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AN INTELLIGENT FINANCIAL RATIO SELECTION MECHANISM FOR EARNING FORECAST

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Abstract Conventionally, linear and univariate time series models are broadly used in earning forecast. However, their forecasting accuracies are seriously limited without considering sufficient important factors. On the other hand, using more variables does not guarantee to obtain better forecasting accuracy and may cause inefficiency. The Multi-Objective Genetic Algorithms (MOGA) have been shown to be able to select the variable set with population diversity and to perform efficient search in large space. In addition, the multiple regression model can efficiently evaluate the predicting accuracy by using the least sum of squared errors (SSE). We therefore combine the advantages of both multiple regression and MOGA to form a new efficient forecasting mechanism which maximizes the forecasting accuracy with minimal number of financial ratios. Furthermore, this mechanism includes the SWMR (Sliding Window Multiple Regression) mechanism which retrains our predictor periodically in order to get more accurate earning forecast.

1. Introduction

Most investors have great difficulty in the stock selection decisions of their investment behavior due to their cognitive, informational or psychological limitations. Previous studies have shown that the stock selection ability can be enhanced by good earnings forecasts [23] and have established the relationship between quarterly earnings forecast performance and abnormal stock returns [2, 3, 4, 19, 27, 30]. Therefore, good earnings forecast plays an important role in stock selection decisions.

Currently, the univariate time series models [8] and multiple regression models [15] are most frequently used to predict future EPS (earnings per share). Univariate time series models, such as the simple exponential model, moving average model, and the simple auto regression model, mainly predict future EPS from previous EPS. Since the actual EPS depends not only on the previous EPS but also on various financial ratios, the forecasting accuracies of these univariate methods will be seriously limited without considering sufficient important factors.

On the other hand, although the multiple regression model uses multiple variables to predict EPS, its variable selection methods are essentially linear. The commonly used selection methods include the stepwise method, the forward selection method, and the backward elimination method [15]. These methods select variables one at a time according to a specific order without backtracking and thus may only produce suboptimal solutions.

Genetic algorithms (GA), introduced by Holland in 1975, are a well-known efficient nonlinear search method in large space [10]. Many variable selection problems have been efficiently solved by using GA [1, 13, 14, 16, 18, 21, 22, 24, 29]. These GA-based variable selection algorithms combine many different optimization targets into a single fitness function without considering the trade-off between forecasting accuracy and variable number.

```
procedure SGA
   Initialize population
   Evaluate population
   while (termination condition is false)
      Selection
      Crossover
      Mutation
      Evaluation
   endwhile
   Report the best solution found
endprocedure
```

Figure 1: A simple genetic algorithm

The Multi-Objective Genetic Algorithms (MOGA) have been shown to be able to select the variable set with population diversity and to perform efficient search in large space [6, 7, 17, 25, 28]. In addition, the multiple regression model can efficiently evaluate the predicting accuracy by using the least sum of squared errors (SSE). We therefore combine the advantages of both multiple regression and MOGA to form a new efficient forecasting mechanism which maximizes the forecasting accuracy with minimal number of financial ratios. Furthermore, this mechanism includes the SWMR (Sliding Window Multiple Regression) mechanism which retrains our predictor periodically in order to get more accurate earning forecast.

The rest of this paper is organized as follows. Section 2 reviews the Genetic Algorithms. Section 3 explains the proposed system architecture and the fitness function in detail. Section 4 shows our experimental results. Finally, Section 5 gives our conclusions.

2. Genetic Algorithms

Genetic algorithm is a search method based on natural evolution and genetics. It combines survival of the fittest with a structured and randomized information exchange mechanism. It is a simple but powerful computation tool and makes no restrictive assumptions about the search space [9, 10, 20, 26]. Figure 1 shows the procedure of a simple genetic algorithm (SGA) which consists of 3 genetic operators: selection, crossover and mutation.

