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# A Nonlinear Autoregressive Exogenous (NARX) Neural Network Model for the Prediction of Timestamp Influence on Bitcoin Value

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**ABSTRACT** The transaction and market of bitcoin is volatile, meaning it's uncertain because it changes frequently. There have been a number of research studies that have presented bitcoin price prediction models, but none of them have looked at the controlling variables linked with bitcoin transaction timestamps. It might be that price is not the only key criteria influencing bitcoin transactions, or the available model for bitcoin price prediction is yet to consider timestamp as a determining factor in its transaction. A better and more accurate model would be required to predict how the Timestamp influences changes of bitcoin transactions. That is why this current study utilized a Nonlinear Autoregressive Exogenous (NARX) Neural Network Model for the prediction of timestamp influence on Bitcoin value. Bitcoin historical datasets which are converted to a nonlinear regression into a "well-formulated" statistical problem in the manner of a ridge regression are used. Simulation analysis indicates that bitcoin digital currency's performance variation is highly influenced by its transaction timestamp with the prediction accuracy of 96%. The contributions of this research lies with the fact that specific Bitcoin transaction events repeat themselves over and over again, meaning that the Open-Price, High-Price, Low-Price, and Close-Price of Bitcoin price over timestamp developed a pattern that was predicted by NARX with less. That means those involved in the transaction of bitcoin at the wrong timestamp will certainly face the uncertainty negative effect of the bitcoin market.

**INDEX TERMS** Bitcoin (digital currency), volume of BTC, bitcoin, timestamp.

## I. INTRODUCTION

At the middle of May 2021, the vast majority of cryptocurrency platforms dropped sharply. Among the major leading cryptocurrencies-based market that were affected include: Dogecoin-31.06%, Ethereum-27.40%, Bitcoin-18.55%, Binance-33.48%, and Shiba On the same day, the Coinbase page was down indicating a message that reads "We're having connection issues. We're looking into it right now. Please quit the app and try again. Your funds are safe." The whole catastrophe was associated with China's announcement of a cryptocurrency crackdown and Tesla CEO Elon Musk's announced a week earlier saying that the company would no longer accept bitcoin for its vehicles

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because of the environment's impact. Within this premise, one can understand that the cryptocurrency-based market is highly influenced by "Time." More importantly, activities at the lower levels are all closely tied to the relationship between cryptocurrencies and businesses which occur simultaneously with the time frame [1], [2].

Bitcoin is one of the major cryptocurrency types which its transactions dwell on time series. A Bitcoin's weighted price is defined as the ratio of the value of bitcoin traded to the total volume traded per day, measured by the average price at which a Bitcoin is traded over the course of a trading day or trading week. This means that it is influenced by the open price of a bitcoin at the start time window in a day, the high price within that day window, the low price within that day window, and the close price at the end of that day window. Its price is part and parcel of the complex process involved in the

transactions and the system is seriously affected by; “Block delivery time” [3], Time-varying long-term memory [4], Transaction-confirmation time [5]. This is what yields a lot of interest in studying modern cryptocurrencies-type money and their rising and/declining rates of growth is one of today’s issues in cross-disciplinary studies. It can be seen recently that cryptocurrencies’ principal investment objective is to increase. They are now considered as assets and can be expanded on as much as they are stable over time [6]. Now, however, it has become the most important issue and has become much less productive. Bitcoin, besides being a form of exchange, is additionally a type of investment, since it can be used to purchase products and services. Manufacture products that can be sold via a secure digital supply chain of distribution can use it appropriately. It leads banking and monetary policies to become segregated from the rest of the economic system [7]. Unfortunately, but unsurprisingly, bitcoin’s increases and decreases are not absolute. The rules of the bitcoin market on-or offside, the general public has the ability to watch. There will be a continued increase in the number of bitcoin transactions and its uniformity each day, predictable rate of expansion. In regard to price, those that expand their capability, make correct decisions [8]. When it comes to cryptocurrency, there is a lot of interest in researching and developing new theories about it. As society continues to expand and to include various disciplines, new questions will be raised about growth and its contemporary elements. Much research has been done regarding its price. Now, however, it has been about timing and has become an issue in determining “when” uncertainties might happen that will affect the volume of BTC [4].

Most likely, when dealing with bitcoin, the effect on business is less, but certainly with regards to the transaction levels, Bitcoin (digital currency) has a great impact. Unfortunately, Bitcoin’s timing has always been a crucial issue. Global markets currently identified bitcoin as the world’s largest that fails to ensure consumer protection, such as the unregulated [9]. Some people are impressed by the sophisticated features of bitcoin, including its relationship with an immaterial network and decentralised third-party counterpart, while others admire its underlying technology and association with people who are trusted as the middlemen of cash that uses algorithms. It has no geographic boundaries and, therefore, cannot be expanded; it has no memory issues, and it has characteristics that may vary between individuals. It used to be that people felt safer when they invested in things than when they dealt with something that is uncertain over time, so this current research focuses on time uncertainty with bitcoin [10].

With regards to bitcoin operation, a “Timestamps” are a way of proof that data that preceded a certain point in time did exist, that is some data existed prior to a certain point in time [11], Every single transaction time stamp in Bitcoin software has not been mandated by either Satoshi or Bitcoin developers. That is why we have several confirmations to wait for. That needs to be resolved – for each transaction, each

payment system has an integrated time-stamp [12]. In Bitcoin terms, timestamp servers are widely implemented. Every transaction has its own timestamp that links back to the one before it. When Bitcoin was first created, the timestamping feature was incorporated into the software’s code [13]. Using the block chain network, it was able to assign timestamps to each and every transaction recorded in the ledger [14]. This is the information that will guide through the process of establishing a Proof of Transaction, which is a type of Proof of Existence that allow for an understanding on when exactly a transaction was created and what was contained within it [15]. The reason for using timestamp in this study is that the “open price at the beginning of the time window,” the “high price within the time window,” the “low price within the time window,” and the “close price at the end of the time window” all have an impact on the bitcoin transaction associated with timestamp, but it is unclear whether they can show patterns in their influence. That is why, it was decided to use timestamps in this study because the prices of bitcoin transactions associated with timestamps can be influenced by the open, high, low, and close prices, but previous research studies, ignored investigating patterns or to examine if patterns could be detected.

Machine learning models has been used to help predict the price and uncertainty of Bitcoin transaction, but ignore the time-based uncertainty associated with its transactions [16]. There have been a significant number of studies carried out using machine learning algorithms in the timeline domain. In addition, such studies can be used to perform analyses that are suitable for evaluating features of bitcoin associated to timeline. Bayesian network models, however, are crucial to the timeline predictions. which gives better insight into predicting the time-base effect of Bitcoin transaction. Complex and uncertain domains can benefit greatly from the use of Bayesian networks. In systems and decision-making, Bayesian networks can make use of inherent uncertainties in nature and can place related information in a consistent and comprehensive framework. With Bayesian networks, uncertain information can be included with ease, resulting in a model output that reflects the uncertainty. That is why this study aims to predict time-effect on the volume of BTC.

## II. RELATED WORK

Considering the fact that transactions of Bitcoin fluctuate almost every minute, several research was performed but mostly focusing on predicting the “price” of bitcoin and still using time series data in general and Bayesian neural networks in order to forecast the log price and volatility in particular [17]. In an attempt to get to the bottom of the digital currency problem, research was conducted to examine the relationship between global bitcoin prices and other monetary resources, precious metals, commodities, and stock market data, which showed that Bitcoin might soon take them over [18]. This means that “time” is the essence and we are just waiting for it. This issue is in the context of giving a detailed exposition of the fundamental points of

bitcoin adoption now as well as in the near-term and long-term considerations.

