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A variable *P* value rolling Grey forecasting model for Taiwan semiconductor industry production

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Abstract

The semiconductor industry plays an important role in Taiwan's economy. In this paper, we constructed a rolling Grey forecasting model (RGM) to predict Taiwan's annual semiconductor production. The univariate Grey forecasting model (GM) makes forecast of a time series of data without considering possible correlation with any leading indicators. Interestingly, within the RGM there is a constant, *P* value, which was customarily set to 0.5. We hypothesized that making the *P* value a variable of time could generate more accurate forecasts. It was expected that the annual semiconductor production in Taiwan should be closely tied with U.S. demand. Hence, we let the *P* value be determined by the yearly percent change in real gross domestic product (GDP) by U.S. manufacturing industry. This variable *P* value RGM generated better forecasts than the fixed *P* value RGM. Nevertheless, the yearly percent change in real GDP by U.S. manufacturing industry is reported after a year ends. It cannot serve as a leading indicator for the same year's U.S. demand. We found out that the correlation between the yearly survey of anticipated industrial production growth rates in Taiwan and the yearly percent changes in real GDP by U.S. manufacturing industry has a correlation coefficient of 0.96. Therefore, we used the former to determine the *P* value in the RGM, which generated very accurate forecasts.

Keywords: Grey forecasting; RGM; Semiconductor industry

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1. Introduction

Forecasting of total production revenue in high-tech industries is useful for companies to prepare marketing strategies/production capacity planning and for financial institutions to make investment decisions. However, volatility, cyclic, and vulnerability to technology enhancements and demand shifts are common characteristics in high-tech industries. Therefore, production forecasting in high-technology industries, like the semiconductor industry, is much more difficult than in traditional industries, such as food manufacturing [1].

Industry practitioners use both quantitative and qualitative methods [2] to do forecasting. Qualitative forecasting methods include the expert system, the Delphi method, etc. Quantitative forecasting methods include regression analysis, time series analysis, exponential smoothing, neural networks, and Grey forecasting model (GM).

Several studies have proposed time series models for industrial production and revealed the applicability of time series models to industrial production forecasting [3–6]. These methods typically require large amounts of data to construct the forecasting model. Hsu [7] showed that the GM requires minimal data and is the best among all existing models for short-term predictions. Xu and Wen [8] applied the GM to accurately forecast the number of passengers on international air transportation. Lin and Wang [9] used the model to predict the number of engineering officers for a ship in Taiwan and showed that the GM has higher prediction validity than the Markov chain model. Lin and Yang [10] also applied the GM to forecast Taiwan optical-electronics industry production. Because GM can work with as few as four observations, it is an ideal model to forecast Taiwan semiconductor industry production based on data only in the past decade.

A rolling Grey forecasting model (RGM) reconstructs itself whenever a new observation rolls in. RGM takes advantage of the latest information in updating a forecasting model. The original univariate RGM has the limitation of making forecast of a time series of data without considering possible correlation with any leading indicators. Within the RGM, there is a constant, P value, which was customarily set to 0.5. It is a hypothesis of this paper to make this P value a variable of time and shall be determined by a leading indicator. Because the annual semiconductor industry production in Taiwan is closely tied with U.S. demand, we hypothesized that the yearly percent change in real gross domestic product (GDP) by U.S. manufacturing industry could be a good representation of the U.S. demand change. We let the P value be affected by the yearly percent change in real GDP by U.S. manufacturing industry. This variable P value RGM did generate better forecast than RGM model with P value fixed at 0.5. Nevertheless, the yearly percent change in real GDP by U.S. manufacturing industry is not a leading indicator for the same year's U.S. demand.

We found out that the correlation between the yearly survey of anticipated industrial production growth rates in Taiwan and the yearly percent change in real GDP by U.S. manufacturing industry has a high correlation coefficient of 0.96. Fortunately, the former is a leading indicator because it is done at the end of each year and publicized at the beginning of the next year. Therefore, we used the yearly survey of anticipated industrial production growth rates in Taiwan to determine the P value in the RGM. The forecasts of the variable P value RGM (1,1) were superior to those of a fixed P value RGM (1,1) as well as to the forecasts made by the industry watchers in Industrial Technology Research Institute, Taiwan.

