Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications (MECSJ)
Issues (52) 2022
ISSN: 2616-9185
www.mecsj.com

A Review of Time Series Forecasting Modeling: Definition, Components and Models

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Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications (MECSJ)
Issues (52) 2022
ISSN: 2616-9185
www.mecsj.com

Abstract:

Time-series forecasting is of great importance not only in industry, but also academia. In fact, huge efforts have been done by researchers over the past decades for the development of efficient models to improve the forecasting accuracy of time-series. Given the importance of time series analysis and its use in forecasting in various disciplines and fields, this research paper came to theoretically review the definition of time series and its components, and provide a state of the art for the latest methods and models dedicated to analyzing and modeling time series, with the ultimate goal and the importance of forecasting. There are many types of forecasting methods, and using forecasts from a method that is not applicable to the given time series may result in inaccurate forecasts. Accordingly, the forecaster must be careful in choosing a forecasting method that is suitable for the investigated situation. It was found that there are different types of prediction models that are classified according to three characteristics: stationarity (Fixed & Non-fixed), memory (Long memory time series & Short memory time series) and the length of the time step (Equidistant time series & Non-equidistant time series); each has different uses and features from the other. It was concluded that there are three commonly used models in forecasting and widely used by researchers, namely: ARIMA, ES and ANN. Comparing these three models concluded that ANNs are the best models and represent an alternative to traditional methods, which offer certain advantages such as less statistical training is required; compound nonlinear relationships between dependent and independent variables can be detected implicitly, all possible interactions between predictor variables can be identified, and multiple training algorithms are available.

Keywords: Time Series Forecasting; Auto-Regressive Integrated Moving Average (ARIMA), Exponential Smoothing (ES), Artificial Neural Network (ANN)

1. Introduction:

Time series data are among the most pervasive types of data that provide information and record action in many fields and specialties. In any field including fleeting estimations by means of censuses, sensors, exchange records, the catch of an arrangement of perceptions ordered by time stamps initially permits to give prediction on the past development of some quantifiable amount (Dama & Sinoquet, 2021). Other than this objective, the inescapability of time series has created an expanding interest for performing different undertakings on time series information (detection of frequent patterns, relationship disclosure, visualization, clustering, segmentation, classification, forecasting, detection of outlier and stimulation) (Susto et al., 2018; Esling & Agon, 2012).

Time series analysis is one of the important statistical methods used in predicting the values of random phenomena in the future. It requires a deep understanding and a conscious knowledge of the theoretical aspects of time series analysis methods. Time series represent time-dependent phenomena, and their observed values represent time, where time is the independent phenomenon (Adhikari & Agrawal, 2013). It is customary for the observed values of the time series to be the return of time in successive and equal time periods, although this does not preclude that the time periods are not equal. The study and analysis of time series is of great importance at the present time, because these studies indicate the changes and factors that cause them and enable planners to develop the required treatments (Shah, 2020).

The modeling of time series represents a dynamic field of research, and has attracted a large group of researches and researchers in the past decades. Time series modeling aims to gather time data from the past, analyze it and thoroughly study the past and foster a proper model which depicts the intrinsic design of the series. This model is then used to clarify the Time Series and anticipate future values of it, in other words “forecast” (Ben Baccar, 2019; Athiyarath et al., 2020)

This prediction (forecasting) represents one of the important applications in time series, and it is an important area of machine learning. Machine learning is a subset of artificial intelligence (AI) focused on creating systems that learn—or improve performance—based on the data they consume. Artificial intelligence is an umbrella term that refers to systems or devices that simulate human intelligence. Through machine learning and its models, the computer learning process is automatically improved based on previous computer experiences, but without programming, that is, without human assistance (Thrall et al., 2018).

