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Stock Price Prediction in Malaysia Retail Industry with First-Order Linear Difference Equation

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Abstract

This paper studies the prediction of stock prices in Malaysia's retail industry using a first-order linear difference equation. A retailer's historical stock price data from 1 April 2023 to 1 April 2024 are collected and visualized. A least squares optimization problem is introduced, where the objective function is to minimize the sum of square errors. The first-order necessary conditions are derived, and recursion equations are obtained. The least squares optimization problem is solved using the gradient method, where the model parameters are optimally estimated, giving an updating solution for the linear model iteratively. Once the convergence is achieved, the optimal solution of the linear model approximates the stock prices closely with a small mean square error value. For illustration, two linear difference equations are considered as the initial models; the first is exponential, and the second is decay. Simulation results show that these initial models provide a satisfactory prediction solution with a small mean square error value. Thus, the predictive model for using different initial models is expressed. In addition, some trial models are examined to provide a better simulation result in fewer iterations and lesser elapsed time in the calculation for the stock price prediction. In conclusion, the first-order linear difference equation model efficiently predicts the retailer's stock prices.

1. Introduction

The retail sector involves selling goods and providing services to consumers. There are many different retail sales and store types worldwide, such as supermarkets, hypermarkets, convenience stores, speciality shops, and online platforms [1]. The Malaysian retail market includes food and beverages, personal and household, apparel, footwear, accessories and electronics. As of March 2021, approximately 15 per cent of retail shops in Malaysia have closed due to declining revenues, and brick-and-mortar retail formats such as supermarkets and department stores have experienced negative growth. However, online retailing continues to strengthen. Malaysia's retail sector contributes nearly 45 per cent of GDP [2-3], with the retail trade GDP reaching RM155 billion in 2023 [4]. The market size was US$84.63 billion in 2023, with a projected compound annual growth rate (CAGR) of 5.94% to reach US$119.64 billion by 2029 [1].

Because of the nonlinear fluctuation behaviour of the stock price movement and the uncertain volatility, the stock price movement prediction will not be as accurate as desired [5]. Various computational and technical methods have been developed to forecast the movement of stock prices, such as the time series method, machine learning and deep learning approaches [6-7]. Support vector machine (SVM) is a machine learning method that learns from a training dataset and aims to summarize its knowledge to predict accurately the outcome of new data [8]. The long short-term memory (LSTM) model is also a stock price prediction method, where the LSTM algorithm provided a low error rate in predicting the stock price [9].

Economic growth depends on two main factors: the efficiency of capital in generating output and the level of investment in capital in the economy. The Harrod-Domar One Sector Model, a linear difference equation, is an essential tool in economic analysis using the theory of linear difference equations [10]. The trajectory modelling of quadcopters in the presence of crosswind disturbance was investigated [11], where the study used a linear difference equation to model the wind-induced trajectory deviations and concluded that the linear approach would be insufficient if there were more complex controllers.

This paper studies the stock price prediction for the retail industry in Malaysia using a first-order linear difference equation model. The historical data on stock prices, which are the daily closed prices, are collected from the Yahoo Finance website. A least squares optimization problem, which minimizes the differences between the stock prices and the linear model solution, is introduced for prediction. The necessary conditions are derived to obtain the recursion equations. The gradient method is applied to solve the least squares optimization problem and, in turn, estimate the model parameters optimally and update the linear model solution iteratively. At the end of the convergence, the iterative solution approximates the stock prices closely with a small mean square error value. For illustration, two linear difference equation models are demonstrated to predict the stock prices.

Using the first-order linear difference equation model will contribute to the computational tool in the stock price prediction. The proposed computational algorithm only estimates two model parameters during the parameter estimation procedure. Moreover, the model solution is updated iteratively by observing the historical stock prices and closely approximates the stock prices once convergence is achieved. Hence, the algorithm calculation is tractable. In contrast, machine learning approaches, such as the LSTM method, involve estimating many unknown parameters, and the calculation requires a longer time and large iteration numbers.