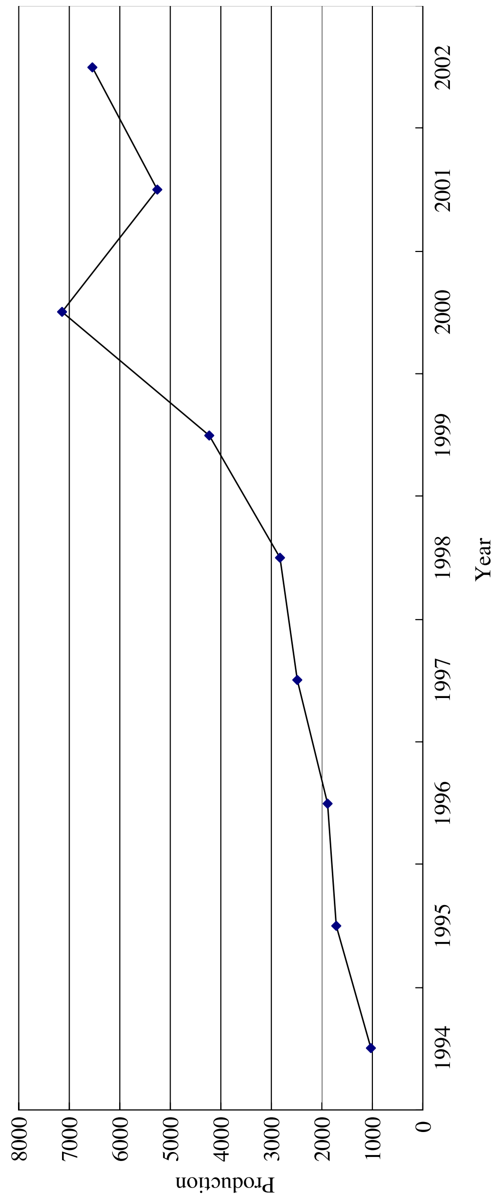

Fig. 1. The production of Taiwan's semiconductor industry.

This paper is organized as follows. Section 2 gives a brief introduction to the semiconductor industry in Taiwan. Section 3 reviews of RGM (1,1). Section 4 describes production forecast by RGM (1,1). Section 5 presents the variable P value RGM (1,1), and Section 6 gives the conclusions.

2. The semiconductor industry in Taiwan

Taiwan's semiconductor industry has grown and evolved mainly over the past 20 years. The overall semiconductor production revenue reached NTD 652.9 billion in 2002, equivalent to US$18.65 billion calculated at the exchange rate of 35 NTD to 1 dollar. In the rest of this paper, forecasts are all based on the currency of NTD. In 2001, Taiwan semiconductor industry consists of more than 100 design companies, 20 firms producing wafers, over 40 packaging firms, and 30 testing firms. Taiwan Semiconductor Manufacturing (TSMC) and United Microelectronics (UMC) have become the number 1 and 2 IC foundry operators in the world. Fig. 1 shows Taiwan's semiconductor industry production from 1994 to 2002 [11].

3. Rolling GM (1,1)

Grey forecasting requires only few observations for model construction [7,12–15]. This section briefly reviews the RGM to illustrate the method used to construct the model we adopted by creating a sequence of one-order linear moving [10,14,16].

