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A Survey on state-of-the-art Financial Time Series Prediction Models

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Abstract: Designing of a sophisticated financial time series prediction model helps in resolving many real world problems like stock market predictions, exchange value forecasting and oil price prediction etc. In general, the time series data values are non-linear and chaotic in nature. Time series data values cannot record the steady growth and their frequent rises and falls makes it more inconsistent. Forecasting the next value of the dataset criterion variable is more dependent on several aspects like predictor attributes, correlations, trends, seasonal variance etc. Many farmer researches concentrated on time series predictions and proposed several ways to predict the future values based on their historical data. This paper describes the prominent time series prediction models like random walks, ARIMA, ANN and SVR with detailed information. Description of these prediction models and the detailed comparison of them helps to choose the appropriate model for real-time applications.

Keywords: Time series prediction models, random walks, ARIMA, ANNs, SVR

I. Introduction

With the advent of digitalization, financial organizations started storing the business data periodically and is termed as financial time series data [1]. By analyzing this stored data, financial firms can assess the trends and plan the future activities accordingly. Time series prediction model is a paradigm, which is designed using several machine learning technologies and plays a vital role in financial decision makings [2]. Stock price estimation, foreign exchange value prediction, sales forecasting and oil price assessment are some popular financial applications [3], in which the time series prediction model is widely used.

In reality, the financial time series data contains a lot of missing values, noisy characteristics, non-stationary growth and unknown dependencies [4]. Along with this the external aspects like market sentiments, global affairs and geo political changes also effects severely on financial time series predictions. All these factors, data attribute dependencies and data inabilities made the financial time series prediction process too complex. Today the time series prediction model becomes an essential object for rapid assessment of changes in financial environment. Hence prediction process must be fine-tuned in terms of architecture and computation.

To lead the race of profitable trading, financial analysts are encouraging the research on development of the efficient time series forecasting models. Due to this reason, the area of time series prediction remained as an important research area since decades. Most of the former time series prediction models were designed using several machine learning techniques like Artificial Neural Networks (ANNs) [5, 6 and 8] , Random Walks[6], Auto Regressive Integrated Moving Average (ARIMA) [7] and Support Vector Regression (SVR) [9] etc. Although the former researches were proposed several efficient time series prediction models, they need to be rejuvenated with sophisticated technologies to catch up the present demands of the financial analysts. Improvement of speed, accuracy, reliability and resilience are the notable demands from the end users of the time series prediction systems.

As part of the analysis on time series prediction, we went through many former researches [5, 6, 7, 8 and 9] of this area and thoroughly evaluated the pros and cons associated with each prediction model they proposed. This knowledge certainly helps the present scholars to clearly understand about several time series prediction models and their limitations in detail. The identified gaps in this area of research and the proposed future works will guide them to set the target research goals. In this paper, our major contributions can be summarized as follows:

1) Explaining the nature of the time series dataset and exploring the relations among the dataset attributes
2) Describing the state-of-the-art financial time series prediction models in detailed manner
3) Discussion on various metrics used with the prediction models and comparison of them
4) Identifying the research gaps and proposing the future research directions.

The rest of the paper is organized as follows: Section-II explains the back ground of the financial time series dataset. Section-III describes the popular time series prediction models in detail. Section-IV discusses about the metrics and comparison, whereas Section-V concludes the paper with future research directions.

II. Background and Related Work

Time series dataset contains the data in the form of records, which are collected periodically from the source applications and stored for the future usage. The main job of the time series prediction model is analyzing this stored data and predicting the future values. Time series prediction models are widely used in various real life applications as shown in figure-1, to forecast the next level information. Although many applications use the time series prediction models in real life, few of them are financial time series, medical time series and social time series.