2. Materials and Methods

Consider a minimization problem [12],

$$\text{Minimize} \quad J = \frac{1}{2}\sum_{k=0}^{N-1}(y_k - x_k)^2, \tag{1}$$

where J is the objective function represented the sum of squared errors, y_k is the historical data of stock prices at the time step k in year for a retailer, and N is the number of stock prices. While, x_k is the solution sequence to a first-order linear difference equation [13],

$$x_{k+1} = ax_k + b, \tag{2}$$

where a and b are the model parameters given the initial solution x_0. Therefore, this problem, which is also known as a least squares optimization problem, is the stock price prediction problem using a linear difference equation.

In this prediction problem, a set of historical data on stock prices is used to estimate the model parameters and the solution sequences of the model are updated when the objective function is evaluated. During the iterative procedure, the solution sequences of the model shall move toward the stock prices provided convergence occurs. Thus, the accuracy of the prediction is expressed by a mean square error metric.

The gradients of the objective function (1) with respect to the model parameters a and b are defined by

$$\frac{\partial J}{\partial a} = \frac{1}{2}\sum_{k=0}^{N-1}(-1)(2)(y_k - x_k)(x_k), \tag{3}$$

$$\frac{\partial J}{\partial b} = \frac{1}{2}\sum_{k=0}^{N-1}(-1)(2)(y_k - x_k)(1). \tag{4}$$

By using the gradient method [14], the model parameters are estimated from the following recursion equations,

$$a^{(i+1)} = a^{(i)} - \alpha_1\left(\frac{\partial J}{\partial a}\right)^{(i)}, \tag{5}$$

$$b^{(i+1)} = b^{(i)} - \alpha_2\left(\frac{\partial J}{\partial b}\right)^{(i)}, \tag{6}$$

with the initial values $a^{(0)}$ and $b^{(0)}$ are required to start the iteration, where α_1 and α_2 are the step sizes ranging from 0 to 1, whereas i is the iteration number starting from 0, 1, 2 until the stopping criteria

$$\| a^{(i+1)} - a^{(i)} \| < \varepsilon_1, \tag{7}$$

$$\| b^{(i+1)} - b^{(i)} \| < \varepsilon_2 , \tag{8}$$

for small tolerance values ε_1 and ε_2, are met. Moreover, the first-order necessary conditions [15]

$$\frac{\partial J}{\partial a} = 0 \text{ and } \frac{\partial J}{\partial b} = 0 \tag{9}$$

are satisfied to give the optimal parameter estimates

$$a^{(i+1)} \approx a^{(i)} \text{ and } b^{(i+1)} \approx b^{(i)} . \tag{10}$$

We denote the optimal parameter estimates as $\hat{a}$ and $\hat{b}$, respectively. Then, the linear dynamic model (2) is written by

$$\hat{x}_{k+1} = \hat{a} x_k + \hat{b} , \tag{11}$$

with

$$x_k = \hat{x}_k + \alpha_3 (y - \hat{x}_k) \tag{12}$$

is a line search equation that satisfies the first-order necessary conditions. Thus, the solution sequences of the difference equation (11) approximate closely the retailer's stock prices. These solution sequences are regarded as the prediction solution to the stock prices.

For convenience, we assign the solution sequences of the difference equation (11) to the output measurement,

$$\hat{y}_k = \hat{x}_k , \tag{13}$$

where $\hat{x}_k$ is the solution to the linear dynamic model (11). Then, the prediction accuracy is determined by a mean square error (MSE) [17, 18],

$$\text{MSE} = \frac{1}{N} \sum_{k=0}^{N-1} (y_k - \hat{y}_k)^2 . \tag{14}$$

Here, we remark that a small MSE value expresses a high accuracy of the prediction solution in the study.

In summary, we express the calculation procedure as an iterative algorithm given below.