The data sequence is given as $\{x^{(0)}(k),\ 1 \le k \le n\}$. Assume that $x^{(0)}(k)$ is positive for all k. Let r denote the length of the rolling interval. Suppose we wish to forecast $x^{(0)}$ at time t_0, $r+1 \le t_0 \le n$. The one-step-ahead RGM (1,1) means that we forecast the outcome at time t_0 based on r observations occurring before t_0. The first-order differential equation for the model is:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{1}$$

where t denotes the independent variables in the system, a represents the developed coefficient, and b is the Grey controlled variable. The parameters to be determined in the model are a and b. The primitive sequence used to build the model to forecast the output at time t_0 is:

$$x^{(0)}(i;k) = [x^{(0)}(i), x^{(0)}(i+1), x^{(0)}(i+2), \ldots, x^{(0)}(k)], \text{ where } r = k - i + 1 \tag{2}$$

when $i=1$, $x^{(0)}(1;r)$=[$x^{(0)}(1)$,$x^{(0)}(2)$,$x^{(0)}(3)$,. . .,$x^{(0)}(r)$] r is the length of the rolling interval.

In constructing the model, the Grey system must apply a one-order accumulated generating operation (AGO) to the primitive sequence to provide the middle message for building a model and to weaken the tendency toward variation. The AGO of $x^{(0)}(i;k)$ is defined as $x^{(1)}(i;k)$. That is,

$$x^{(1)}(i;k) = [x^{(1)}(i), x^{(1)}(i+1), x^{(1)}(i+2), \ldots, x^{(1)}(k)]$$
$$= \left(\sum_{j=i}^{i} x^{(0)}(j), \sum_{j=i}^{i+1} x^{(0)}(j), \sum_{j=i}^{i+2} x^{(0)}(j), \ldots, \sum_{j=i}^{k} x^{(0)}(j) \right) \tag{3}$$

From Eqs. (1) and (3) and the ordinary least-square method, coefficient $\hat{a}$ becomes:

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (\mathbf{B}^T\mathbf{B})^{-1}\mathbf{B}^T \boldsymbol{Y}_N \tag{4}$$

Furthermore, the accumulated matrix $\mathbf{B}$ is:

$$\boldsymbol{B} = \begin{bmatrix} -[Px^{(1)}(i) + (1-P)x^{(1)}(i+1)] & 1 \\ -[Px^{(1)}(i+1) + (1-P)x^{(1)}(i+2)] & 1 \\ \vdots & \vdots \\ -[Px^{(1)}(k-1) + (1-P)x^{(1)}(k)] & 1 \end{bmatrix}$$

where P is equal to 0.5 in the original model. The constant vector $\boldsymbol{Y}_N$ is:

$$\boldsymbol{Y}_N = [x^{(0)}(i+1), x^{(0)}(i+2), \ldots, x^{(0)}(k)]^T$$

The approximate relationship can be obtained by substituting $\hat{a}$ obtained in the differential equation and solving Eq. (1) as follows:

$$\hat{x}^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-at} + \frac{b}{a} \tag{5}$$

When $\hat{x}^{(1)}(1) = \hat{x}^{(0)}(1)$, the sequence one-order inverse-accumulated generating operation (IAGO) is acquired. The sequence that must be reduced as Eq. (6) can be obtained.

$$\hat{x}^{(0)}(t+1) = \hat{x}^{(1)}(t+1) - \hat{x}^{(1)}(t) \tag{6}$$

Given t= 1, 2,..., k, obtain the sequence of reduction as follows:

$$\hat{X}^{(0)}(i;k) = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(k+1)) \quad (7)$$

where $\hat{x}^{(0)}(k+1)$ is the Grey elementary forecasting value for $\hat{x}^{(0)}(k+1)$.

To obtain the forecast of $\hat{x}^{(0)}(t)$ for each $r+1 \leq t \leq n$, repeat the above procedure systematically. After generating and developing the model, further tests are necessary to understand the error between the forecasted value and the actual value. To demonstrate the efficiency of the proposed forecasting model, we adopted the residual error test to compare the actual value and forecasted value. $e(k+1)$ is the residual percentage between the forecasted value and actual value when the model at t_{k+1}. To calculate the residual percentage, we used:

$$e(k+1) = \left| \frac{x^{(0)}(k+1) - \hat{x}^{(0)}(k+1)}{x^{(0)}(k+1)} \right| 100\%, k+1 \leq n \quad (8)$$

