Response to the Reviewers

Dear Reviewer # 1,

Thank you for reviewing the paper and providing your valuable comments. Please find here my response to our comments/suggestions.

Comments/Suggestions	Response
- The paper had contributed an interesting technique for technical analysis for stock trading specifically the calculation of spring force rates of support and resistance levels.	Thank you for your kind words and support in this field of research.
- Author could explain why the data included only a 3-month duration and been applied to foreign stocks like Microsoft and Apple. Users of the paper may be interested in local stocks and with a longer duration of time.	Thank for your comment on the data coverage. The initial length of data coverage is 3 months due to the limitations of hourly data that can be downloaded in a single instance of request. As a consequence, the evaluation of this strategy is implemented for short to medium term traders. The data coverage is now expanded to 4 months of hourly data. Microsoft and Apple are two of the common stocks that are normally tested for implementing strategies due to its popularity. I have now included PLDT stocks in this study based on your suggestion.

Dear Reviewer #2,

I am grateful for your constructive comments and suggestions. Please find here my responses and actions

Comments/Suggestions	Response
The study provides an interesting topic and technique in identifying support and resistance levels. However, it would have been useful if the author provides an explanation as to why Microsoft and Apple were chose for this particular study, and also perhaps, why the author chose the period between November 15, 2020 and February 15, 2021.	Thank you for your interest and comments in this topic. Microsoft and Apple are two of the common stocks that are normally tested for implementing strategies due to its popularity. I have now included PLDT stocks in this study based on your suggestion.. The initial length of data coverage is 3 months due to the limitations of hourly data that can be downloaded in a single instance of request. As a consequence, , the evaluation of this strategy is implemented for short to medium term traders.. The data coverage is now expanded to 4 months of hourly data
Although the author presents interesting results using graphs and tables, it would have been more useful if the author provides more discussion on the key results, e.g., explain in more detail the results presented in Tables 1 and 2.	Thank you for your appreciation and suggestion. There are now three tables (adding results for PLDT). I have added 4 paragraphs discussing those tables, and 1 paragraph discussing the key results which can be found on page 4 and page 5.

Quantification of Support and Resistance Levels in Stock Trading

Al Rey Villagracia[1,2*]
[1] *Physics Department, De La Salle University 2401 Taft Avenue Malate Manila 1004*
[2] *Financial Engineering, WorldQuant University*

**Corresponding Author: al.villagracia@dlsu.edu.ph*

Abstract: One of the famous strategies in market trading is support and resistance. Stock price springs up when it hits support while it springs down when it hits resistance. These are horizontal levels created by strong buyers and sellers, respectively. It allows traders to determine trading entries and exits coupled with other strategies. However, no study is found measuring the spring Force Rates of support and resistance levels. In this study, support and resistance are modelled as conical springs with different spring force rates when stock prices hit the support and resistance. The conical springs of support can reverse to become conical springs of resistance with different spring force rates. The support and resistance levels were calculated using the Fibonacci ratios, and the spring force rates were measured based on curvatures of stock prices as it hits the support and resistance levels. These force rates may also be referred as the strengths of the support and resistance levels for possible trend reversals. The numerical data of the hourly stock prices of Apple, Microsoft, and PLDT Inc. for November 1, 2020 to March 3, 2021 were obtained from Yahoo Finance. The mathematical methods were implemented using Python programming. Maximum elastic strengths of support and resistance and cumulative values were computed and used as the reference for the 'Villagracia' strategy in buying or selling stocks. Evaluation of the returns using Villagracia strategy was compared to Long Position strategy and Relative Strength Index (RSI) strategy. Results showed that the Villagracia strategy provides better profit compared to the other mentioned strategies for volatile price movements. Further studies are needed to analyze for the trend reversal predictions, and conjunct it with momentum strategy to improve the returns.

Key Words: support, resistance, stocks, trading, physics

1. INTRODUCTION

Both classical and quantum Physics are commonly applied in stock or forex trading to determine the trend, area of support, and entries or exits of trading (Cotfas, 2013; Diep & Desgranges, 2019; Pedram, 2012; Wang & Deng, 2008). The movement of stock prices are identified as memoryless following a random walk model while the efficient market hypothesis tells that all information is found in the stock prices: new and old(Rodriguez et al., 2014;

Timmermann & Granger, 2004). This implies that the stock prices can follow certain probabilities. Though stock prices are difficult to predict its exact value, its movement going up or down is more manageable. A long position is normally used by investors. Different strategies have been created to increase the returns based on different technical indicators such as Bollinger Bands, momentum, relative strength index (RSI), moving average, Donchian channels and others for traders. Among the different strategies, support and resistance strategy is one of the commonly used for identifying the entry and exits for trades. Support is created when there are numerous buyers on a certain price level such that it is difficult for the price to go below that level. Resistance is formed when the sellers are stronger than the buyers that the price is resisting to increase beyond a certain price level. Previous studies have shown that the Fibonacci ratios can identify these support and resistance levels, while others determine these levels based on the high, low, open, and close prices of the previous trading day (Hartle, 2015; Kumar, 2014). An example of resistance and support levels is found on Figure 1.

