# Improving Stock Market Prediction through Reinforcement Learning: A Case Study of Nigerian Telecommunication Companies.

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**Abstract**

Stock prediction a viable tool in building a robust economy for a nation. It provides the impetus of the how, the who and when to invest in a stock primarily used by investors. There is a need for a more effective model of stock prediction which manages the volatile and dynamic nature of the stock market. As such, this research aims at developing a more efficient predictive model; using the Reinforcement Learning RL technique that involves an agent learning to interact with an environment in order to maximize a reward signal. The research focuses on the improvement of the benchmark model, Ordinary Least Square (OLS) model of stock prediction achieved by the value-based RL technique; the reinforced model predict close to actual when compared to the OLS model. Statistical evaluation metric was employed to confirms the efficiency of the reinforced model against the OLS model for real life application.

**Keywords:** *Stock Market, Machine Learning ML, Ordinary Least Square OLS, value-based Reinforcement Learning RL, Statistical Evaluation Metric.*

## 1.1 Introduction

Precise stock market predictions encourage investors to go into stock marketing as it yields huge profit when there is no loss recorded and in return it supports the economy growth of the world. A study by Gurav & Sidal (2018), found that, there is a strong correlation between reduction of investment risk in stock market investments when there is reduction in forecasting error. However, the process of trying to forecast the future performance of stock market is a cumbersome task, yet is a necessity in today's world economy, as it involves analyzing past trends and using statistical and mathematical models to predict future trends. Stock market predictions can be broadly classified into two namely: the fundamental analysis and the technical analysis, as substantiated with the study by Reddy, V.K.S., & Sai, K. (2018). The fundamental analysis involves the study of financial performance of companies and the analyses of macroeconomic factors such as; gross domestic products (GDP), inflation, and interest rates. On the other hand, the technical analysis involves the study of past market data with a view of identifying patterns and trends in stock prices, trading volumes, and other market indicators.

Machine learning models are prone to overfitting generally, as verified by Zhang et al. (2021), which occurs when a model is trained on a limited dataset and fails to generalize on a new data. This is particularly problematic for stock market data, which is complex and non-linear, making it easy for models to overfit and gives inaccurate prediction. Nevertheless, a recent study by Sun et al. (2020) proposed, the application of reinforcement learning technique in stock market prediction, which can be used for dynamic optimization, where an agent learns how to allocate funds across different assets to maximize returns proves capable. This is evident also as a recent study by Li et al. (2020), used RL to optimize portfolio allocation and achieved better results than traditional statistical portfolio optimization techniques.

Stock markets are non-stationary in nature. This implies that market conditions can change rapidly over time. Hence, RL can be used to adapt to non-stationary environments by learning from past experiences and the adjustment of the relevant trading strategies. The above assertion was corroborated when a study by Sun et al. (2020) used RL to adapt to non-stationary environment and achieved good results.

More so, Thakur, A., & Anand, V. K. (2020) proposed; most models are developed based on assumptions (insubstantial data) on the underlying data; and the violations of these assumptions can lead to inaccurate predictions afterward. However, the application of RL that interacts constantly with the environment guarantees the usage of concrete data in prediction through the optimization policy.

In view of the challenges embedded in the stock market predictions, investors are often reluctant to relinquish their hard-earned money. Since, the primary risk of investing is not just in temporary price fluctuations (volatility), but entails a permanent loss of capital. Thus, in trying to determine the future value of a company stock or other financial instrument traded on an exchange, the successful prediction of a stock's future price could help to yield significant profit for investors and at same time build their trust and confidence Gurav & Sidal (2018).

In conclusion, this research aim at developing a model with actual historic data of stock obtained from Yahoo Finance, theoretical framework explaining scenario showing drawbacks in the traditional predictive model and the significance of RL to stock marketing, the methodology; explained the procedure followed to have an organized and well reliable data for the analysis and the results section shows the outcome of the application of value-based RL technique which curb the menace of stock market volatility in the midst of limited data available in training model for stock prediction.

## 1.2 Theoretical framework

In as much as many models are valuable in stock price prediction but they also have limitations that should be taken into account. Evidently, exposed by Afolabi et al. (2020), found that statistical models, including ARIMA and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH), had limited predictive power for the Nigerian stock market. However, statistical methods can't be avoided because they are very useful in stock price prediction, they also have several limitations.