As the forecasting model adopted in this paper is a rolling model, the model will be reconstructed when a new observation rolls in. The RGM is then a reasonable method for gaining the time varying tendency because the RGM parameters are updated continuously with time. The average residual error, e, is the RGM accuracy assuming that the data adopted in the RGM have four points. We used Eq. (9) to compute the model accuracy.

$$e = \frac{1}{n-4} \sum_{k=4}^{n-1} e(k+1)\% \quad (9)$$

4. Forecast Taiwan semiconductor production with RGM (1,1)

The data adopted in this paper were from ITRI, the most preeminent research institute in the Taiwan semiconductor industry.

According to RGM (1,1) and the data adopted (in million NTD), this study forecasted Taiwan semiconductor industry production from 1998 to 2002 in the following procedures:

Obtain the data sequence from year 1994 to 2002 as:

$$X^{(0)} = (1019, 1720, 1882, 2479, 2834, 4235, 7144, 5269, 6529)$$

Set the length of the rolling interval as 4. From Eq. (2), we obtain the primitive sequence $x^{(0)}(1;4)$ as

$$x^{(0)}(1;4) = (1019, 1720, 1882, 2479)$$

From Eq. (3), we obtain the one-order AGO sequence $x^{(1)}(1;4)$ as

$$x^{(1)}(1;4) = (1019, 2739, 4621, 7100)$$

Accumulate matrix **B** and constant vector $\boldsymbol{Y}_N$ as follows when P is equal to 0.5:

$$\mathbf{B} = \begin{bmatrix} -1879 & 1 \\ -3680 & 1 \\ -5860.5 & 1 \end{bmatrix} \qquad \boldsymbol{Y}_N = \begin{bmatrix} 1720 \\ 1882 \\ 2479 \end{bmatrix}$$

From Eq. (4) then solve $\hat{a}$ to get

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} -0.19352 \\ 1290.4 \end{bmatrix}$$

From Eq. (5), acquire the forecasting model as

$$\hat{x}^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{1290.4}{(-0.19352)}\right)e^{-(-0.19352)t} + \frac{1290.4}{(-0.19352)}$$

From Eq. (6), obtain the forecasting value for the year 1998 ($t=4$) as

$$\hat{x}^{(0)}(4+1) = \hat{x}^{(1)}(4+1) - \hat{x}^{(1)}(4) = 10\,002 - 7069 = 2933$$

According to the data sequence, we acquire five primitive sequences when the length of the rolling interval is set at four. By repeating the above procedures, we obtained the forecasted semiconductor industry production from 1998 to 2002. From Eqs. (8) and (9), we calculated and compared the absolute value of the residual errors and the average residual error of RGM (1,1), the results were shown in Table 1.

ITRI releases yearly production forecasts for the semiconductor industry at the beginning of each year [17–21]. Based on the forecasts, RGM (1,1) is better than ITRI's forecast for 1998 and 2002. Although ITRI's forecast outperformed RGM, RGM is a much simpler and more economical

Table 1
Forecasts of RGM (1,1)

Year	$\hat{a}$	Actual value	Forecast value	Residual percentage
1998	$a=-0.19352$, $b=1290.4$	2834	2933	3.49
1999	$a=-0.19455$, $b=1425.6$	4235	3483	17.75
2000	$a=-0.28968$, $b=1424.1$	7144	5447	23.76
2001	$a=-0.47141$, $b=896.2$	5269	10 851	105.93
2002	$a=-0.08104$, $b=4673.0$	6529	6512	0.25
Average residual error				30.24

compared to ITRI's forecast based on ITRI experts' industry experience and domain knowledge. Table 2 shows the forecasts of ITRI. The average residual error of ITRI's forecast is 21.27%, which was smaller than 30.24% of RGM.

