Experimental Validation of Mesa Sine Wave in Stock Price Prediction

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Abstract. Rising dissemination of learning algorithms in almost all spheres of life has been witnessed in the last 5 years. In this regard, stock market has provided a huge landscape for data science to introduce computational intelligence in otherwise traditional method of handling the global economy. This study evaluates whether Lead Mesa Sine Wave (LMSW) can be a good marker in stock price prediction. Our results reflect that LMSW cannot be used for stock price prediction. We validate our result using learning algorithms. Moreover we have also observed that the future price prediction using historical closing price data can be used as a dependable marker. Due to the time scale nature of the data, we have used recurrent neural network (specifically Long Short-Term Memory (LSTM)) for our prediction model design. The results from the prediction model exhibit better performance with respect to literary counterparts. We have used three publicly available datasets from Reliance, Infosys, and Grasim for the study. We claim two results in this study – LMSW cannot be used as stock price predictor, and LSTM can be used as a good predictor using historical closing price data.

Keywords: Mesa Sine Wave, LSTM, Stock Price Prediction, Learning Algorithms, Closing Price.

1 Introduction

Stock market prediction has been a topic of computational interest for almost two decades. Technological advancements have recently added fuel to the global interest with loads of scope being witnessed in the use of machine learning (ML) and deep learning (DL) frameworks for stock analysis [1] [2]. One of the most popular research questions (RQ) being which learning algorithm suits best in determining the future trend of a stock. Certain proposals have been observed in literature which furnish new frameworks or improvised algorithms to deal with the RQ. In this study, we try to address the RQ using Lead Mesa Sine Wave (LMSW). Although LMSW being a technical indicator basically depicts the nature of the market whether the market exhibits cycle mode (CM) or trend mode (TM) [3], our quest for better alternatives for RQ initiated the present study. CM or TM is decided using two sine plots, judging the sinusoidal mode or wander mode of the plots. Readers are directed to [3] [4] [5] for complete understanding of the utilization of LMSW. The equations governing the LMSW as a CM or TM analyzer are provided in Equation (1) through Equation (5).

$$Real_k = \sum_{i=0}^{n-1}(\cos\left(\frac{360*i}{n}\right) * close_k) \tag{1}$$

$$Imag_k = \sum_{i=0}^{n-1}(\sin\left(\frac{360*i}{n}\right) * close_k) \tag{2}$$

$$Phase_k = \text{atan}\left(\frac{Real_k}{Imag_k}\right) + 90 \tag{3}$$

$$\begin{aligned}
&If\ Real_k > 0.001 \quad Phase_k = arctan\,(Imag_k/Real_k)\\
&else\ if\ Imag_k < 0\ then\ Phase_k = (\tfrac{360°}{2}) * -1\\
&else\ Phase_k = (\tfrac{360°}{2}) * 1\\
&If\ Real_k < 0\text{: } Phase_k = Phase_k + 180°\\
&If\ (Phase_k < 0)\text{: } Phase_k = Phase_k + 360°\\
&If\ (Phase_k > 360°)\text{: } Phase_k = Phase_k - 360°
\end{aligned}$$

$$Sine_k = \sin(Phase_k) \tag{4}$$

$$LeadSine_k = \sin(Phase_k + 45) \tag{5}$$

Where $n = time$ during which the indicator is calculated. We would like to mention that to the best of our knowledge, study is the first study in experimental validation of LMSW for stock price prediction. The second part of the study involves Stock Market Prediction (SMP) using DL framework. Since the data happens to be a time series data, hence we used Recurrent Neural Network (RNN) for SMP. Minutely, we used the LSTM model for SMP.

The rest of the paper is organized as follows. Section 2 presents the existing notable literature in this domain. Our experimental analysis of LMSW viability for stock price prediction followed by proposed prediction model using LSTM, along with the experimental results is presented in Section 3. Section 5 concludes the paper.

2 Literature Survey

Use of artificial intelligence for SMP can be observed in the last four to five years. This has further led to the debate as to which algorithm suits better. In this regard, the authors in [6] have presented a brief study. Certain amount of notable literature exists in use of ML and DL frameworks for proper stock price prediction. A comprehensive survey of such approaches can be observed in [1] [2]. Also the work by the authors in [7] provide a comparative analysis of such frameworks with independent attention to use case application of the frameworks, or algorithms. Use of DL for SMP can be observed in [8] [9] [10] [11]. Since the historical data in case of stock market is often time series data, considerable amount of RNN have been used till date, notably the studies in [12] [13]. One of the frequently used stock momentum indicators is the moving average convergence divergence (MACD) [14]. Analysis between two important factors in SMP lies in the momentum guided trend and the moving averages [15]. In this study the authors have claimed that the moving average rule fares better in comparison to the momentum rule in SMP. Usually there two approaches in SMP, short term and long term. Authors in [16] have proposed a DL framework for short term SMP in which they have used an LSTM model in the penultimate step. In another study, the authors in [17] have done SMP taking into account unexpected incidents that can affect the trend.

