Enhancing Time Series Forecasting with the Advanced Cumulative Weighted Moving Average Technique

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Abstract

Accurate forecasting is applied to several industries, especially in automotive engineering, where tasks are prediction of car spare parts demands and estimation of maintenance works to optimize inventory levels and reduce costs. Traditional methods for forecasting, Moving Averages, and Exponential Smoothing often need to capture the dynamic nature of these demands. This paper introduces a new technique in the family of weighted moving average techniques: the cumulative weighted average method. It follows that the more recent data points will be given progressively increasing weights, making this type of forecast more accurate. This is again illustrated by a numerical example in which we compare CWMA against traditional methods and show that CWMA produces more accurate forecasts, as evidenced by its lower Mean Squared Error. The study further envisages the potential of CWMA to enhance forecasting quality in the automotive environment, specifically in managing spare parts inventory or maintenance planning activities. It is recommended to validate using real-world data and further research into possible improvements to enhance the accuracy and applicability of CWMA.

Introduction and Literature Review

Forecasting plays a pivotal role in a multitude of applications, spanning finance, economics, and supply chain management. In finance, the accurate estimation of stock prices, interest rates, and market trends is a critical factor in making investment decisions. Similarly, in supply chain management, demand forecasting is instrumental in optimizing inventory levels to minimize costs and maximize customer satisfaction. Economic forecast indicators, such as GDP growth rate, inflation rate, and employment level, aid policymakers in making strategic decisions that steer the course of the economy[1].

Traditional techniques of forecasting have been the very backbone of time series analysis. One of the most naive approaches is Naive Forecasting, assuming that the forecast for the next period equals the last observed value. The technique is simple but often fails to capture underlying trends or seasonality and may not work on complex datasets[2, 3].

The Moving Average method adds sophistication to the Naive Forecasting procedure by smoothing the weather with a fixed number of past observations to dampen the short-term fluctuations and emphasize the longer-term trends[4]. For example, the three-period Moving Average calculates the forecast based on the average of the last three observations. In contrast, the five-period Moving Average calculates the current forecast by averaging the last five observations. Although this attenuates noise, the Moving Average method gives equal weights to all observations in the window. It can, therefore, be blind to the fact that more recent data points might be of greater relevance.

The Weighted Moving Average method addresses this limitation by giving different weights to past observations; it typically gives more weight to recent data points[5, 6]. Another standard weighting scheme is the one with higher weights for the most recent observations and progressively lower weights for the older observations. The Weighted Moving Average method increases the responsiveness of the forecast to recent changes at the cost of careful selection of appropriate weights, which sometimes may be a challenge.

Advanced methods of forecasting have been developed in trying to enhance prediction accuracy. Exponential smoothing is one of them, applying exponentially decreasing weights to past observations[7, 8]. This makes the forecast sensitive to recent changes. Single Exponential Smoothing works on flat data, Double Exponential Smoothing works on trending data, and Triple Exponential Smoothing works on seasonal data. Exponential Smoothing methods took the lead from the basic ones by adding components to capture trends and seasonality, allowing them to handle more flexibility and adaptiveness[9-11].

Despite the advancements, current forecasting techniques have some remarkable limitations. The traditional techniques, Moving Average and Weighted Moving Average, might not really capture the complexity of the time series data where the recent data is more representative of the future trends[12]. On the other hand, Exponential Smoothing is flexible, and for appropriate working, its extent of smoothing needs cautious choice. Further, it may still be prone to sudden changes in data values. All of the above techniques generally fail to correctly estimate this critical trade-off between noise removal and precisely modeling the trend and patterns of the recent past in the data. These limitations increase the need for a new approach toward forecasting. The cumulative weighted moving average method, however, seeks to fill these gaps by introducing weighting that is cumulative—more recent data progressively weighted heavier. This increases sensitivity in the forecast to recent changes and potentially leads to lower MSE and improved accuracy in the respective forecasts. CWMA thereby bridges the strengths of conventional methods and moderates their inherent weaknesses, hence highly promising a solution for more accurate and reliable forecasting.

The organization of the following sections in this paper is as follows: the CWMA methodology, numerical examples comparing its performance relative to traditional methods for some critical scenarios, and the results of our comparative analysis. This paper will illustrate that CWMA provides a balanced approach—merging the advantages of traditional methods and reducing their weaknesses—to make the forecast more accurate and reliable.