5. Forecast Taiwan semiconductor production with variable *P* value RGM (1,1)

From Table 1, we found that the RGM (1,1) forecast for 2001 deviated obviously from the actual value. The September 11 attacks decreased the market demand resulting in an unexpected downturn in the semiconductor industry. What is more important is that the original RGM (1,1) was based only on past data without considering the economic factors in the forecasted year. In other words, if we take the leading factor into RGM consideration, the accuracy of the RGM forecast could be significantly improved. We therefore make the P value a variable of time, a parameter that influences matrix **B** in Eq. (4). To construct the leading factor and P value relationship, the first step is to determine the best P value. We experimented a series of P values from 0.1 to 0.9 to determine and then put these values into the forecasting model to obtain the forecasts. We selected the best P value that generated the smallest residual errors to be the one for our variable P value RGM (1,1). Appendix A shows the results of such

Table 2
Forecasts of ITRI

	ITRI	
	Forecast value	Residual percentage
1998	3348	18.14
1999	3523	16.81
2000	6753	5.47
2001	8545	62.17
2002	6283	3.77
Average residual error		21.27

Table 3
Forecasts of variable P value RGM (1,1)

	Variable P value RGM (1,1)[a]			Variable P value RGM (1,1)[b]		
	P value	Forecasted value	Residual error (%)	P value	Forecasted value	Residual error (%)
1998	0.70	3132	10.52	0.59	3020	6.56
1999	0.74	3775	10.86	0.72	3749	11.48
2000	0.74	6298	11.84	0.80	6546	8.37
2001	0.07	6811	29.27	0.04	6624	25.72
2002	0.55	6511	0.28	0.66	6498	0.48
Average residual error			12.55			10.52

[a] P value figured out from Eq. (10).
[b] P value figured out from Eq. (11).

experiments. The optimal P values from 1998 to 2002 are 0.4, 0.9, 0.9, 0.1, and 0.5, respectively.

The critical point for improving the RGM (1,1) accuracy is how to determine the appropriate P value. Because the annual semiconductor industry production in Taiwan is closely tied with U.S. demand, we hypothesized that the yearly percent change in real GDP by U.S. manufacturing industry [22] could be a good representation of the U.S. demand change. The yearly percent changes in real GDP by U.S. manufacturing industry from 1998 to 2002 are 4.12, 4.82, 4.72, -6.00, and 1.80, respectively. According to the data, we constructed the relationship between P value (P) and the yearly percent change in real GDP by U.S. manufacturing industry (m) in Eq. (10).

$$P = 0.441813 + 0.062467m \tag{10}$$

We also used the P values figured out from Eq. (10) to make forecasts. The average residual error was 12.55%, better than 21.27% of ITRI's forecast and 30.24% from the fixed P value RGM (1,1). Table 3 shows the forecasts.

Table 4
All forecasts compared with actual values

	Actual	ITRI	RGM (1,1)	RGM (1,1)[a]	RGM (1,1)[b]
1998	2834	3348	2933	3132	3020
1999	4235	3523	3483	3775	3749
2000	7144	6753	5447	6298	6546
2001	5269	8545	10 851	6811	6624
2002	6529	6283	6512	6511	6498
Average residual error (%)		21.27	30.24	12.55	10.52

[a] Variable P value RGM (1,1) using the P value figured out from Eq. (10).
[b] Variable P value RGM (1,1) using the P value figured out from Eq. (11).

