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# The Application of Genetic Programming on the Stock Movement Forecasting System

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**ABSTRACT**

The financial tsunami is a crisis that happened in 2007. It broke out in the United States, and then spread to the whole world. Taiwanese economy exhibited a negative growth of 7.53%, and the fluctuation is manifest in Taiwan stock index. It has been even dramatically losing 60%. Now, TAIEX has exceeded the level before the financial crisis. TAIEX closed at 10,383.94 on September 30, 2017. The establishment of the Stock Movement Forecasting System has become an important issue. This paper intends to demonstrate the application of an artificial intelligence system named GPLAB on the prediction of stock price movement in Taiwan Stock Exchange (TWSE). GPLAB was built on biological evolutionary concept to realize fittest surviving rules in the natural selection process. This concept has been applied on the field of finance to build up forecasting models predicting future price movement within one day, one month and one season. The empirical results of this inter-discipline study has revealed this bio-financial hybrid system successfully predicted the stock price movement in a one-month forecasting range by 23% and 22% lower than the appointed benchmark during a random chosen period and a bear market period respectively. This empirical evidence suggests the market efficiency in TWSE is a semi-strong form market that stock price movement could be predicted with the analysis of historical data. This paper also further indicates the credibility of different technical and fundamental factors regarding to the prediction of future price movement in four different market situations including non-specific, static, bull and bear market period. At the end of this paper also revealed the strength and weakness of GPLAB as a financial forecasting tool. A short discussion concerning the system improvements regarding to the application of GPLAB is also included.

**Keywords:** Stock Movement Forecasting, Genetic Programming, Bio-financial Hybrid System
**JEL Classifications:** G1, C9, C6

## 1. INTRODUCTION

Financial crisis has spread to world, precipitating a global financial crisis that economically affected countries in East Asia, including Taiwan. Taiwanese economy exhibited a negative growth of 7.53%, and the export value in December 2008 was 41.9% less than that for the same period in 2007. The fluctuation is manifest in Taiwan Stock Exchange (TWSE). On the other hand, it has been even dramatically losing 60% of the market value within six months. During such a drastic change, economic systems might also result in changes of stock prices to some extent. According to TWSE statistics, TAIEX closed at 10,383.94 on September 30, 2017. TAIEX has exceeded the level before the financial crisis. The establishment of the Stock Movement Forecasting System has become an important issue.

The traditional approach to appreciate and forecast stock price movement has been generally done through the establishment of mathematic statistical models. While researches such as Treynor (1961; 1962) Sharpe (1964), Lintner (1965) and others proposed that return premium of any stock shall be awarded according to its own β value (market risk premium).Researches such as Dow (1920), Gordon (1959), Fama and French (1988; 1989), Chan et al. (1991) and others tried to explain stock return with the fundamental factors drawn from the relative financial statements of the firm. Researches such as Fama and French (1992; 1993), Chan et al. (1998) and others has also indicated the evaluation of stock return could be done through the approaches with both risk factor and fundamental factors. However, the nature of stock price movement in reality is a much more complex situation involves interactions of multiple factors including fundamental factors, technical factors, macroeconomic factors, statistical factors, market factors and others. How these different factors interact is almost impossible to be concluded by one or two simple linear equations illustrated by the above studies.

During the past 20 years, systematic machine trading with artificial intelligence adaptive software has been developed to predict stock movements by constructing complex models and sometimes non-linear models. These models possess ability to capture complex pattern involving multiple factor interaction and to forecast the future stock price movement from series learning digest of historical relevant data. Some of the well-known systematic trading programs after the 90's were built on the concept of artificial neuron networks. A neural network is a non-linear statistical data modeling tool which deals situation with complex multiple inputs and simulates an optimized solution. Other artificial systems such as Ant Colony System, Grey Decisions Firefly Algorithm and Genetic Algorithm provided similar solution with different approaching methods. The nature of these artificial intelligence systems provides useful solutions with time and cost efficiency advantage; especially in those cases where the exact solution is deemed almost impossible to be calculated. With the assistance of these tools, researchers are now capable of reexamining some of the previous controversial topics failed to be explained by traditional statistical approach.