To solve a problem with genetic algorithms, an encoding mechanism must first be designed to represent each possible solution of the problem by a fixed length binary string called chromosome or individual. Each chromosome will be evaluated by a fitness function for its goodness. Genetic algorithms use a population, which is simply a set of binary strings, to search the solution space. During each generation, the three genetic operators, selection, crossover, and mutation, are applied to the population.

Selection operator picks individuals in the population based on their fitness. Each pair of individuals or parents undergo crossover at random by exchanging their information with each other to generate new individuals or offspring. Each bit is randomly mutated (flipped) with a small mutation rate. The process continues until the termination criterion or the predetermined generation number is reached.

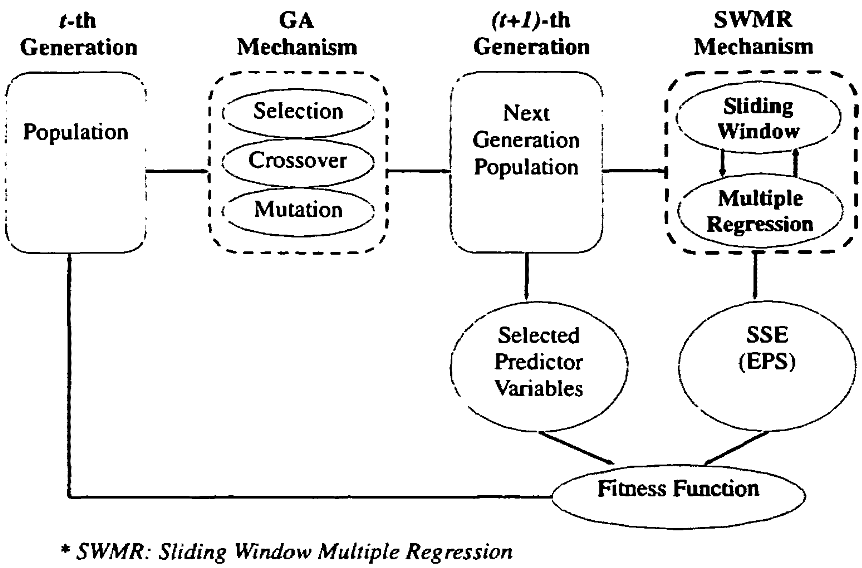

Figure 2: SWMR MOGA-based architecture

Table 1: List of the initial 65 financial ratios (partial)

No.	Ratio ID	Description
1	R100	Return on total assets
2	R308	Book value per share
3	R432	Operating income growth rate
⋮	⋮	⋮
65	R835	Operation income per employee

3. System Architecture

In this study, we propose an efficient SWMR MOGA-based (Sliding Window and Multiple Regression model based on Multi-Objective Genetic Algorithms) architecture as shown in Figure 2 to predict more accurate EPS. In this architecture, 65 financial ratios, including R308 (Book value per share), R408 (Total growth rate), R432 (Operating income growth rate), R612 (Fixed asset turnover), and R835 (Operation income per employee), are selected to be the initial predictor variable set as partially listed in Table 1. Then, the GA mechanism generates the next-generation population from the parent population according to the fitnesses of chromosomes (individuals). The Sum of Squared Errors (SSE) of each individual in the newer population will be evaluated by the SWMR mechanism. The fitness function considers both the SSE and the number of selected predictor variables.

3.1. Encoding and fitness function

To represent a set of selected predictor variables, we use a 65-bit string as chromosome, one for each candidate financial ratio. Each '1' in a chromosome indicates the inclusion of the corresponding financial ratio. The search space of the predictor variables for genetic algorithms is thus 2^{65}. The fitness of each individual will be evaluated by a fitness function.

