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Full Length Research Paper

A hybrid method for improving forecasting accuracy utilizing genetic algorithm and its application to J-REIT (office type) stock market price data

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We proposed earlier that the equation of the exponential smoothing method (ESM) is equivalent to (1,1) ARMA model equation, a new method of estimating the smoothing constant in the exponential smoothing method which satisfied the minimum variance of forecasting error. Generally, the smoothing constant is selected arbitrarily, but in this paper, we utilize the above theoretical solution. Firstly, we estimate the ARMA model parameter and then estimate the smoothing constants. Thus, the theoretical solution is derived in a simple way and it may be utilized in various fields. Furthermore, combining the trend removal method with this method, we aim to improve forecasting accuracy. An approach to this method is executed in the following method. Trend removal by the combination of linear, 2nd order non-linear function and 3rd order non-linear function is executed on the stock market price data of J-REIT (Japan Real Estate Investment Trust) for office type. Genetic algorithm is utilized to search optimal weights for the weighting parameters of linear and non-linear function. For the comparison, monthly trend is removed after that. Theoretical solution of the smoothing constant of ESM is calculated for both the monthly trend removal data and the non monthly trend removing data. Then the forecasting is executed on these data. This new method shows that it is useful for the time series that has various trend characteristics. The effectiveness of this method should be examined in various cases.

Key words: Minimum variance, exponential smoothing method, forecasting, trend, genetic algorithm.

INTRODUCTION

Many methods for time series analysis have been presented such as Autoregressive model (AR Model), Autoregressive Moving Average Model (ARMA Model) and Exponential Smoothing Method (ESM) (Jenkins, 1994; Brown, 1963; Tokumaru et al., 1982; Kobayashi, 1992). Among these, ESM is said to be a practical simple method.

For this method, various improving methods such as adding compensating item for time lag, coping with the time series with trend (Winters, 1984), utilizing Kalman Filter (Maeda, 1984), Bayes Forecasting (West and Harrison, 1989), adaptive ESM (Ekern, 1982), exponentially weighted Moving Averages with irregular updating periods (Johnston, 1993), making averages of forecasts using plural method (Makridakis and Winkler, 1983) are presented. For example, Maeda (1984) calculated smoothing constant in relationship with S/N ratio under the assumption that the observation noise was added to the system. But he had to calculate under supposed noise because he could not grasp observation noise. It can be said that it does not pursue the optimum solution from the very data themselves which should be derived by those estimations. Ishii (1991) pointed out that the

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optimal smoothing constant was the solution of infinite order equation, but he did not show the analytical solution. Based on these facts, we proposed a new method of estimating smoothing constant in ESM before (Takeyasu, 2002, Takeyasu and Nagao, 2008). Focusing that the equation of ESM is equivalent to (1,1) order ARMA model equation; a new method of estimating smoothing constant in ESM was derived.

In this paper, utilizing the above method, a revised forecasting method is proposed. In making forecast such as stock market price data, trend removing method is devised.

In the application, the following five typical stocks are selected in which investment is concentrated on office rental field:

・Nippon Building Fund Inc. "NBF"
・Japan Real Estate Investment Corporation "JRE"
・Global One Real Estate Investment Corp "GOR"
・NOMURA REAL ESTATE OFFICE FUND, INC ("NOF")
・Daiwa Office Investment Corporation ("DOI")

Forecasting is executed on these data. This is a revised forecasting method. Variance of forecasting error of this newly proposed method is assumed to be less than those of previously proposed methods. The rest of the paper is organized as follows. In section 2 (Description of ESM using ARMA model), ESM is stated by ARMA model and estimation method of smoothing constant is derived using ARMA model identification. The combination of linear and non-linear function is introduced for trend removing in section 3 (TREND REMOVAL METHOD). The monthly ratio is referred to in section 4 (MONTHLY RATIO).
Measuring method of forecasting accuracy is exhibited in 5 (FORECASTING ACCURACY). GA model to search optimal weights for the weighting parameters of liner and non-linear function is introduced in 6 (SEARCHING OPTIMAL WEIGHTS UTILIZING GA). Forecasting is executed in section 7 (NUMERICAL EXAMPLE), and estimation accuracy is examined.

Description of ESM using ARMA model (Takeyasu and Nagao, 2008)

In ESM, forecasting at time t +1 is stated in the following equation.

$$\hat{x}_{t+1} = \hat{x}_t + \alpha\left(x_t - \hat{x}_t\right) \tag{1}$$

$$= \alpha x_t + (1-\alpha)\hat{x}_t \tag{2}$$

Here,
$\hat{x}_{t+1}$: forecasting at $t+1$
x_t : realized value at t
α : smoothing constant $(0 < \alpha < 1)$
(2) is re-stated as:

$$\hat{x}_{t+1} = \sum_{l=0}^{\infty} \alpha(1-\alpha)^l x_{t-l} \tag{3}$$

By the way, we consider the following (1,1) order ARMA model.

$$x_t - x_{t-1} = e_t - \beta e_{t-1} \tag{4}$$

Generally, (p,q) order ARMA model is stated as:

$$x_t + \sum_{i=1}^{p} a_i x_{t-i} = e_t + \sum_{j=1}^{q} b_j e_{t-j} \tag{5}$$

Here,
$\{x_t\}$: Sample process of Stationary Ergodic Gaussian Process $x(t)$ $t = 1,2,\cdots,N,\cdots$
$\{e_t\}$: Gaussian White Noise with 0 mean σ_e^2 variance

MA process in (5) is supposed to satisfy convertibility condition.

Utilizing the relation that:

$$E\left[e_t \middle| e_{t-1}, e_{t-2}, \cdots\right] = 0$$

we get the following equation from (4).

$$\hat{x}_t = x_{t-1} - \beta e_{t-1} \tag{6}$$

Operating this scheme on t +1, we finally get:

$$\begin{aligned}\hat{x}_{t+1} &= \hat{x}_t + (1-\beta)e_t \\ &= \hat{x}_t + (1-\beta)(x_t - \hat{x}_t)\end{aligned} \tag{7}$$

If we set $1-\beta = \alpha$, the above equation is the same with (1), that is, equation of ESM is equivalent to (1,1) order ARMA model.

Comparing (4) with (5) and using (1) and (7), we get,

$$\begin{aligned}a_1 &= -1 \\ b_1 &= -\beta\end{aligned} \tag{8}$$

From the above, we can get estimation of smoothing constant after we identify the parameter of MA part of

ARMA model. But, generally MA part of ARMA model becomes non-linear equations which are described below.

Let (5) be:

$$\tilde{x}_t = x_t + \sum_{i=1}^{p} a_i x_{t-i} \tag{9}$$

$$\tilde{x}_t = e_t + \sum_{j=1}^{q} b_j e_{t-j} \tag{10}$$

We express the autocorrelation function of $\tilde{x}_t$ as $\tilde{r}_k$ and from (9), (10) we get the following non-linear equations which are well known (Tokumaru et al., 1982).

$$\tilde{r}_k = \begin{cases} \sigma_e^2 \sum_{j=0}^{q-k} b_j b_{k+j} & (k \le q) \\ 0 & (k \ge q+1) \end{cases}$$

$$\tilde{r}_0 = \sigma_e^2 \sum_{j=0}^{q} b_j^2 \tag{11}$$

For these equations, recursive algorithm has been developed. In this paper, parameter to be estimated is only b_1, so it can be solved in the following way.
From (4) (5) (8) (11), we get:

$$\begin{aligned} q &= 1 \\ a_1 &= -1 \\ b_1 &= -\beta = \alpha - 1 \\ \tilde{r}_0 &= \left(1 + b_1^2\right)\sigma_e^2 \\ \tilde{r}_1 &= b_1 \sigma_e^2 \end{aligned} \tag{12}$$

If we set:

$$\rho_k = \frac{\tilde{r}_k}{\tilde{r}_0} \tag{13}$$

the following equation is derived.

$$\rho_1 = \frac{b_1}{1 + b_1^2} \tag{14}$$

We can get b_1 as follows,

$$b_1 = \frac{1 \pm \sqrt{1 - 4\rho_1^2}}{2\rho_1} \tag{15}$$

In order to have real roots, ρ_1 must satisfy,

$$|\rho_1| \le \frac{1}{2} \tag{16}$$

As

$\alpha = b_1 + 1$

b_1 is within the range of

$-1 < b_1 < 0$

Finally we get,

$$b_1 = \frac{1 - \sqrt{1 - 4\rho_1^2}}{2\rho_1}$$
$$\alpha = \frac{1 + 2\rho_1 - \sqrt{1 - 4\rho_1^2}}{2\rho_1} \tag{17}$$

which satisfy the above condition. Thus we can obtain a theoretical solution by a simple way.