Some of the recent demonstration of the artificial intelligence application on the field of finance could be seen on the works of Kazem et al. (2013) in the attempts of predicting stock market price with chaos-based firefly algorithm. Cai et al. (2013) have combined Fuzzy time series and Genetic Algorithm to establish a novel stock forecasting model to reduce root mean square error in prediction process. Researchers such as Ravi et al. (2017) have attempted to establish prediction system by applying hybrids of chaos theory, multi-layer perceptron and multi-objective evolutionary algorithms to predict financial time series data. These recent studies have illustrated the capability of artificial intelligence in the capture of time series data and prediction ability.

The application of these biological based algorisms in the field of finance has motivated this paper to introduce the concept of population genetics to simulate situations in stock market. This paper has demonstrated the application of an artificial intelligence system based on biological evolution concepts known as Genetic Programming (GP) on the prediction of stock price movements in Taiwan Stock Exchange (TWSE) market.

## 2. METHODOLOGIES AND SYSTEM DESIGN

### 2.1. Simulation Concepts

The similarities between genetic evolution and stock market have inspired the study conducted in this paper. The strength of genetic material of specie generally dominates the evolution process through generations. Nevertheless, genetic material may not be always fully expressed under selection stress caused by environment irrational reasons. Ideally it will take a few generations for the stronger genes overriding the weaker genes to dominate the population genotype. However, sometimes the weaker gene may possess dominate position due to selection randomness and other irrational factors. Nevertheless, since that environmental selection factors will change through time to time and form different selection criteria. These changes will cause evolutional stress to the specie and favor the stronger gene. Therefore genetic composition of specie will keep adjusting itself according to its fitness facing different environmental stress. Eventually only the fittest individuals survive and this process is known as "evolution."

These similarities could be often observed in the stock market. The previous evidences have shown that the market is not always rational due to many unknown reasons. The true quality of a stock may not have been always fully reflected on the market price immediately. However, by assuming that the market possesses sufficient efficiency; theoretically the stock market price shall eventually reach its potential price within a few trading days. This shall provide an opportunity window for the investors to detect stock price movements prior to the event.

The essential task required for the signal of stock price movement to be detected must be done by determine the potential value of the stock. Stocks with better potential are expected to have better performance on the stock price. On the other hand that over rated stock will eventually return to its fair price. Some indication factors of the stock might be adopted as prediction reference. These indication factors shall be represented as genetic material in the GP evolutionary system to be constructed in this paper.

This paper assumes that although stock market is in a chaotic environment full of uncertainties, it is still following some complex rational rules to decide which stock shall be more valuable than others. In another word, it possesses the resemblance of biological evolution nature in population genetics discipline that "the fittest survives". Since (GP) is a dynamic evolving system capable of redefining the market trading rules instantaneously, such similarities would expect GP developed models having advantages in forecasting price movements more accurate than other known fixed methods.

### 2.2. Fundamental Factors

The first factor to be considered is the risk factor which was originally proposed by Sharpe (1964), Lintner (1965) and Fischer (1972) in the construction of CAPM (Capital Asset Pricing Model.) The model assumes any rational investor would be expecting a higher return for their higher risk investment than lower risk investment. The model also assumes that all investors are capable to acquire or deposit funds with same interest rate and on equal terms and have identical expectation for their investments. Such assumptions may be slightly unrealistic but does not fully deny the value of risk factors.

D/P (Dividend/Price) ratio and E/P (Earning/Price) ratio are sometimes considered to be the most useful information to determine the possible stock return. Studies including Basu (1983), Fama and French (1988; 1989; 1992) and Chan et al. (1998) found D/P and E/P tends to explain stock return in their research sample during the observation period. B/E (book-to-market) equity was also discussed in the study of Fama and French (1992; 1993) and Chan et al. (1998) and found to have excellent explanation power in capturing variation of average stock returns.