In this paper, the most accurate predicting EPS under considering less variables are preferred. Thus, both the predicting accuracy criterion and the number of predictor variables

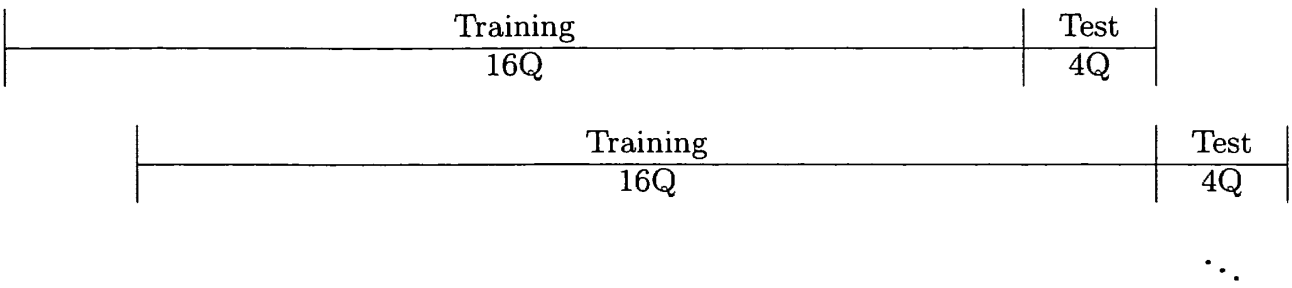

Figure 3: Sliding windows simulation process

criterion are considered simultaneously. Let $F(V)$ denote the fitness function which is defined as follows.

$$F(V) = \lambda * (1/SSE) + \gamma * (|U| - |V|)/|U| \tag{1}$$

$$SSE = \sum_{i=1}^{t}(EPS_{G,i}(V) - EPS_{T,i})^2 \tag{2}$$

In the above equations, SSE denotes the sum of squared errors between forecasted EPS and actual EPS by SWMR mechanism. $EPS_{G,i}(V)$ denotes the forecasted EPS by SWMR mechanism using variables V selected by GA mechanism in the i-th observation. $EPS_{T,i}$ denotes the actual EPS in the i-th observation. U is the set of initial 65 financial ratios. V is the set of financial ratios selected by GA mechanism. λ, γ are positive real numbers representing the relative preference between SSE and number of used variables and are set at about 10:1 in our experiments. In general, the smaller the SSE is or the smaller the $|V|$ is, the higher the F is.

3.2. SWMR mechanism

Each sliding window in the SWMR mechanism consists of one training phase and one test phase. The predictor is trained during the training phase and used in the test phase. The predictor is retrained periodically in order to get more accurate earning forecast as shown in Figure 3.

In each sliding window, the selected predictor variables (X_1, X_2, ..., X_m) are used in the estimated multiple regression function as shown below.

$$\hat{Y} = b_0 + b_1X_1 + b_2X_2 + \cdots + b_mX_m \tag{3}$$

The $\hat{Y}$ denotes the forecasted quarterly earning (EPS) value in the corresponding sliding window.

4. Experimental Results

The programs of our proposed mechanism was written in Borland C++ Builder 5.0 with Sugal 2.1 library [11, 12]. The stepwise method was simulated in SPSS 8.0 package.

4.1. GA parameters

The parameters used in our GA runs are set as follows. The population size is 50 and chromosome length is 65. The number of generations is set to 2000. The selection method is roulette wheel and the crossover method is one-point crossover. The crossover rate is set to 0.6 and mutation rate is set to 0.001 as suggested in [26]. Minor changes in theses parameters did not seem to have a major effect on the performance in our preliminary tries.

Table 2: Descriptive statistics of the 109 sample companies

	Mean	No. > Mean	Maximum	Minimum
Net sales (millions)	89.96	26	1035.65	1.07
Total assets (millions)	694.67	27	7410.03	23.38
Market value of equity (millions)	589.76	18	17493.45	6.63
Sales growth rate (%)	0.11	32	4.33	-0.52
Return on total assets (%)	0.16	50	12.16	-9.41
Current ratio (%)	1.63	34	7.93	0.20
Leverage (%)	0.45	50	0.45	0.22
Turnover (%)	2.05	34	10.99	0.25

4.2. Sample data

There are more than 500 companies currently listed in Taiwan Stock Exchange (TSE), we remove companies which are listed less than 10 years or have missing financial ratios in Taiwan Economic Journal (TEJ) Data Bank. The results are 109 companies distributed among 17 industries. These 109 companies are used as our simulation samples for simple exponential model, moving average model, simple auto regression model, stepwise method and our SWMR MOGA.