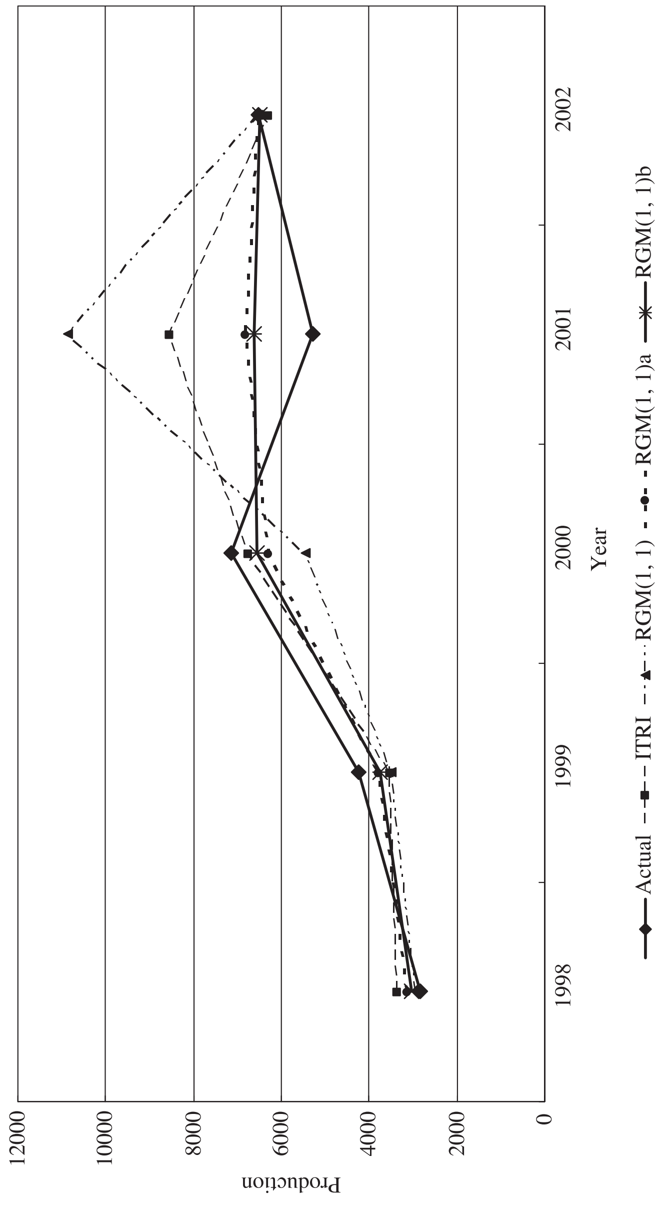

Fig. 2. The curves of the actual and forecast data.

Nevertheless, the yearly percent change in real GDP by U.S. manufacturing industry is not a leading indicator for the same year's U.S. demand. The yearly survey of anticipated industrial production growth rates in Taiwan is a leading indicator because it is done at the end of each year and publicized at the beginning of next year. We found out that its correlation with the yearly percent changes in real GDP by U.S. manufacturing industry has a correlation coefficient of 0.96. Therefore, we used the yearly survey of anticipated industrial production growth rates [23–27] in Taiwan to determine the P value in the GM and the data from 1998 to 2002 are 4.13, 7.00, 8.60, -7.40, and 5.60, respectively.

According to the data, we constructed the following equation to show the relationship between the P value (P) and the anticipated industrial production growth rate (g).

$$P = 0.389138 + 0.047647g \tag{11}$$

Eq. (11) helps determine the appropriate P value when the coming year is forecasted. To test the accuracy of the regression, use Eq. (11) to determine the P values. The average residual error of the variable P value RGM (1,1) using Eq. (11) was 10.52%, which was still better than the fixed P value RGM (1,1) and the ITRI's forecast. Table 3 shows the forecasts.

We also compared all forecasts with the actual values in Table 4. From Table 4, we found the forecasts of the variable P value RGM (1,1) adopting Eqs. (10) or (11) are superior to the fixed P value RGM (1,1) or the ITRI's forecast, especially in 2001. Fig. 2 shows the curves of the actual and forecast data.

6. Conclusions

Original univariate GM has the limitation of making forecast of a time series of data without considering possible correlation with any leading indicators. We believe that the annual semiconductor industry production in Taiwan should be closely tied with the U.S. demand. This study made an enhancement to the traditional GM, which customarily fix the P value at 0.5, by changing the P value in accordance to the yearly percent change in real GDP by U.S. manufacturing industry. This variable P value RGM (1,1) did generate better forecast than the fixed P value RGM (1,1). Nevertheless, the yearly percent change in real GDP by U.S. manufacturing industry is not a leading indicator for the same year's U.S. demand.