The last of fundamental factor discussed is DER (Debt/Equity Ratio) which concerns the leverage status of the firm. Bhandari (1988) and Fama and French (1992) has revealed DER to be a natural proxy for the risk of common equity of a firm and therefore having influence on investor expectation of stock return.

### 2.3. Technical Factors

Technical factor was founded in the early 18th century in Ojima Rice market in Osaka, Japan by the dealing merchant Honma Munehisa during the Tokugawa Shogunate period. His contribution was the invention of "candlestick" chart used to observe the current psychological status of market investors by analyzing the variation of a three to five accumulative trading day "candlestick pattern." The basic concept is to observe the opening price, closing price, highest price and lowest price of a stock in a single trading day to collect information regarding to the trading trend in the market. The fundamental fabric of technical analysis is composed by trading price and trading volume during an observation period. The research of Jensen and Benington (1970) have found the movements of stock price were not independent movements consistent with the basic standard required for random walk and hence stock price movement could be captured into specific patterns. Studies such as Carhart (1997) also suggest continuous trend for the direction of stock price shift is observed and momentum effect existed.

The application of technical factors has been tested in the studies such as Brock et al. (1992) to reveal popular trading rules including moving-average and trading range break possess sufficient power in the stock return forecasting. On the other hand those studies such as Gallant et al. (1992) and Gervais et al. (2001) have found stock price return relevant to the co-movement of price and volume. These studies indicate trading volume is directly proportional to the stock return and may reveal signal of stock price movement trend.

This study shall adopt daily trading volume and price data as the most basic technical factors and test some of the useful indicators which are commonly used to monitor stock market activity including moving-average line, KD, OBV, BIAS and RSI.

### 2.4. Market Efficiency

The efficiency of stock market acts as a selection mechanism in practical world. Just as in population genetics that a selection mechanism too strong or too weak may result to an inefficient evolution process. A strong efficient market may leave no opportunity for stock return prediction that all information public announced or private-hold was to be immediately reflected on the stock price and the market shall always maintain in an equilibrium status. A non-efficient market demonstrates an entirely opposite situation that the stock price movement follows a "random walk" behavior. Which means the changes in stock price shall be totally irrelevant to the changes of the nature of a company and the expected return becomes impossible to be predicted.

Whether the stock market possesses efficiency remains controversial for a long time and yet, has no precise conclusion. The issue of market efficiency was first discussed by Fama (1970) in his work defined three types of market according to the difference of haste for market to digest newly entered valuable information and fully reflect such changes in price. He has defined a strong form market as a market fully and quickly reflects all valuable public or privet-hold information of a company in its present trading price. A semi-strong form market is defined as a market fully and quickly reflects all valuable public announced information of a company in its present trading price. A week form market is defined as a market fully and quickly reflects all past valuable information in its present trading price.

No strong evidence so far has been proved to prove that stock market has been always efficient through time to time and applicable to global-wide. Whether valuable information has been "fully" reflected in the market has always remained debatable. One of the dilemmas for researchers is setting a precise equilibrium price for the haste of such target price restoration could be widely measured. Such measurement was usually done by predicting the equilibrium price with the CAPM model, which has been adopted by many scholars to evaluate market efficiency. The CAPM model is based on an assumption that all investors shall act rational and expect stock return to be rewarded with risk premium.

However, empirical studies have showed risk and return is not directly proportional in real market. These findings suggest CAPM may have illustrated the concept of equilibrium price in an ideal scenario but may not always truly reflect the market practical situation. Therefore instead of observe market efficiency directly through the restoration of market equilibrium, this paper may provide another approach to reveal the degree of market efficiency in TWSE. By first assuming TWSE is a semi-efficient market shall allow this research to analyze the valuable information in the market and predict the future movement of stocks. This assumption shall then be examined by the empirical evidence to conclude the market efficiency in TWSE.