TREND REMOVAL METHOD

As ESM is a one of a linear model, forecasting accuracy for the time series with non-linear trend is not necessarily good. How to remove trend for the time series with non-linear trend is a big issue in improving forecasting accuracy. In this paper, we devise a way to remove this non-linear trend by utilizing non-linear function.

As trend removal method, we describe linear and non-linear function, and the combination of these.

Linear function

We set:

$$y = a_1 x + b_1 \tag{18}$$

as a linear function, where x is a variable, for example, time and y is a variable, for example, stock market price, a_1 and b_1 are parameters which are estimated by using least square method.

Non-linear function

We set:

$$y = a_2 x^2 + b_2 x + c_2 \tag{19}$$

$$y = a_3x^3 + b_3x^2 + c_3x + d_3 \quad (20)$$

as a 2nd and a 3rd order non-linear function. (a_2, b_2, c_2) and (a_3, b_3, c_3, d_3) are also parameters for 2nd and 3rd order non-linear functions which are estimated by using least square method.

The combination of a linear and a non-linear function

We set:

$$y = \alpha_1(a_1x + b_1) + \alpha_2(a_2x^2 + b_2x + c_2) + \alpha_3(a_3x^3 + b_3x^2 + c_3x + d_3) \quad (21)$$

$$0 \le \alpha_1 \le 1 \quad ,0 \le \alpha_2 \le 1 \quad ,0 \le \alpha_3 \le 1$$
$$\alpha_1 + \alpha_2 + \alpha_3 = 1 \quad (22)$$

as the combination of linear and 2nd order non-linear and 3rd order non-linear function. Trend is removed by dividing the original data by (21). The optimal weighting parameters $\alpha_1, \alpha_2, \alpha_3$ are determined by utilizing GA. GA method is precisely described in 6(SEARCHING OPTIMAL WEIGHTS UTILIZING GA).

MONTHLY RATIO

For example, if there is the monthly data of L years as stated below,

$$\{x_{ij}\} \ (i = 1, \cdots, L) \ (j = 1, \cdots, 12)$$

where $x_{ij} \in R$ in which j means month and i means year and x_{ij} is shipping data of i-th year, j-th month, then monthly ratio $\tilde{x}_j \ (j = 1, \cdots, 12)$ is calculated as follows,

$$\tilde{x}_j = \frac{\frac{1}{L}\sum_{i=1}^{L} x_{ij}}{\frac{1}{L} \cdot \frac{1}{12}\sum_{i=1}^{L}\sum_{j=1}^{12} x_{ij}} \quad (23)$$

Monthly trend is removed by dividing the data by (23). Numerical examples for both the monthly trend removal case and the non-removal case are discussed in 7 (NUMERICAL EXAMPLE).

FORECASTING ACCURACY

Forecasting accuracy is measured by calculating the variance of the forecasting error.

Variance of forecasting error is calculated by:

$$\sigma_\varepsilon^2 = \frac{1}{N-1}\sum_{i=1}^{N}(\varepsilon_i - \bar{\varepsilon})^2 \quad (24)$$

Where, forecasting error is expressed as:

$$\varepsilon_i = \hat{x}_i - x_i \quad (25)$$

$$\bar{\varepsilon} = \frac{1}{N}\sum_{i=1}^{N}\varepsilon_i \quad (26)$$

SEARCHING OPTIMAL WEIGHTS UTILIZING GA

Definition of the problem

We search $\alpha_1, \alpha_2, \alpha_3$ of (21) which minimizes (24) by utilizing GA. By (22), we only have to determine α_1 and α_2. $\sigma_\varepsilon{}^2$ ((24)) is a function of α_1 and α_2; therefore we express them as $\sigma_\varepsilon^2(\alpha_1, \alpha_2)$. Now, we pursue the following:

Minimize: $\sigma_\varepsilon^2(\alpha_1, \alpha_2)$ (27)

Subject to: $0 \le \alpha_1 \le 1 \quad ,0 \le \alpha_2 \le 1 \quad ,\alpha_1 + \alpha_2 \le 1$

We do not necessarily have to utilize GA for this problem which has small member of variables. Considering the possibility that variables increase when we use logistics curve in the near future, we want to ascertain the effectiveness of GA.

The structure of the gene

Gene is expressed by the binary system using {0,1} bit. Domain of variable is [0,1] from (22). We suppose that variables are taken down to the second decimal place. As the length of domain of variable is 1-0=1, seven bits are required to express variables. The binary bit strings <bit6, ～, bit0> is decoded to the [0,1] domain real number by the following procedures (Sakawa and Tanaka, 1995).

Procedure 1: Convert the binary number to the binary-coded decimal.

$$(\langle bit_6, bit_5, bit_4, bit_3, bit_2, bit_1, bit_0 \rangle)_2 = \left(\sum_{i=0}^{6} bit_i 2^i\right)_{10} = X' \quad (28)$$

Table 1. Corresponding table of the decimal, the binary and the real numbers.

The decimal number	The binary number							The corresponding real number
	Position of the bit							
	6	5	4	3	2	1	0	
0	0	0	0	0	0	0	0	0.00
1	0	0	0	0	0	0	1	0.01
2	0	0	0	0	0	1	0	0.02
3	0	0	0	0	0	1	1	0.02
4	0	0	0	0	1	0	0	0.03
5	0	0	0	0	1	0	1	0.04
6	0	0	0	0	1	1	0	0.05
7	0	0	0	0	1	1	1	0.06
8	0	0	0	1	0	0	0	0.06
…								…
126	1	1	1	1	1	1	0	0.99
127	1	1	1	1	1	1	1	1.00

Table 2. The gene structure.

α_1							α_2						
Position of the bit													
13	12	11	10	9	8	7	6	5	4	3	2	1	0
0-1	0-1	0-1	0-1	0-1	0-1	0-1	0-1	0-1	0-1	0-1	0-1	0-1	0-1

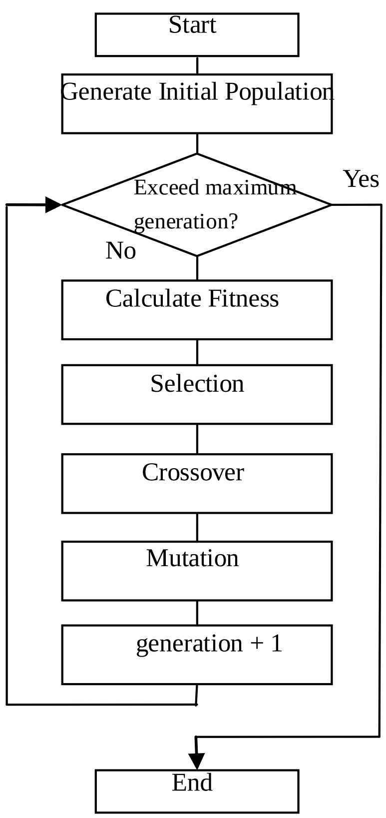

Figure 1. The flow of algorithm.

Procedure 2: Convert the binary-coded decimal to the real number.

The real number = (Left head starting point of the domain) + X' ((Right hand ending point of the domain) / $(2^7 - 1)$) (29)

The decimal number, the binary number and the corresponding real number in the case of 7 bits are expressed in Table 1.

1 variable is expressed by 7 bits; therefore, 2 variables need 14 bits. The gene structure is exhibited in Table 2.

The flow of algorithm

The flow of algorithm is exhibited in Figure 1.

Initial population

Generate M initial population. Here, $M = 100$. Generate each individual so as to satisfy (22).

