International Journal of Innovative Research in Computer Science & Technology (IJIRCST)
ISSN: 2347-5552, Volume-12, Special Issue-1, March-2024
https://doi.org/10.55524/CSISTW.2024.12.1.17
Computing for Sustainable Innovation: Shaping Tomorrow's World (CSISTW-2024) on 16th-17th February, 2024
Organized by B.N. College of Engineering and Technology, Lucknow, India

Comparative Analysis of Simple Moving Average and Cumulative Moving Average in Financial Time Series Forecasting

Prakhar[1], and Chhavi Bajpai[2]

[1]M.Tech Scholar, Department of CSE, BN College of Engineering and Technology, Lucknow, India
[2]Assistant Professor, Department of CSE, BN College of Engineering and Technology, Lucknow, India

Correspondence should be addressed to Prakhar; prakhar5252@gmail.com

ABSTRACT- Predicting the future is an essential aspect of contemporary life, involving the anticipation of upcoming events based on historical or current information, often accompanied by trend analysis. Various forecasting techniques are employed, depending on the data source and the forecast's objective.This article focuses on fundamental time series methods utilized in financial forecasting, specifically the simple moving average method, weighted moving average method, and exponential moving average method.The cumulative moving average, a variant of the simple moving average, is also briefly discussed in the short term. These methods are typically utilized to forecast time series that lack a discernible trend or seasonal component. The analysis of forecasting methods includes an exploration of basic concepts, potential applications, and a comparison of the irrespective limitations.

KEYWORDS- Simple Moving Average(SMA), Cumulative Moving Average (CMA), Timeseries, financial forecasting, economics, trend.

I. INTRODUCTION

The practice of forecasting, as surprising as it may seem, has been present in human societies since ancient times. Often viewed with fascination, it has traversed diverse perceptions, ranging from divine inspiration to sinister magic. In ancient Babylon, individuals had their futures divined by analyzing maggot patterns in rottensheeplivers, while desperate Greeks sought pronouncements from the Oracle of Delphi, fueled by ethylenevapors. However, not all societies embraced such practices. Emperor Constantine banned consultations with sooth sayers, mathematicians, and forecasters, aiming to silence them forever. Similarly, 18thcentury England criminalized the act of charging money for predictions, deeming it a fraudulent act punishable by three months of hard labor[1].This historical tapes try demonstrates the multifaceted and ever-evolving relationship between humanity and the allure of predicting the future.

Forecasting is the crucial practice of predicting future trends using historical and present data, often through analysis of trends. It plays an essential role in our daily lives, guiding our planning and decision-making. While uncertainty is inherent to forecasting, best practices involve incorporating all available information and clearly communicating the associated uncertainty. Accurate forecasts rely on up-to-date data, and sometimes even the data used for prediction itself is forecasted [2, 3]. Distinguishing between economic and financial forecasts is crucial, as forecasting plays a pivotal role in various fields such as predicting earthquakes, political outcomes, sales trends, and technological advancements, alongside weather, flood, and land use projections. While forecasting finds applications in diverse areas, its prominence is particularly evident in economics and finance.

Economic forecasting involves the endeavor to anticipate the future state of the economy through ablend of significant and widely monitored indicators. This process entails constructing statistical models that incorporate key variables or indicators to project future gross domestic product (GDP) growth rates. Primary indicators in economic forecasting encompass inflation, interest rates, industrial production, consumer confidence, worker productivity, retail sales, and unemployment rates[4].

In contrast, financial forecasting is the preparation undertaken by a company to equip itself for the future. It revolves around estimating future financial outcomes specific to a company or project. Financial forecasting bears similarities to financial modeling, yet distinctions exist. Financial modeling integrates the assumptions of the forecast and applies them to calculate financial variables utilizing a company's financial data. Financial modeling entails building an abstract representation, or model, of a real-world financial scenario [5]. This mathematical model aims to simplify the performance of a financial asset, business, project, or investment portfolio.