### 2.5. System Construction

In order to simulate a biological evolutionary condition this paper has adopted a toolbox designed for MATLAB namely GPLAB Ver.3 for such purpose. The function of GPLAB has been illustrated from its name Genetic Programming (GP) indicating its nature of biological scenario simulation. This program was published as the third version of the series by the Evolutionary and Complex Systems Group (ECOS) of Coimbra University in Portugal. GPLAB has been published as a freeware which could be obtained with no compensation from website (http://gplab.sourceforge.net/.).

The system is to be adjusted by inbuilt variables. GEN POP decides the initial population number (INIT POP) to start each evolution series and calculates the fitness (FITNESS) of each individual. Fitness represents the difference between the expected outcome each individual proposed and the desired outcome from reality data. Since the fitness is designed to measure the distance between expected and desired outcome, therefore fitness is always a positive value regardless whether the expected outcome is greater or smaller than the desired outcome. A smaller fitness means the forecasted value is closer to the practical value and indicates better prediction ability of the individual. Such fitness design will ensure the learning mechanism to be supervised by the feedback reward. The initial population set in the tests of this paper is forty individuals (unless marked to be otherwise) and this number shall remain fixed through all generations.

Generation function controls the process of making new individuals (offspring generation) from the old individuals (parent generation.) In order to ensure the new generation will keep evolving towards a smaller and more accurate fitness, SAMPLING came into play as a selection mechanism. In GPLAB Ver.3 four SAMPLING methods is available (Roulette, SUS, Tournament and Lexicographic Parsimony Pressure Tournament.) This paper has adopted the Lexicographic Parsimony Pressure Tournament method, which randomly selects a random number of individuals and only picks the individual with best fitness in the selected group. In the case more than one individual with same fitness appear in the group, only the individual with shortest node and depth shall be chosen. The EXPECTED number of offspring produced by each mating shall then follow one of the three rules provided by GPLAB Ver.3 (absolute, Rank85, Rank89.) This paper has adopted Rank85, which expected number of children for each individual is based on its rank in the population.

Such methods allow the fittest individuals in the parent generation to be selected without doubt in almost every rotation and ensure them to produce the most offspring. To enhance the variability of gene pool composition CROSSOVER and MUTATION function were also adopted in the system. CROSSOVER acts as the main source of variation during the evolution process, by exchanging the strains followed below a random node from both parents that shall create unique new genotype in the gene pool. On the other hand, MUTATION has occurred in a random node of parent tree replacing it by a new random strain provides another source of gene pool variation.

The above process shall proceed and creating new offspring individuals until the number of population appointed by generation gap is fulfilled (in the case of this paper – 40 individuals.) The GENERATION module shall repeat the process until the stop condition is reached which could be either best fitness of any single individual being lower than the desired benchmark or the maximum generation number of the test is reached. In the case of this paper the stop conditions are either best fitness in population reach zero or after sixty generations (unless marked to be otherwise.)

## 3. EXPERIMENTAL RESULTS

This paper intends to test two aspects concerning the relationship between system prediction accuracy and the forecasting chronological range. Considering that the input data carries information with time value and such value shall depreciate with time. The reduction of the amount of valuable information provided by the input data shall raise the difficulty of prediction in the system. It would be reasonable to assume the accuracy of the system shall decrease as the forecasting range increases. On the other hand, the newly entered information requires time to be reflected in the market. It may also suggest that a forecasting range too short could also decrease system accuracy.

In order to observe these two aspects, this paper divided testing subjects into three groups from Group 1 to 3. Group 1 shall focus on the prediction of the testing subject in one trading day after the training period. This one-day forecasting system intends to collect historical data up-to-date and predict the movement of closing price for the next trading day. Group 2 shall focus on the prediction of the testing subject twenty trading days after the training period. This one-month forecasting system intends to collect historical data up-to-date and predict the movement of a three-day closing price moving-average in the future. The three-day closing price moving-average was taken instead of single-day closing price to smooth the volatility of testing subjects in a mid-range forecasting system. Group 3 shall focus on the prediction of the testing subject sixty trading days after the training period. This one-season forecasting system intends to collect historical data up-to-date and predict the movement of a five-day closing price moving-average in the future. The testing subjects were once again smoothed by a five-day moving-average to reduce data volatility in the long-range forecasting system.