Velankar, *et al.* [19] proposed a system that predicts the Bitcoin price, in order to understand and identify the daily trends in the Bitcoin market as well as obtaining a better understanding of optimal features surrounding the Bitcoin price. Similarly, Chen *et al.* [20] distinguish between daily and high-frequency prices for Bitcoin, and utilized Random Forest, XGBoost, Quadratic Discriminant Analysis, Support Vector Machine and Long Short-term Memory to predict future prices with a 67.2% accuracy level. Another study from Phaladisailoed, & Numnonda [21], takes into account the fluctuations in price of bitcoin and investigates the most efficient and highest accurate model for the prediction of Bitcoin prices. An accuracy of 97.8% was found by regression models for different time intervals. Many studies have attempted to forecast the price of bitcoin using a variety of methods. A bitcoin price prediction using neural network ensembles was presented in [22], where the effect of the sequence size on classification accuracy on deep neural network (DNN) is 50.43% and long short-term memory 50.14%. It suggests that for price increases and decreases of bitcoin, DNN-based models performed better. Similarly, bitcoin price prediction using regularized deep learning with various variables was proposed in [23]. The findings suggest that the autoregressive integrative moving average is effective at a minimum reported residual sum of squares of 0.002. In another study, bitcoin price prediction was performed by parametrized value-machine learning in [24].

Particle swarm optimization-parameters were utilized for bitcoin price prediction where autocorrelation test, the cross-correlation tests show minimal coefficient violations within the 95% confidence limits [25]. A gated-value based recurrent unit (GRU) technique has been proposed for bitcoin price prediction in [26]. The findings of the prediction accuracy when modelling future Bitcoin price trends with the predictors reveal that the future Bitcoin price trends prediction accuracy with an RMSE of 0.016 was highly significant. It is possible to predict the volatility of Bitcoin's price by analyzing public sentiment on Twitter and determining the relationship between the sentiments expressed by Bitcoin users on Twitter. A recurrent neural network model has been used along with historical bitcoin price data in [27]. The finding of the study reveals that the accuracy for sentiment classification of tweets in two classes, positive and negative, was 81.39%, and the accuracy for price prediction using Recurrent neural network was 76.52%. A symmetric-deep learning approach with value parameters has been used to determine the impact of bitcoin price prediction with respect to socio economic variables in [28]. It is demonstrated that when a positive tweet is posted in the context of bitcoin, the price of bitcoin is expected to rise, and that when a negative tweet is passed in the context of bitcoin, the price of bitcoin is expected to decrease. The Root Mean Square Error is 61.23. Bitcoin price prediction with long short-term memory has been proposed in [29]. The

predictions were validated and the results showed that it could be applied in various cases, where the Bitcoin price sequence is non-stationary and has unit roots (t-statistic:  $-2.209$ , p-value: 0.204). The Bitcoin Price Index was used to predict the price of bitcoin using machine learning in [30]. A Bayesian optimized recurrent neural network (RNN) and a Long Short Term Memory (LSTM) network were utilized. The LSTM achieves the highest classification accuracy of 52% and a RMSE of 8%. A novel way to de-anonymize Bitcoin in order to predict its price has been proposed in [31]. The finding of the study reveals that a mean cross-validation accuracy of 80.42% and an F1-score of about 79.64% using the Gradient Boosting algorithm with default parameters. Despite this several research on bitcoin, its direct time impact can be seen to be ignored by the research community.

"Abraham *et al.* [32] were able to accurately forecast the direction of price increases by employing a linear model that takes as input tweets and Google Trends data," according to the researchers. Their findings demonstrated that by applying the model, a person will be able to make more educated judgments about the buy and sale of Bitcoin and Ethereum. This finding can be supported by the fact that the combination of aggressive twitter filtering based on length and structure, as well as hierarchical tweet clustering and ranking of the resulting clusters, yields promising results as revealed by Ifrim *et al.* [33]. Furthermore, there could be a doubt if cryptocurrency-related Twitter data may be used to generate profitable crypto coin trading methods as pointed out by Colianni *et al.* [34]. The interrelationships between Bitcoin price and Twitter and Google search patterns were discovered using the Bitcoin price, tweets, and a Google search [35]. There is a link between Bitcoin pricing, Tweet and Google search habits, according to the study. As a result, it employs "Polynomial regression" on "tweet volume" and "Google trends" for analysis. The findings show that Linear regression's accuracy in predicting "bitcoin price" is 77.01 percent and "66.66 percent for polynomial regression" with Tweet Volume and Google trends, respectively. The interrelations between investor sentiment and the returns, volatility, trading volume, and liquidity of bitcoin has been investigated in Meng *et al.* [36]. The findings show that "bullishness from a socio-finance model," "bitcoin tweets," and future realised volatility of "bitcoin trading volume," which is assumed to capture information from well-informed investors in the Bitcoin market, are significantly connected.

Choi [37] examine the number of tweets effect as a proxy for investor attention to invest in bitcoin and the influence of tweets' real-time effects on Bitcoin liquidity. The study uses high-frequency data to investigate tweets' real-time effects on Bitcoin liquidity. The finding indicates that a 1% increase in the volume of tweets leads to a 7% of Bitcoin liquidity improvement within the next five to 10 min, and the positive effect of tweets on liquidity statistically decays after the 60 min time interval as well as the real-time impacts of bitcoin investment are stronger when tweets draw more attention by being retweeted, liked, and

replied. Machine learning and Deep learning has been used to investigate the relationship between Bitcoin-related tweets and sentiment analysis of such tweets, as well as comparing and assessing different data has been presented in Balfagih and Keselj [38] The findings reveals a partial association between variations in the Bitcoin price and fluctuations in the sentiment class accuracy using variety of machine learning. Considering the impact of COVID-19 pandemic, Pano and Kashef [39] explore alternative text preprocessing algorithms for linking the sentiment scores of Twitter text with “Bitcoin prices.” The findings indicate that, out of 13 strategies tested, splitting sentences, removing Twitter-specific tags, or their combination generally improve the correlation of sentiment scores and volume polarity scores with Bitcoin prices,” and that the prices only correlate well with sentiment scores that are measured over shorter time periods, according to the findings.

Matta *et al.* [40] investigated if the spread of the Bitcoin’s price is related to the volumes of tweets on bitcoin or Web Search media results on bitcoin, by comparing the trends of price with Google Trends data, volume of tweets and particularly with those that express a positive sentiment. According to the research finding it reveals that the patterns volumes of bitcoin tweets and bitcoin price exhibit a strong relationship, there has been a considerable increase in cross correlation values, particularly between bitcoin price and Google Trends Data Using public opinion on Twitter, Sattarov *et al.* [41] investigate the extent to which Bitcoin returns can be predicted. Following the application of a sentiment analyzer called Valence Aware Dictionary and Sentiment Reasoner to Bitcoin-related tweets and financial data, it was discovered that tweets with positive sentiment have predictive value for Bitcoin’s results. On bitcoin-related tweet sentiment and historical bitcoin price predictions, an accuracy of 62.48 percent was achieved. According to Ibrahim [42], there is a clear link between “Twitter mood” and “future price changes in Bitcoin.” Specifically, Logistic Regressions, Binary Classified Vector Prediction, SVM, and Naive Bayes were employed for sentiment analysis and text mining. Each model’s capacity to forecast public sentiments states was examined. The XGBoost-Composite ensemble model outperformed the best prediction models.