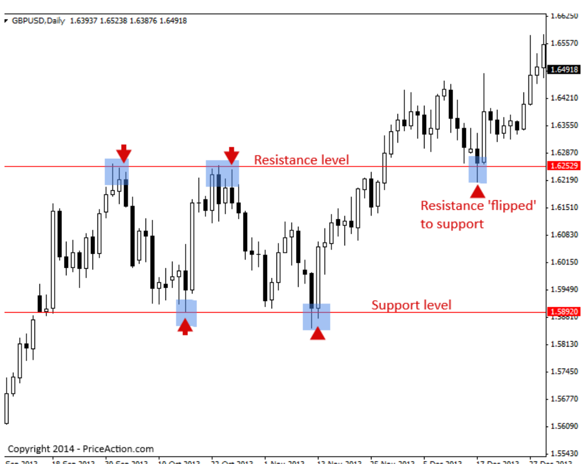


Fig. 1. Support and Resistance Levels under Candlesticks model of market prices

When market prices hit the support level it may spring up and follow a trend or create a breakout. If it strongly hit the support and break, it becomes a resistance level. Market prices hitting the resistance level mostly springs down unless volume of buyers break the resistance level. Instead of modelling these levels as walls, it can be modelled as conical springs as shown in Figure 2. When prices hit the conical springs of support or resistance, it reverses the direction of the price. However, if the price is boosted by strong buyers/sellers, it can reverse the conical spring, and create a breakout for the prices. Thus, this action of buyers/sellers, which creates the support and resistance levels with certain spring force rates, also guides the movement of the market prices.

In this study, Fibonacci ratio is used to determine the support and resistance levels. Spring force rates of support and resistance levels were calculated. The net force from the buyers/sellers are derived based on the movement of the market price. Moreover, through the net force, the movement of the market price is predicted.

Fig. 2. Conical Spring

2. METHODOLOGY

2.1 Data and Tools

The daily stock price of Apple and Microsoft were downloaded from Yahoo Finance for the duration of November 1, 2020 to March 3, 2021. The first 80% of the data was used for training, while the remaining 20% of the data was used for testing. The mathematical model was implemented using Python programming. Functions from Pandas and Numpy packages were used to handle data frames and mathematical operations for the dataset.

2.2 Mathematical Model

The resistance and support levels of prices in stock trading is modelled as a conical spring. A spring follows the Hooke's Law which is given by equation 1.

$$F_i = k_i x_i \qquad \text{(Eq. 1)}$$

where:

F_e = Elastic Force
k_i = Force rate
x_i = Displacement referenced to the support/resistance level

If only the elastic force acts on the prices and following Newton's Second Law,

$$\sum F = F_e = m\frac{d^2 x_i}{dt^2} = k_i x_i \qquad \text{(Eq. 2)}$$

where:

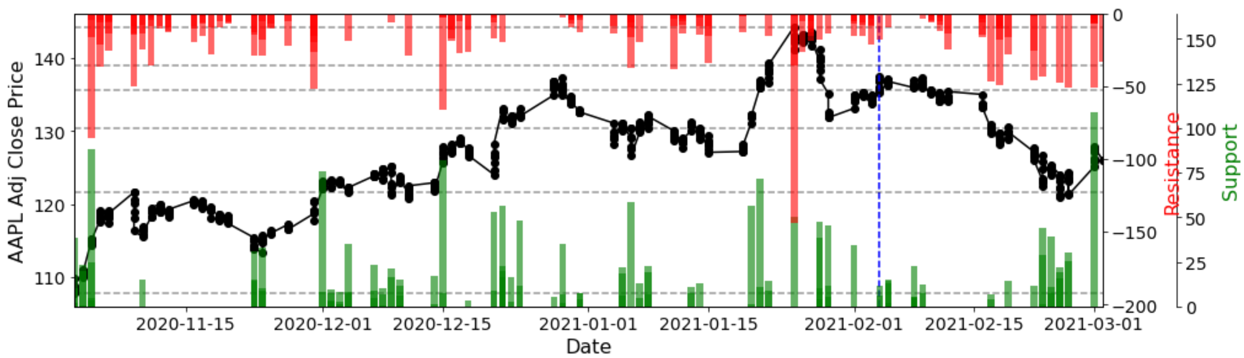
m = mass
t = time

Derivates were computed using backward finite difference method. In this study, it is assumed that the stocks density is equal is constant with a value of 1, and the time interval was set to 1. The values of the spring force rates are calculated using equation 3 for each level.