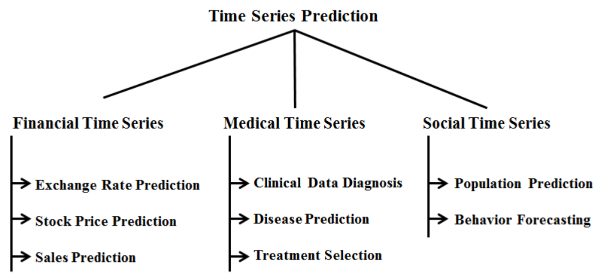

Figure-1. Utilization of Time series prediction in various domains

Financial Time series prediction [10 and 11] is the most prominent category under the time series prediction process. Since decades the prediction models are widely using in financial trends forecasting. Accurate assessment of the future trends in financial environment will decide the profits and loses of organizations. Even the very low variances in predictions will also leads to losses in billions of their currency. To overcome these losses, the financial organizations started embedding the time series prediction tools in their applications. Foreign exchange rate predictors, stock price predictors, oil value predictors and sales value predictors are some popular real life financial time series applications. Tay et al (in 2001)[10], designed the stock price prediction models using SVM and the Back Propagation Neural Networks (BPNN) to forecast the future values of Chicago Mercantile Market dataset. Alamili Mohamood et al (2011) [13], designed the foreign exchange rate prediction models using the Support Vector Regression (SVR) and the Artificial Neural Networks (ANNs). They conducted the experiments on EUR-USD dataset using ANN and SVR, to forecast the next 30 days exchange values based on the past data. Deboeck et al (1994) [8], explored the flow and nature of various machine learning models (i.e. Genetic algorithms, Neural networks and fuzzy logic) in dealing with chaotic time series prediction on the financial time series dataset.

Since a decade, the time series prediction models were started using with medical time series applications to analyze the complex clinical data and to predict the diseases and their treatment plans. By analyzing the patient's medical history, these prediction models will forecast the disease stage (type), disease progress, future risks and the mortality rate etc. Bui et al (2017) [12], explored the use of time series forecasting models in health care diagnosis. They proposed couple of medical data forecasting models in health care domain, which become a comprehensive reference for the next generation research scholars. Now days, time series prediction models are expanding their horizons to analyze and predict the social time series data. In many social research projects (i.e. Population prediction & Behavior forecasting), the times series analytic models are playing a vital role. Freeman et al (2014) [14] discussed about various analytic methods and their usage in time series analysis models for social research. In order to know about the nature of the financial time series datasets, attributes and their relations, we have analyzed various time series datasets from the reliable websites [15 and 16]. After the thorough analysis of different types of financial time series datasets, we observed many characteristics of them. Financial time series datasets contains plenty of records with two or more columns (attributes). Some of these columns are the criterions and the others are the predictors. Again these predictions are having different levels of priorities (i.e. high, low and less) among them.

Date	Price	Open	High	Low	Volume	Chg%
May 29, 2020	75.605	75.700	75.742	75.440	4.31K	-0.07%
May 28, 2020	75.660	75.804	75.905	75.634	5.41K	-0.34%
May 27, 2020	75.920	75.547	75.971	75.520	4.51K	0.61%
May 26, 2020	75.459	75.843	75.855	75.407	1.83K	-0.56%
May 25, 2020	75.887	75.950	76.110	75.854	0.31K	-0.08%
May 22, 2020	75.950	75.655	76.023	75.625	4.41K	0.44%
May 21, 2020	75.620	75.545	75.826	75.398	3.45K	0.09%
May 20, 2020	75.555	75.710	75.870	75.468	4.51K	-0.12%

Figure 2. USD-INR dataset with respective attributes

For example, figure -2 is presenting the USD-INR dataset records with 7 columns. In them the price column is criterion and the remaining are predictors. Among the six predictor columns, some of the columns (i.e. open, volume and change) are having high priority and others columns (i.e. high, low and date) are having low priority in price determination. Apart from these priorities among the predictors, the predictors and criterions are having some hidden relations too. In case of USD-INR dataset the volume and price columns are having some math relation; it means the fluctuations in volume column are highly affecting the value of price column. In addition to this, the criterion column values of the financial time series datasets are having the irregular variations, which are unpredictable but identifiable. Due to these absurd characteristics and nature of the time series data, designing the common and efficient time series prediction model become the complex operation.

III. Financial Time Series Prediction Models

This section thoroughly describes the prominent machine learning technologies used in designing the financial time series prediction models. Although many learning models were using with time series prediction, the prominent ones are Artificial Neural Networks (ANNs) [5 and 6], Random Walks [6], Auto Regressive Integrated Moving Average (ARIMA) [7], and Support Vector Regression (SVR) [9].