The descriptive statistics of those 109 sample companies are given in Table 2. The variables in Table 2 are calculated using year 2000 TEJ data unless otherwise specified. The simulation period is from the first quarter of 1991 to the last quarter of 1999. Thirty-six observations are collected for each company. Each observation can use the 65 candidate financial ratios (predictor variable) of current quarter to predict the EPS (response variable) of next quarter. The training phase is 16 quarters and the test phase is 4 quarters in each sliding window as shown in Figure 3. Furthermore, the sliding window shifts one year (four quarters) gradually until the last quarter in 1999. Finally, the four quarters in 2000 (unseen data) is the validation phase, which verifies the forecasting accuracy of each simulation method, respectively.

A number of interesting points about the characteristics of the 109 companies can be drawn from Table 2. First, the mean net sales is $89.96 million (with 26 companies greater than mean) and the mean total assets is $694.67 million (with 27 companies greater than mean) which indicate that the net sales and total assets of most sample companies are less than their respective mean values. That is, most of the selected companies belong to the small and middle enterprises. Second, the mean market value of equity $589.76 is significantly larger than net sales, and both the mean leverage (0.45) and current ratio (1.63) fall into normal range. Third, the low sales growth rate reflects the current global depression. Finally, the selected companies experience greater profits and higher daily turnover whose means are 0.16 and 2.05, respectively.

4.3. Analysis of results

For brevity, we summarize the performance of each forecasting method by industry as shown in Figures 4–8.

Table 3 summarizes the descriptive tests for 3 forecasting methods, namely, Auto Regression, Stepwise and SWMR MOGA, again by industry. In Table 3, the mean and minimum of adjusted R^2 (0.87 & 0.56) for our proposed SWMR MOGA mechanism are better than those for stepwise method (0.78 & 0.38) and simple auto regression model (0.11 & -0.03). On the other hand, the values of Durbin-Watson (DW) test on both the SWMR MOGA

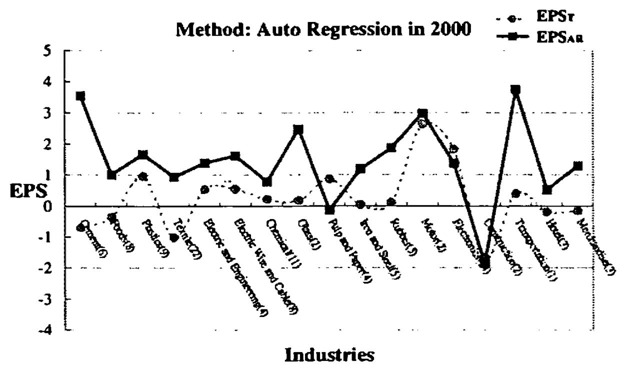

Figure 4: Actual EPS (EPS_T) and forecasted EPS by Auto Regression (EPS_{AR}) in 2000

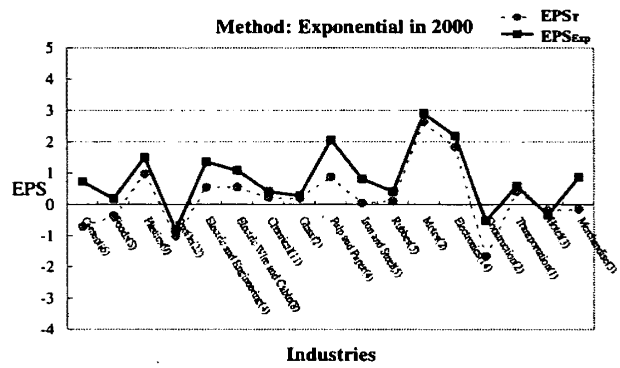

Figure 5: Actual EPS (EPS_T) and forecasted EPS by Exponential (EPS_{Exp}) in 2000