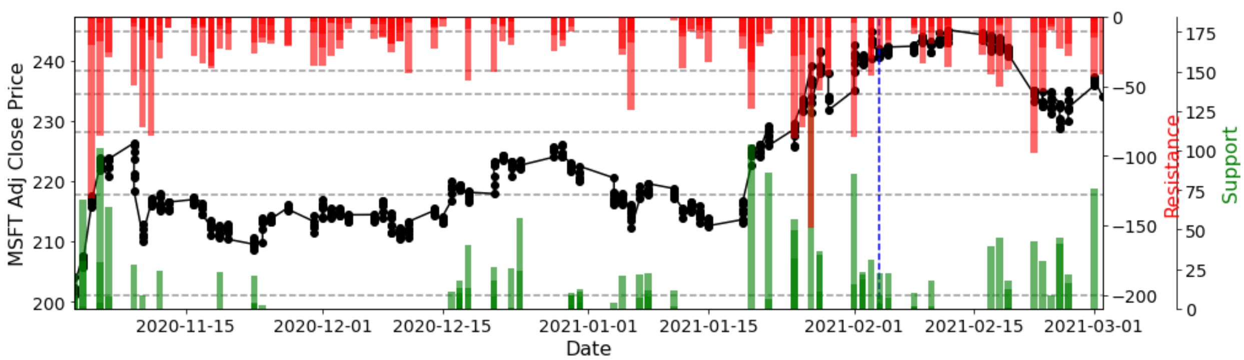
$$k_i = \frac{1}{x_i}\frac{d^2x}{dt^2} \qquad \text{(Eq. 3)}$$

The normal length of the spring is located at the centers of each enclosed region by the support/resistance levels.

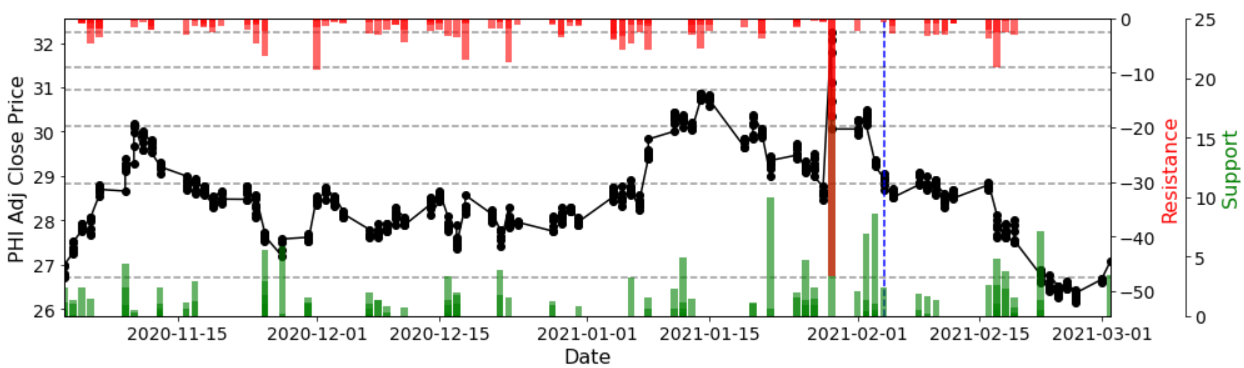
3. RESULTS AND DISCUSSION



(a)



(b)



(c)

Fig. 3. Resistance/support levels and strengths for (a) Apple (b) Microsoft (c) PLDT Inc

Figure 3 the stock prices for Apple, Microsoft and PLDT Inc. The horizontal dashed lines are the support/resistance levels derived using Fibonacci ratios. The blue vertical dashed lines separate the training data (left) and the testing data (right). The green/red bars are the elastic strengths calculated using equation 2 for each support and resistance level, respectively. The figure shows that there are more frequent resistances as compared to support which indicates that stock prices are more inclined to increase than to decrease over time.

The bar lines on both figures matches with the peak and trough for the resistance and support levels. The length corresponds to the strengths. The calculated maximum spring force rates for each support/resistant level are found in Table 1, Table 2 and Table 3 for Apple, Microsoft, and PLDT, Inc.