It should be recognized that most research on the area of bitcoin is also redirecting at investigating cryptocurrencies attributes in general. A lot of studies tend to use bitcoin with other cryptocurrency-type together. They mostly looked at their nature of improvement in the long-term situation in ensuring more important their reducing price volatility, legality, increases in their use, financial diversification, market and widening the audience attention [22]–[29], [32]–[42]. This allows us to establish these research gaps while considering the micro-transaction issues involving time in both processing and the effect on the volume of the bitcoin unit price. This current research established that there is a relationship between time and the weighted price of bitcoin. In order to get to know more about the current practices of

time into more detail the data streams over time to see if there is a relationship between the time associated with the uncertainty of Bitcoin. That is whether or not bitcoin tends to be evaluated on the basis of how it can be accessed over time. However, for marketing strategies, the goal of a lot of many cryptocurrency and associated market research studies is to predict and study price movements and metrics [30]. Several factors have been taken into consideration when researchers have used flexible mechanisms in their investigation [31], however, this study is motivated by the finding on the previous research associated utilizing machine learning for the prediction of bitcoin tweets [32]–[42].

### III. METHODOLOGY

Throughout this paper, we will be referring to the architecture of the NARX Neural Network Model. The study conceptualized variables from Bitcoin transactions in order to perform prediction simulations under several scenarios designed for the simulation in order to gain a better understanding of the influence of the timestamp on the value of Bitcoin, which was the goal of the research. Despite the fact that there is “advanced research in time series prediction,” the reason for using the NARX model in this study is due to the fact that the NARX model predicted the timestamp data based on the “root mean square error, RMSE, the mean absolute error, MAE, and the correlation coefficient, R, and that the “NARX model” could be associated with either a linear or nonlinear or both attributes. While it is clear that attributes such as “open price at the beginning of the time window” and “close price at the end of the time window” have an impact on the bitcoin transaction associated with timestamp, it is not clear whether they can exhibit patterns in their influence on the bitcoin transaction associated with timestamp.

#### A. ARCHITECTURAL FRAMEWORK

The architectural framework of this current study is presented in Figure 1. It represents the conceptualization of the ideological approach in the first phase and the experimental network evaluation in the second phase. The first phase draws the attention of the reader towards the time-effect on the volume of bitcoin digital currency, in which it dwells on emphasizing the work is within the effect of timing on bitcoin transactions. Hence, the conceptualization of the time-based Bitcoin volume and returns was developed. This simply means that since our data sources are time series data, then our analysis is going to be a time series analysis involving neural network time series analysis. Then we proposed the use of three training algorithms to train a neural network involving Bayesian inference.

Regularization as the major algorithm because it is the best in time series analysis based on its prediction accuracy [17], and Levenberg-Marquard, as well as Scaled Conjugate Gradient algorithm for Bitcoin transaction model associated with time and volume. Finally, this study formulates a hypothesis which entails that: the Bitcoin transaction model for time-based is associated with its weighted price. This is

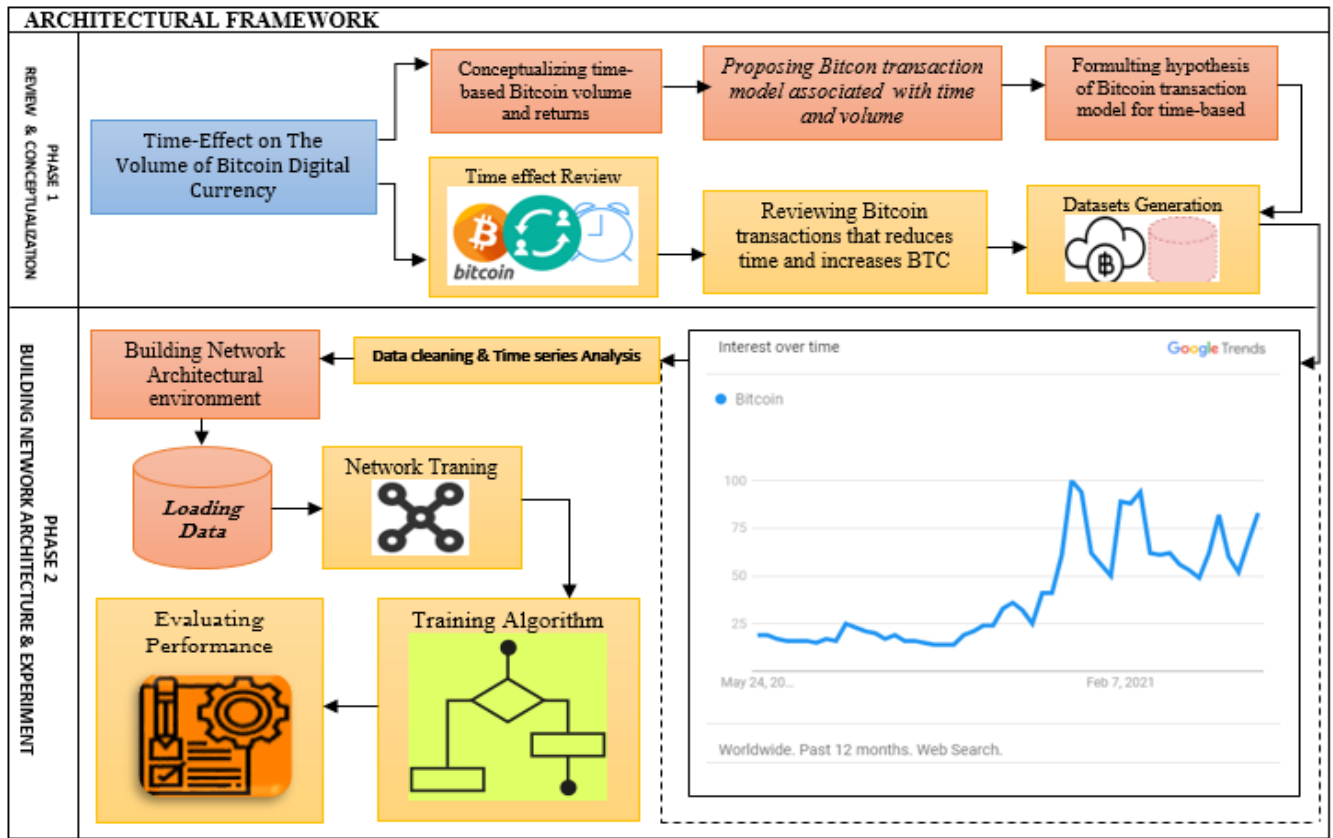


FIGURE 1. Architectural framework.

the end of the first part of the conceptualization. The other part of the conceptualization involves the reviews associated with time effect, how time reduces the transaction effect and increases the BTC. That is where the motivation for the study was established.

The second phase of the architectural framework provides the details of the implementation of the dynamic time series approach towards the prediction of the time-effect. This kind of analysis is important because prediction is a kind of dynamic filtering, in which previous time of one or more-time series is used to predict future values. That is if the weighted price of bitcoin that was experienced in the market could be used to predict the future values. In addition to tapped delay lines, dynamic neural networks, which include weighted tapped delay lines, are used for nonlinear filtering and prediction as applied to this Bitcoin situation. There are many areas in which prediction is this kind of analysis is important. An important aspect of predictive time values is to see if the changes in bitcoin transactions have a pattern with respect to time.

Before performing experimental analysis and evaluation, the research first runs through various steps that lead up to the analysis and evaluation. To predict “when” in terms of time, it would be more likely that time is necessary. Google Trends for web search of “Interest over time” for bitcoin for worldwide of the past 12 months (March 2020

to February 2021) web search express how people are likely concerned about time in relation to bitcoin transactions, and most importantly its profit. That is over time, people always feel the need to get information about the interest rate of Bitcoin. That is why they search for it more often.