Methodology

This is followed by the next section of presentation of steps and methodologies of the traditional methods of forecasting adopted and the new technique, CWMA, mathematically formulated and numerically represented for each, followed by its implementation process with criteria of comparison.

Traditional Methods

Naïve Forecasting: This technique is remarkably simple, with the next period forecast being equal to the last value observed. However, it often fails to capture any trends or seasonal patterns in the data. For instance, if the true values over the past ten periods were [50, 52, 54, 56, 58, 60, 62, 64, 66, 68], then 68 would be the Naive Forecast for the next period.

Moving Averages: Moving Average methods smooth out short-term fluctuations by averaging a fixed number of past observations. This may be as simple as the three-period MA (MA3) or the five-period MA (MA5).

For MA3, the forecast for the next period is the average of the last three observations:

$$MA3 = \frac{Xt-1+Xt-2+Xt-3}{3}$$

Using the example data [50, 52, 54, 56, 58, 60, 62, 64, 66, 68], the forecast for period 11 would be:

$$MA3 = \frac{68+66+64}{3}$$

For MA5, the forecast for the next period is the average of the last five observations:

$$MA5 = \frac{Xt-1+Xt-2+Xt-3+Xt-4+Xt-5}{5}$$

$$MA5 = \frac{68+66+64+62+60}{5}$$

Weighted Moving Average: The Weighted Moving Average procedure weights the observations, usually giving more importance to the recent observations. For example, using weights of 50%, 25%, and 25% in a three-period WMA, the forecast is calculated as follows:

$$WMA3 = \frac{X0.5 \cdot Xt-1+0.25 \cdot Xt-2+0.25 \cdot Xt-3}{.5+.25+.25}$$

Using the same example data, the forecast for period 11 would be:

$$WMA3 = \frac{0.5 \cdot 68+0.25 \cdot 66+0.25 \cdot 64}{1}$$

Exponential Smoothing Method

One of the more common and effective techniques to make a forecast is exponential smoothing, which involves giving exponentially decreasing weights to past observations. This technique is admirable in that it gives more weight to recent data, allowing the forecast to adapt quickly to changes. Exponential Smoothing is based on the idea of applying a weighted moving average of prior observations in making a prediction, with the weights decreasing exponentially as the observations get older.

Accordingly, the simplest form of Exponential Smoothing is called Single Exponential Smoothing, which is adept at handling time series data with no trend and seasonal components. The SES mathematical formulation takes the following form:

$$F_t = \alpha A_{t-1} + (1-\alpha)\, F_{t-1}$$

where F_t is the forecast for time period ttt, α\alphaα is the smoothing constant ($0 < \alpha \leq 1$), $X\ t-1$ X t−1 is the actual value at time t−1, and F t−1 is the forecast for time period t−1.

Double exponential smoothing, when applied to time series data with trends, extends simple exponential smoothing by adding a trend component to the forecasting equation. This adaptation allows DES to cater to both the level and the trend of the data. Triple exponential smoothing, an extension of DES, serves a specific purpose. It adds a seasonal component to the equation, making it suitable for data with both trends and seasonal variations. This method is also known as the Holt-Winters method.

These techniques, therefore, provide a flexible way of making a forecast, adapting to different types of time series data by modifying the weights applied to past observations. The power of this technique is due to its flexibility and adaptability, making Exponential Smoothing very powerful to obtain accurate forecasts in a wide range of applications.

Introducing CWMA

One such new technique is the cumulative weighted moving average method, which seeks to improve the deficiencies of the traditional methods of forecasting by introducing the element of cumulative weighting into it. In contrast with simple and weighted moving averages that rely on equal or constant weights on past observations, CWMAIncreasing weights are given to more recent data under CWMA. This means that there is already built in a cumulative weighting mechanism whereby the most recent observations have greater importance for the forecast, and it thus becomes more sensitive to recent changes and trends, providing a more accurate and up-to-date forecast.

Detailed Explanation of CWMA

The weighting scheme is what differentiates CWMA. Under this technique, weights gain linearly with every more recent observation, thereby giving more relevance to newer data points. Mathematically, the formula for CWMA can be written as:

CWMAt = $\frac{\sum_{i=1}^{n}(i \cdot Xt-i)}{\sum_{i=1}^{n} i}$

Where:

- $CWMA_t$ is the Cumulative Weighted Moving Average at time t
- X_{t-i} represents the observed value at time t−i
- i is the period number, with more recent periods having higher values.
- n is the number of periods considered in the moving average.