The financial modeling process involves creating a series of a company's financial information in numerical spreadsheet form, often using tools like Excel. These models serve as a basis for adjusting variables to assess the potential impact on financial outcomes. This iterative process aids companies in evaluating the consequences of management decisions or anticipating the impact of future events. Both financial forecasting and financial modeling find applications in budgeting, investment research, project financing, capital raising, and, significantly, insecurities valuation and trading.

Forecasting involvement imaging the future value of a variable or variables. This process aids decision-making and future planning by addressing various forecasting problems. The classification of forecasts is based on the timescale of the predictions relevant to business decisions. There are three main groups:

A. Short-Term (operating) Forecasts:

These cover a 3 to 6-month time scale and address issues like inventory control, production planning, and distribution.

B. Medium-Term (tactical)Forecasts:

With a horizon of 6 months to 2 years, these forecasts deal with matters such as predicting leasing of plant and equipment, employment changes, and similar considerations.

C. Long-Term(strategic)Forecasts:

Extending beyond 2 years, these forecasts factor in market opportunities, environmental influences, and internal resources. Specific issues may include research and development, acquisitions, mergers, and product changes.

This classification is essential because different forecasting methods are suitable for different situations. For instance, a short-term forecasting method suitable for predicting sales next month may not be appropriate for forecasting sales five years into the future. However, certain areas, like the stock market and weather forecasting, may involve a combination of short-term, medium-term, and long-term forecasting.

The fundamental stages in the forecasting process typically encompass five crucial steps [7]:

- **Identification of the Problem:** Recognizing the problem marks the initial and often the most challenging step in forecasting. To accomplish this, the forecaster must comprehend how the forecasts will be utilized, identify the stakeholders requiring the forecasts, and understand the role of the forecasting function within the organization. Engaging with individuals involved in data collection, database maintenance, and decision-making is essential during this phase.
- **Data Gathering:** Forecasting necessitates two primary types of information: statistical data and the accumulated expertise of individuals involved in data collection and forecast utilization. Depending on the situation, assembling adequate historical data for a reliable statistical model may prove challenging. In such cases, qualitative (judgmental) forecasting methods become a preferred option. Alternatively, recent data might be more suitable than older information for making predictions.
- **Preliminary Analysis:** The third step involves preliminary analysis through graphing and data decomposition for explanatory purposes. This includes identifying consistent patterns in graphs, determining significant trends, recognizing seasonality, detecting business cycles, and explaining any outliers. Examining the relationships among variables is also crucial at this stage.
- **Model Selection and Fitting:** The reliability of a forecasting model hinges on historical data availability and the strength of relationships between the forecast and explanatory variables. The purpose of the forecast and its intended use are vital considerations. It is recommended to compare at least two or three potential models. A model, an artificially constructed representation of reality based on explicit and implicit assumptions, consists of one or more parameters that need estimation using available historical data.
- **Application and Evaluation of the Forecasting Model:** After selecting a model and estimating its parameters, it can be applied to make forecasts. Typically, the performance of the forecasting model is assessed through forecasting errors. Various methods, such as mean absolute deviation (MAD) and mean squared errors (MSE), have been developed to evaluate the accuracy of forecasts.

II. FORECASTING METHODS

Numerous forecasting approaches exist, and the most suitable one depends largely on the availability of data. If there is a lack of relevant data or the existing data is deemed irrelevant for forecasting, qualitative forecasting methods, also known as judgmental methods, must be employed. Despite the name, these methods are not mere guesswork; instead, they involve well-structured approaches to generating accurate forecasts without relying on historical data[8].