3.1 Random Walks

In general, the financial time series dataset values are reporting the irregular (non-linear) growth as shown in fig 2. Hence the linear or direct prediction models are incompatible with time series datasets to obtain the satisfactory next values of the series. From the USD-INR dataset records (shown in fig-2) we noticed that, the criterion variable (price) value $\gamma(k)$ is having the change($\pm\mathcal{E}$) from its previous value $\gamma(k-1)$. To find the next values of the time series, random walk is proposing to use the change ($\pm\mathcal{E}$) value along with the criterion values as follows:

$$\pm\mathcal{E} = \gamma(k) - \gamma(k-1)$$

$$\gamma(k) = \pm\mathcal{E} + \gamma(k-1)$$

The value of $\mathcal{E}$ is determined by calculating the mean of the differences among the series of criterion variables or the mean of the differences among the series of recent wave ($\pm$) criterion variables. Finally the random walk adds up the change($\pm\mathcal{E}$) with the recent past value $\gamma(k-1)$to find the next value $\gamma(k)$ of the series. In this way the random walk based prediction model will predict the next level values and it performs better than the linear or direct prediction models, by estimating the change among the criterion values. Killan et al (2003) [17] conducted the experiments on exchange rate predictions using the random walk based time series prediction models. He had proven that the random walks are the best among the available prediction models, while dealing with the long-horizon predictions. Apart from these advantages, the random walks suffering from few limitations also. Random walks are unable to tune the directions according to the trends. It means, if the change ($\mathcal{E}$) value is positive, than the next values will move in up direction or else the next values will move in down direction. Random walks cannot identify the seasonal and irregular variations, to auto tune the next value predictions.

3.2 Auto Regressive Integrated Moving Average (ARIMA)

Traditional prediction technologies like regressions and random walks can predict the future values based on the past data, but they cannot identify the additional structures (i.e. episodic and residuals), which are important and hidden in the data itself. These technologies cannot turn the prediction directions at run-time, hence the predictions will be biased in long run. Apart from this, maintaining the interpretability among several functions of the prediction models become too complex.

In 1970, Box-Jenkins at el [18], proposed the ARIMA model to assess the attributes range, to identify the correlations among attributes and to forecast the future values in a standard manner. In ARIMA model, the selected time series data will be represented using graphs to analyze the nature of the data. Timestamps associated data values are presented with graph, to find the periodical rises and falls of data. At this stage, the anomalies which have the strange values will be notified and they were marked to reduce the priority in predictions. After the primary analysis, the serial data values with time being variance will be stabilized, by using the power transformation techniques of ARIMA as follows.

$$\nabla \log(\mathrm{k_t}) = \log(\mathrm{k_t}) - \log(\mathrm{k_{t-1}}) = \log\left(\frac{\mathrm{k_t}}{\mathrm{k_{t-1}}}\right)$$

Here the $\nabla \log(\mathrm{k_t})$ denotes the growth rate or variance value ($\pm \mathrm{v_t}$), which is find between the serial values $\mathrm{k_{t-1}}$ and $\mathrm{k_t}$. If the $\pm \mathrm{v_t}$ is a stable and steady among the all values of the series, than $\nabla \log(\mathrm{k_t}) \approx \pm \mathrm{v_t}$ is considered as propositionally stable. Now the transformed values are processed using the auto regression and the differences will be identified to make the series stable and to alleviate the need of calculating the seasonal variance. After obtaining the prediction parameters like difference, regression order and the moving average values, the prediction models starts the forecasts, using the Auto Correlation Functions (ACF) or the Partial Autocorrelation functions (PACF).

Although the ARIMA is capable enough to manage the non-linear and chaotic time series data, it is still suffering from few limitations too. ARIMA records the high accuracy in predictions, when the input data is large. Due to the multi-dimensionality and the frequent human support, the automation process of ARIMA becomes too complex to implement. ARIMA is the univariate model, hence it is not suitable for the multivariate operations

3.3 Artificial Neural Networks (ANNs)

Inspired from the human brain neurons functionality, the Artificial Neural Networks (ANNs) model was designed for the real life computations. ANNs are widely using in many computational environments like Machine Learning, Artificial Intelligence, Data science and knowledge engineering etc. ANN is a layered processing model which contains input layer, hidden layers and output layer. Input layer specifies the nodes with several input values, hidden layers are responsible to process the input data at various levels and the final output layer presents the results obtained from hidden layer processing.