The computer learning and modeling process begins with the entry of high-quality data, and then the choice of algorithms depends on the type of data and the type of works that have been planned for automation. A machine learning algorithm, also known as a model, is a mathematical expression that presents data in the context of a "problem", often a business, management, and question. The goal of this process is to gain insight through the data, which is exactly what the time series algorithm does (Fahle et al., 2020)

Time series forecasting is one of the most well-known and utilized learning errands, as it is also used in a large number of application areas including weather forecasting, decision-production in money and business, quality cycle control in industry, the executives of influence streams, and hazard appraisal in medication. Companies and firms use daily time series forecasting for a variety of purposes such as determining daily stock costs, gauging unfamiliar money trade rates, determining paces of joblessness; meteorologists use it to give a gauge of the breeze speeds, day by day greatest and least temperatures and estimated the precipitations (Shah, 2020; Ben Baccar, 2019).

All of these tasks and other numerous tasks show the significance of time series and the significance of having a decent estimation of the future as it might be fundamental for organizations to get ready for possible spike/plunge of their deals and get ready for it or to keep away from disaster while noticing meteorological information (Ben Baccar, 2019).

Forecasting time series is the process of predicting the future after doing a deep analysis and study of the past data, which requires a great and broad understanding of these models and their mechanism of action and their parts, given the vital significance of this task in many fields such as engineering, finance, business, meteorology and science as well as mentioned earlier. Setting up a satisfactory model to fit and afterward foresee the series is not an obvious task as each sign/series has own properties and conditions on exogenous boundaries cannot be effectively addressed in the model. Throughout the long term, a plenitude of exploration and models have been proposed by scholastics, analysts and financial specialists to further develop the forecasting precision (Adhikari & Agrawal, 2013; Raicharoen et al., 2003)

Given the aforementioned importance of the time series and their versatility, proper care should be taken to fit an appropriate model of the underlying time series. It is clear that successful prediction of the

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications (MECSJ)
Issues (52) 2022
ISSN: 2616-9185
www.mecsj.com

time series depends on the fitting of appropriate model. Over many years, researchers have put a lot of effort into developing effective models to improve prediction accuracy. As a result, several important time series prediction models have been developed in the literature (Zhang, 2007; Puthran et al., 2014).

Thus, different time series models have been put to work/improved, yet this plenitude of models does not really imply that these models are universally applicable material. The most common and utilized methodologies are as yet statistical models like autoregressive integrated moving average (ARIMA), exponential smoothing (ES) and artificial intelligence (AI) machine learning models (suitably applied to Time Series) like Support Vector Regression (SVR). Yet, in the beyond couple of years, generalized regression neural network (GRNN) models and recurrent neural network (RNN) have become increasingly more cutthroat to the conventional methodologies and give substantially more expandability on the previously mentioned models. They can be utilized with a wide assortment of data (exogenous) that can improve the knowledge given by time series (Ben Baccar, 2019).

Given the importance of time series analysis and its use in forecasting in various disciplines and fields, this research paper came to theoretically review the definition of time series and its components, and provide a state of the art for the latest methods and models dedicated to analyzing and modeling time series, with the ultimate goal and the importance of forecasting. This review aims to provide a structured and comprehensive view of the entire process flow, and includes time-series analysis, static testing, modeling, and forecasting.

2. Time Series Forecasting Modeling Definition:

When define time series it is necessary to trace the source of the word “prediction” or “forecasting”. Prediction originates from a Latin statement "praedicere", which was initially denoted by implications "to mention in advance" or "to say beforehand". Today, "forecast" is typically alluded to some sort of message or assessment on an occasion that is relied upon to occur in future. Inside the more conventional science setting, the most common way of making expectations about future by utilizing logical strategies is normally signified by term "forecasting". Processes that are normally needed to be estimated, are the most frequently put away in an alleged time series design (Box et al., 2015).

The expression "time series" itself, signifies an information storing arrangement, which comprises of the two obligatory parts - time units and the relating esteem (value) assigned for the given time unit. Time series’ values need to signify similar significance and correspond among the close by values. Limitation is, that simultaneously there can be at most one value for each time unit. For instance, sequences, which simply count a few values, they do not satisfy the time series prerequisites (Ostashchuk, 2017).