Calculation of fitness

First of all, calculate forecasting value. There are 36 monthly data for each case. We use 24 data (1 to 24) and

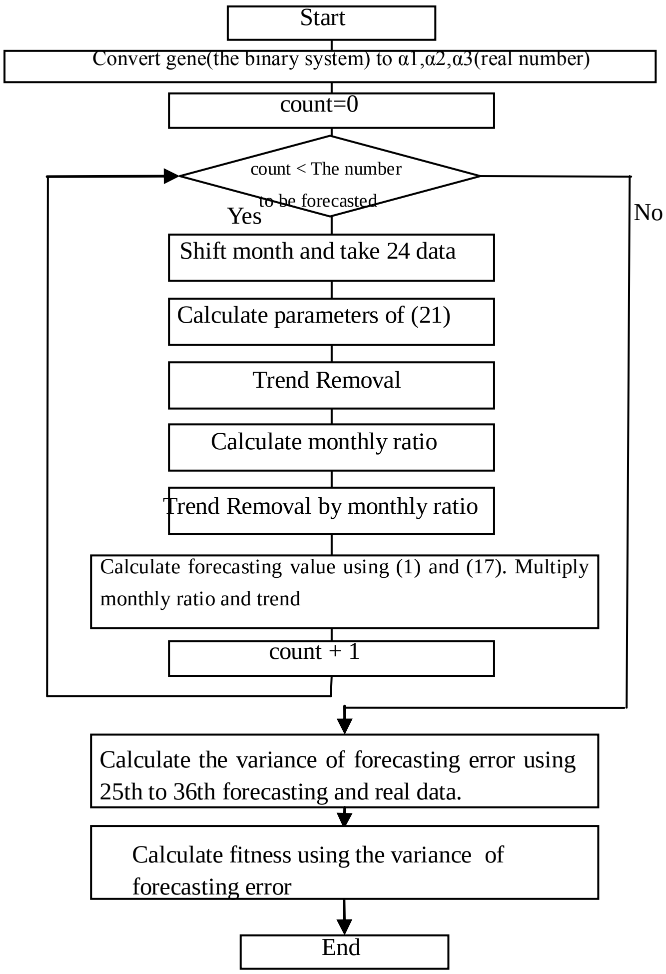

Figure 2. The flow of calculation of fitness.

remove trend by the method stated in 3. Then we calculate monthly ratio by the method stated in 4. After removing monthly trend, the method stated in 2 is applied and Exponential Smoothing Constant with minimum variance of forecasting error is estimated. Then 1 step forecast is executed. Thus, data are shifted to 2nd to 25th and the forecast for 26th data is executed consecutively, which finally reaches forecast of 36th data. To examine the accuracy of forecasting, variance of forecasting error is calculated for the data of 25th to 36th. Final forecasting data are obtained by multiplying monthly ratio and trend. Variance of forecasting error is calculated by (24). Calculation of fitness is exhibited in Figure 2.

Scaling (Iba, 2002) is executed such that fitness becomes large when the variance of forecasting error becomes small. Fitness is defined as follows:

$$f(\alpha_1,\alpha_2)=U-\sigma_\varepsilon^{\ 2}(\alpha_1,\alpha_2) \tag{30}$$

Where U is the maximum of $\sigma_\varepsilon^{\ 2}(\alpha_1,\alpha_2)$ during the past W generation. Here, W is set to be 5.

Selection

Selection is executed by the combination of the general elitist selection and the tournament selection. Elitism is executed until the number of new elites reaches the predetermined number. After that, tournament selection is executed and selected.

Crossover

Crossover is executed by uniform crossover. Crossover rate is set as follows:

$$P_c = 0.7 \tag{31}$$

Mutation

Mutation rate is set as follows:

$$P_m = 0.05 \tag{32}$$

Mutation is executed to each bit at the probability P_m; therefore, all mutated bits in the population M become $P_m \times M \times 14$.

NUMERICAL EXAMPLE

Application to stock market price data

The following five typical stocks are selected in which investment is concentrated on office rental field.

・Nippon Building Fund Inc. "NBF"
・Japan Real Estate Investment Corporation "JRE"
・Global One Real Estate Investment Corp. "GOR"
・NOMURA REAL ESTATE OFFICE FUND, INC.("NOF")
・Daiwa Office Investment Corporation ("DOI")

The above mentioned 5 companies for 2 cases (from January 2009 to December 2011) are analyzed. Furthermore, GA results are compared with the calculation results of all considerable cases in order to confirm the effectiveness of GA approach. First of all, graphical charts of these time series data are exhibited in Figures 3 to 7.

Execution results

GA execution condition is exhibited in Table 3. We made repetition10 times; the maximum, average and minimum

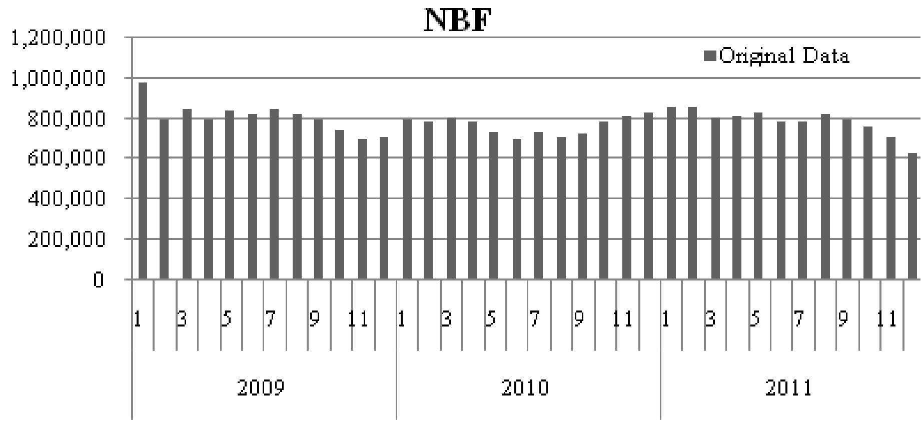

Figure 3. Data of NBF.

Figure 4. Data of JRE.

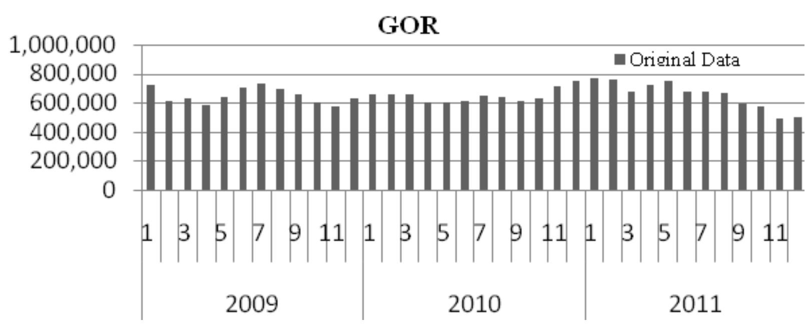

Figure 5. Data of GOR.

Table 3. Execution condition.

GA execution condition	
Population	100
Maximum generation	50
Crossover rate	0.7
Mutation ratio	0.05
Scaling window size	5
The number of elites to retain	2
Tournament size	2

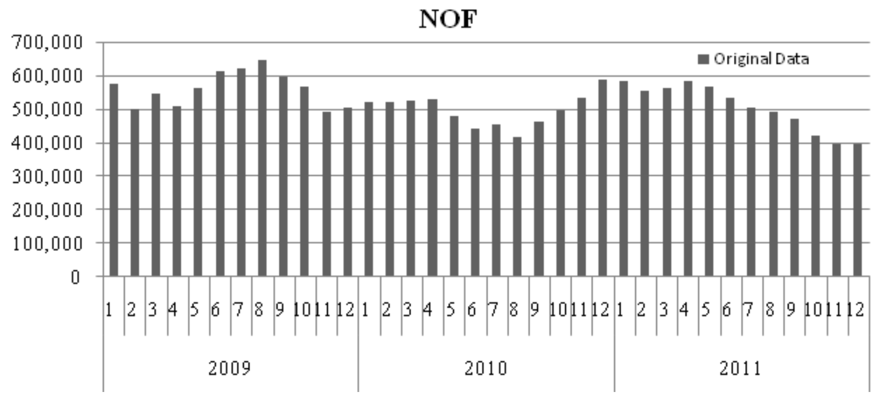

Figure 6. Data of NOF.