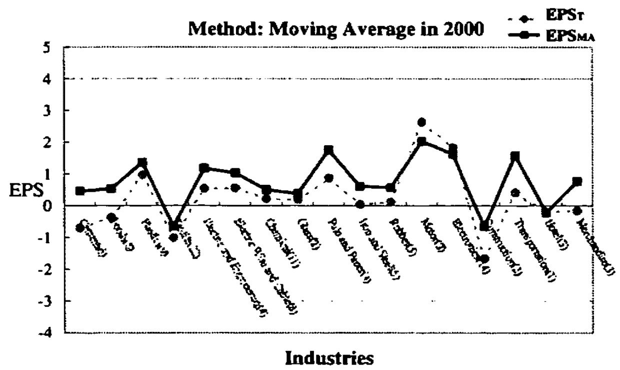

Figure 6: Actual EPS (EPS_T) and forecasted EPS by Moving Average (EPS_{MA}) in 2000

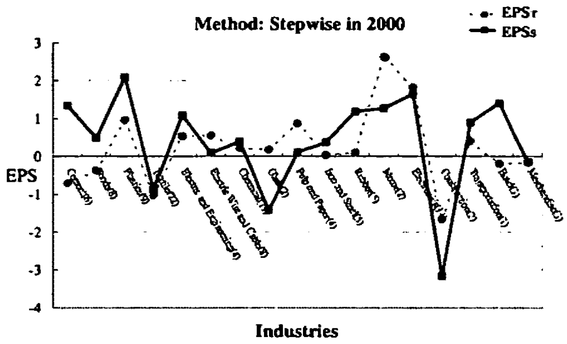

Figure 7: Actual EPS (EPS_T) and forecasted EPS by Stepwise (EPS_S) in 2000

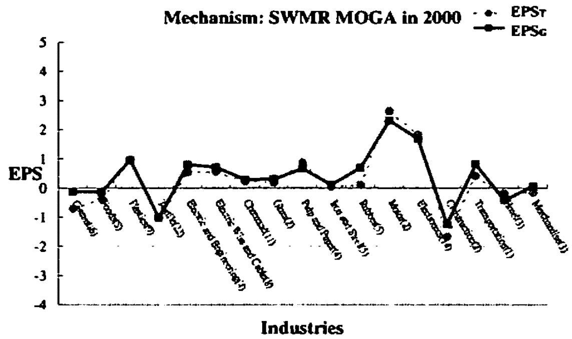

Figure 8: Actual EPS (EPS_T) and forecasted EPS by SWMR MOGA (EPS_G) in 2000

Table 3: The descriptive tests for Auto Regression, Stepwise and SWMR MOGA

	Auto Regression	Stepwise		SWMR MOGA	
Industry (no. of companies)	Adj. R^2	Adj. R^2	DW	Adj. R^2	DW
Cement (6)	0.41	0.90	2.14	0.90	2.53
Foods (8)	0.09	0.63	2.11	0.92	2.22
Plastics (9)	0.02	0.78	1.86	0.89	2.09
Textile (22)	0.11	0.80	1.86	0.91	2.10
Electric and Engineering (4)	0.23	0.87	1.96	0.96	2.24
Electric Wire and Cable (8)	0.09	0.75	2.00	0.79	2.34
Chemical (11)	0.15	0.77	2.04	0.81	2.24
Glass (2)	0.02	0.82	1.86	0.84	1.72
Pulp and Paper (4)	0.00	0.75	1.67	0.83	2.03
Iron and Steel (5)	0.05	0.54	1.86	0.83	2.38
Rubber (5)	0.03	0.72	2.29	0.86	2.38
Motor (2)	0.17	1.00	2.08	0.82	2.00
Electronics (14)	0.12	0.85	1.96	0.92	2.21
Construction (2)	0.22	0.80	2.11	0.83	2.41
Transportation (1)	0.11	0.62	1.93	0.67	1.74
Hotel (3)	0.13	0.91	1.98	0.83	1.97
Merchandise (3)	0.04	0.76	2.01	0.89	2.44
Mean (109)	0.11	0.78	1.97	0.87	2.20
Maximum (109)	0.66	1.00	3.02	1.00	3.03
Minimum (109)	-0.03	0.38	1.13	0.56	1.06
Standard deviation (109)	0.15	0.20	0.39	0.11	0.40