Statistical models may not always have high predictive power because they rely on historical data solely, which may not be a good indicator of future market trends. This is evident in a study by Arora and Verma (2017), used dataset consisting of stock prices of 12 companies from the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) in India, by applying linear regression analysis to develop a model that can predict the future stock prices of these companies. They utilized opening price, closing price, high price, low price, and trading volume of the stocks as variable. They also use the moving average (MA) of the stock prices as an input variable and cross-validation to evaluate the accuracy of their model. The results of the study show that the linear regression model can predict stock prices with reasonable accuracy. The authors further note; that the model can be further improved by including additional variables and by using more advanced statistical techniques.

As Gurav & Sidal (2018), unfolded, the strong correlation between reduction of investment risk in stock market investments when there is reduction in forecasting error. Hence, understanding the limitations posed by the available models can help researchers and practitioners to choose appropriate models and interpret the results more accurately, which in turns encourage investors to add to their portfolio in stock marketing when risk is undoubtedly mitigated. RL is becoming increasingly important in stock prediction as it can adapt to non-stationary environments, optimize portfolio allocation, and learn from complex market data. This research would utilize the strengths of reinforcement learning in improving the outcome of the generic OLS model for stock market prediction.

## Methodology

### 2.1 System Architecture

This is the general overview of the model that highlights the major components of the system.

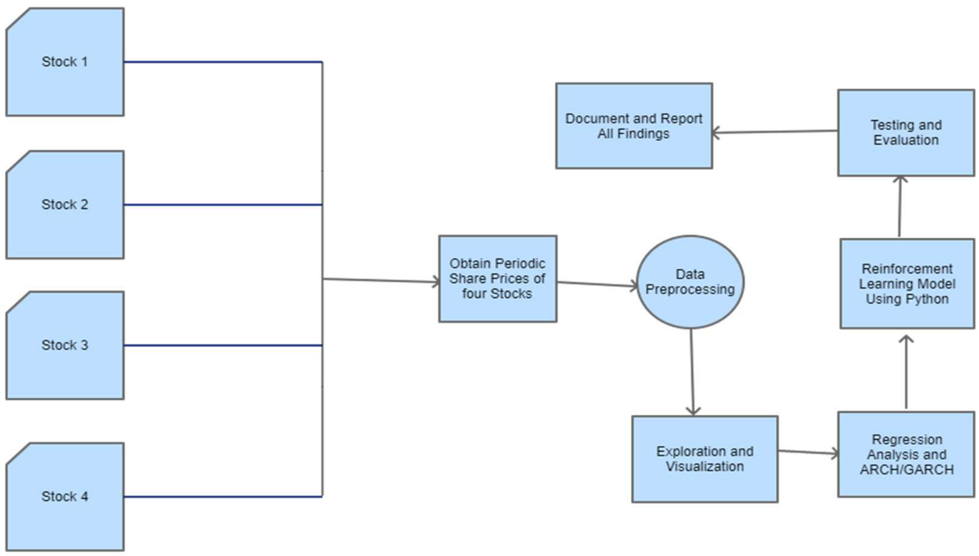


*Figure 1 System Architecture*

### 2.2 Historical Data

The dataset used in stock prediction model is pertinent for building a model. It matters a lot in determining how effective and useful such model will be (Yang et al., 2020). Data source; Yahoo. Finance the stocks used for the research purpose are stocks on the Nigeria Stock Exchange (NS/). The research focus on four selected stocks for a period of three to four years and does not account for events that spans beyond these periods. The four competing companies offering the same services, operating locally in Nigeria are; MTN Group Limited, Airtel Networks Limited, Globacom Nigeria Limited (Glo), and 9Mobile telecommunication company multinational mobile telecommunications company in Nigerian Stock Exchange.

### 2.3 Data preprocessing

Data preprocessing is necessary to have a well-ordered data for analysis in order to avoid conflicting results (Yang et al., 2020). Data preprocessing involves cleaning, transforming, and preparing raw data into a format that can be easily analyzed. The goal of preprocessing the historic data is to ensure that the data is accurate, complete, consistent, and relevant to the task at hand.