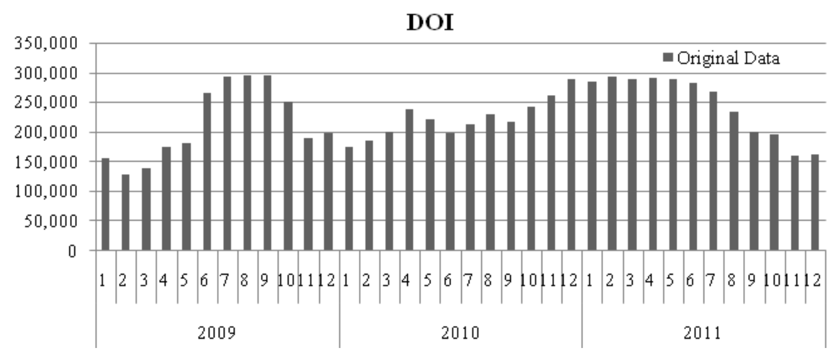

Figure 7. Data of DOI.

Table 4. GA execution results (Monthly ratio not used).

Variable	The variance of forecasting error			Average of convergence generation
	Maximum	Average	Minimum	
NBF	1,088,146,306	1,088,146,306	1,088,146,306	4.9
JRE	622,323,409	612,640,873	609,228,939	19.4
GOR	1,884,674,063	1,878,367,620	1,877,666,904	16.7
NOF	259,788,011	259,788,011	259,788,011	8.7
DOI	245,057,177	239,710,519	237,419,094	6.8

Table 5. GA execution results (Monthly ratio used).

Variable	The variance of forecasting error			Average of convergence generation
	Maximum	Average	Minimum	
NBF	1,274,502,902	1,273,045,651	1,272,421,115	15.1
JRE	1,385,530,597	1,385,530,597	1,385,530,597	10.4
GOR	2,626,387,232	2,625,942,748	2,625,893,361	9.9
NOF	570,750,000	570,750,000	570,750,000	18.1
DOI	474,911,255	474,911,255	474,911,255	16.4

of the variance of forecasting error and the average of convergence generation are exhibited in Tables 4 and 5.

The case of monthly ratio is not used is smaller than the case monthly ratio used in the variance of forecasting

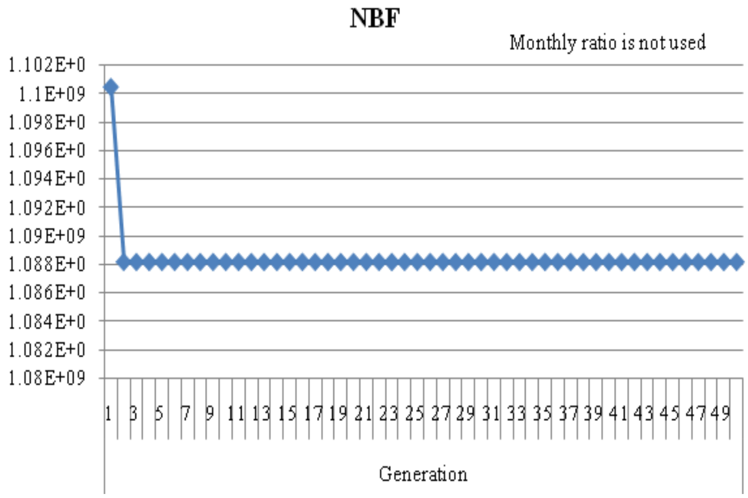

Figure 8. Convergence process in the case of NBF (monthly ratio is not used).

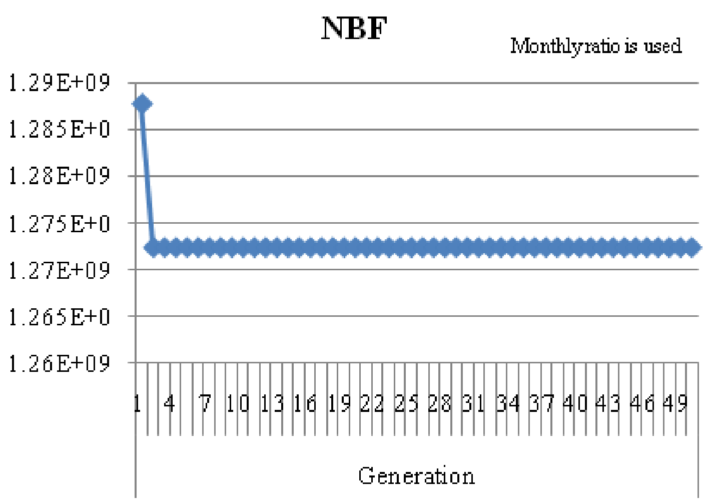

Figure 9. Convergence process in the case of NBF (Monthly ratio is used).

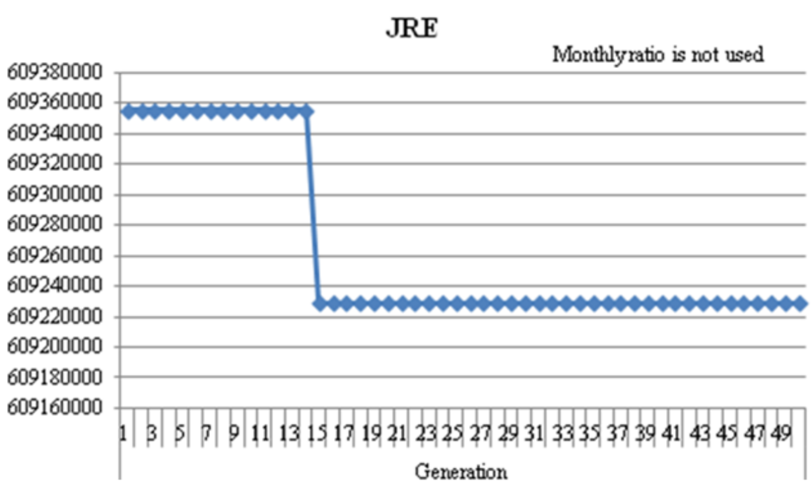

Figure 10. Convergence process in the case of JRE (Monthly ratio is not used).

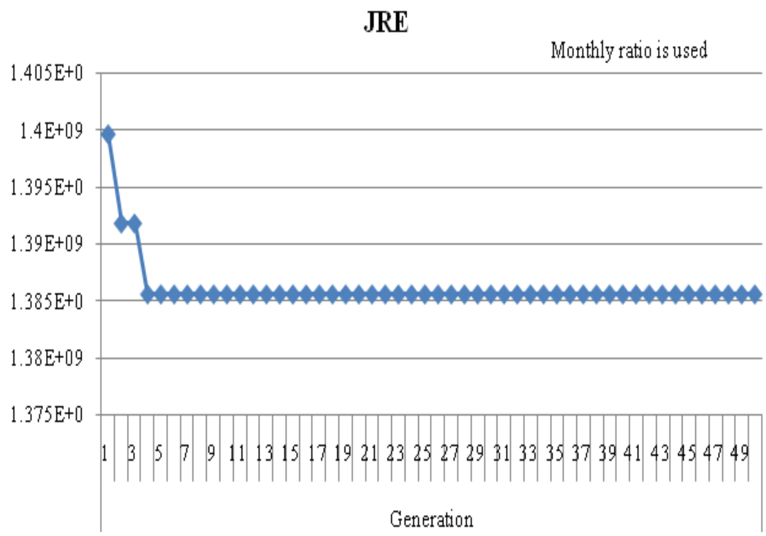

Figure 11. Convergence process in the case of JRE (Monthly ratio is used).