Data Given the retail's stock closing prices, the model initial values $a^{(0)}$ and $b^{(0)}$.

Step 1 Solve the linear difference equation from (2) for the initial solution curve $x^{(0)}$. Set $i = 0$.

Step 2 Evaluate the objective function from (1).

Step 3 Compute the gradients of the objective function from (3) and (4).

Step 4 Estimate the model parameters from (5) and (6).

Step 5 Update the model solution from (11) and (12).

Step 6 Calculate the mean squares error from (14) using the prediction solution (13).

Step 7 Check the convergence. If the model parameters in (10) are satisfied, stop the iteration. Otherwise, set $i = i + 1$, repeat from Step 2.

There are many types of prediction suited for stock price forecasting. Still, each type of prediction has advantages and disadvantages, and their performance depends on the specific characteristics of the data. Other previous studies were done in using forecasting method with the mathematics technique in worldwide according to various fields of studies [19-21].

3. Result and Discussion

Consider the retail's stock closing prices [16], as shown in Fig. 1. The stock prices fluctuated significantly with high volatility in the year from 01 April 2023 to 01 April 2024, ranging from RM1.37 to RM1.65. The highest stock price lay on 3 April 2023 at RM1.65, and starting from 3 July 2023, there was a significant drop from RM1.62 to RM1.37 within a month, which recorded the lowest stock price of the year. However, the stock price spiked drastically to RM1.57 a week later. The stock price was inconsistent and changing rapidly. At the end of January 2024, the stock price came to another low point, which was RM1.38, and then the stock price increased steeply to around RM1.60 at the end of February 2024.

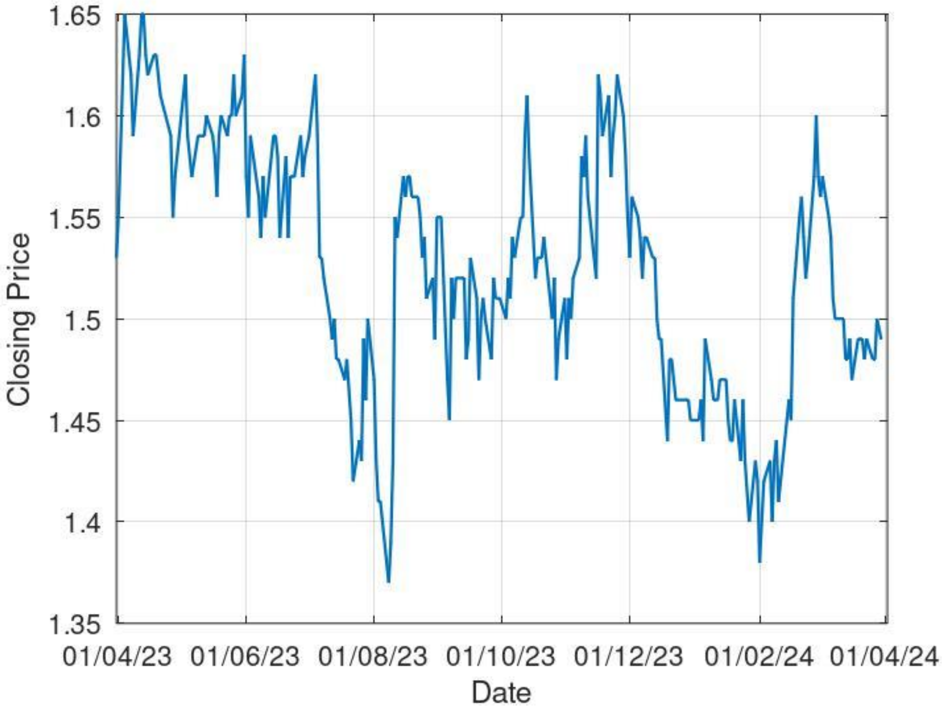

Fig. 1 *Actual data curve*

3.1 Initial Solution of Linear Dynamic Model

In this study, we consider two initial models, exponential growth and decay, to generate the appropriate predictive model for stock price prediction. These models are examples of the first-order linear difference equation. We select the model parameters a = 0.38 and b = 0.95 for a growth model after doing the numerical experiments for a nice-to-see curve, and the model is given by