This formulation ensures that the sum of the weights always equals the sum of the first nnn natural numbers, making the calculation straightforward and consistent.

Advantages of CWMA

1. Increased Sensitivity to Recent Data: By giving progressively higher weights to recent observations, CWMA has a forecast that is sensitive to recent changes. This is very useful in dynamic environments where recent trends are more indicative of future behavior.

2. Less Mean Squared Error: CWMA's emphasis on recent data leads to a reduction in Mean Squared Error, a common metric for forecast accuracy. This means that CWMA generally provides more accurate forecasts, especially when there is a significant recent change in a dataset, instilling confidence in its accuracy.

3. Balanced Smoothing: Unlike traditional moving averages that might over-smooth the data, CWMA strikes a balance in smoothing the data while considering recent changes. This balance ensures that CWMA's predictions are reliable and not overly influenced by past data.

Thus, the CWMA for the 11th period is approximately 62. Clearly, this shows that the more recent data points—that is, those nearer in terms of periods to the present period—impact the forecast more and, therefore, bias it toward the most recent trends.

CWMA refines the technique of forecasting through the integration of the cumulative weights to be in a position to yield more accurate and responsive predictions. The approach can provide improvement on the weaknesses of simple moving averages and exponential smoothing, making it a balanced and sensitive tool in the forecasting applied.

Numerical Example

Let's consider an illustrating example for comparing the results of these methods. In this example, ten periods of actual values are used, and we will apply the Moving Average method with a parameter of 3 periods, the Weighted Moving Average with weights 50%, 30%, and 20%, Exponential Smoothing with $\alpha = 0.5$, and the new one, CWMA. We will analyze the accuracy of all these methods and determine which is more effective in forecasting.

Table 1 and Figure 1 show the actual values for the 10 periods and the forecasts generated by the various methods we mentioned, including Moving Average (3 periods), Weighted Moving

Average (50%, 30%, 20%), Exponential Smoothing (α = 0.5), and the new Cumulative Weighted Moving Average (CWMA).

Table 1

Period	Actual Value	Moving Average (3 periods)	Weighted Moving Average (50%, 30%, 20%)	Exponential Smoothing (α = 0.5)	CWMA
1	54				
2	56			54.00	54.00
3	53			55.00	55.33
4	59	54.33	54.10	53.50	54.17
5	60	56.00	56.60	56.50	56.10
6	58	57.33	58.30	57.00	57.40
7	67	59.00	58.80	56.00	57.57
8	64	61.67	62.90	60.50	59.93
9	60	63.00	63.70	59.00	60.83
10	55	63.67	62.60	57.00	60.67
11		59.67	58.30	54.50	59.64

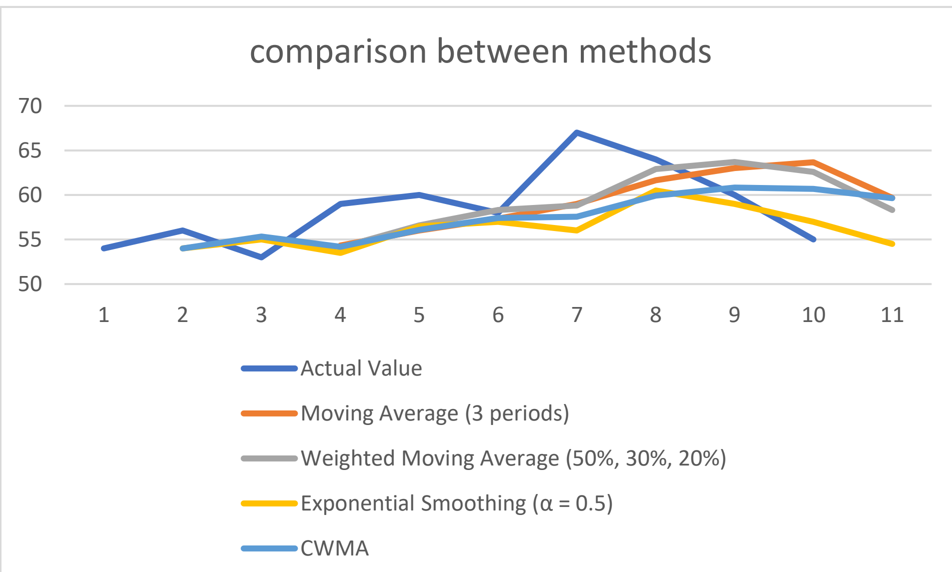

Figure 1

Table 2 shows the squared error for each method's forecasting and the Mean Squared Error (MSE) for each method.