Former researchers [19 and 20] were applied the ANN based prediction models on time series datasets to forecast the future trends accurately. Among different types of ANN models, the Multi-Layer Perceptron (MLP) model is the compatible one to tackle with financial time series datasets. With many dedicated hidden layers for processing, the MLP model supports the supervised, unsupervised and hybrid training methods. Among these training methods, supervised approach with activation functions (to find the degree of non-linearity) and error back propagations is the adoptable model for time series data prediction.

For ANN, the time series data with random attribute weights is given as the input data for training. A set of hidden layers appointed to analyze and transform the input values to predict the output value. Increase of the hidden layers count will increase the processing complexity and improves the accuracy and reliability of the results. Similarly decrease of the hidden layer count will decrease the processing complexity and the accuracy and reliability. At the hidden layer, each attribute is mapped against all pre-defined constraint models for processing and knowledge extraction. Similarly each layer performs the input data transformation, to result the finally expected data value as the output. These predicted (output) result will be compared against the actual values, to confirm the accuracy and reliability. If the results are in acceptable range of relevance, than the model is considered as valid, or else through the back propagation model, the data will be processed again with updated weights. This process will be continued till the model generates the acceptable range output. While training, ANN learns the prediction behavior from all valid result generated models and utilizes this knowledge for future processing. Unlike the ARMA models, ANNs are supportive to deal with multivariate processing models. ANN is intelligent enough to find the dependencies and correlations existed among the dataset attributes.

As the ANNs are self-correctives through back propagation techniques, they can be automated with less complexity. Compared to the former traditional models, ANNs are designed with nominal constraints and assumptions. By incorporating various transforming techniques at hidden layers, ANNs achieved high prediction accuracy, while dealing with the chaotic financial time series data. Similar to past research models, ANNs are not comfortable with small amount of training data. The black box nature of output generation will make the interpretation complex, which is very important to correct the prediction errors. Due to the deep learning involved at hidden layers, the prediction model needs the high computational resources than the other machine learning technologies.

3.4 Support Vector Regression (SVR)

Regression is the process of predicting the criterion variables based on the predictor variables by using the suitable computational intelligence. Support Vector Machines (SVMs) [21] are the most popular data classification models of the machine learning domain. Support Vector Regression (SVR) [22] is maximum similar to the SVM technology, but it is designed for regression process instead of classification. SVR generates the hyper planes by applying various kernel models [23] to predict the accurate and reliable output values. SVR is insensitive from the changes in epsilon values, using the loss less functions it can assures the predicted result variance, which is always less than the max acceptable variance. By using the kernel functions, SVR transforms the complex non-linear input data into the high dimensional feature space. This transformation makes the prediction process feasible using the linear disjunction models, which are working on the high dimension feature space. According to Vapnik et al [22], the non-linear SVR function $f(x)$, is designed as follows:

$$f(x) = y = W^T . \Phi\ (\varkappa_i) + b$$

In this function, $\Phi(\varkappa_i)$ is the transformed high dimensional feature space, b is the scalar value and W^T is the weighted vector designed from the training data. In order to deal with non-linear and chaotic time series data, SVR utilizes the gradient-descent [24] model cost functions in forecasting. By controlling the under-fit and over-fit problems in threshold detection, SVR mitigated the biased results, which are generated due to the outliers. As they are comfortable with very less training data, SVR is the best suitable model for implementing the non-linear regression with small size datasets. SVR cannot assign the appropriate dynamic weights to the predictor variables.