3 Proposed Work

This study focuses on two parts. The first one is whether LMSW can predict future prices of stocks, and how well LSTM (DL RNN framework) can work in SMP. The next two sub-sections detail each of the two parts.

3.1 Experimental Validation of Lead Mesa Sine Wave for Stock Market Prediction

For the experimental validation, three stock datasets have been used from Reliance, Infosys, and Grasim. The data instances in each of the dataset are as follows: Grasim = 4903, Infosys = 6598, and Reliance = 6598. The view of the data fetched is presented in Table 1. Using Equation (4) and Equation (5), the sine and the LMSW values are calculated and presented in Table 2 as per the algorithm presented in AL01. In this regard, we have taken a period of 2, and a phase angle of 45°. It can be observed that the values for LMSW lies in the range $[-1,1]$.

AL01 Mesa Sine & Lead Sine

```
Define libraries
Begin Load_closing_prices_and_period_value
        Begin Iteration_over_closing_prices
                Calculate RealPart_and_ImagPart_for_closing_price_after_period
                Calculate Phase_from_RealPart_and_ImaginaryPart
                Check Phase_valid_or_not:    If not valid: Update Phase
                End Check
                Calculate Sine_from_Phase && Calculate Leadsine_from_Phase
        End Begin
End Begin
```

Table 1. View of the raw data

Date	Close	Date	Close
1-1-2020	100	7-1-2020	130
2-1-2020	105	8-1-2020	135
3-1-2020	110	9-1-2020	140
4-1-2020	115	10-1-2020	145
5-1-2020	120	…	…
6-1-2020	125		

The prediction model used the data presented in Table 2 and generated the results as shown in Fig. 1, Fig. 2, and Fig. 3. The Red line and the Blue line in Fig. 1, Fig. 2, and Fig. 3 represent the actual and the predicted values respectively. It can be observed from the three figures that the prediction of future stock prices by far don't follow the actual prices. Hence, we conclude that the LMSW does not serve as a trend indicator in predicting future stock prices.

Table 2. View of the data for Sine and LMSW

Date	Close	Sine	LMSW
1-1-2020	100	-	-
2-1-2020	105	-	-
3-1-2020	110	0.78	-0.88
4-1-2020	115	0.19	0.67
5-1-2020	120	-0.90	0.96
6-1-2020	125	-0.49	-0.56
7-1-2020	130	0.84	-0.86
8-1-2020	135	-0.99	0.23
9-1-2020	140	0.71	-0.52
10-1-2020	145	0.90	0.14
…	…	…	…

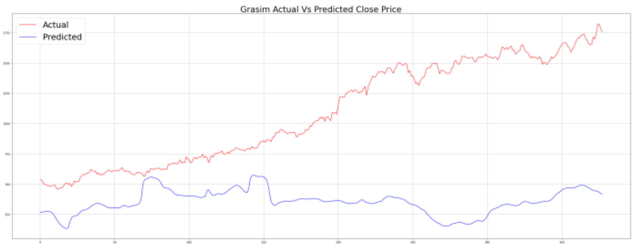

Fig. 1. Actual vs. LMSW predicted price for Grasim using LMSW

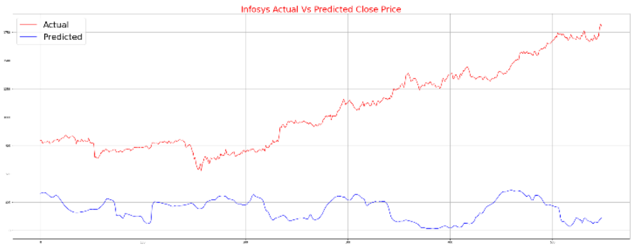

Fig. 2. Actual vs. LMSW predicted price for Infosys using LMSW

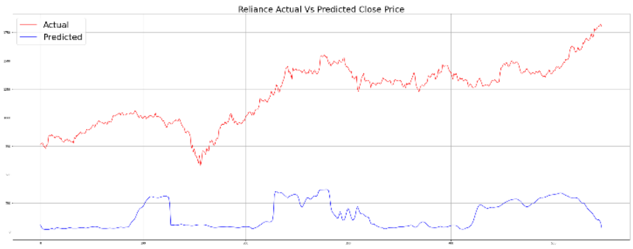

Fig. 3. Actual vs. LMSW predicted price for Reliance using LMSW

3.2 Stock Price Prediction using Historical Closing Values

In this section, we propose a SMP framework based on LSTM. The block diagram for LSTM is presented in Fig. 4 with Fig. 5 presenting an LSTM memory cell. The complete workflow is presented in Fig. 6.