Four different types of simulation period were introduced to test the system accuracy. Group A is set to be a randomly selected period with high volatility and no specific direction or pattern. Group B is set to be a randomly selected period with low volatility and stock price is stabilized in a 10% up and down range. Group C is set to be a typical bull market period with a 36% stock price increase within sixty trading days. Group D is set to be a typical bear market period with a 32% down fall in stock price within sixty trading days. Such design shall allow the research to observe system application fitness in different market situations.

### 3.1. Group-1: Result Summary

In the summary of the tests performed in Group 1 that the system forecasting ability is generally weak in the attempts of building up reliable models. The uncertainties presented in one-day stock price movement is considered as the most difficulty for the system. The amount of information could be brought to the system within 20 to 30 training data is very limited. Therefore the judgment of the system is also limited with the variables introduced. However, under the present structure of GPLAB that the system could not bear too much variables in one single training data. The overload of variables could greatly reduce the processing speed of the currently available researching tool. It would require research tool with powerful calculation hardware to support more complex evolution settings. Furthermore, the exclusiveness effect between variables could also become the resistance of advance model formation (Tables 1 and 2).

### 3.2. Group-2: Result Summary

The results in Group 2 demonstrated excellent forecasting ability in Group 2-A and 2-B. The overall forecasting performance of the system in Group 2 is superior to Group1. The main reason could be contributed to the extension of the forecasting range from 1 day to 20 days. Which has reduced the relative stock price volatility and give the system opportunity to outperform the benchmark. The other reason could be contributed to the increase of market efficiency during the extended forecasting period. The strengthen effect of the market efficiency has allowed the valuable information brought in by the input data to be reflected in the market and improve system accuracy (Tables 3 and 4).

### 3.3. Group-3: Result Summary

The results in Group 3 indicate the forecasting ability is generally powerless in the attempts of building up a reliable mode. Some possible assumption for such disability could be concluded as the result of relative prediction uncertainties out-cost the benefit of volatility reduction in the forecasting range extension. The disability of long-term technical factors and fundamental factors introduced to the system may suggest price-moving factors of TWSE are mainly decided by short and mid-term variables. Such result is consistent with the findings of Fama [10] that E/P and D/P are both long term factors capturing stock return in a two year base. This observation is also supported by Ku (2005) found E/P and D/P has no significant explanation power for stock return in TWSE. The findings illustrated in Tables 5 and 6 suggest stock movement in TWSE may not be foreseeable when the prediction range is greater than 20 days.

**Table 1: Fitness result in Group 1A and 1B**

| Testing input | Group 1-A | | Group 1-B | |
|---|---|---|---|---|
| | Average | Best | Average | Best |
| Price | 0.6890 | 0.6195 | 0.6652 | 0.6016 |
| Price + KD | 0.7293 | 0.6451 | 0.7438 | 0.6735 |
| Price + RSI | 0.7435 | 0.6889 | 0.7070 | 0.6910 |
| Price + Volume | 0.7183 | 0.6663 | 0.6679 | 0.5941 |
| Price + MA | 0.7030 | 0.6683 | 0.6604 | 0.6288 |
| All variable | 0.7058 | 0.6355 | 0.6507 | 0.6047 |
| Bench mark | 0.5617 | | 0.5917 | |

**Table 2: Fitness result in Group 1C and 1D**

| Testing input | Group 1-C | | Group 1-D | |
|---|---|---|---|---|
| | Average | Best | Average | Best |
| Price | 0.8619 | 0.8216 | 1.3110 | 1.2275 |
| Price + KD | 0.8732 | 0.7569 | 1.2107 | 1.1261 |
| Price + RSI | 0.8262 | 0.7743 | 1.3475 | 1.2684 |
| Price + Volume | 0.8886 | 0.8484 | 1.2161 | 1.0965 |
| Price + MA | 0.8269 | 0.7636 | 1.2873 | 1.2172 |
| All variable | 0.8852 | 0.8543 | 1.2188 | 1.1001 |
| Bench mark | 0.7587 | | 1.1362 | |