IV. Metrics and Comparisons

Metrics: In order to evaluate the performance of the financial time series prediction models, some metrics have been used very frequently by the former researchers [13, 21 and 25]. Mean Square Error (MSE), Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Max

Positive Prediction Error (MPPE) and Max Negative Prediction Error (MNPE) are the popular performance evaluation metrics. In MSE, the predictor variable ($\varkappa$) values are inserted into the non-linear regression equation to obtain the criterion value ($\bar{y}$). After the criterions obtained for all predictor values, the variance is calculated for each criterion variable, by subtracting the criterions from their actual output values. To avoid the negative ness in calculation, the predicted variances are squared. Finally the squared values are added to calculate the mean value, which is called MSE and is implemented in math as follows:

$$MSE = \left(\frac{\sum_{i=1}^{n}(\boldsymbol{y_i} - \bar{y}_i)^2}{N}\right)$$

Here $\boldsymbol{y_i}$ is the actual value, $\bar{y}_i$ is the predicted value and N is the size of predicted set. By applying the square root to the MSE, the RMSE is calculated. MSE shows the distance from the data points to the fitted curve, whereas the RMSE represents the standard deviation of error to find the erroneous outliers. NRMSE stands for the normalized RMSE, which applies the normalization techniques like mean and standard deviations on RMSE, to evaluate the prediction results with more accuracy. NRMSE is proven as an unbiased metric, because it is aware about the over-fitting and under-fitting prediction values. MPPE and MNPE are used to find the maximum positive and negative error boundaries. MPPE displays the maximum positive prediction error, whereas the MNPE displays the maximum negative prediction error, which is used to find the error boundaries to determine the accuracy.

Comparison of the Prediction Models: As part of the analysis on financial time series data prediction models, we analyzed the prominent ones like Random Walks, ARIMA, ANN and SVR. In order to identify the advantages and limitations of them, they were thoroughly analyzed in various dimensions. From Random Walks to SVR, each time series prediction model related advantages and limitations are listed in table-1. This table information helps us to understand the prediction models capability and to plan the future research developments on time series predictions. These models comparison is specifying that, the Random Walks and ARIMA models were belongs to the former prediction models, whereas the ANN and SVR are the state-of-the-art prediction models.

Table-1. Comparison of the time series data prediction models

Prediction Model Name	Advantages	Limitations
Random Walk Prediction Model	-Easy to Implement -Cost Effective Prediction model -Underlying Knowledge is not required for predictions -Small memory foot prints	- Trend detection is not possible - Seasonal variances are not applicable - Doesn't considers the attribute dependencies and relations - Biased predictions in long-run - Automation is difficult - Cannot guarantees the result variance with in the acceptable or tolerable range
ARIMA prediction model	- Eliminates the anomalies (unusual values) from data -Identifies the trends among the data values using the variance - Transforms the non-stationary data to stationary to avoid the dependency on time - Residuals are converted to white noise	-Not a multivariate prediction model -Need large datasets for accurate predictions - Doesn't considers the Seasonal variances - Automation is difficult to implement - In efficient to deal with the seasonal data - In consistent assumptions in processing may leads to poor predictions in long term
ANN Prediction Model	-Flexible model to deal with non-linear time series - It is a data driven model, hence not required to feed the assumptions with primary prototypes - Automatically detects the non-linear relations among the predictor and criterion variables -supports various training models -Auto correction with error back propagation functions made them highly reliable in predictions	- More complex than traditional prediction algorithms - Comfortable with large data only - Black box nature made the interpretations complex - Need more computational power - risk of over-fitting with training data
	- Easy to implement and consumes the computational resources less than the other prediction modes	- SVR need high memory than other models, to store the all support vectors generated

SVR Prediction Model	-SVR is enough capable to process the high dimensional spaces - It even performs better, when the count of data dimensions are greater than the training records - Suitable prediction model for small datasets - Attribute correlations and dependencies are identified automatically - Implements generalization to avoid the training over fit issues - Supports various kernel functions like linear, polynomial and RBF etc. - Stable to resist the changes in result, due to the infrequent noisy input data - Assures the max $\mathcal{E}$ deviation	- Selection of kernel model, according to the target metrics is not an easy task -Complex to manually understand and interpret the whole process - Complex to customize the standard regression process with our own business logic - Dataset attributes co-efficiency not calculated -Assigning the uniform weights leads to increase error rate in predictions

Although, the ANN and SVR both can predict the time series values with high accuracy, many researches proven that, SVR is having some considerable advantages than ANN. Nantha Kumaran et al[25] conducted the experiments on EUR/LKR and JPY/LKR datasets using the ANN and SVR prediction models. They noticed that, the SVR recorded the high directional accuracy and low error range. They have verified different kernel models with SVR to choose the adoptable kernel function with high prediction result accuracy. Alamili M et al [13], implemented the ANN and SVR model to conduct the experiments on EUR/USD dataset. Comparison of the prediction results specified that, the SVR model recorded the high hit rate and less margin errors, when compared to the ANNs. Apart from this they mentioned that, the SVR kernel models are less sensitive to constant C and gamma γ value changes.