$$x_{k+1} = 0.38x_k + 0.95, \tag{15}$$

while the model parameters a = 0.77 and b = 0.35 are chosen for the decay model,

$$x_{k+1} = 0.77x_k + 0.35, \tag{16}$$

with x_0 = 1.53, k = 0, 1, ..., 245. The solution curves for these two models are shown in Fig. 2 and Fig. 3, respectively. The growth model presents that the solution curve increases from the initial value of 1.53 and stays along the value of 1.581 after three days. From the decay model, the solution curve decreases from the initial value of 1.53 toward the steady state of 1.522 five days later and remains at this value until the end. In reality, these stock price trends are impossible to happen. We only use them as the initial solution curve to begin the calculation procedure in prediction.

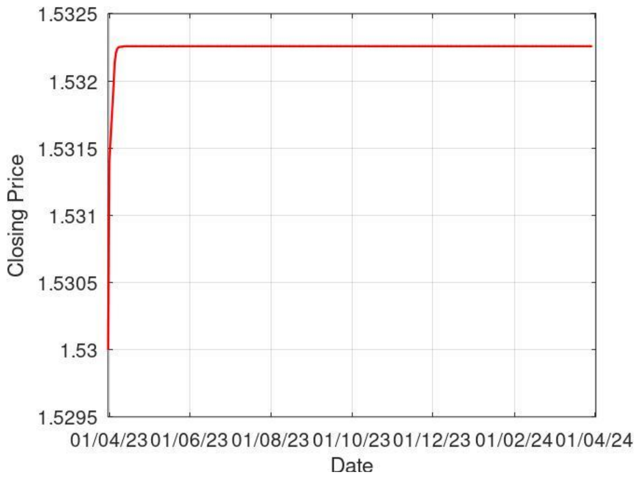

Fig. 2 Growth *model solution curve*

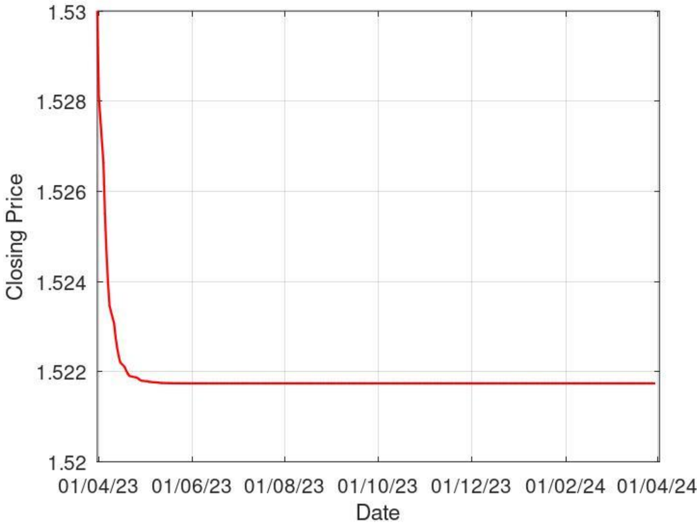

Fig. 3 Decay model solution curve

3.2 Prediction Solution of Stock Prices

To start the iteration procedure, we assign the tolerance of 1×and the maximum iteration number of 50,000, while the values of step size are set at $\alpha_1 = 0.0001$, $\alpha_2 = 0.001$ and $\alpha_3 = 0.8$. We use these step size values to ensure the algorithm can converge within the maximum iteration for a desired result. Table 1 shows the simulation results when the initial models (15) and (16) are applied. The initial model (15) takes 20,385 iterations to converge in the elapsed time of 45.46 seconds, and the initial model (16) takes 12,471 iterations to reach the convergence in 24.44 seconds elapsed time. These two different models express the same mean square error value of 3.394×10^{-4} and the final model for prediction is given by

$$x_{k+1} = 0.9308x_k + 0.1054. \quad (17)$$

The solution curve for the final model (17) is shown in Fig. 4, which approximates closely to the actual stock prices. The prediction error, ranging from -0.07 to 0.12, is shown in Fig. 5.