Qualitative (judgmental) methods typically lack a formal mathematical model, often due to the absence of available data or the belief that the existing data does not adequately represent future trends [9]. These methods are commonly utilized for long-term forecasting and occasionally for intermediate decisions. There are instances where judgmental forecasting becomes the sole option, such as during the launch of a new product or the entry of a new competitor into the market. Qualitative forecasting techniques are subjective, relying on the opinions and judgments of consumers and experts. Judgmental forecasting methods integrate intuitive judgment, opinions, and subjective probability estimates. Formal forecasting tools in this category include Composite forecasts, the Delphi method, Forecast by analogy, Scenario building, Technology forecasting, and others [10].

Quantitative methods involve the use of forecasting models to predict future data based on historical information. These models are commonly applied to two types of data: time series data, collected at regular intervals over time, and cross-sectional data, gathered at a single point in time. The application of quantitative forecasting models requires two conditions to be met: the availability of numerical information about the past and a reasonable assumption that certain patterns from the past will persist into the future [11].

Time series forecasting models analyze data collected at regular intervals over time. While most time series data follows a consistent time frame (e.g., hourly, daily, weekly, monthly, quarterly, annually), there are rare instances of irregularly spaced observations. Examples of time series data encompass various fields such as daily stock prices for GM, monthly rainfall measurements, quarterly sales figures for Tesla, and annual profits for Microsoft. These models leverage historical data of avariable to predict its future outcomes. They focus on a single variable that evolves overtime, and the future values are presumed to be correlated with its past values.

For instance, a time series model for stock prices assumes that past historical prices provide valuable insights into future stock prices. The primary goal of forecasting is to estimate and project how the sequence of observations will unfold in the future.
Several popular time series forecasting methods exist, including Simple Moving Average, Weighted Moving Average, Single Exponential Smoothing, Double Exponential Smoothing (Holt's method), Triple Exponential Smoothing (Holt-Winter's method), Autoregressive Moving Average(ARMA), Auto regressive Integrated Moving Average(ARIMA,e.g.,Box–Jenkinsmethod), Seasonal ARIMA or SARIMA, Drift Model, Naïve Model, and others.
A shared characteristic among the aforementioned models is that the prediction of the observed variable relies on its past values. These models do not incorporate external variables into the system. However, their equations feature an "error" term on the right side, accounting for random variation and the impact of pertinent variables not explicitly included in the model. Consider the scenario of forecasting the stock price of Amazon. Since the daily stock prices of Amazon(Pam) constitute a time series, employing a time series
model for prediction becomes relevant. In this context, a generalized time series forecasting model might be represented as:
[1] $Pam_{t+1}=(Pam_t,Pam_{t-1},Pam_{t-2},Pam_{t-3},..., error)$;
The stock price of Amazon on the following day is influenced by its past daily prices, which is a characteristic of explanatory time series models. In some instances, these models may incorporate one or more external (predictor) variables during the forecasting process. This type of model is referred to as an explanatory model because it aids in elucidating the factors contributing to the fluctuations in the observed variable of interest. In the current scenario, we assume that the forthcoming stock price of Amazon is influenced by the sales volume, Dow Jones stock market index, and the reference interest rate. The simplified explanatory model now functions with all three predict or variables in the following manner:
[2] $Pam=(SalesVolume,DowJones,ReferenceRate,error)$;
Additionally, there exists a third explanatory model, a hybrid, that amalgamates the characteristics of the preceding two models. In this case, historical stock prices serve as an additional predictor variable in the prediction of future stock prices, along side factors such as sales volume, market index, and interest rate.
[3]Pam_{t+1}
$=f(Pam_t,SalesVolume,DowJones,ReferenceRate,error)$;
A predictive model proves beneficial as it integrates information from various variables rather than solely relyingonhistoricalvaluesofthevariableunderconsideration. Nevertheless,there are instances where a single-variable time series model might outperform a model incorporating explanations or a combination of both[13]:

- First, the forecaster may lack a comprehensive understanding of the system, and even if understanding exists, measuring the relationships between predictors and the forecasted variable could be exceedingly challenging.
- Second, there might be a need to predict or measure future values of different predictors to effectively forecast the variable of interest.
- Third, the primary goal might be to predict outcomes rather than understanding the underlying reasons for those outcomes.
- Finally, it is not uncommon for a time series model to yield more accurate forecasts compared to an explanatory or hybrid model.