### 2.4 Data Exploration and Visualization

Data exploration and visualization is critical in any data analysis task, it presents the pictorial view of the data for a better understanding and further analysis. This steps involves understanding and exploring the data to identify patterns, relationships, which gives insights that can be used to guide further analysis.

The steps involved are:

i. Understanding the data: This involves getting a basic understanding of the data, such as its size, structure, and format.
ii. Descriptive statistics: This involves computation of descriptive statistical measure i.e. mean, median, standard deviation, and other summary statistics to gain insight into the data.
iii. Data visualization: it involves creating visual representations of the data, for instance scatter plots, histograms, and box plots, to identify patterns and relationships between stocks.
iv. Correlation analysis: This has to do with the analyses of the correlation between different variables for the purpose of identifying the relationships and dependencies of the stocks.

### 2.5 Regression Analysis and ARCH/GARCH

Regression analysis is used to model the relationship between a dependent variable and one or more independent variables. It is commonly used to estimate the effect of one or more explanatory variables on a particular outcome or response variable.

Regression analysis used a given linear function for predicting continuous values:

$y = \beta 0 + \beta 1x + \varepsilon$

where:

- y is the dependent value (continuous variable)
- x represents the known independent value
- $\beta 0$ is the intercept or the constant term

- $\beta 1$ is the slope or the coefficient of the independent variable x
- $\varepsilon$ is the error term or the random variation in the dependent variable that is not explained by the independent variable

The goal of linear regression is to estimate the values of $\beta 0$ and $\beta 1$ that minimize the sum of the squared errors between the predicted values of y and the actual values of y. This is done using a method called Ordinary Least Squares (OLS) regression.

OLS regression involves calculating the difference between the predicted values of y and the actual values of y for each data point. The sum of the squared differences is then minimized to find the best estimates of $\beta 0$ and $\beta 1$. The estimates of $\beta 0$ and $\beta 1$ can be used to predict the value of y for a given value of x.

Conversely, ARCH/GARCH models are used to analyze the volatility of financial time-series data. ARCH stands for Autoregressive Conditional Heteroskedasticity, while GARCH stands for Generalized Autoregressive Conditional Heteroskedasticity. Both models are designed to capture the conditional volatility of a financial asset or a portfolio of assets.

**2.6 Reinforced Model**

Reinforcement learning (RL) is an aspect of machine learning technicality, in which an agent interacts with an environment and learns to make decisions based on the feedback it got from that environment. The agent learns to maximize a reward signal that is received from the environment. The goal of RL is to find an optimal policy, which is a mapping from states to actions, that maximizes the expected cumulative reward over time. The researcher uses the value-based RL techniques in this research to strengthen prediction of an OLS model by retraining the model with the predicted value of the OLS model.

**2.7 Model Evaluation**

Evaluation of a machine learning model is an important process to assess the performance of the model on hidden data. The evaluation process helps to determine whether the model is overfitting or underfitting the data and provides a measure of its generalization ability.

The model evaluation is done using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

### 3.1 Results and Discussion

| | AIR | ETI | GLO | MTN |
|---|---|---|---|---|
| AIR | 1.000000 | 0.072274 | 0.019581 | -0.030296 |
| ETI | 0.072274 | 1.000000 | -0.053170 | 0.064961 |
| GLO | 0.019581 | -0.053170 | 1.000000 | -0.009574 |
| MTN | -0.030296 | 0.064961 | -0.009574 | 1.000000 |

*Figure 2: Correlation Matrix for daily returns*

Figure 2 shows the correlation matrix of the daily returns of four stocks. From the result it can be seen that AIR and ETI have the highest correlation of 0.07 which is a very weak positive correlation, also a very weak positive correlation exists between AIR and GLO (0.02) and also a very weak positive correlation also exists between ETI and MTN (0.06). These shows that a minimal relationship exist between the stocks, however deeper analysis would reveal other hidden patterns within the stocks. furthermore, multicollinearity exist among the stock; this implies each stock have less inference on the other.

### 3.2 **Regression Analysis and ARCH/GARCH Analysis**

### 3.2.1 ARCH/GARCH

ARCH/GARCH models used to analyze the volatility of financial time-series data. ARCH/ GARCH both models are designed to capture the conditional volatility of the financial asset or a portfolio of assets.