Table 1 Simulation results for using different initial models

Model	Iteration Number	Mean Square Error	Elapsed Time(seconds)
Grwoth	20,385	3.3941×10^{-4}	45.4559
Decay	12,471	3.3941×10^{-4}	24.4377

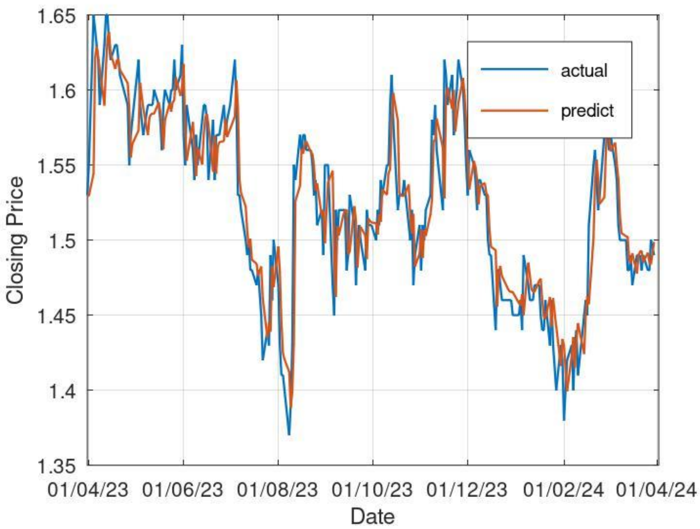

Fig. 4 Prediction solution curve

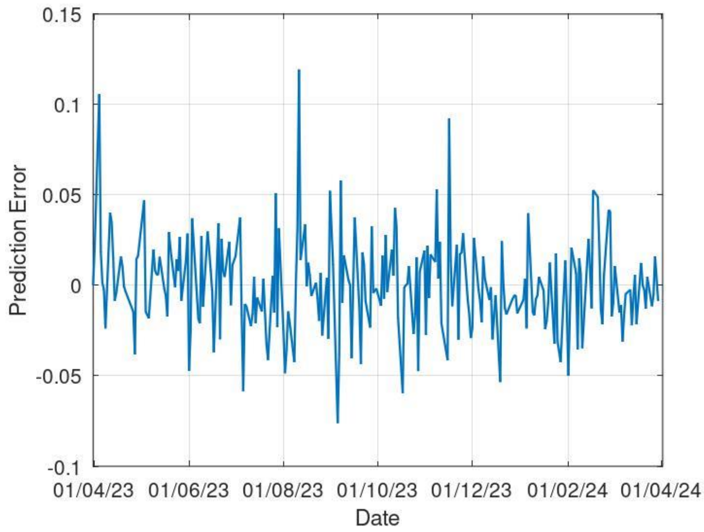

Fig. 5 Prediction error

The model parameters a and b for initial models (15) and (16) are estimated from the computation algorithm by observing the stock prices. At the end of the iteration, they reach the respective equilibrium points at a = 0.9308 and b = 0.1954, as given in the final model (17). Fig. 6 shows that for the model (15), the model parameter a increases slowly from the initial value of 0.38 and stays at the value of 0.9308, and the parameter b decreases gradually to 0.1054 after 15,000 iterations during the calculation procedure. On the other hand, Fig. 7 show the parameters a and b for the model (16), where the parameter a increases to 0.9308 and the parameter b reduces to 0.1054 after 8,000 iterations.