Table 4: List of financial ratios selected by Stepwise method (partial)

Company ID	Financial ratios	Number
1	R609, R614	2
2	R513, R108, R411, R403	4
3	R613, R206	2
⋮	⋮	⋮
109	R502, R304, R608, R201	4
Mean		3.00
Maximum		9
Minimum		1
Standard deviation		1.30

Table 5: List of financial ratios selected by SWMR MOGA (partial)

Company ID	Financial ratios	Number
1	R107, R201, R205	3
2	R306, R507, R534, R537	4
3	R103, R302, R401	3
⋮	⋮	⋮
109	R308, R401	2
Mean		3.19
Maximum		9
Minimum		1
Standard deviation		1.79

mechanism and the stepwise method are close to 2 which means that the selected financial ratios are not autocorrelated.

Tables 4 and 5 partially list the variables selected by the Stepwise method and our SWMR MOGA method respectively. These selected financial ratios are used by multiple regression to forecast the EPS's in 2000 as shown in Table 6 along with those forecasted by the 3 univariate time series models, namely, simple exponential (EPS_{Exp}) model, moving average (EPS_{MA}) model and simple auto regression (EPS_{AR}) model. Table 7 summarizes the differences between the actual EPS and the forecasted EPS of each of the 5 forecasting methods by industry. The overall mean difference of SWMR MOGA (0.36) is the smallest one among the 5 forecasting methods under consideration. In addition, the mean difference in each industry of SWMR MOGA is also the smallest one. This demonstrates the robustness and stability of our proposed mechanism.

4.4. Encompassing tests

The goal of encompassing is to encompass its competitors, explain their results, and hence characterize the properties of the data series at least as well as its rivals [5]. By implementing the forecast encompassing test, we proved that our proposed mechanism explains the forecast errors significantly without incorporating the other methods. The forecast encompassing test is formulated as follows.

$$EPS_{T,i} - EPS_{G,i} = \alpha(EPS_{G,i} - EPS_{j,i}) + \epsilon_i, \qquad j = Exp, MA, AR, S \tag{4}$$

Table 6: The means of actual EPS (EPS_T) and forecasted EPS by Exponential (EPS_{Exp}), Moving Average (EPS_{MA}), Auto Regression (EPS_{AR}), Stepwise (EPS_S) and SWMR MOGA (EPS_G)

Industry (no. of companies)	EPS_T	EPS_{Exp}	EPS_{MA}	EPS_{AR}	EPS_S	EPS_G
Cement (6)	-0.70	0.73	0.46	3.55	1.35	-0.12
Foods (8)	-0.37	0.18	0.54	1.01	0.49	-0.12
Plastics (9)	0.97	1.50	1.37	1.68	2.10	0.95
Textile (22)	-1.02	-0.81	-0.65	0.94	-0.86	-1.01
Electric and Engineering (4)	0.55	1.36	1.18	1.40	1.09	0.81
Electric Wire and Cable (8)	0.56	1.09	1.03	1.62	0.10	0.72
Chemical (11)	0.22	0.41	0.50	0.79	0.39	0.29
Glass (2)	0.19	0.28	0.38	2.48	-1.42	0.30
Pulp and Paper (4)	0.87	2.07	1.76	-0.13	0.11	0.67
Iron and Steel (5)	0.04	0.82	0.61	1.20	0.38	0.11
Rubber (5)	0.11	0.42	0.57	1.88	1.19	0.70
Motor (2)	2.64	2.91	2.03	2.98	1.27	2.31
Electronics (14)	1.83	2.19	1.62	1.38	1.65	1.69
Construction (2)	-1.66	-0.51	-0.67	-1.85	-3.17	-1.24
Transportation (1)	0.41	0.58	1.58	3.76	0.90	0.82
Hotel (3)	-0.19	-0.33	-0.21	0.53	1.41	-0.41
Merchandise (3)	-0.16	0.87	0.76	1.30	-0.15	0.06
Mean (109)	0.18	0.68	0.61	1.32	0.48	0.27
Maximum (109)	5.75	4.59	4.59	6.49	7.14	5.57
Minimum (109)	-6.38	-4.85	-5.50	-5.74	-6.49	-5.51
Standard deviation (109)	1.81	1.63	1.54	1.77	1.90	1.69