**B. THE DATASET**

The first step in the analysis is to gather the dataset. The dataset for this study was aquired from “Kaggle” Bitcoin historical data generated by Bitcoin data which was obtained “at 1-min intervals from select exchanges, Jan 2012 to March 2021” [43]. The column of “Timestamp,” and “Weighted Price” for the datasets were used for this study. “Timestamp” is the independent variable and “Weighted Price” is the dependent variable. In this case, it can be seen that the independent variable is what caused the effect and the dependent variable is the result. Here it means that “Timestamp” influences the “weight price” in terms of the research conceptualization. The other columns apart from “Timestamp” and “weighted price” are the “Open price at start of time window” field, the “High price within time window” field, the “Low price within time window” field, the “Close price at end of time window” field. The data was made available in order to provide more specifics and context about how Bitcoin transactions are performed over time. The data is intended to be made public. The data

has been retrieved at 1-minute intervals for a select number of exchanges where trading takes place. When there are no transactions or activities, the Timestamps field is set to have null values, indicating that there are no transactions or activities. It is also possible that an error might occur during the transaction because of a problem with the data collection or reporting. If an error occurs during the transaction, the record of the transaction will be cancelled.

The next step after the dataset collection is transformation of the dataset in order to make it ready for use in the predictions. That is, before processing the dataset obtained in the kaggle (the raw data, see Figure 2 below),

	A	B	C	D	E	F	G	H
1	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
869781	1377504660	112.63	112.63	112.63	112.63	0.7541951	84.94499411	112.63
869782	1377504720	112.62	112.62	112.52	112.52	13.32520122	1500.000001	112.5686566
869783	1377504780	112.52	112.52	112.5	112.5	7.88880988	887.5399996	112.5061972
869784	1377504840	112.5	112.57	112.48	112.48	12.66697747	1425.040535	112.5004397
869785	1377504900	112.48	112.48	112.47	112.47	10.97836974	1234.773913	112.47334
869786	1377504960	112.47	112.47	112.45	112.45	11.38920505	1280.765	112.4542928

FIGURE 2. The dataset from Kaggle [43].

### C. THE EXPERIMENTAL SETUP

The dataset from Kaggle [43] is scaled up to a uniform scale in the process called transformation. The next step is where data analysis, cleansing, and preparation are all completed, and then the data enters the processing stage of the analysis using Matlab. The computer system used for this experiment is equipped with an Intel® Core™ i7-10750H CPU @5.0 GHz, and 16 GB Ram capacity.

In order to train the NARX network, it is done in parallel and series-parallel modes, starting from the “input layer,” progressing to the “hidden layer,” and finally ending at the “output layer” (see Figure 3). A dynamic filtering process is used in the input later to establish and set up the “prediction process,” which involves defining the input and output training data values of one or more-time series in order to forecast the future values. This is the first stage in the input layer. The “nonlinear filtering and prediction” are accomplished through the use of dynamic neural networks that feature “tapped delay lines.” The next stage is “loading the data,” which is accomplished through the use of a Input data element and a Targets represents target data. Training data is presented to the network during training, and the network is adjusted according to its error, while validation data is used to measure network generalisation, and training is stopped when generalisation stops improving, and Testing data has no effect on training and thus provides an independent measure of network performance during and after training.

The hidden layer is established as where the training is performed, in which the activation function and number of neurons and the delay involved are determined. In a neural network, the activation function is in charge of converting each node’s summed weighted input into node activation or

output for that input [44]. Many researchers use different activation functions, such as Binary activation function, Linear activation function, Exponential Linear activation function, Rectified Linear Unit (ReLU), Softmax activation function,” and “Sigmoid activation function,” among others. The activation function used in this study for the input and hidden layers is the Sigmoid activation function. Classifiers frequently outperform when “Sigmoid functions” and their combinations are used. Other popular activation functions such as GReLU and other normalising functions such as A-Softmax cannot be derivable like Sigmoid, [45] but for this study it makes learning the weights easier and allows for a reasonable degree of accuracy in approximating the weighted price of bitcoin’s timestamp. However, when used in back propagated neural networks, they can occasionally cause a vanishing gradient problem, despite the fact that their functionality is especially beneficial, according to the study. Classification rate was compared using “Sigmoid” and ReLU on soft-committee machine in Hara *et al.* [46], the research clarifies the reason for the speedup of ReLU, to rely on training convergence. On the other hand, Fu *et al.* [47] highlighted that ReLU ANN based on finite element method can keep the number of grid-points constant but change their relative location, which will be a major drawback given the volatility of the weighted price of bitcoin’s timestamp. Similarly, Chen and Wu [48] found that using ReLU on neural networks achieves “exponential convergence” without the curse of dimensionality for a function class but not for functions with “intrinsic low complexity.” Furthermore, Wang *et al.* [49] highlighted the degradation on the Open-set task caused by larger margin training strategies on Softmax loss, AM-Softmax loss, and AAM-Softmax loss.”

The estimated output of the NARX is returned back to the input of the feed forward neural network, in parallel mode whereas series-parallel mode goes with the actual output of the neural network and fed into the neural network’s input rather than being fed back to the estimated output. After the hidden layer has been defined, then training in open loop form, the network will be produced at the end of the process. Following training, the network can be transformed to a closed loop configuration, when generalisation no longer improves, training is automatically terminated by the system.

The Levenberg-Marquard is typically used to solve the non-linear least squares curve fitting problem. It is a combination of the Gauss-Newton and gradient descent methods for minimization. It is a fast algorithm with a high memory utilisation rate. That is for the majority of the networks, the classic Levenberg-Marquard algorithm is an efficient way to learn. In this case, it is nearly impossible to use this method with larger neural networks, whose computational complexity grows [50]. However, Scaled Conjugate Gradient is popular due to its simplicity but slow execution speed and suitability for objective functions with a simple objective function. It is an improved training algorithm for neural networks that is a second order iteration. Its learning curve is far more rapid, while simultaneously offering superior test

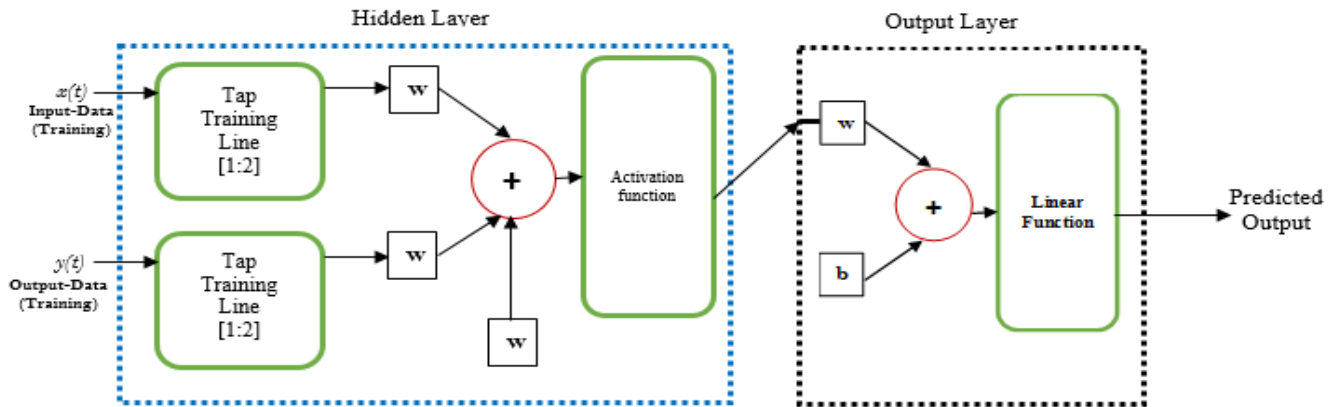


FIGURE 3. The process involved in the prediction.