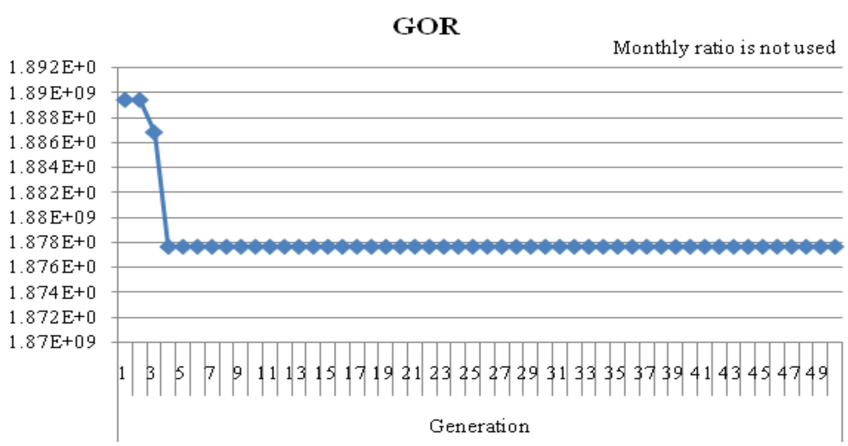

Figure 12. Convergence process in the case of GOR (monthly ratio is not used).

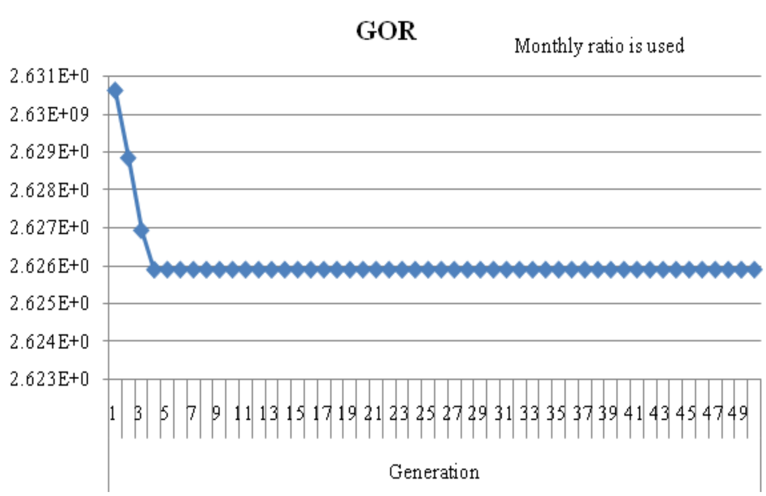

Figure 13. Convergence process in the case of GOR (Monthly ratio is used).

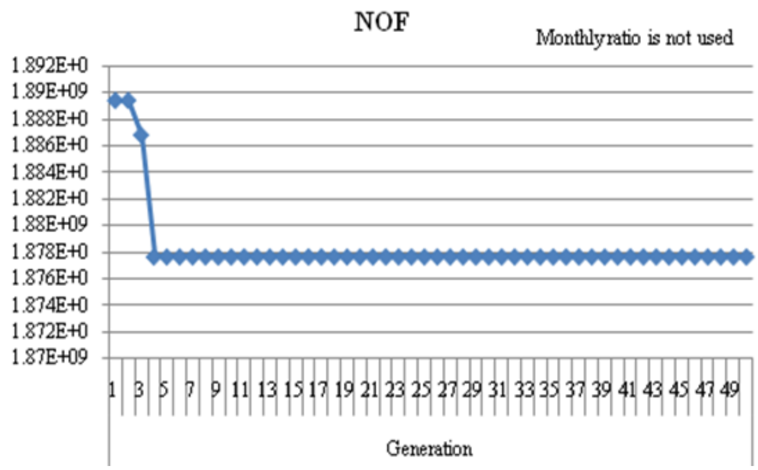

Figure 14. Convergence process in the case of NOF (Monthly ratio is not used).

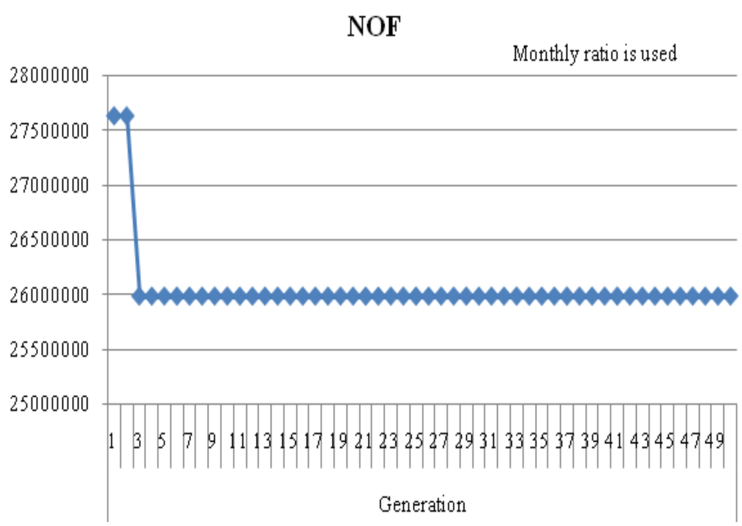

Figure 15. Convergence process in the case of NOF (Monthly ratio is used).

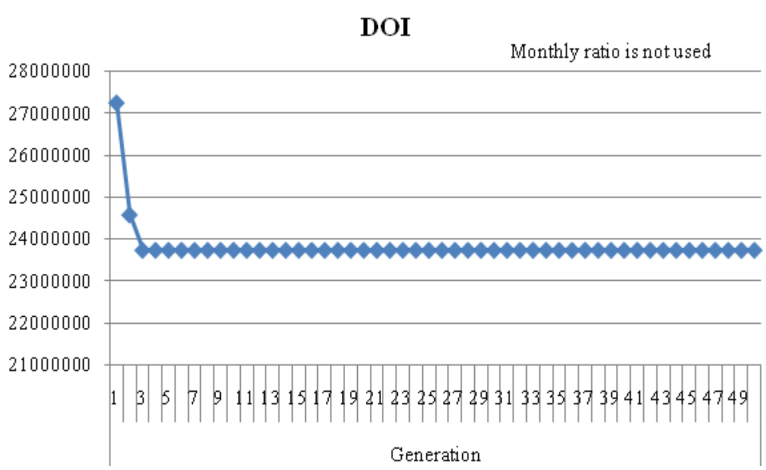

Figure 16. Convergence Process in the case of DOI (Monthly ratio is not used).

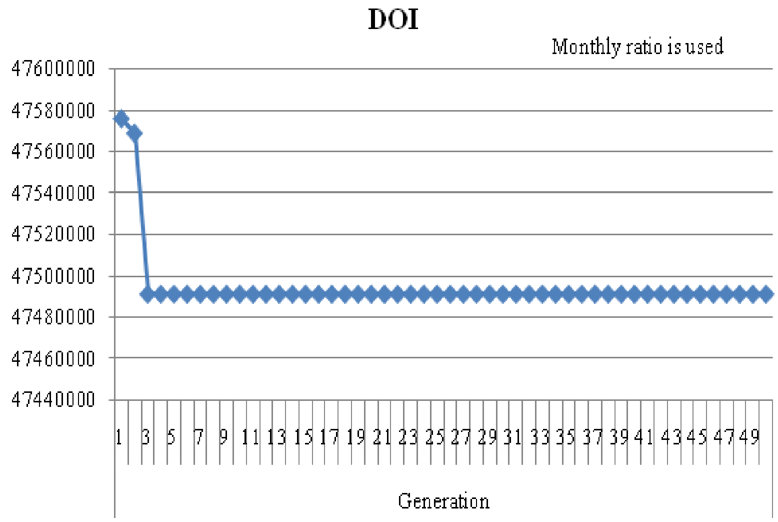

Figure 17. Convergence process in the case of DOI (Monthly ratio is used).

Table 6. Optimal weights and their genes (Monthly ratio is not used).

Variable	α_1	α_2	α_3	Position of the bit													
				13	12	11	10	9	8	7	6	5	4	3	2	1	0
NBF	0.00	0.83	0.17	0	0	0	0	0	0	0	1	1	0	1	0	0	1
JRE	0.01	0.89	0.00	0	0	0	1	1	1	0	1	1	1	0	0	0	1
GOR	0.74	0.01	0.25	1	0	1	1	1	1	0	0	0	0	0	0	0	1
NOF	0.67	0.00	0.33	1	0	1	0	1	0	1	0	0	0	0	0	0	0
DOI	0.54	0.00	0.46	1	0	0	0	1	0	0	0	0	0	0	0	0	0

Table 7. Optimal weights and their genes (Monthly ratio is used).