III. BASIC TIME SERIES FORECASTING METHODS

This article emphasizes the fundamental time series techniques applied in financial forecasting, which are also valuable across various domains, including economics. The methods discussed include the simple moving average, weighted moving average, and exponential moving average. Another uncomplicated yet useful approach, known as the naive forecasting method, will be addressed separately. These methods are typically employed for forecasting time series lacking a trend and seasonal component. Before delving into the details of these methods, it is essential to establish a clear understanding of accuracy in forecasting.
The precision of the prediction technique is assessed through forecasting errors. A time series refers to a sequence of observations gathered at regular intervals for a specific quantity of interest, such as the number of phone calls per hour, daily stock prices, or the number of students per semester [14]. If y1, …,y n denotes a time series, ŷt signifies the forecasted value for the ith observation, where t is less than or equal to n. The forecast error et for the predicted variable ŷt is defined as:
[4]$et=yt-\hat{y}t$
The objective is to discover a forecast that minimizes errors. Various metrics, such as mean absolute deviation (MAD or mean absolute error, MAE), mean squared error (MSE), and root mean squared error (RMSE), are commonly employed to assess the accuracy of a forecast [15]. While there are additional metrics, these are the most straightforward and widely used. Shifts by substituting the oldest observation with the most recent one, thereby smoothing out short-term irregularities in the data series[16].
To reiterate, with a basic moving average model, we predict the upcoming observation ŷt by averaging a set, finite number (m) of preceding observations from the time series variable.
1
[8]$\hat{y}=[yt+yt-1+\cdots+yt-m+1]$
In simpler terms, if we want to predict Amazon's stock price for tomorrow using the simple moving average method, we look at the last 3 daily prices and calculate the average of today's, yesterday's, and the day before yesterday's prices. For a 10-day moving average, we average the closing prices of the first 10 days as the initial data point. The next data point drops the earliest price, adds the price on day 11, and calculates the average, and so forth. Similarly, a 50-daymoving average considers 50 consecutive days of data on an ongoing basis. The challenge is deciding the value of "m"(the number of days) to use. One rule of thumb is to choose the value of "m" that provides the best forecasting accuracy,

minimizing Mean Absolute Deviation (MAD) or Mean Squared Error (MSE). Alternatively, the choice of "m" may align with the purpose of the forecasting method, such as using a 50 or 200-day simple moving average to identify death cross or golden cross possibilities in price trend patterns [17].

The potential for utilization: In the realm of technical analysis, a simple moving average serves as a valuable tool

$1n$ for gauging whether the price of an asset is likely to persist

[5] $MAD=n\sum et$

$t=1$

The mean squared error (MSE) is expressed as the summation of squared errors divided by the total number of periods in the forecast.

n

[6] $MSE=1\sum e2$

$n \quad t$

$t=1$

The third one, RMSE (Root Mean Squared Error), is essentially the square root of MSE (Mean Squared Error).

[7] $RMSE=\sqrt{MSE}$

A. Simple Moving Average

The most straight forward forecasting approach is the simple(or single) moving average forecast. In this method, the forecast is determined by averaging the last m observations, using the average of the m most recent observation stopredict the next period's observation. This method is particularly effective for time series with a gradually changing mean. As each new period arrives, the average

in its current direction or undergo a reversal in a bull or bear trend. This effectiveness stems from the rapid responsiveness of short-term averages to fluctuations in the underlying security's price, in contrast to the slower reaction of long-term averages. Essentially, it functions as a crucial analytical instrument for identifying prevailing price trends and assessing the likelihood of a shift in an established trend. The primary application involves swiftly determining if a security is in an upward or downward trend. Additionally, a widely employed and insightful application involves comparing two simple moving averages, each covering distinct time frames. When a shorter-term simple moving average surpasses a longer-term average, an uptrend is anticipated. Conversely, if the long-term average exceeds the shorter-term average, a downtrend may be expected[18].