efficiency [51]. The Bayesian Regularization algorithm is used to regularize the neural network and determine the optimal parameters using Bayesian techniques. It lets the artificial neural network usefully integrate different kinds of data. This means the neural network can be employed in quantitative studies to build a robust model [52]. As a result, this current research study uses all the three training algorithms. In all of them, the training process will terminate automatically when it reaches a point where there is no improvement in the generalization. This can be observed by the increase in the mean square error of the validation trials. When the initial configuration is changed and the data samples are altered, the neural network is trained and produces distinct results. Several partitions within three training algorithms (Bayesian Regularization, Levenberg-Marquard, and Scaled Conjugate Gradient algorithms) were used. What it is with respect to the speed, data and prediction components was obtained in the regression plot. The Regression (R) coefficient can be thought of as measuring how well the predictions in the dataset were achieved. A correlation coefficient of 1 means that the regression predictions exactly match the observed data.

The evaluation metrics use for determining the performance of a prediction are typically estimated on the basis of indicators presented in Table 2. Where each evaluation parameter is defined on the basis of accepting or rejecting a non-relevant class, and how well the performance finds all the relevant classes fit. As a result, a confusion matrix below was created.

		Assignment $z$	
		Predicted +	Predicted -
label $x$	Actual +	TP	FN
	Actual -	FP	TN

The evaluation is on the basis of a binary label  $x$  as the actual against the assignment  $z$ , as predicted, where  $x$  represents the correctness and  $z$  shows relevance. Hence, the positive and negative signs represent relevance and

non-relevance; TP is “true positive” FP is “false positive,” TN is “true negative,” and FN is “false negative.” Thus from these defined notation, the prediction performance evaluation is derived (see Table 2).

#### IV. ANALYSIS AND PRESENTATION OF THE RESULTS

The analysis started with the evaluation of the model by neural linear “fitting” in order to identify the model fits with few samples size. During our preliminary research, we discovered that the Levenberg–Marquardt algorithm is most commonly used to solve problems involving the least-squares curve fitting problem, where it finds local minimums at a very fast rate and solves generic curve-fitting problems, as well as other problems involving the least-squares curve fitting problem. Performing this step is necessary in order to establish an initial relationship among the input variables and determine the degree to which they interact with one another. The matlab analysis and the results for the fitting were collected. Several cases have been run, and among them, the best scenarios is reported, within the randomly selected partition at at 65% for training and 15% for validation and testing 20% testing being the most suitable partitions that provide the results for all the Levenberg-Marquard as well as Scaled Conjugate Gradient algorithms. In the analysis, ten hidden neurons and two delays were utilized within this partition. The fitting analysis of the Levenberg-Marquard is presented in Figure 4. Where the performance of the model was measured by  $R^2$  (0.99879, 0.74205, and 0.8737 for training, validation, and testing, respectively), and this was accomplished under MSE (1.0774, 1.0924, 1.3874), The colors in the graph differentiate the performance measures. Black color is for the all the combination of the fittings, while red color is for the testing data and green for validation whereas blue color is for the training data.

The Scaled Conjugate Gradient algorithms are used in the simulation model that follows. In a similar vein, several cases have been tested. For training, validation, and testing, the random (65%, 15%, and 20%) were used for training, validation, and testing, respectively, with ten hidden neurons and two delays being used. In order to reach this



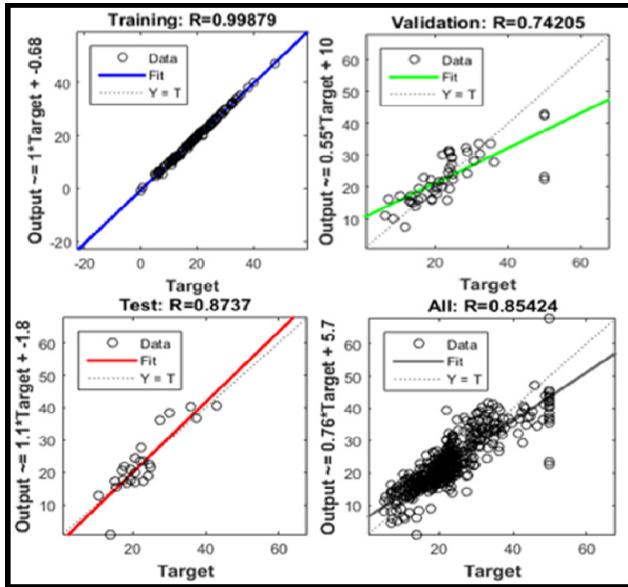


FIGURE 4. The performance of the Levenberg-Marquardt model.

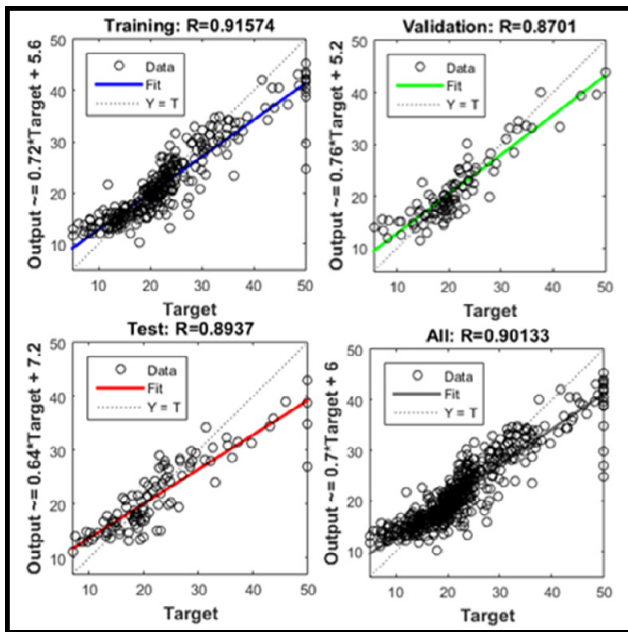


FIGURE 5. The performance of Scaled Conjugate Gradient analysis.

conclusion, the model's performance was measured by the  $R^2$  (0.91574, 0.8701, and 0.8937 in the three stages of training, validation, and testing respectively), which was calculated under the MSE of (1.2152, 1.1261, and 1.4429). (see Figure 5). Comparing the performance of the Levenberg-Marquardt algorithm and the Scaled Conjugate Gradient training algorithm using a variety of network structures, it was clearly demonstrated that the Levenberg-Marquardt algorithm outperformed the Scaled Conjugate Gradient training algorithm by a factor of two to one. It was necessary to average the various initialization parameters in order to obtain the average accuracy, which necessitated the use of an