Variable	α_1	α_2	α_3	Position of the bit													
				13	12	11	10	9	8	7	6	5	4	3	2	1	0
NBF	0.00	0.53	0.47	0	0	0	0	0	0	0	1	0	0	0	0	1	1
JRE	0.00	0.89	0.11	0	0	0	0	0	0	0	1	1	1	0	0	0	1
GOR	0.44	0.00	0.56	0	1	1	1	0	0	0	0	0	0	0	0	0	0
NOF	0.37	0.00	0.63	0	1	0	1	1	1	1	0	0	0	0	0	0	0
DOI	0.33	0.00	0.67	0	1	0	1	0	1	0	0	0	0	0	0	0	0

error in every company. It may be because stock market price does not have definite seasonal trend in general.
The minimum variance of forecasting error of GA coincides with those of the calculation of all considerable cases and it shows the theoretical solution. Although it is a rather simple problem for GA, we can confirm the effectiveness of GA approach. Further study for complex problems should be examined hereafter.

Next, optimal weights and their genes are exhibited in Tables 6 and 7.

In the case of monthly ratio not used, the combination of linear and 2nd+3rd order non-linear function model is best in GOR. On the other hand, the combination of linear and 3rd order non-linear function model is best in NOF and DOI. And the combination of linear and 2nd order non-linear function model is best in JRE and the combination of 2nd+3rd order non-linear function model is best in NBF. In the case of monthly ratio used, the combination of 2nd plus 3rd order non-linear function model is best in NBF and JRF. On the other hand, the combination of linear and 3rd order non-linear function model is best in GOR, NOF and DOI. Parameter estimation results for the trend of equation (21) using least square method are exhibited in Table 8 for the case of 1st to 24th data.

Trend curves are exhibited in Figures 18 to 22.

Table 8. Parameter estimation results for the trend of equation (21).

Variable	a_1	b_1	a_2	b_2	c_2	a_3	b_3	c_3	d_3
NBF	-4,402	844,688	739	-22,882	924,771	21	-45	-14,881	906,426
JRE	1,444	737,612	500	-11,055	791,776	5	310	-9,115	787,327
GOR	135	646,399	400	-9,860	689,710	68	-2,153	16,187	629,986
NOF	-3,957	578,795	31	-4,722	582,110	137	-5,113	47,767	461,758
DOI	2,667	184,915	-172	6,976	166,243	116	-4,512	51,268	64,685

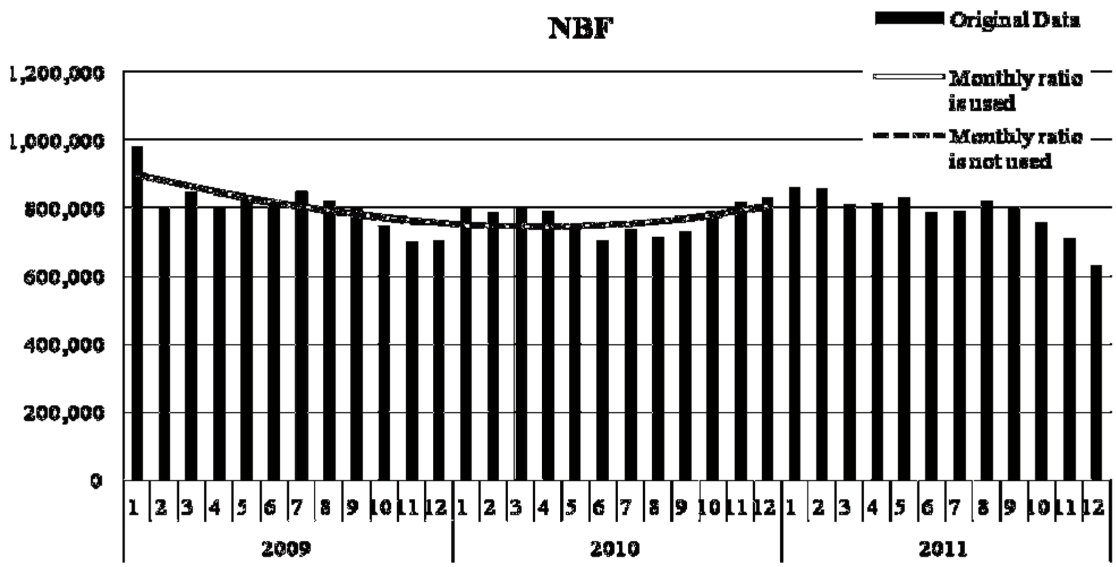

Figure 18. Trend of NBF.

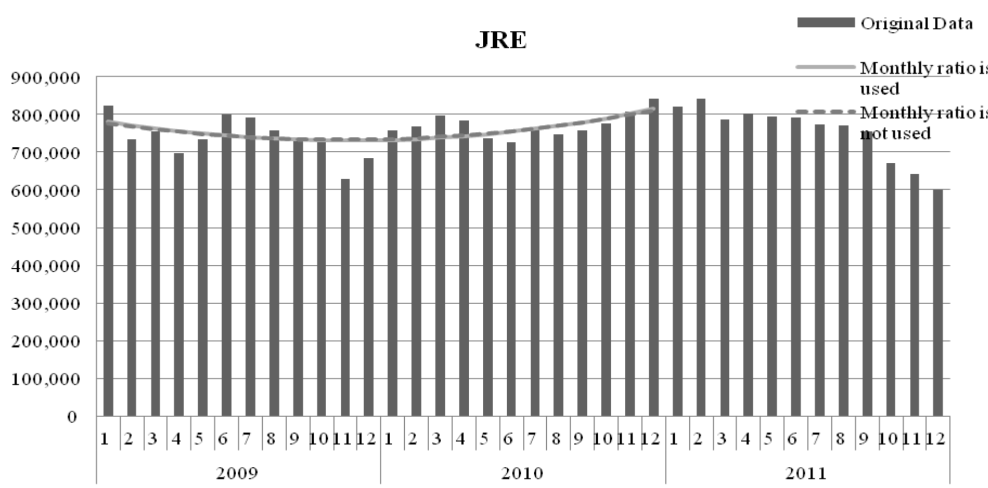

Figure 19. Trend of JRE.

Calculation results of monthly ratio for 1st to 24th data are exhibited in Table 9.

Estimation result of the smoothing constant of minimum variance for the 1st to 24th data is exhibited in Tables 10

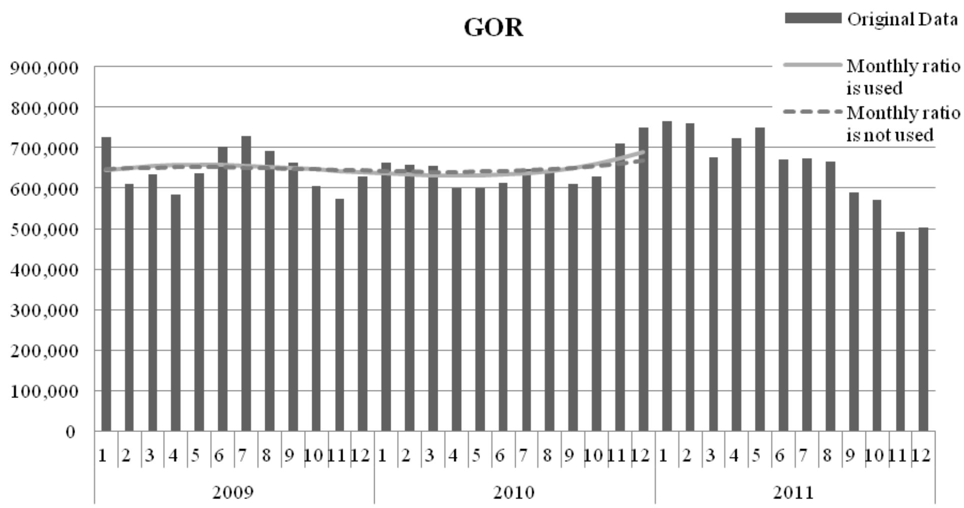

Figure 20. Trend of GOR.