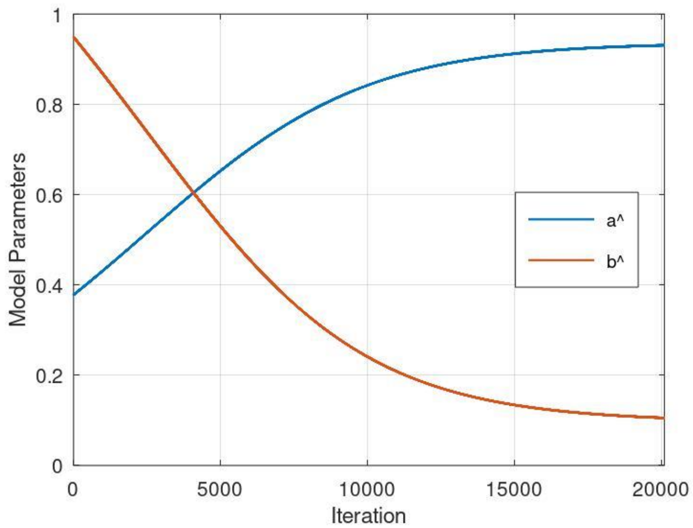

Fig. 6 Parameter estimates in growth model

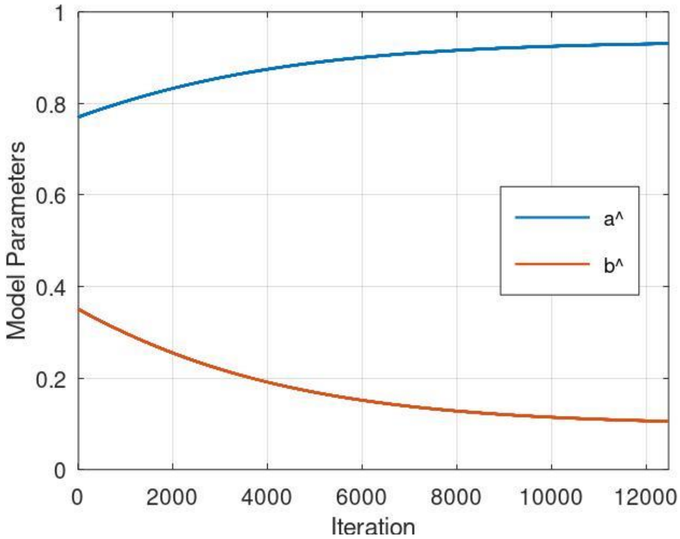

Fig. 7 Parameter estimates in decay model

3.3 Testing Results of Trial Models

In this section, we test different values of the model parameters used in the first-order linear difference equation model to predict stock prices. Referring to the simulation results in Table 1, the initial model in decay expressed a better iteration number than the initial model in growth. Thus, we shall examine the performance of trial models with different values of the model parameters for a better simulation result. The testing values for the model parameters are divided as follows,

(a) a = 0.17, 0.27, 0.37, 0.47, 0.57, 0.67, 0.77, 0.87, 0.97 with b = 0.35.
(b) b = 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95 with a = 0.77.

Table 2 shows the simulation results for nine different values of the model parameter a, which range from 0.17 to 0.97, and the value of the model parameter b is fixed at 0.35. The trial models with a = 0.17 to a = 0.77 are decay models, where the related iteration numbers decrease from 18,302 to 12,471. The trial models with a = 0.87 and a = 0.97 are growth models, where the trial model with the parameter a = 0.87 takes 17,572 iterations to converge. Still, the divergence happened for the trial model with the parameter a = 0.97. These trial models have the mean square error value of 3.39×10^{-4} and provide a satisfactory prediction solution in the study. Therefore, the final model (17) can be obtained after 12,471 iterations when using the initial model (16).