We found out that the yearly survey of anticipated industrial production growth rates in Taiwan and the yearly percent change in real GDP by U.S. manufacturing industry are highly correlated. Fortunately, the former is a leading indicator because it is done at the end of each year and publicized at the beginning of the next year. Therefore, we used the yearly survey of anticipated industrial production growth rates in Taiwan to determine a new P value for next year in the variable P value RGM. The forecasts of the variable P value RGM (1,1) were superior to those of a fixed P value RGM (1,1) as well as to the forecasts made by the industry watchers in Industrial Technology Research Institute, Taiwan.

Appendix A

A.1. 1998 Production forecast for the semiconductor industry under different *P* values

P	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
a	− 0.18049	− 0.18359	− 0.1868	− 0.1901	− 0.19352	− 0.19704	− 0.20069	− 0.20446	− 0.20835
b	1193.6	1216.5	1240.2	1264.8	1290.4	1316.9	1344.4	1373.1	1402.8
Forecasted value	2594	2672	2755	2841	2933	3030	3132	3240	3355
Actual value	2834	2834	2834	2834	2834	2834	2834	2834	2834
Error rate (%)	8.45	5.70	2.80	0.26	3.49	6.90	10.51	14.34	18.38

A.2. 1999 Production forecast for the semiconductor industry under different *P* values

P	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
a	− 0.18101	− 0.18422	− 0.18755	− 0.19098	− 0.19455	− 0.19824	− 0.20206	− 0.20603	− 0.21015
b	1319.6	1344.6	1370.6	1397.6	1425.6	1454.7	1484.9	1516.4	1549.1
Forecasted value	3077	3170	3269	3373	3483	3600	3723	3854	3994
Actual value	4235	4235	4235	4235	4235	4235	4235	4235	4235
Error rate (%)	27.34	25.14	22.81	20.35	17.75	15.00	12.09	8.99	5.69

A.3. 2000 Production forecast for the semiconductor industry under different *P* values

P	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
a	− 0.26117	− 0.26779	− 0.27474	− 0.28203	− 0.28968	− 0.29773	− 0.30619	− 0.31511	− 0.3245
b	1264.7	1301.3	1339.9	1380.8	1424.1	1470	1518.8	1570.6	1625.9
Forecasted value	4393	4623	4873	5147	5447	5777	6142	6546	6994
Actual value	7144	7144	7144	7144	7144	7144	7144	7144	7144
Error rate (%)	38.50	35.29	31.79	27.96	23.76	19.13	14.03	8.37	2.10

A.4. 2001 Production forecast for the semiconductor industry under different *P* values

P	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
a	− 0.39685	− 0.4132	− 0.43094	− 0.45027	− 0.47141	− 0.49463	− 0.52023	− 0.54862	− 0.58025
b	751.74	783.32	817.66	855.13	896.19	941.37	991.32	1046.8	1108.9
Forecasted value	7007	7732	8589	9613	10 851	12 366	14 249	16 626	19 686
Actual value	5269	5269	5269	5269	5269	5269	5269	5269	5269
Error rate (%)	32.98	46.74	63.01	82.44	105.93	134.70	170.42	215.55	273.62

A.5. 2002 Production forecast for the semiconductor industry under different *P* values

P	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
a	− 0.09828	− 0.09436	− 0.09018	− 0.08574	− 0.08104	− 0.07609	− 0.07088	− 0.06544	− 0.05976
b	4268.5	4371.9	4474.1	4574.6	4673	4768.8	4861.5	4950.7	5035.8
Forecasted value	6416	6457	6487	6506	6512	6507	6489	6459	6417
Actual value	6529	6529	6529	6529	6529	6529	6529	6529	6529
Error rate (%)	1.73	1.10	0.64	0.36	0.25	0.34	0.61	1.07	1.71

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