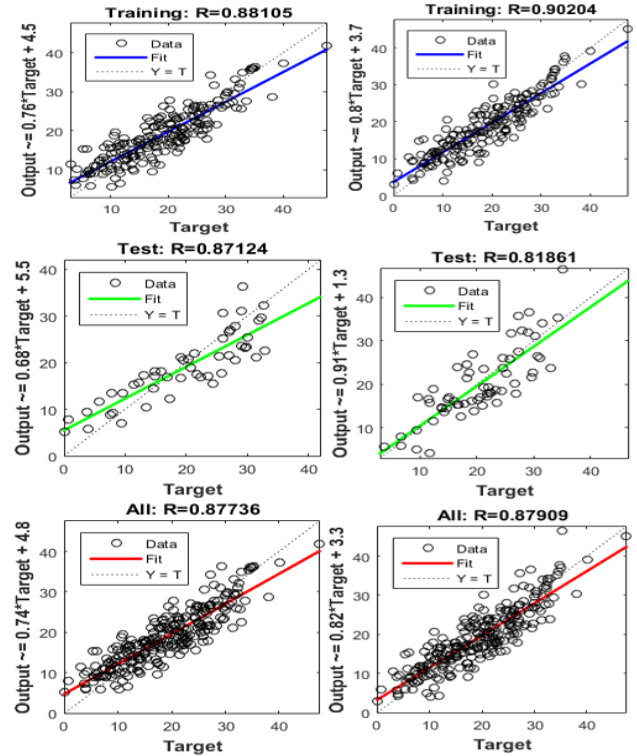


FIGURE 6. The performance of the Bayesian Regularization.

average in this case. When it comes to accuracy in this area, it is undeniable that the two algorithms achieved high levels of performance accuracy in their respective experiments.

The final simulation is with the Bayesian Regularization algorithm (see Figure 6). Similar parameters were used, however, two scenarios are presented. The performance of the best model by  $R^2$  are 0.90204, 0.81861, and 0.87909 for training, validation, and testing, respectively.

While having great results in the prediction by the linear model and established that the interaction among the variables fitted well. The next analysis uses the same three training algorithms in evaluating the model with the dynamic time series, specifically, Nonlinear autoregressive exogenous. That is because the next value of the input can be predicted and used for the non-linear removal of a dynamic system. Generally, this prediction model is used to take known input and output data series and plug them into historical values.

The training phase for this model makes use of the output as one of the input parameters to train a model, and is repeated as a static backpropagation system to achieve an accurate result. This Nonlinear Autoregressive Exogenous Neural Network (NARX) is a decent time series predictor, and it is employed in this research study. This is because it can be used to model a large number of nonlinear dynamic systems [53]. A wide variety of applications have found the use of these techniques, such as time-series modelling. This Nonlinear Autoregressive Exogenous recurrent dynamic neural network modulates a different exogenous input periodically. In order to boost the

**TABLE 1. Summary of the literature review.**

Author(s)	Methodology	Key Findings
[17]	Bayesian neural networks forecasting the log price and volatility of bitcoin	Prediction results of the log value of the Bitcoin price and the log volatility of the Bitcoin price shows consistent trend
[19]	Use ANN and SVM for predicts the Bitcoin price	Provide 80% prediction accuracy and 100% precision values for Bitcoin price
[20]	Use Random Forest, XGBoost, SVM. LSTM to predict future prices of bitcoin	Provide a 67.2% highest prediction accuracy for Bitcoin price
[21]	Prediction of Bitcoin prices by regression.	An accuracy of 97.8% was found by regression models for different time interval
[22]	Use DNN and LSTM to predicts Bitcoin price	An accuracy of 50.43% on DNN was obtained 50.14% on LSMT.
[23]	bitcoin price prediction using regularized deep learning	Autoregressive integrative moving average is effective at a minimum reported residual sum of squares of 0.002.
[24]	Particle swarm optimization-parameters were utilized for bitcoin price prediction	Autocorrelation test, the cross-correlation tests show minimal coefficient violations within the 95% confidence limits
[26]	A gated-value based recurrent unit (GRU) technique has been proposed for bitcoin price prediction	The prediction accuracy when modelling future Bitcoin price trends with the predictors reveal that the future Bitcoin price trends prediction accuracy with an RMSE of 0.016 was highly significant.
[27]	A recurrent neural network model has been used along with historical bitcoin price data in	The accuracy for sentiment classification of tweets in two classes, positive and negative, was 81.39%, and the accuracy for price prediction using Recurrent neural network was 76.52%.
[28]	A symmetric-deep learning approach prediction of bitcoin price with respect to socio economic variables	RMSE of 61.23 was obtained when the price of bitcoin is predicted to climb at the time of favorable tweet is posted about bitcoin, and to fall when a negative tweet is posted about bitcoin.
[29]	Bitcoin price prediction with LSTM has been proposed	The predictions results revealed a good fit for LSTM model, where the RMSE, MAE, MAPE, are 247.33, 176.37, and 2.553 respectively
[32]	Forecast the direction of price increases by employing a linear model that takes input tweets and Google Trends data,	Pearson R of the correlation of 0.817 with a p-value of 0.000 was obtained between Bitcoin and Google trends data.
[34]	Naive Bayes, and SVM was used Twitter data relating to cryptocurrencies can be utilized to develop advantageous crypto coin trading strategies.	Naive Bayes, and SVM leads to a final hour-to-hour and day-to-day prediction accuracy exceeding 90%.
[35]	Linear regression and polynomial regression are used to predict the correlation among Bitcoin price and Twitter and Google search patterns	Prediction accuracy on Linear regression for bitcoin price is 77.01% and 66.66% for polynomial regression with Tweet Volume and Google trends respectively.
[36]	vector autoregressive (VAR) models was used to simulate study concerning the proposed socio-finance model.	"bullishness from a socio-finance model", "bitcoin tweets", and future realized volatility of "bitcoin trading volume," are interrelated
[37]	Uses high-frequency data to investigate tweets' real-time effects on Bitcoin liquidity	After about an hour, the favourable influence of bitcoin tweets fades. when tweets receive greater attention, the effects on bitcoin liquidity are larger. active investor attention can boost Bitcoin liquidity in real time.
[38]	Data mining classifiers and deep learning methods sentiment classification of Bitcoin tweets	partial correlation between Bitcoin price volatility and sentiment class accuracy using machine learning were obtained.
[39]	The impact of Sentiment scores of Twitter text with	Prices of bitcoin only have a strong relationship with sentiment scores during shorter time periods
[40]	"SentiStrenght" was used to identify sentiments of tweets in the matter of Bitcoin	There is a significant increase in "cross correlation values," particularly between "Bitcoin price" and "Google Trends data,
[41]	The "Valence Aware Dictionary and Sentiment Reasoner" was utilised to determine the degree of Bitcoin returns based on public opinion expressed on Twitter,	It achieve 62.48 % accuracy in predicting bitcoin-related tweet sentiment and historical bitcoin price using this method.
[42]	Tweets sentiment influence on the early market movements of bitcoin were predicted using Logistic Regressions, Binary Classified Vector Prediction, SVM, and Naive Bayes.	XGBoost-Composite ensemble model was the best prediction models with 72% accuracy in predicting bitcoin-related tweet sentiment

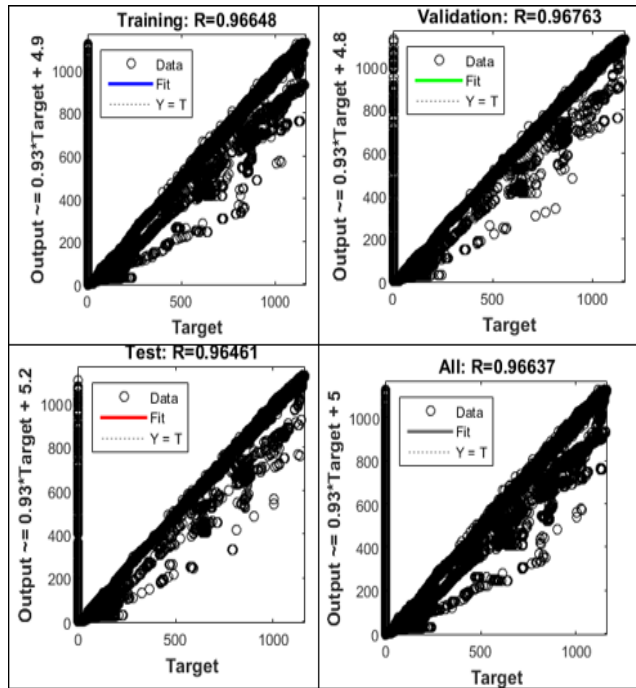


FIGURE 7. The performance of the Levenberg-Marquard on NARX.