Table 2 Simulation results for trial models with a different values and b=0.35

Model	Model Type	Iteration number	Mean Square Error	Elapsed Time(seconds)
0.17	Decay	18,302	3.3941×10^{-4}	36.1303
0.27	Decay	17,410	3.3941×10^{-4}	35.7508
0.37	Decay	16,546	3.3941×10^{-4}	43.6998
0.47	Decay	15,665	3.3941×10^{-4}	35.6888
0.57	Decay	14,716	3.3941×10^{-4}	30.8313
0.67	Decay	13,625	3.3941×10^{-4}	31.1163
0.77	Decay	12,471	3.3941×10^{-4}	24.4377
0.87	Growth	17,572	3.3941×10^{-4}	31.2801
0.97	Growth	-	-	-

Table 3 shows the simulation results for a fixed value of the model parameter a = 0.77 and different values of the model parameter b, ranging from 0.15 to 0.95. The first three trial models are decay models, where the iteration numbers increase from 11,480 to 12,471. The rest of the trial models express growth solution curves, with the iteration numbers rising from 14,062 to 22,197. These trial models can give the prediction solution with the mean square error value of 3.39×10^{-4}. However, the trial models with the model parameter b values of 0.75, 0.85 and 0.95 are not converged and cannot present the prediction solution. Hence, the initial model

$$x_{k+1} = 0.77x_k + 0.15, \quad (18)$$

can produce the final model (17) after 11,480 iterations.

Table 3 Simulation results for trial models with a = 0.77 and b different values

Model	Model Type	Iteration number	Mean Square Error	Elapsed Time(seconds)
0.15	Decay	11,480	3.3941×10^{-4}	23.0130
0.25	Decay	11,596	3.3941×10^{-4}	23.4774
0.35	Decay	12,471	3.3941×10^{-4}	24.4377
0.45	Growth	14,062	3.3941×10^{-4}	27.5238
0.55	Growth	16,644	3.3941×10^{-4}	35.5473
0.65	Growth	22,197	3.3941×10^{-4}	54.6990
0.75	Growth	-	-	-
0.85	Growth	-	-	-
0.95	Growth	-	-	-

Overall, we can use various trial models as the initial model for applying the proposed algorithm in the prediction of stock prices. These trial models perform satisfactorily with different iteration numbers to converge and give the same small mean square error value. Moreover, the predictive model appropriately predicts retail stock prices, demonstrating the accuracy of the proposed algorithm to predict stock prices.

4. Conclusion

This paper discussed using a first-order linear difference equation model to predict stock prices in the Malaysian retail industry. The historical data on stock prices from April 2023 to April 2024 were considered in the study. A least squares optimization problem was introduced to minimize the differences between the stock prices and the model used. For this goal, we used the gradient method to solve the least squares optimization problem and to estimate the model parameters. In this way, the computational algorithm updated the linear model solution iteratively. At the end of convergence, the iterative solution approximated the stock prices closely with a small mean square error value. The simulation results showed the accuracy of the prediction solution. Hence, the study achieved the research objective successfully. In conclusion, the first-order linear difference equation model is an efficient model that effectively reflects the evaluation of stock prices and proves to be a reliable tool for short-term forecasting.

