profits down, and some of the suppliers begin to leave the market [30] during the maturity stage. DRAM vendors should accelerate their pace of process shrinkage, leverage professional DRAM foundries, and establish joint venture relationships, by transferring techniques to the semiconductor vendors in exchange for license fees and royalties, so as to cut DRAM manufacturing costs. Additionally, assembly and testing costs might be reduced by shortening the test time and leveraging lower-cost assembly parts. Meanwhile, legal actions may be undertaken— like the filing of anti-dumping lawsuits against competitors who are leveraging low-price strategies.

In the decline stage, starting in the 9th year, tier one DRAM vendors should initiate the introduction of the next generation DRAM. Meanwhile, in order to sustain the profit margin, second and third tier DRAM vendors should transfer existing lines, so as to produce niche specialty DRAMs for graphic memories or other peripheral applications, as well as for logic foundries. At this stage, DRAM vendors without competitive advantages will be forced out of the market. Finally, the analytic framework can be applied to other multiple-generation products, like personal computers, automobiles and cell phones.

6. Conclusions

In this paper, the authors proposed a forecast methodology for predicting both PLT and non-linear PLC, based upon a two-stage, fuzzy, piecewise regression analysis model. Indifferent to traditional time-based forecast methodology, a generation-based approach was applied, which predicts PLC by deriving the annual fuzzy regression lines, based upon the annual shipments of earlier generation products. This forecast methodology was proven effective, accurately predicting the 16 Mb DRAM life-time to be twelve years, and successfully predicting the change points of the 16 Mb DRAM PLC, by deriving 12 regression lines based on historical data on multiple earlier-generation DRAMs.

In future studies, the proposed methodology can be applied to forecast other multiple-generation products like PCs, semiconductor processes, etc. Meanwhile, the results of this forecast methodology can be applied as a foundation for policy foresight and strategic definitions for each stage of the PLC.

Appendix A. Explanation of the weakness of interval regression analysis and the unavailability of feasible solution for the necessity regression analysis

The interval regression analysis is sensitive to outliers (changing points) (e.g., the black points in Fig. A1). The interval regression analysis results used to have larger possibilities than the system should have.

The interval regression analysis results tend to become fuzzier (wider in width) as more data (e.g., newly collected data points in Fig. A2) is collected. "No operational definition or interpretations for the outliers are available" means the definitions of the outliers are unavailable since the only available information is the center and width of the interval regression analysis results.

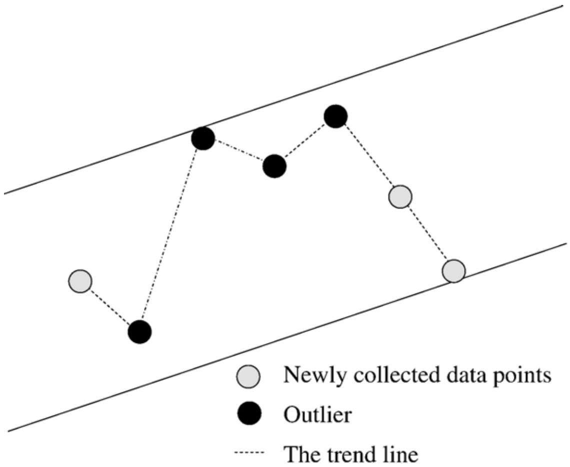

Fig. A1. Interval regression results of the collected points.

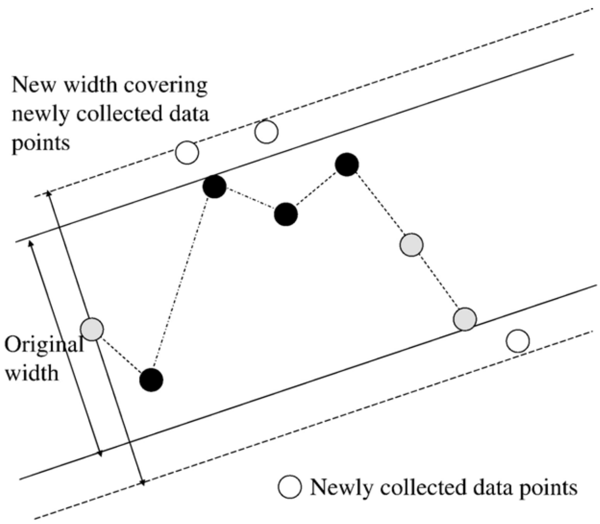

Fig. A2. Interval regression results covering newly collected data points.

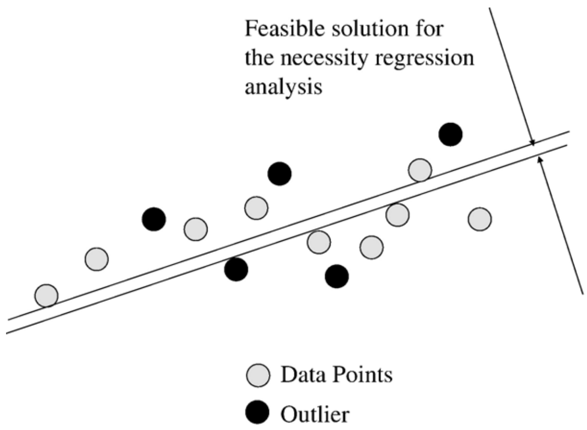

Fig. A3. Feasible solution for the necessity regression analysis covering newly collected data points.

Finally, although feasible solution maybe available for some data sets (i.e., the case in Fig. A3), feasible solution is usually unavailable for the given data with large fluctuations.

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