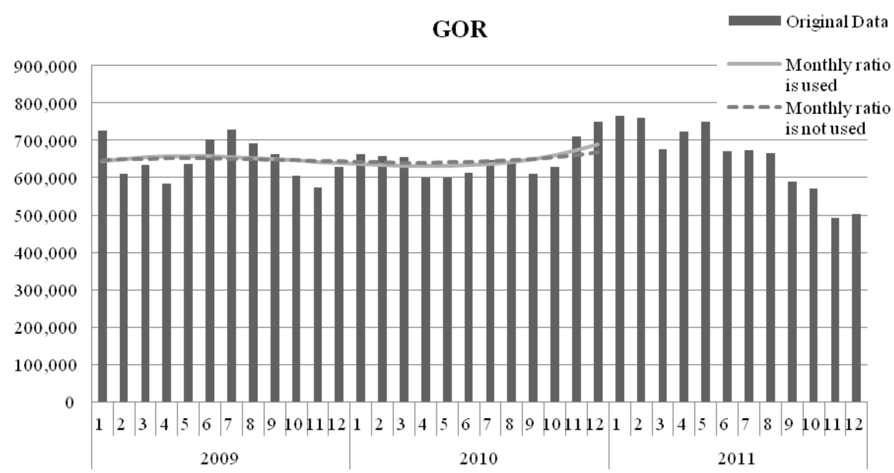

Figure 21. Trend of NOF.

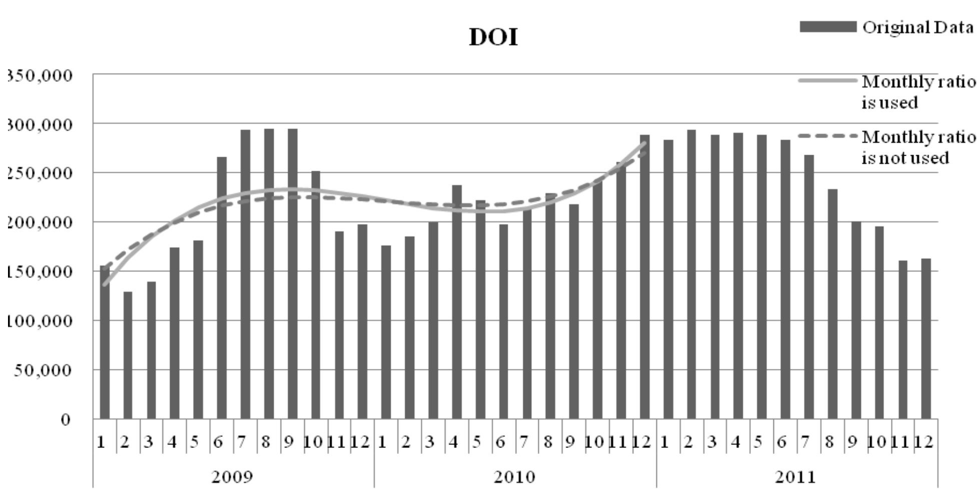

Figure 22. Trend of DOI.

Table 9. Parameter estimation result of monthly ratio.

Month	1	2	3	4	5	6	7	8	9	10	11	12
NBF	1.078	0.981	1.030	1.001	1.000	0.975	1.017	0.986	0.988	0.989	0.975	0.983
JRE	1.044	0.998	1.035	0.990	0.983	1.019	1.038	0.999	0.987	0.988	0.934	0.984
GOR	1.083	0.988	1.002	0.921	0.958	1.018	1.065	1.029	0.979	0.946	0.974	1.037
NOF	1.042	0.965	1.009	0.984	0.982	0.992	1.016	0.999	1.006	1.008	0.973	1.024
DOI	0.971	0.825	0.845	0.998	0.954	1.066	1.143	1.160	1.112	1.046	0.923	0.957

Table 10. Smoothing constant of minimum variance of equation (17) (Monthly ratio is not used).

Variable	ρ_1	α
NBF	-0.1504	0.8460
JRE	-0.0441	0.9558
GOR	-0.2501	0.7320
NOF	-0.0185	0.9815
DOI	-0.3369	0.6126

Table 11. Smoothing constant of minimum variance of equation (17) (Monthly ratio is used).

Variable	ρ_1	α
NBF	-0.3266	0.6283
JRE	-0.4058	0.4877
GOR	-0.3099	0.6527
NOF	-0.5662	0.0800
DOI	-0.3789	0.5415

to 11.

Forecasting results are exhibited in Figures 23 to 27.

REMARKS

In all cases, that monthly ratio was not used had a better forecasting accuracy (Tables 4 and 5). JRE had a good result in $1^{st}+2^{nd}$ order, NBF had a good result in $2^{nd}+3^{rd}$ order and GOR had a good result in $1^{st}+2^{nd}+3^{rd}$ order. NOF and DOI had a good result in $1^{st}+3^{rd}$ order.

The minimum variance of forecasting error of GA coincides with those of the calculation of all considerable cases and it shows the theoretical solution. Although it is a rather simple problem for GA, we can confirm the effectiveness of GA approach. Further study for complex problems should be examined hereafter.

Conclusion

Based on the idea that the equation of exponential smoothing method (ESM) was equivalent to (1,1) order ARMA model equation, a new method of estimation of smoothing constant in the exponential smoothing method was proposed before by us which satisfied the minimum the variance of forecasting error. Generally, the smoothing constant was selected arbitrarily. But in this paper, we utilized the above stated theoretical solution. Firstly, we made an estimation of ARMA model parameter and then estimated smoothing constants. Thus the theoretical solution was derived in a simple way and it might be utilized in various fields.

Furthermore, combining the trend removal method with this method, we aimed to improve forecasting accuracy. An approach to this method was executed in the following method. Trend removal by a linear function was applied to the stock market price data of J-REIT for office type.

The combination of linear and non-linear function was also introduced in trend removal. Genetic algorithm is utilized to search the optimal weight for the weighting parameters of linear and non-linear function. For the comparison, monthly trend was removed after that. Theoretical solution of smoothing constant of ESM was calculated for both of the monthly trend removal data and the non monthly trend removal data. Then forecasting was executed on these data. The new method shows that it is useful for the time series that has various trend

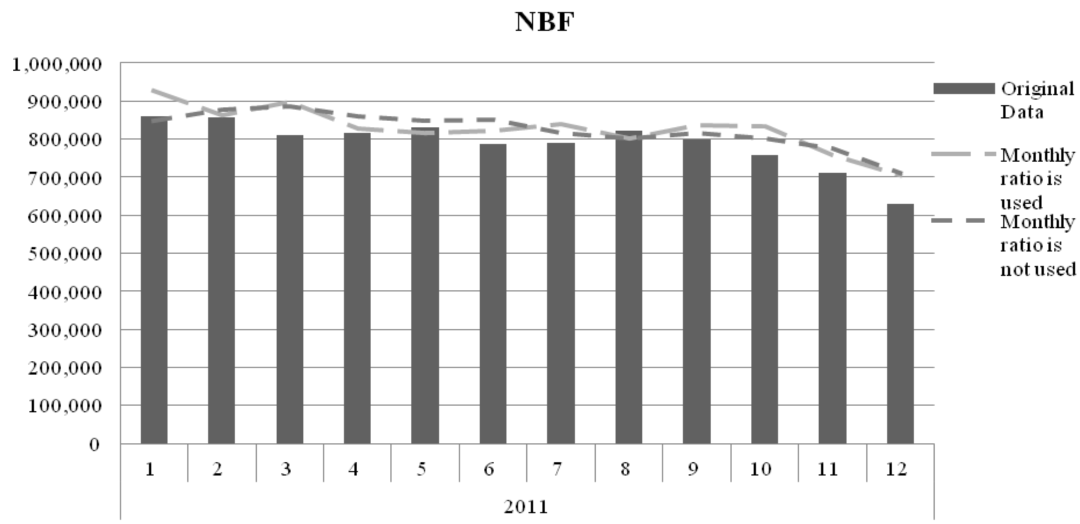

Figure 23. Forecasting result of NBF.