The final point aligns with the recognition of common trading patterns in stock markets. Two frequently observed trading patterns utilizing simple moving averages are the death cross and the golden cross[19]. The death cross materializes on a chart when a stock's short-term moving average, typically the 50-day, intersects beneath its long-term moving average, usually the 200-day. This occurrence signals a bearish price trend and the potential for a

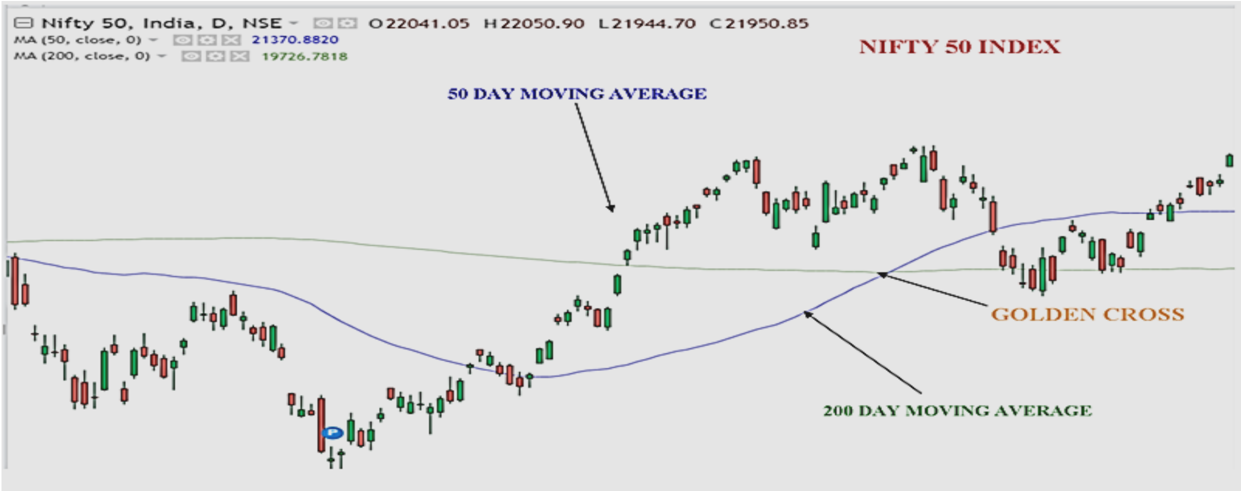
Significant market decline. Historically, the death cross has demonstrated its reliability as an indicator for some of the most severe bear markets throughout the last century, including in1974,2008, and 2021.

(Source:Investing.com 2023)

Figure 1: Illustration of a death cross on the NIFTY50 in 2020

Conversely, a chart displays a golden cross when a stock's shorter-term 50-day moving average surpasses its longer-term 200-daymoving average. This occurrence is considered a bullish signal, suggesting the likelihood of a significant upward movement. The golden cross unfolds in three stages. Initially, the first stage involves the conclusion of a downtrend as selling activity diminishes. The second stage witnesses the shorter moving average crossing upward through the larger moving average, signifying a breakout and confirming a reversal in the trend. The final stage is characterized by a sustained uptrend, leading to continued increases in prices [20].

It is important to consider that the majority of indicators are "lagging" and cannot accurately forecast the future. A golden cross, often observed, may sometimes generate a misleading signal, leading a trader who initiates a long position at that point to face immediate challenges. In contrast to death crosses, historical data suggests that golden crosses frequently do not materialize. Consequently, it is advisable to validate a golden cross with additional signals and indicators before entering into a trade [21].