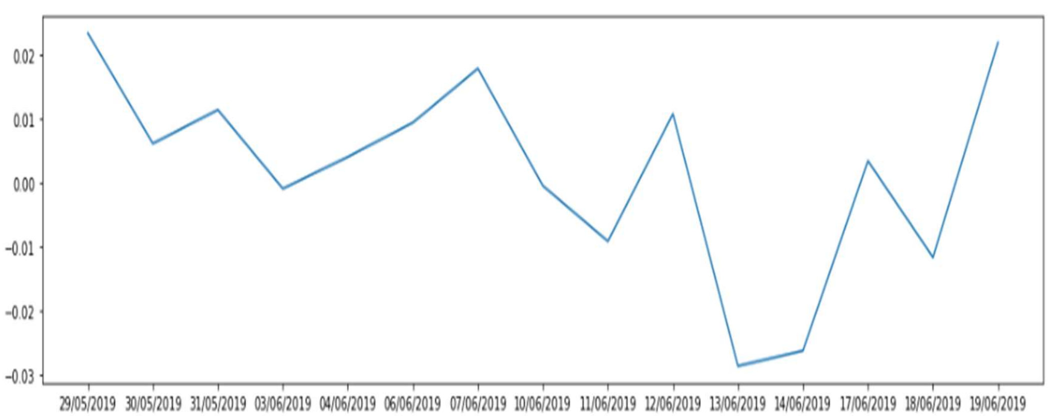


*Figure 3. Trend for first 15 returns for AIR*

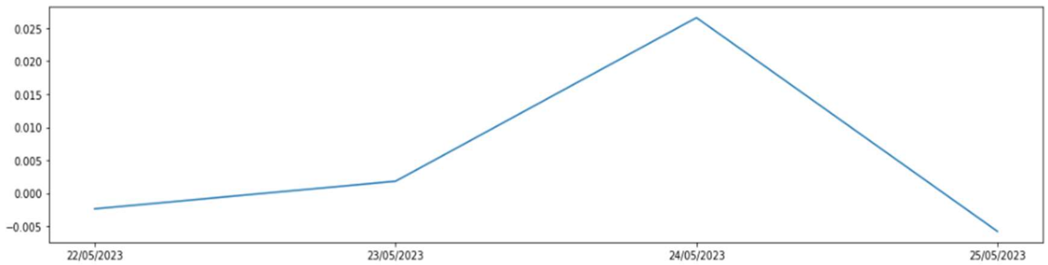


*Figure 4: Trend for last 4 returns for AIR*

Figure 3 shows the trend plot for the daily returns for Airtel Telecommunication Limited (AIR) within the first 15 days. It can be seen that there is instability within the market, hence this calls for a deeper analysis in order to have higher accuracy in future prediction. Similarly Figure 4 shows the trend for the last 4 returns and can be seen to show fluctuations in the daily returns with the instability suggesting high volatility and a need for in-depth analysis.

### 3.2.2 Regression Analysis

Regression analysis frequently uses the Ordinary Least Squares (OLS) approach to model the relationship between variables. The association between the stock's previous prices and its future prices was estimated using OLS in the context of stock prediction for this research. The study's findings demonstrate that, when the returns of the four related stocks are used as the training set, the OLS model gave decent predictions for the future returns for the chosen stock 'MTN'.