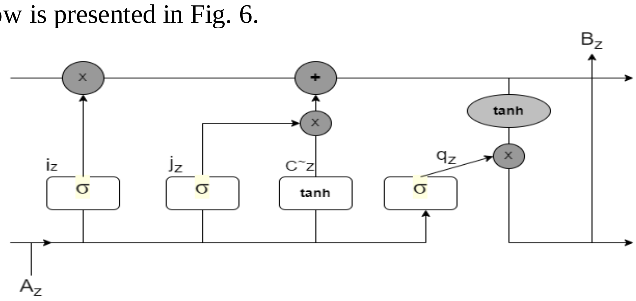

Fig. 4. Block diagram of LSTM

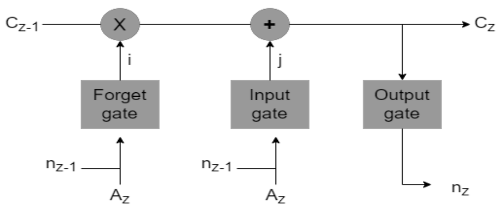

Fig. 5. LSTM Memory Cell

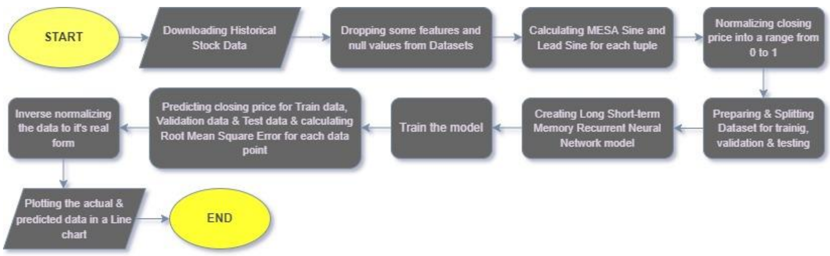

Fig. 6. Workflow diagram

The choice of LSTM framework lies in the fact that the data is a time series data, and RNN is the best approach to deal with such data as has been observed technically and historically. As we have already observed that the LMSW values range $[-1.1]$, hence the closing values were scaled in the range $[0,1]$. The curated dataset thus obtained was split into three parts for training, validation, and testing purpose. The ratio of $train: validate: test$ was $0.7: 0.2: 0.1$. Thereafter a timestamp was created based on which the dataset was designed for training the LSTM model, i.e. if the timestamp = 4, then the first 4 closing prices as input, and the 5th closing price as the output.

$$if\ (timestamp == 4): input = CP_i \forall i \in [1,4]\ \&\&\ output = CP_5$$

$$if\ (timestamp == 5): input = CP_i \forall i \in [1,5]\ \&\&\ output = CP_6\ and\ so\ on\ ...$$

Where $CP_i = i^{th}\ Closing\ Price$. Therefore the training dataset thus generated is presented in Table 3. Fig. 7, Fig. 8, and Fig. 9 present the actual and the predicted values with respect to our proposal. The figure itself depicts the accurateness of the model.

Table 3. Training dataset

100	105	110	115	120
105	110	115	120	125
110	115	120	125	130
115	120	125	130	135
120	125	130	135	140
125	130	135	140	145
…	…	…	…	

Fig. 7. Actual vs. LMSW predicted price for Grasim using Closing Price

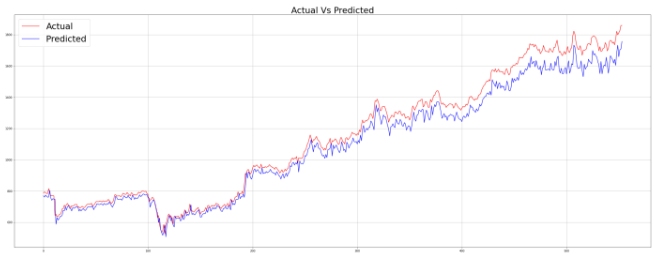

Fig. 8. Actual vs. LMSW predicted price for Infosys using Closing Price

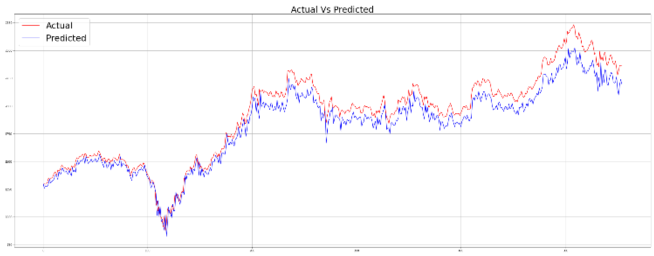

Fig. 9. Actual vs. LMSW predicted price for Reliance using Closing Price

From Fig. 7, Fig. 8, and Fig. 9, it can be observed that the predicted values closely follow the actual value thereby validating the effectiveness of the model for all the three datasets. Further tuning of the model can generate even better predictions.

4 Conclusion

Although Lead Mesa Sine Wave is a pair of sine waves used for predicting whether the stock is in cyclic mode or trend mode, this study experimentally establishes the fact that Lead Mesa Sine Wave cannot be used as an indicator for future stock price prediction. Moreover prediction can be made much more efficiently using closing prices using Recurrent Neural Networks, typically LSTM. It has been observed that the predicted results using closing prices closely follow the actual price using the basic LSTM model. The work in this study can be extended further to design more efficient networks/models using deep learning for future stock price prediction. Moreover, tuning the proposed model can be done to experimentally check if LSTM serves as a better model for prediction post tuning.

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