(Source:investing.com 2023)

Figure 2: Illustration of a golden cross

Limitations exist with the simple moving average method. One challenge is the uncertainty surrounding whether greater emphasis should be placed on recent data within the time period or on more distant data. While some argue that prioritizing new data provides a more accurate reflection of the current trend in the security, others contend that favouring specific dates may introduce bias to the trend. Consequently, the simple moving average may tend to rely excessively on outdated data. Another drawback is its reliance on historical data in general, which contradicts the efficient market hypothesis. If markets are indeed efficient, the use of historical data should provide little insight into the future direction of asset prices [22].

B. Cumulative Simple Moving Average

Informally, this approach could be seen as a variant of the simple moving average technique. Typically, the simple moving average involves considering a finite number of observations (m) that define the average, where m is less than the total number of observations in the time series (m <N).

In contrast, the cumulative moving average incorporates all relevant observations from the time series observed at any given point, denoted by m=t. As data arrives in a chronological time stream, users may desire the average of all data accumulated up to the current time segment. For instance, calculating the average price of stock transactions from the beginning to the present moment. With each new transaction, the cumulative average at the time of the transaction can be computed for all transactions up to that point using the cumulative average method.

In conceptual terms, if we have a sequence of t observations ranging from the first to the last (y1.yt), the cumulative average at time section t can be expressed as an equally weighted average of the entire sequence of t observations. When all data points have been received (t=N), the cumulative average will be equal to the final average.

IV. CONCLUSION

In simpler terms, forecasting involves estimating the future value of a variable based on historical data. Technically, it's a method that uses past information to make predictive estimates, especially in determining the direction of future trends. Forecasting is essential in various scenarios like predicting earthquakes, weather forecasts, and most commonly, anticipating financial and economic variables. Modeling aids in forecasting by creating a simplified representation of a real-world situation.

There are different classifications, but a practical one considers the time span of decisions. Operational decisions require short-term forecasts, tactical decisions involve intermediate forecasts, and long-term (strategic) business decisions align with long-term forecasts. The forecasting process involves specific steps:

- Identifying the problem
- Gathering information
- Preliminary evaluation
- Choosing a suitable model
- Utilizing the forecasting model

Various forecasting methods are available, depending on the forecasting goal and the information at hand. Essentially, forecasting methods can be categorized into three groups: qualitative (judgmental) methods, quantitative methods, and time series methods. Time series models typically involve a single variable that changes over time, and its future values are linked to its historical values. Explanatory time series models may include external (predictor) variables in addition to the historical values.

This article focuses on basic time series methods utilized in financial forecasting, specifically the simple moving average method, weighted moving average method, exponential moving average method, and the cumulative moving average model. The simple moving average model predicts;

$$t(CMA) = \overline{y_1+\cdots+y_t t}$$

Yet, in the event that a new observation (yt+1) emerges, updating the cumulative average can be effortlessly accomplished using the formula:

$$y_{t+1} - \hat{y}_{t(CMA)}$$

the next observation based on the average of a fixed number of previous observations from the time series variable. This model facilitates the prompt identification of whether a security is in an uptrend or downtrend and is commonly used to detect trading patterns in stock markets, such as the death cross and golden cross.

$$\hat{y}_{t+1(CMA)} = \hat{y}_{t(CMA)} + \underline{\qquad\qquad} \, t+1$$

This implies that the cumulative average of a new data point at the current moment equals the sum of the previous cumulative average and the difference between the latest data point and the previous cumulative average, all divided by the total number of received points or observations up to that point, denoted as t+1.The consequence of this is that However, the simple moving average model has limitations. It is a lagging model that heavily relies on outdated data, and its reliability is contingent on historical data. A modified version of the simple moving average is the cumulative moving average method, where the average is determined by all relevant observations from the time series observed at any point in time(m=t), rather than relying solely on the last m observations.

CONFLICT OF INTERREST

The authors declare that they have no conflict of interest.

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