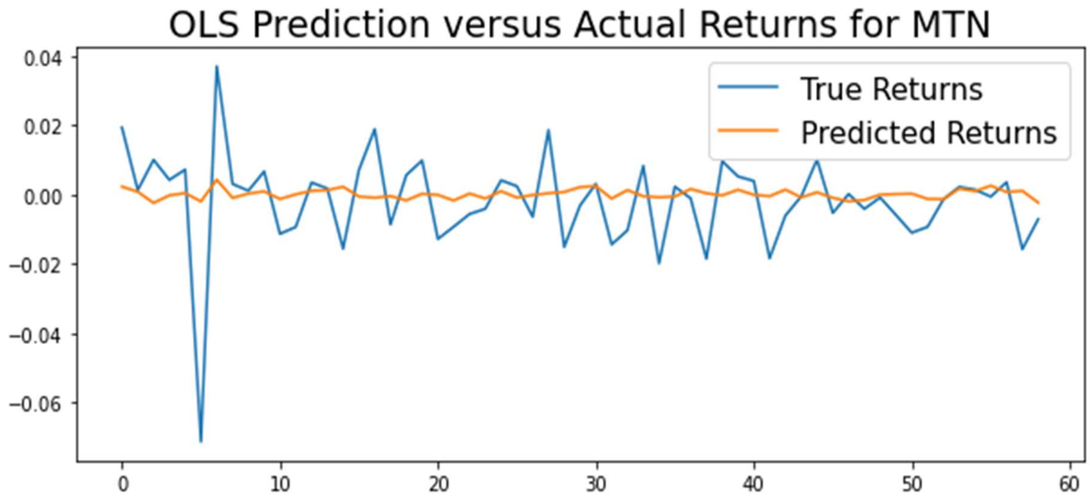


*Figure 5: OLS Predicted Returns vs Actual Returns*

Figure 5 shows a trend chart comparing the daily return predictions made by the OLS regression model and the actual daily returns obtained from the stock. It shows a significant improvement when compared with the ARCH and GARCH predictions. It is eminent that both true data and predicted data follow similar path in the trend although with significant variations on a phase view. Thus a better accuracy matrix needed to be applied to the prediction in order to proffer more insight to the comparison. The proceeding figure 6 shows the Mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) which are all commonly used metrics in evaluating the performance of regression models.

```
Prediction - MSE: 0.0001838614720944296, RMSE: 0.013559552798467567, MAE: 0.00885215900591612
```

*Figure 6: OLS Model Standard Error of Mean*

Both parameters show good accuracy scores, however, a better precise comparison would be made after performing the same operation for the reinforces model.

**3.3 Reinforced OLS Model**

The reinforced model developed with the OLS predicted values as additional attribute which forms that training set and the model was retrained using 4/7th part of the new dataset. The reinforced model summary is shown in figure 7.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    MTN   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                  0.002
Method:                 Least Squares   F-statistic:                     1.809
Date:                Wed, 06 Dec 2023   Prob (F-statistic):              0.144
Time:                        17:13:05   Log-Likelihood:                 2323.6
No. Observations:                 989   AIC:                            -4639.
Df Residuals:                     985   BIC:                            -4620.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0003      0.001      0.462      0.644      -0.001       0.002
AIR           -0.0401      0.036     -1.100      0.272      -0.112       0.031
ETI            0.0898      0.043      2.107      0.035       0.006       0.174
GLO           -0.0067      0.040     -0.167      0.867      -0.086       0.073
==============================================================================
Omnibus:                      171.861   Durbin-Watson:                   2.118
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1651.842
Skew:                           0.479   Prob(JB):                         0.00
Kurtosis:                       9.258   Cond. No.                         59.0
==============================================================================
```

*Figure 7: Reinforced Model Summary*

### 3.4 Comparison of Reinforced Model Predictions and Actual Returns for MTN

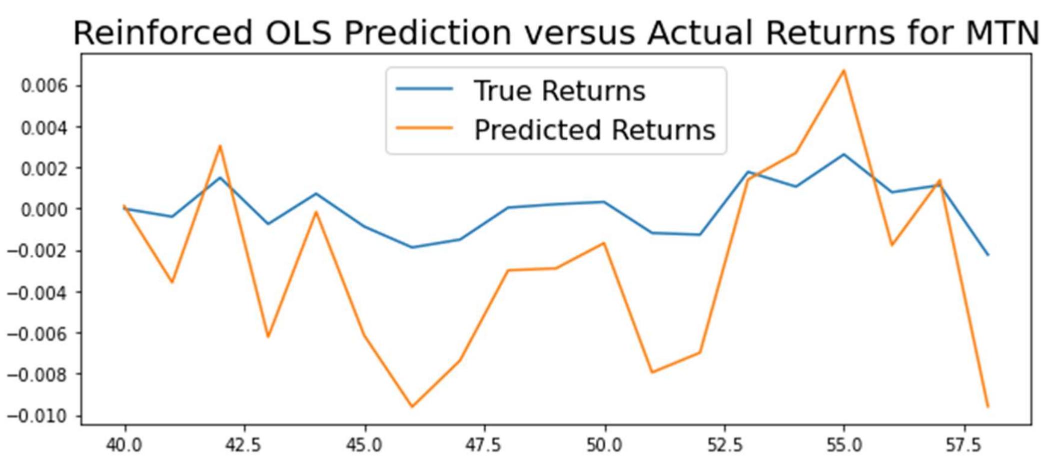


*Figure 8: Reinforce outcome versus Actual Returns*

Figure 8 shows a comparison between the reinforced model and actual Returns for the selected stock. The trend chart shows that both outputs follow a similar path but a better evaluation matric is used to provide statistically acceptable argument. The proceeding Figure 9 shows the Standard Error of Mean and other associated accuracy parameters.