signal-to-noise ratio, the network is built using feedback connections, which enclose multiple layers of the network. Enabling the capacity of the neural network’s memory using past predicted or true time series prediction to obtain the full performance of the Nonlinear autoregressive exogenous neural network for nonlinear time series prediction is an interesting strategy. Although different machine learning algorithms offer different ways of describing the parameters being investigated, the Nonlinear autoregressive exogenous neural network allows a simpler, physical interpretation of the parameters based on the relationship between exogenous inputs and the target parameter [54] Hence, using the full dataset obtained from [55], the analysis was performed again. The best partition for validation and testing purposes, selected at random data are: Training data entry of 734003, Validation data entry of 157286 and Testing data entry of 157286 comprising of 70%:15%:15% ratio respectively. Although running huge data entry takes some time, the performance evaluation involving the Mean Squared Error (MSE), which is the average squared difference between outputs and targets, was used. Furthermore, ten hidden neurons and two delays were utilized.

The performance of the model measured by R2 in all cases under the Levenberg-Marquardt algorithm is above 0.96 (see Figure 7). Where in the first model, the R2 values of 0.96648, 0.96763, and 0.96461 for training, validation, and testing, respectively. A substantial advantage was demonstrated by comparing the performance of the Levenberg-Marquardt algorithm in this scenario with the previous scenarios. As previously stated, it was necessary to calculate the average accuracy by averaging the various initialization parameters

before establishing comparison measures. The Scaled Conjugate Gradient training algorithm failed in the NARX due to the size of the dataset. Hence, the Levenberg-Marquardt algorithm unquestionably has a significant improvement over the previous state.

The time-series response on the simulation indicates the inputs, targets, and errors against the sequence of time. This specifies which time intervals were chosen for training, testing, and validation purposes (see Figure 8). An analysis of the model’s errors versus time has revealed that the majority of the errors are concentrated near the end of the model and in a specific area. This demonstrates that, for all training, test, and validation samples, the majority of time series models represent the association between the actual and predicted timestamps and the weighted price of a Bitcoin transaction. Also shown in this figure is the magnitude of the error, expressed as the difference between the actual and predicted values. Although the visual representation strongly suggests that the NARX network is a good fit for predicting the timestamp effect, MSE and R values computed for the training and test datasets presented earlier, quantitatively support the claim of goodness of fit.

Similarly, further evaluation by Bayesian Regularization algorithm on the same dataset, shows R<sup>2</sup> concerning the NARX training and test predictive modelling performance for experimental (see Figure 9).

The time-series response on the simulation’s entries, targets and errors are similar to previous simulation. Considering this, it can be seen that Bayesian Regularization performs very with NARX. However, on further evaluating the accuracy of the prediction, performance evaluation assessment metrics were used (See Table 2).

TABLE 2. Evaluation metrics.

Evaluation Metrics	Value	Formula
Sensitivity	0.9845	$TPR = TP / (TP + FN)$
Specificity	0.5455	$SPC = TN / (FP + TN)$
Precision	0.9836	$PPV = TP / (TP + FP)$
Negative Predictive Value	0.5588	$NPV = TN / (TN + FN)$
False Positive Rate	0.4545	$FPR = FP / (FP + TN)$
False Discovery Rate	0.0164	$FDR = FP / (FP + TP)$
False Negative Rate	0.0155	$FNR = FN / (FN + TP)$
Accuracy	0.9692	$ACC = (TP + TN) / (P + N)$
F1 Score	0.984	$F1 = 2TP / (2TP + FP + FN)$

True Positive (TP) rate is also called sensitivity, it associated with the measure of the degree of the total number of data points that influencing the effect of the Timestamp on weighted price in the prediction model. That is how the algorithm correctly predicted the model. This is one of the most important measure, and it indicate a high value close to 1. This shows that the model was predicted with a high degree of accuracy. What this is suggesting is that if there could be more history data or more input variables added to a time series model this study proposed, it can still be measured at each time step, with increasing

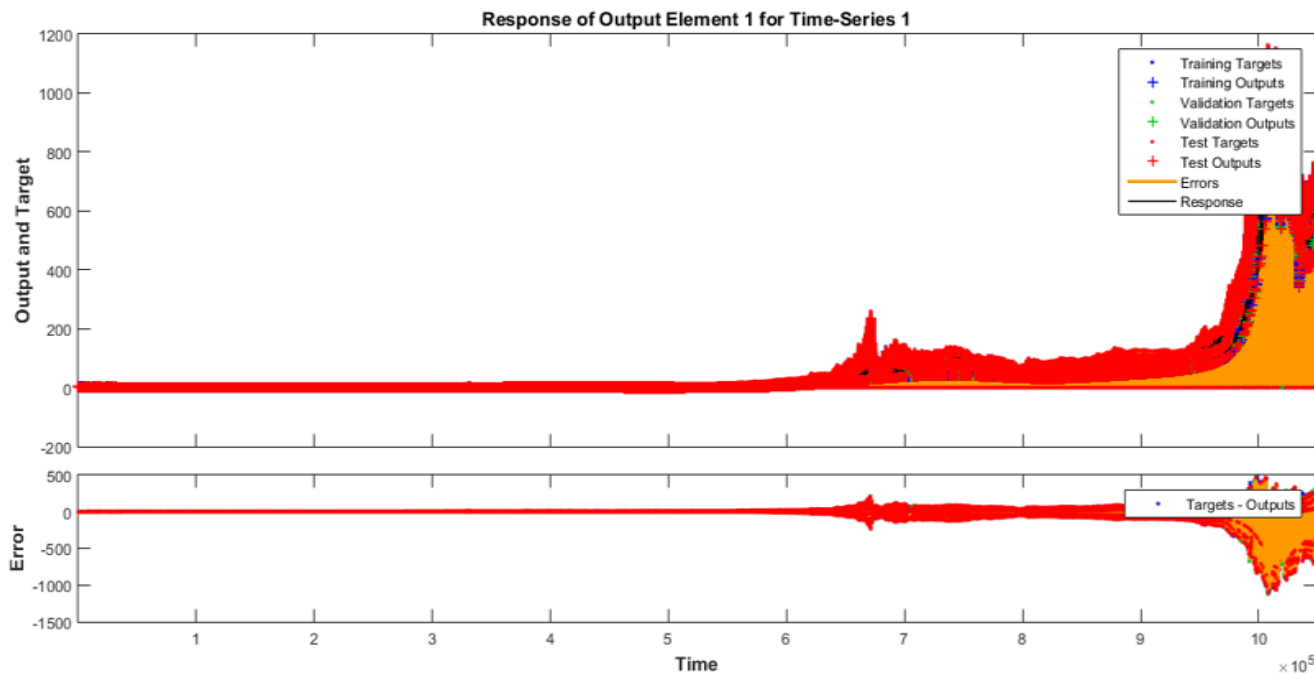


FIGURE 8. The time-response on NARX.