**Table 3: Fitness result in Group 2A and 2B**

| Testing input | Group 2-A | | Group 2-B | |
|---|---|---|---|---|
| | Average | Best | Average | Best |
| Price | 2.5164 | 2.4580 | 3.4342 | 3.3023 |
| Price + $MA_{10}$ | 2.5779 | 2.4506 | 3.2358 | 3.0051 |
| Price + $MA_{20}$ | 2.5867 | 2.3282 | 3.0722 | 2.8873 |
| Price + $MA_{10}$ + $MA_{20}$ | 2.3439 | 2.2295 | 2.8674 | 2.2831 |
| Price + $V_{10}$ | 2.6942 | 2.4374 | 2.9683 | 2.8468 |
| Price + $V_{20}$ | 2.6355 | 2.4225 | 2.7529 | 2.5535 |
| Price + $V_{10}$ + $V_{20}$ | 2.8423 | 2.6497 | 2.5385 | 1.6655 |
| Price + $MA_{10}$ + $V_{10}$ | 2.6890 | 2.5988 | 2.8762 | 2.4328 |
| Price + $MA_{20}$ + $V_{20}$ | 2.5981 | 2.3213 | 2.8782 | 2.1451 |
| All variable | 2.7144 | 2.4086 | 2.4639 | 1.8285 |
| Bench mark | 2.8828 | | 1.3667 | |

## 4. CONCLUSION AND SUGGESTIONS

This paper intended to construct a biological evolutionary based artificial intelligence system to test the possibility of stock price movement prediction. The empirical result of the 20-days

**Table 4: Fitness result in Group 2C and 2D**

| Testing input | Group 2-A | | Group 2-B | |
|---|---|---|---|---|
| | Average | Best | Average | Best |
| Price | 4.7509 | 4.1500 | 6.0281 | 5.3471 |
| Price + $MA_{10}$ | 5.1257 | 4.8879 | 5.3095 | 3.7489 |
| Price + $MA_{20}$ | 5.2744 | 4.8104 | 4.7393 | 4.1486 |
| Price + $MA_{10}$ + $MA_{20}$ | 5.4061 | 4.9744 | 4.6748 | 4.4346 |
| Price + $V_{10}$ | 4.0582 | 3.5645 | 5.6144 | 5.1503 |
| Price + $V_{20}$ | 3.8966 | 3.4716 | 5.5269 | 4.9043 |
| Price + $V_{10}$ + $V_{20}$ | 3.9601 | 3.5659 | 5.8566 | 5.3050 |
| Price + $MA_{10}$ + $V_{10}$ | 4.2638 | 3.9933 | 5.2793 | 3.8547 |
| Price + $MA_{20}$ + $V_{20}$ | 4.9377 | 4.6197 | 4.6466 | 4.1262 |
| All variable | 4.4021 | 3.3855 | 5.2754 | 4.4498 |
| Bench mark | 3.1183 | | 4.7584 | |