```
Reinforced Prediction - MSE: 0.00037786624769936436, RMSE: 0.019438782052879865, MAE: 0.016054463808490467
```

*Figure 9: Reinforced Model Standard Error of Mean*

### 3.5 Comparison of OLS predictive model and reinforced model

In order to evaluate the performance of the reinforced model, a comparison is made between the outcome of the OLS model and the reinforced model. The scores are presented thus;

```
print("Prediction - MSE: {}, RMSE: {}, MAE: {}".format(mse, rmse, mae))
print("Reinforced Prediction - MSE: {}, RMSE: {}, MAE: {}".format(mse_r, rmse_r, mae_r))

Prediction - MSE: 0.00018383614720944296, RMSE: 0.013559552798467567, MAE: 0.00885215900591612
Reinforced Prediction - MSE: 1.820642227398648e-05, RMSE: 0.004266898437271092, MAE: 0.003520677271335314
```

*Figure 10: Error Scores for OLS and reinforced OLS model*

From figure 10 it can be seen that for the three parameters the reinforced model has lower scores consistently. Thus, it is appropriate to conclude that the reinforced OLS model is an improvement over the previous OLS model and can therefore be applied to stock price predictions in the real world.

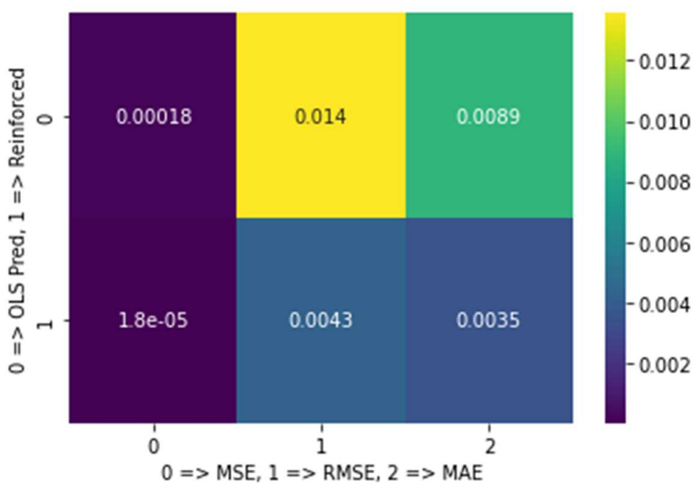


*Figure 11: heatmap Comparing OLS and Reinforced OLS model*

Figure 11 is a heatmap which shows a consistent improvement in the reinforced model compared to the initial OLS model.

### 4.1 Recommendation and Conclusion

Ordinary Least Squares (OLS) is a commonly used method for modeling the relationship between variables in regression analysis. In the context of stock prediction for this paper, OLS was used to estimate the relationship between the stock's historical prices and its future prices. Result from this study shows that the OLS model produced commendable prediction for the future returns for the selected MTN stock when the returns for the three associated stocks are used as training set.

However, by adding an attribute to the training set, value-based reinforcement learning RL was applied to the OLS model in this study and its was retrained, and the results demonstrate a considerable improvement in the reinforced model's performance compared to the generic Ordinary Least Square OLS model. These findings from this study concludes that, the OLS model performance was significantly enhanced through the adoption of reinforcement learning, which minimizes the Mean Squared Error and other evaluation criteria presented in the results. As a results, it is recommended that the approach be adopted in the real world.

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