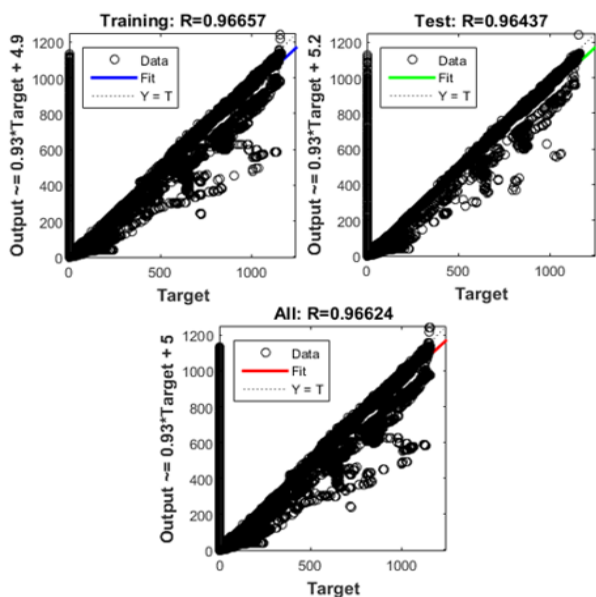


FIGURE 9. The performance of the Bayesian Regularization on NARX.

accuracy. Similarly, along with the sensitivity, there other evaluation metric: “Specificity” “Precision,” “Negative Predictive Value,” “False Positive Rate,” “False Discovery Rate,” “False Negative Rate,” “Accuracy” and “F1 Score.” Based on Table 1, all the metric yield a good acceptable results.

### V. DISCUSSION OF THE FINDINGS

The NARX Neural Network prediction is, in fact, a nonlinear generalization of the standard Autoregressive Exogenous. Nonlinear dynamic systems can be modelled by using it,

however in this case, it was used after running the linear model with some sample of the dataset for (Jan 1, 2012 to Jan 31, 2016,). The reason for doing this lies with the fact that the nature of the datasets of bitcoin associated with timestamp can exhibit patterns which might be linear or nonlinear or both attributes. The result of the simulation after several iterations and adjustments of the number of neurons in the hidden layer indicates that Scaled Conjugate Gradient algorithms outperformed both the Levenberg-Marquard and Bayesian Regularization (see Figure 4 and 4). The second and third rows of the regression plot are for the Scaled Conjugate Gradient where it can be seen that the training, testing and validation are better than the first. It can also be seen that they are better than for BR in Figure 5.

After the first evaluation, from which some of the samples of the dataset were put on linear modelling, the next is the “Time-series modelling” in which “NARX” was used. This means that the predictive approach here seeks to discover the appropriate neural network structure for the entire dataset of the research. Several simulations are also carried out in order to determine the different parameters of the NARX model. As it was obtained from the simulation, SCG could not be able to work with the complete dataset, and that is why it was not presented in the regression plot above. The dataset used is very huge, but still LM and BR run appropriately. The performance of BR and LM is good and BR is the best. The regression plot for BR and LM (see Figure 6 and 7), based on their prediction impact. It can be revealed from the regression plot for which the training and validation were presented, BR outperformed LM. The choice of activation function, neuron number, is important in determining the overall performance of the model. Thus, activation functions

**TABLE 3. Comparative finding among related studies.**

Author(s)	Methodology	Key Findings
Velankar et al. [19]	ANN and SVM for predicts the Bitcoin price	80% prediction accuracy
Chen and Sun [20]	Random Forest, XGBoost, SVM, LSTM to predict prices of bitcoin	67.2% prediction accuracy
Phaladisailoed and Numnonda [21]	Prediction of Bitcoin prices by regression.	97.8% prediction accuracy
Sin and Wang [22]	Use DNN and LSTM to predicts Bitcoin price	50.43% on DNN 50.14% on LSMT prediction accuracies
Pant et al. [27]	A recurrent neural network to predict bitcoin price	76.52% prediction accuracy
Colianni et al. [34]	Naive Bayes, and SVM to predict crypto coin trading strategies.	90% prediction accuracy
Sattarov et al. [41]	VADER to determine the degree of Bitcoin returns based on public opinion expressed on Twitter	62.48 % prediction accuracy
Ibrahim [42]	Logistic Regressions, Binary Classified Vector Prediction, SVM, and Naive Bayes to Tweets sentiment on bitcoin price	72% prediction accuracy
This research	NARX	96% prediction accuracy

in each layer of the neural network are crucial constituents. The activation function in the input and hidden layers is the sigmoid. The functionality is particularly useful in neural networks that are back propagated. The neural network has the advantage of being derivable, making it easier to learn the weights. Thus, for the current study, the network is able to approximate the timestamp of the weighted price for bitcoin. Neuron count varies in each layer of the NARX neural network. The most effective neural network structure is achieved using 8 input neurons, 10 hidden neurons, and just one output neuron. Hence, the MSE is 0.00234. In the next round of training, the same parameter is used, and then it follows by adjusting the partitioning used where the model was initialized to various weights and biases randomly to which each training that precedes has phases that randomly generate weights and biases for each vectors. The best MSE performance was at 0.00225.

The network is able to approximate the real bitcoin time frame and weight of the price in order to estimate the approximate real time of the Bitcoin network. Each layer of the NARX neural network is made up of different numbers of neurons. The most optimized neural network structure is obtained by using 10 neurons in the hidden layer, and just one neuron in the output layer. Under this, another cause of

concern is the initialization of the ANN weights and biases. In fact, the likelihood of one generation is completely altered. The preservation of weight and bias vectors at first training is one way to save these weights and estimate the variation over time, since the training is done regularly. Two alternative calibration approaches have since been used and tested and compared. During the first training stage, only one type of weight or distortion vector is produced randomly once. After exercising periods, weights and bias values are again used in which the same weight and bias values were used. At the beginning of each exercise phase, which depends on the ANN model, weights and biases are randomly assigned. Using ANN, the best results are achieved by randomly generating weights and bias vectors for every training phase. With this in mind, a 0.00225 MSE error achieved the best possible error performance. The result of this study was compared with [56] whose MSE was 0.00279 as the best results, indicating that this current study outperformed them. Similarly, compared with [57], this current study performance is the best.

## VI. CONCLUSION

This research looked at the bitcoin transaction process involving a timestamp. A neural network model developed with the NARX algorithm for the purpose of forecasting how bitcoin's transaction process changes over time. The major finding of this research study is that the training phase of the neural network is carried out at frequent intervals, incorporating two parameters in particular: "timestamp" and "weighted Price." Several simulations were carried out using various evaluation criteria, with MSE as the metric. When comparing results obtained using MSE to other tools, the best results obtained using MSE are when training a dataset that covers the period of Jan 1, 2012 to Jan 31, 2016, in the first linear model. The finding of this study reveals that A NARX model consisting of various neurons was able to use Bitcoin transaction variables (Open price at start time window, High price within time window, Low price within time window, Close price at end of time window) to predicts weighted prices when "Timestamp" mediated the interaction of the Bitcoin transactions. The developed predictor is useful in that it provides a direct mapping of timestamp on a weighted price of Bitcoin. Therefore, weighted price of Bitcoin is influenced by a timestamp. Finally, the study has impact on the prediction accuracy of NARX, in which a high prediction performance was achieved. Even with this recent success, future research should use NARX, and build a network of neurons, and include numerous Bitcoin transaction variables to build a much larger and more accurate network of neurons. Social media has been shown to be an essential variable in Bitcoin transactions specifically. As a result, future study can use them.

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