This study was limited to the prediction of stock price trends. The critical factors such as economic growth, inflation and interest rates, which significantly impact stock prices and have unpredictable effects on stock price value, were not considered in the study. For future research, we recommend applying a polynomial with a higher order to capture the complexity and dynamics of stock price movements. In addition, a comparative study between the linear difference equation and neural network model shall be conducted to show the accuracy and efficiency of the computation methods in the prediction of stock prices. This comparison will contribute to the computational tool applications in stock investment.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *TJW, KSL;* ***solve the linear dynamic model:*** *TJW;* ***analysis and interpretation of results:*** *TJW, KSL;* ***draft manuscript preparation:*** *TJW, KSL. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Mordor Intelligence. (2024). Malaysia retail market report. Retrieved April 18, 2024, from https://www.mordorintelligence.com/industry-reports/malaysian-retail-industry
[2] Sakrabani, P., Teoh, A. P., & Amran, A. (2019). Strategic impact of retail 4.0 on retailers' performance in Malaysia. Strategic Direction, 35(11), 1-3.
[3] Hamim, H., Kadir, M. N. A., & Shariff, M. N. M. (2021). SMEs retailing in Malaysia: Challenges for industrial revolution 4.0 implementation. In Modeling Economic Growth in Contemporary Malaysia (pp. 1-15). Emerald Publishing Limited.
[4] Statista. (2024). Gross domestic product (GDP) from retail trade in Malaysia from 2015 to 2023. Statista Research Department. Retrieved Dec 10, 2024, from https://www.statista.com/statistics/1459747/malaysia-gdp-from-retail-trade/#s-tatisticContainer
[5] Mihova, V., Georgiev, I., Raeva, E., Georgiev, S., & Pavlov, V. (2023). Validation of stock price prediction models in the conditions of financial crisis. mathematics, 12(1), 33.
[6] Xiao, D., & Su, J. (2022). Research on stock price time series prediction based on deep learning and autoregressive integrated moving average. Scientific Programming, 2022, 12.
[7] Phuoc, T., Anh, P. T. K., Tam, P. H., & Nguyen, C. V. (2024). Applying machine learning algorithms to predict the stock price trend in the stock market–The case of Vietnam. Humanities and Social Sciences Communications, 11(1), 1-18.
[8] Chervonenkis, A. Y. (2013). Early history of support vector machines. Empirical inference: Festschrift in honor of Vladimir N. Vapnik, 13-20.
[9] Bhandari, H. N., Rimal, B., Pokhrel, N. R., Rimal, R., Dahal, K. R., & Khatri, R. K. (2022). Predicting stock market index using LSTM. Machine Learning with Applications, 9, 100320.
[10] Hjortso, M. A., Wolenski, P. R. (2018). Linear mathematical models in chemical engineering (Second Edition). Singapore: World Scientific Publishing Company
[11] Allison, S. (2019). Quadcopter trajectory prediction and wind estimation using Machine Learning (Doctoral dissertation, Oklahoma State University).
[12] Pedregal, P. (2004). *Introduction to optimization* (Vol. 46). New York: Springer.
[13] Banasiak, J. (2013). *Mathematical modelling in one dimension: an introduction via difference and differential equations*. Cambridge University Press.
[14] Chong, E., & Zak, S. (2013). An introduction to optimization . 4th edition. New Jersey: John Wiley & Sons, Inc
[15] Metei, A. J., & Jain, V. (2019). *Optimization Using Linear Programming*. Mercury Learning and Information.
[16] Yahoo Finance. (2024) Mr D.I.Y. Group (M) Berhad (5296.KL).Retrieved April 20, 2024, https://finance.yahoo.com/quote/5296.KL/
[17] Lagak, N.E.A.P. and Mohamad M. (2023). Numerical Analysis of An Improved SIR Model For COVID-19 Outbreak in Malaysia Using Variational Iteration Method. Enhanced Knowledge in Sciences and Technology, 3 (2), 138-147.
[18] Fam, C.L. and Mohamad M. (2022). Technical Analysis of Malaysia Stock Performance, Enhanced Knowledge in Sciences and Technology, 2 (1), 332-341.
[19] Bamahel A.S. (2022). Prevalence of Diabetic Nephropathy among Type 2 Diabetes Mellitus Patients in Mukalla City, Yemen. Enhanced Knowledge in Sciences and Technology, 2 (2), 432-440.
[20] Abd Rahman, S., Mohamad, M. and Shab N.F.M. (2021). The Modified Decomposition Method for Solving A Nonlinear System of Two-dimensional Volterra-Fredholm Integral Equation. Enhanced Knowledge in Sciences and Technology, 1 (2), 116-123.
[21] En, T.B. (2021). Prediction of Unemployment Rate in Malaysia Based on Macroeconomic Factors. Enhanced Knowledge in Sciences and Technology, 1 (2), 30-39.