Table-2. Results comparison of time series prediction models

Prediction Model	**Author**	**Model Name**	**MSE**	**RMSE**
ARIMA	M Route et al [27]	ARMA-PSO	1.458	1.989
		ARMA-DE	1.397	1.949
		ARMA-BFO	1.598	2.119
		ARMA-CSO	1.825	2.637
ANN	Wei at el [26]	ANN	1.325	1.151
SVM	Cao et al [28]	SVM	0.54	1.063
		SVM(RBF)	0.542	1.064
		SVM(BP)	0.805	0.961

As part of the prediction model comparison, the former research papers [27, 28 and 29] conducted experimental results on time series datasets are presented with table 2. The standard error value metrics MSE and RMSE are used to present the reliable performance of each model. Route et al [27] proposed ARIMA based PSO, DE, BFO and CSO prediction models and their error values are displayed. Wei at el [26] conducted ANN model resulted error values and Cao at el [28] proposed SVM with RBF and BP models resulted error values also used in comparison of the time series data prediction models.

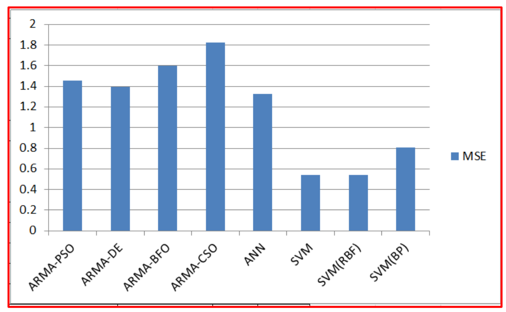

Figure-3 Prediction models Error value comparison using MSE

In case of MSE, SVM model recorded the less error value and the ARMA-CSO recoded the high MSE value. Similarly with RMSE, the SVM (BP) recorded the less error value and the ARMA-CSO recorded the high error value. From both cases, we noticed that the support vector models recorded the low error value than the other models. This comparison hints that, the SVM is having the soft edge in predicting the time series data values than the other participant models like ARIMA and ANN.

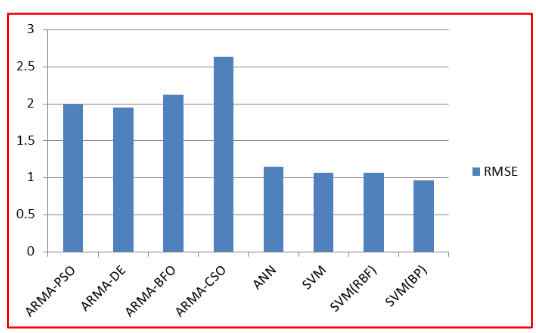

Figure-3 Prediction models Error value comparison using RMSE

V. Conclusion and future works

Non-linear time series prediction became the prominent research topic, due the wide utilization of prediction models in real life applications. The chaotic and irregular growth in values made the predictions more complex and erroneous. This paper conducted the survey on various time series prediction models like random walks, ARIMA, ANN and SVR. All these former prediction models relevant information is presented with their advantages and limitations. This multi-dimensional information helps the upcoming researchers to find the comprehensive knowledge about the prediction models at a glance. Form this analysis we noticed that, support vector regression is having the additional advantages in processing the non-linear data compared to the other prediction models. Another substance observed from this analysis is, the combination of these prediction models with their companion technologies are resulting high result accuracy, when compared to their standalone prediction models. In future the time series prediction researches should do concentrate on implementing the prediction models in combination of different other technologies. As the result classification process plays a vital role in prediction accuracy, the fuzzy membership functions can be used along with the prediction models like SVR. Improved weight functions, advanced kernel selection models, efficient control of residuals and training the multi-source data to prediction models (for more reliable predictions) are the considerable future works in time series prediction.

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