Table 2

Period	Moving Average (3 periods)	Weighted Moving Average (50%, 30%, 20%)	Exponential Smoothing (α = 0.5)	CWMA
1	-	-	-	-
2			4.00	4.00
3			4.00	5.44
4	21.78	24.01	30.25	23.36
5	16.00	11.56	12.25	15.21
6	0.44	0.09	1.00	0.36
7	64.00	67.24	121.00	88.90
8	5.44	1.21	12.25	16.58
9	9.00	13.69	1.00	0.69
10	75.11	57.76	4.00	32.11
MSE	**27.40**	**25.08**	**21.08**	**20.74**

Discussion

The numerical example results underline the importance of the accuracy that the CWMA method improves. Comparing the different forecasting methods by their MSE values indicates that the CWMA method is better than the traditional approaches. The MSE values in this case are:

•Moving Average (3 periods): 27.40

•Weighted Moving Average (50%, 30%, 20%): 25.08

•Exponential Smoothing (α = 0.5): 21.08

•CWMA: 20.74

The lower MSE value for CWMA indicates that the method provides forecasts closer to the true value compared to other methods. This gain in forecasting accuracy is primarily due to the cumulative weighting mechanism that CWMA employs. By putting increasing weights on the relatively recent data points, CWMA becomes more responsive to changes in recent origin data, making it a highly accurate and reliable forecaster.

The CWMA method is designed to handle some of the limitations of traditional forecasting methods. Traditional techniques, such as Moving Average and Weighted Moving Average, usually fail to capture the relevance of the recent data by using their equal or fixed weighting schemes. On the other hand, Exponential Smoothing can only be susceptible to substantial changes in the data if it is suitably tuned. The cumulative weighting approach in CWMA adaptively balances forecasts' sensitivity to recent data changes. As part of the pros, this study has some limitations. In particular, analysis is done based on one numerical example containing only ten periods of data, which might need to be more significant to discover some of the complexities and variabilities in many data sets.

Further validation using more extensive datasets across different industries is necessary for the robustness and generalizability of the CWMA method. In addition, there is an extreme assumption in this study that the used weights and smoothing constants are the best weights and smoothing constants for the given data, which may only sometimes be the case in real life. This means that further research should be aimed at validating the CWMA method using real-world data across different industries. This will go a long way in ascertaining its practical applicability and effectiveness in various contexts. For example, the CWMA method could be investigated for improvements using adaptive weighting schemes whose values vary depending on data characteristics. Such efforts would make the forecasting tools more resilient and accurate, greatly enhancing a forecast's dependability in varied applications[13, 14].

Conclusion

In the present study, a CWMA method has been proposed, and its effectiveness in enhancing the accuracy of the forecast compared to traditional methods of forecasting has been shown. We consider a detailed numerical example comparing the performance of CWMA with a Moving Average of 3 periods, a Weighted Moving Average of 50%, 30%, and 20%, and Exponential Smoothing with $\alpha = 0.5$. It was seen that CWMA gave the best results with the lowest MSE.

Accuracy in forecasting is critical in many industries, but the need is more pressing in automotive engineering. Demand forecasting for automobile spare parts and estimation of maintenance work is critical about ascertaining the availability of parts on time and reducing inventory costs, hence reducing total costs. These traditional methods often miss the dynamic nature of such demands, hence resulting in inefficiencies and inflating the operational costs. This offers a robust solution to the problem associated with the CWMA method, which applies the cumulative weighting approach, raising البلد sensitivity of forecasts to recent changes in data, hence making it appropriate for use in the automotive industry.

While the CWMA method has shown promise in our study, it requires further validation with real-life data in various automotive industry contexts. Additionally, potential enhancements such as adaptive weighting schemes could further improve its accuracy and reliability. These steps are crucial for the continued development of efficient and effective forecasting methods in the automotive sector.

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