Table 1. Apple Support/Resistance Mean Force Rates

Price Level ($)	Mean Support Force Rates	Mean Resistance Force Rates
107.81	66.24	0.00
121.69	15.97	15.35
130.32	45.63	16.55
135.63	266.81	13.50
138.91	54.22	18.96
144.23	0.00	63.33

Table 2. Microsoft Support/Resistance Force Rates

Price Level ($)	Mean Support Force Rates	Mean Resistance Force Rates
201.07	20.93	0.00
217.69	52.34	7.45
228.04	20.94	38.02
234.41	61.80	69.85
238.34	87.30	196.54
244.71	0.00	86.50

The force rates describes how erratic is the movement of the stock prices near those price levels whether it is attacking the resistance levels or it is bouncing on the support levels. The larger the value of the force rates, the larger the stock price movement.

Table 3. PLDT Inc. Support/Resistance Force Rates

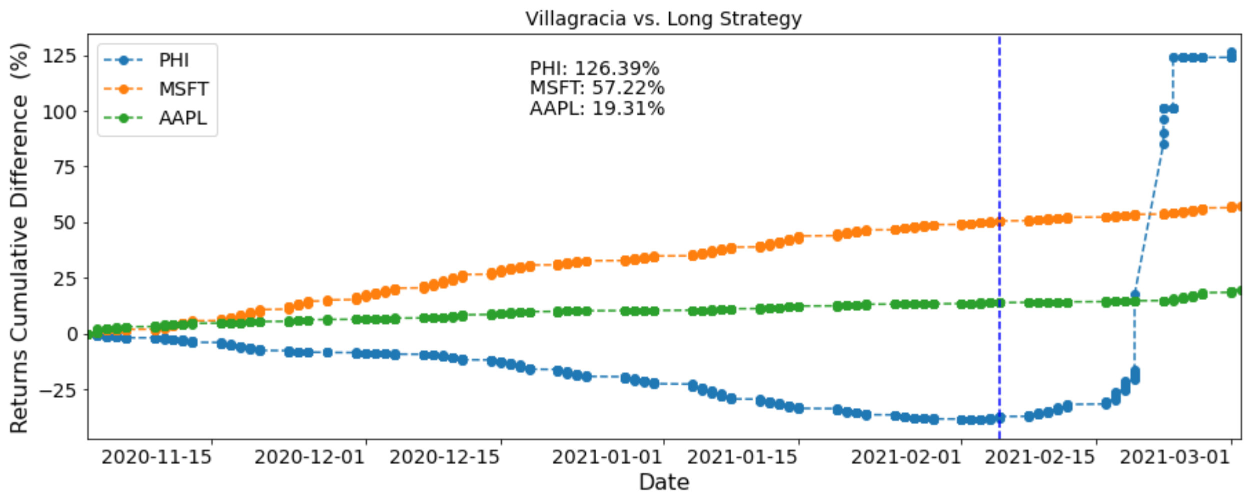
Price Level ($)	Mean Support Force Rates	Mean Resistance Force Rates
26.72	123.46	0.00
28.82	16.93	9.75
30.14	13.24	8.58
30.94	262.22	22.66
31.44	0.00	0.00
32.25	0.00	845.87

It can be seen in Table 1 that there is a strong support force rates at price level $135.63 of Apple stock price indicating multiple bounce as can be seen in Figure 3a. On the contrary, there is a high resistance force rates at price level $144.23 which led to deterioration of the price.

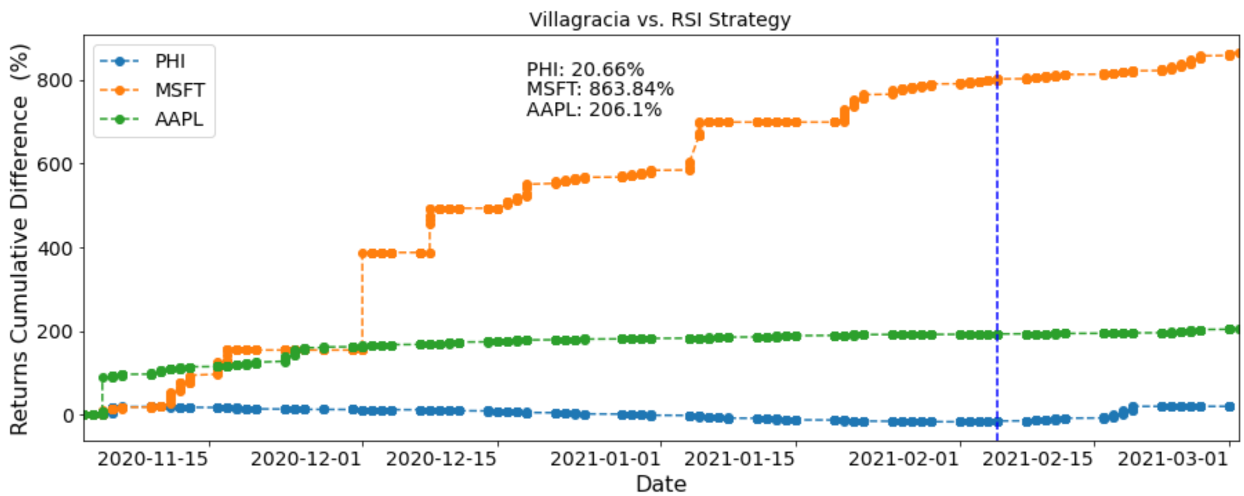
In Table 2, there are high support and resistance force rates at $238.34 of Microsoft stock price indicating a full range motion within the boundary of that price level for the said duration of time as seen in Figure 3b.