Table 7: The mean differences between EPS_T and EPS_{Exp} (D_{Exp}), EPS_{MA} (D_{MA}), EPS_{AR} (D_{AR}), EPS_S (D_S), and EPS_G (D_G)

Industry (no. of companies)	D_{Exp}	D_{MA}	D_{AR}	D_S	D_G
Cement (6)	1.43	1.16	4.25	2.05	0.69
Foods (8)	0.55	0.91	1.88	0.98	0.25
Plastics (9)	0.56	1.04	1.12	1.72	0.25
Textile (22)	0.66	0.73	2.07	0.73	0.45
Electric and Engineering (4)	1.04	0.77	0.85	0.55	0.26
Electric Wire and Cable (8)	0.71	0.77	1.36	1.07	0.43
Chemical (11)	0.24	0.49	1.08	0.52	0.19
Glass (2)	0.22	0.28	2.29	1.71	0.15
Pulp and Paper (4)	1.19	0.88	1.01	0.76	0.32
Iron and Steel (5)	0.90	0.66	1.20	0.88	0.12
Rubber (5)	0.48	0.66	1.76	1.18	0.58
Motor (2)	0.85	0.62	3.01	1.37	0.36
Electronics (14)	1.21	1.07	2.34	1.61	0.38
Construction (2)	1.15	0.99	2.46	1.90	0.51
Transportation (1)	1.20	1.27	1.45	2.09	0.87
Hotel (3)	0.24	0.15	0.72	1.73	0.23
Merchandise (3)	1.02	0.92	1.84	0.27	0.22
Mean (109)	0.75	0.80	1.84	1.10	0.36
Maximum (109)	5.39	4.46	10.18	9.07	2.81
Minimum (109)	0.00	0.02	0.02	0.01	0.00
Standard deviation (109)	0.81	0.64	1.64	1.29	0.42

To examine the forecasting performance, two hypotheses, the null hypothesis ($H_0 : \alpha = 0$) and the alternative hypothesis ($H_1 : \alpha = 0$) are considered. By substituting the EPS_{Exp}, EPS_{MA}, EPS_{AR} and EPS_S methods into the forecast encompassing test, The deduced P-Values for Exponential method, Moving Average, Auto Regression and Stepwise are 0.72, 0.59, 0.15 and 0.06, respectively. At 0.05 significance level, no statistical evidence can reject the null hypothesis effectively. In the other words, our proposed mechanism provides the best explanation capability for the EPS, because the differences between the forecasting errors of our proposed mechanism (SWMR MOGA) and the other 4 methods (Exp, MA, AR, S) cannot help explain the forecast errors of our proposed mechanism. It means that our proposed mechanism could not be improved by incorporating some features of the other methods.

5. Conclusions

A company's EPS is very useful information in the stock selection decision. The forecasting accuracies of linear univariate time series models are seriously limited without considering sufficient important factors. On the other hand, using more variables does not guarantee to obtain better forecasting accuracy and may cause inefficiency. We therefore combine the advantages of both multiple regression and MOGA to form a new efficient forecasting mechanism which maximizes the forecasting accuracy with minimal number of financial ratios. Furthermore, this mechanism includes the SWMR (Sliding Window Multiple Regression) mechanism which retrains our predictor periodically in order to get more accurate earning forecast.

From the results on 109 companies listed and traded in the TSE, we compare the forecasted earnings of our proposed mechanism with simple exponential (Exp) model, moving average (MA) model, simple auto regression (AR) model and stepwise (S) method. The forecasting accuracy of our proposed mechanism is better than that of the other 4 methods. Furthermore, the superior forecasting accuracies on 109 companies and 17 different industries demonstrate the robustness and stability of our proposed mechanism.

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