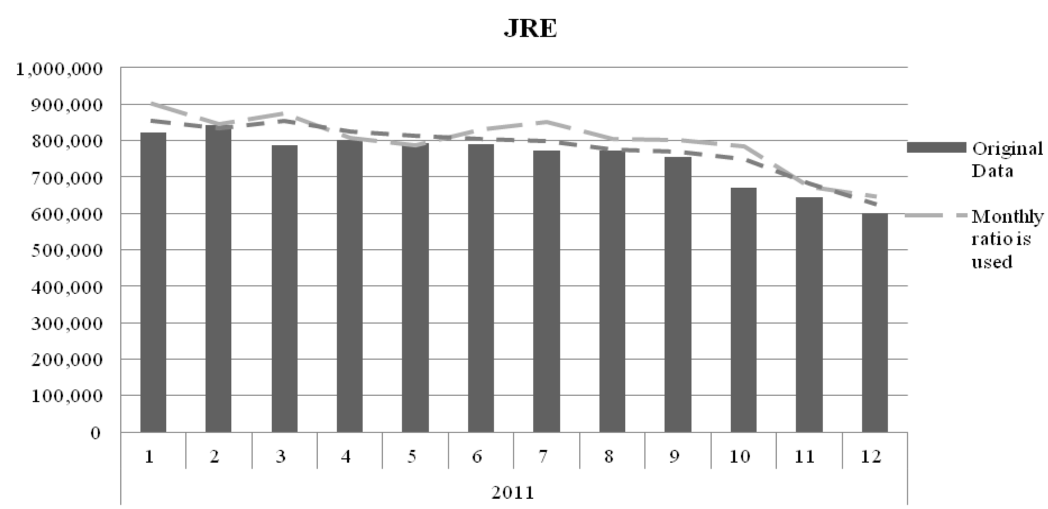

Figure 24. Forecasting result of JRE.

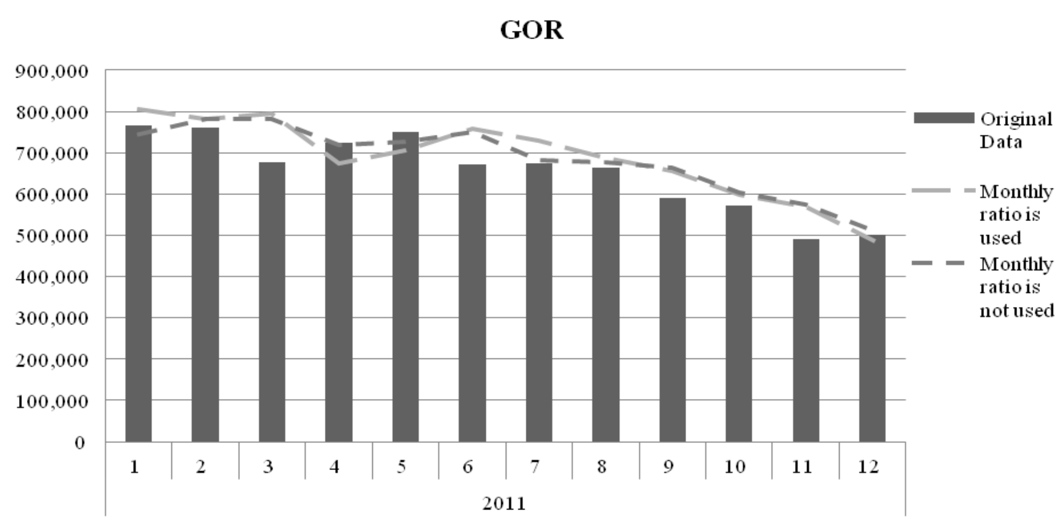

Figure 25. Forecasting result of GOR.

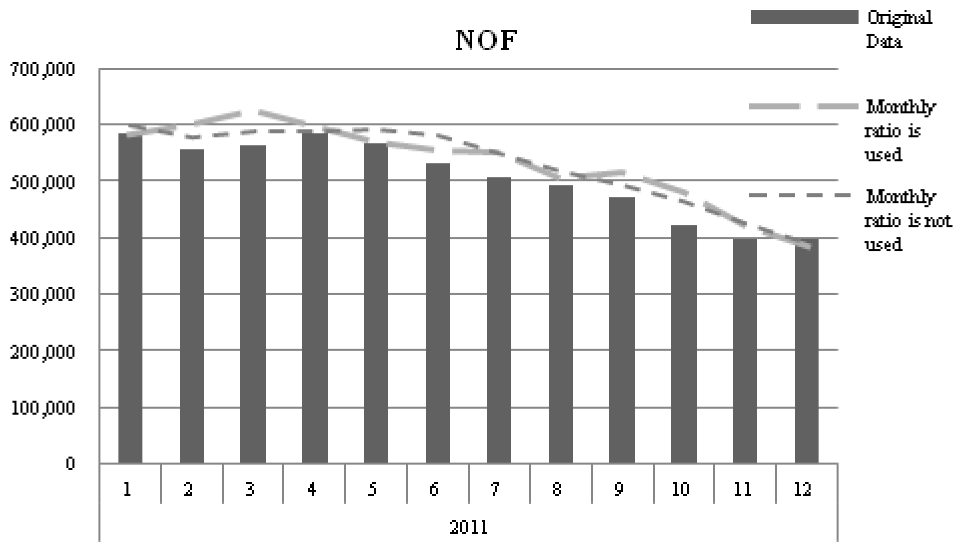

Figure 26. Forecasting result of NOF.

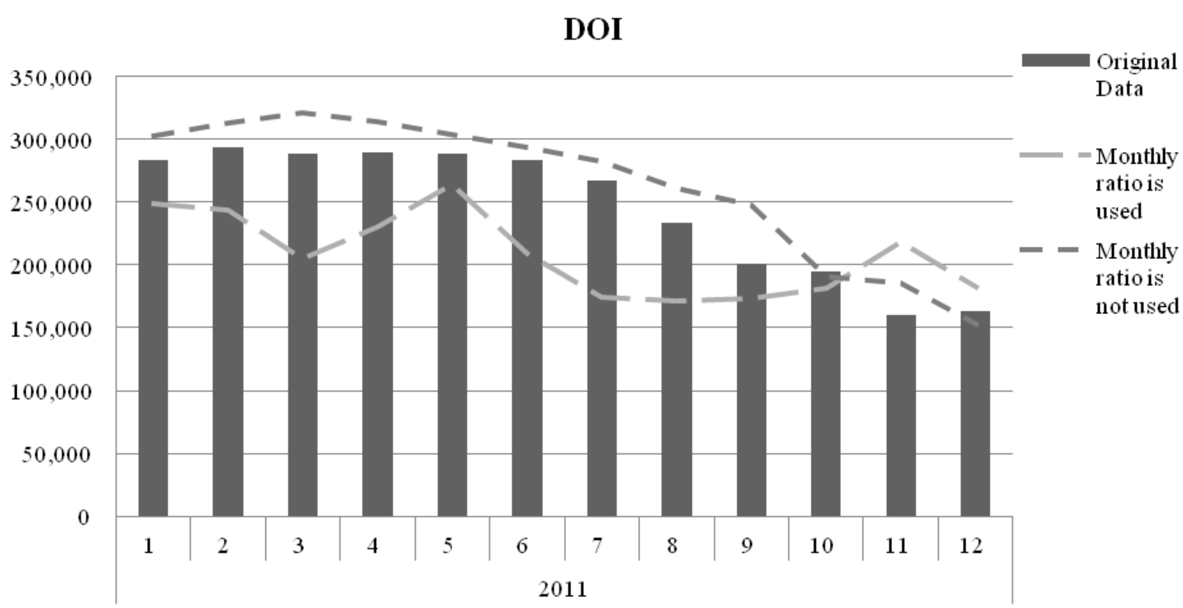

Figure 27. Forecasting result of DOI.

characteristics. The effectiveness of this method should be examined in various cases.

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