For the PLDT Inc. stocks, the support force rate at $30.94 is noticeable indicating a strong bounce occurred on that price level. There were no force rates found on $31.44 price level indicating that there was a big and rapid price hike and decrease from $30.44 to $32.25 as can be seen Figure 3c.

Since these mean force rates are characterization of the support and resistance levels, it cannot predict the price level movement. However, the maximum support and resistance forces can be a reference to determine the possible movement. This strategy known as 'Villagracia Model' calculates the ratio of calculated force with the maximum support/resistance force at each price level. By setting a percent threshold, one can decide to buy or sell stocks. In this study, a single active buy/sell trade was set depending on the force ratio. It can immediately close a long position and set a short position, or the opposite. The returns were computed and compared with the returns using a fixed long (buy) position strategy and with the returns using relative strength index position.



(a)



(b)

Fig. 4 Returns Cumulative Difference of Villagracia Strategy with (a) Long Position (b) RSI

The cumulative percentage difference of returns using Villagracia strategy with the long position strategy and RSI strategy are found in Figure 4. It can be seen that the strategy has better performance than long position all throughout for Apple and Microsoft, while for PLDT Inc, only the latter part that it began to rose up and perform better than the Long Position and RSI strategy.

4. CONCLUSIONS

This study has identified the support/resistance level using Fibonacci retracement method. The net force and acceleration of the stock prices were computed. Support/resistance spring force rates were calculated using Hooke's law. From these force rates, the net forces and acceleration were calculated, and the stock price movements are predicted and calculated for Microsoft, Apple and PLDT Inc. stocks. The computed returns using Villagracia strategy were higher compared to the returns of the long position and RSI strategy. Moreover, machine learning can also be used to find the optimal parameters for the prediction.

5. ACKNOWLEDGMENTS

The author would like to extend the gratitude to the Physics Department of De La Salle University.

6. REFERENCES

Cotfas, L. A. (2013). A finite-dimensional quantum model for the stock market. Physica A: Statistical Mechanics and Its Applications, 392(2), 371–380. https://doi.org/10.1016/j.physa.2012.09.010

Diep, H. T., & Desgranges, G. (2019). Dynamics of The Price Behavior in Stock Markets: A Statistical Physics Approach. In arXiv (Vol. 570, p. 125813). arXiv. https://doi.org/10.1016/j.physa.2021.125813

Hartle, T. (2015). Using Fibonacci Ratios And Momentum. Stocks & Commodities, 15(11), 477–482.

Kumar, R. (2014). Magic of Fibonacci Sequence in Prediction of Stock Behavior. International Journal of Computer Applications, 93(11), 36–40. https://doi.org/10.5120/16262-5926

Pedram, P. (2012). The minimal length uncertainty and the quantum model for the stock market. Physica A: Statistical Mechanics and Its Applications, 391(5), 2100–2105. https://doi.org/10.1016/j.physa.2011.11.043

Rodriguez, E., Aguilar-Cornejo, M., Femat, R., & Alvarez-Ramirez, J. (2014). US stock market efficiency over weekly, monthly, quarterly and yearly time scales. Physica A: Statistical Mechanics and Its Applications, 413, 554–564. https://doi.org/10.1016/j.physa.2014.07.036

Timmermann, A., & Granger, C. W. J. (2004). Efficient market hypothesis and forecasting. International Journal of Forecasting, 20(1), 15–27. https://doi.org/10.1016/S0169-2070(03)00012-8

Wang, J., & Deng, S. (2008). Fluctuations of interface statistical physics models applied to a stock market model. Nonlinear Analysis: Real World Applications, 9(2), 718–723. https://doi.org/10.1016/j.nonrwa.2006.11.017