**Table 5: Fitness result in Group 3A and 3B**

| Testing input | Group 2-A | | Group 2-B | |
|---|---|---|---|---|
| | Average | Best | Average | Best |
| Price | 11.3601 | 8.8384 | 8.9538 | 7.6881 |
| Price + $MA_{20}$ | 11.8241 | 10.6764 | 10.8567 | 8.9838 |
| Price + $MA_{40}$ | 13.5565 | 11.8107 | 12.7644 | 11.7482 |
| Price + $MA_{60}$ | 13.7069 | 12.5617 | 13.8730 | 12.5910 |
| Price + $V_{20}$ | 11.4665 | 8.9990 | 8.9723 | 7.6096 |
| Price + $V_{40}$ | 11.2666 | 9.4660 | 8.9081 | 7.6418 |
| Price + $V_{60}$ | 11.9329 | 8.9450 | 9.0134 | 7.4040 |
| Price + D/P | 11.2927 | 8.8404 | 9.1829 | 8.3754 |
| Price + P/D | 11.1022 | 10.2009 | 9.0591 | 8.1988 |
| Price + E/P | 12.4549 | 9.4953 | 9.6373 | 7.8306 |
| Price + P/E | 11.4887 | 10.9607 | 8.9105 | 7.9637 |
| Price + BE/ME | 12.7229 | 11.2416 | 8.6441 | 7.4285 |
| Price + BE | 11.2054 | 9.7175 | 8.7807 | 7.7669 |
| Price + 1-month ß | 11.8886 | 9.6974 | 8.4471 | 8.0240 |
| Price + 3-month ß | 13.2392 | 11.3675 | 10.0595 | 8.7369 |
| Price + 6-month ß | 13.8923 | 12.3198 | 9.2492 | 7.6222 |
| Bench mark | 2.9427 | | 5.3003 | |

**Table 6: Fitness result in Group 3C and 3D**

| Testing input | Group 2-A | | Group 2-B | |
|---|---|---|---|---|
| | Average | Best | Average | Best |
| Price | 14.9690 | 13.4314 | 13.1141 | 12.6480 |
| Price + $MA_{20}$ | 14.5648 | 13.5147 | 12.2062 | 11.6965 |
| Price + $MA_{40}$ | 13.8389 | 12.9611 | 12.4275 | 10.7209 |
| Price + $MA_{60}$ | 13.3189 | 11.8883 | 11.4540 | 10.7285 |
| Price + $V_{20}$ | 14.2287 | 12.2736 | 11.7141 | 11.0369 |
| Price + $V_{40}$ | 14.0491 | 12.6833 | 11.2979 | 11.0992 |
| Price + $V_{60}$ | 14.2898 | 12.5368 | 10.7559 | 10.1275 |
| Price + D/P | 15.2123 | 13.5836 | 12.1475 | 11.2556 |
| Price + P/D | 13.9944 | 12.9509 | 12.9743 | 11.1081 |
| Price + E/P | 14.6841 | 14.3501 | 11.4911 | 11.3727 |
| Price + P/E | 13.7278 | 12.5077 | 13.8508 | 12.9361 |
| Price + BE/ME | 15.1054 | 13.7341 | 14.2404 | 12.8638 |
| Price + BE | 14.9550 | 13.7851 | 11.1056 | 10.7776 |
| Price + 1-month ß | 14.8387 | 13.5646 | 11.0591 | 10.1740 |
| Price + 3-month ß | 14.7779 | 13.9368 | 11.2824 | 10.1195 |
| Price + 6-month ß | 13.4273 | 12.6393 | 11.6307 | 10.8649 |
| Bench mark | 6.3877 | | 7.7115 | |

prediction system has demonstrated certain accuracy during the randomly chosen period and bear market situation with a 23% and 22% error lower than the appointed benchmark. Such empirical results have indicated TWSE to be a semi-strong form market that newly public announced valuable information could be digested and reflected in the upcoming trading days.

This paper also intended to test the prediction power of the system given by different input variables. Ideally a smart system would be able to filter input information and select the necessary variables for prediction. However, some phenomena of variable contradictions has been observed in this study and caused variable interference results. Variable contradictions has occurred when the information brought in by different variables disagree with each other. The result of such contradictions has established an unstable model causing more damage than contribution to the forecasting system. This could be the major issue of study in the future research to construct a system with better input variable filter ability.

It has also been noted that in the attempts of building up a universal forecasting system which is capable of providing reliable prediction outcomes through all market periods, the forecasting system must be well-balanced in both sensitivity and stability. The fitness performance in the training period has been equally weighted in the prototype system of this paper. However, in the future works that new fitness weighting rules specifically focus on certain training days of the training period could have been designed. This adjustment shall reveal more insights of the forecasting system regarding to the importance of sensitivity and stability in the creation of more advanced models.

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