As mentioned earlier, the time series is a group of observations that are generated in succession over time. Any time series is characterized by the fact that its data are arranged in relation to time, and that successive observations are usually not independent, that is, also characterized as: the values or amounts of this phenomenon in a successive series of dates that depend on each other. It can be defined as months, days, or years, and usually the intervals between consecutive dates are equal (Ben Baccar, 2019).

Many definitions of time series forecasting modeling have been developed by researchers and academics, where it was defined also as: A set of measurements, observations, or data arranged according to multiple time periods. It is preferable to read these series using an appropriate number and not a few of those periods, as changes and influences can appear clearly for a time series with a greater number of periods, i.e. the higher the number of periods, the more accurate the time series forecasting model (Adhikari & Agrawal, 2013).

The purpose of the time series analysis is to know the changes that occur in the phenomenon during a certain period, where the values of the phenomenon can be compared to each other because they are measured in the same units and in the same way in different dates. A

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ISSN: 2616-9185
www.mecsj.com

time series graph is drawn, showing the progress of the phenomenon and its change over time. The graph of the series is a point that moves over time completely as a material part that moves under the influence of physical forces, and instead of physical forces, the movement in the time series is attributed to a group of economic, psychological, political and other forces. The time series graph is called the historical curve of the phenomenon (Shah, 2020; Ostashchuk, 2017) .

A time series is a consecutive arrangement of data points, estimated normally over progressive occasions. It is numerically characterized as a group of vectors $x(t), t = 0,1,2,...$ where t referred to the time passed. The variable $x(t)$ is treated as a random variable. The measurements taken during an occasion in a time series are organized in an appropriate sequential (Adhikari & Agrawal, 2013).

A time series that records a single variable's data is named as univariate. However, assuming records of more than one variable are thought of, it is named as multivariate. A time series can also be either discrete or continuous. In a continuous time series perceptions are estimated at each case of time, though a discrete time series contains perceptions estimated at discrete marks of time. For instance temperature readings, stream of a waterway, convergence of a substance cycle and so forth can be recorded as a continuous time series (Hipel & McLeod, 1994; Raicharoen et al., 2003). However, populace of a specific city, organizations' production, and exchange rates between two distinct monetary currencies might address discrete time series. Typically in a discrete time series the sequential perceptions are recorded at similarly dispersed time intervals like yearly, monthly, daily or hour time detachments. As referenced in Hipel and McLeod (1994), the variable being recorded in a discrete time series is thought to be estimated as a continuous variable utilizing the real number scale. Moreover, a continuous time series can be effectively changed to a discrete one by merging data throughout a predetermined time interval (Adhikari & Agrawal, 2013).

Time series forecasting models are based on a set of assumptions including that the future cannot be fully ascertained, and this uncertainty remains, regardless of the method used in it, until time passes and the real reality can then be seen. The models also assume that there are unclear points in the prediction, for example, the developments of technology cannot be predicted since no information are available to refer to now. Forecasting is used to set policies, whether social or economic, and that these same policies, if implemented, will affect the future and make changes that the prediction itself did not talk about, which makes the difference between what was stated in the prediction and what will be achieved on the ground (Adhikari & Agrawal, 2013; Ben Baccar, 2019).

Forecasting is the main reason for implementing time series analysis, the fundamental idea is to try and use the past observations to predict the future. The model that describes best the data will later be used to predict the future based on past records. A forecasting model is a functional representation that describes a time series, on this basis future will be forecasted. These models have the following objectives (Box et al., 2015; Ben Baccar, 2019; Ostashchuk, 2017) :

- Obtaining an accurate description of the special features of the process from which the time series is generated.
- Create a model to explain and explain the behavior of the string in terms of other variables, linking the observed values to some rules of string behavior.
- Using the results we obtain to predict the behavior of the chain in the future, based on the information of the past. We assume that there is sufficient driving force in the system to confirm that the behavior of the chain in the past is the same as its behavior in the future, and we also have greater insight into the forces affecting the time series process and exploit that to obtain more accurate predictions.
- Controlling the process from which the time series is generated by examining what can happen when some parameters of the model are changed, or by coming up with policies that are used

only to intervene when the series process deviates from the specified goal by more than a certain amount

- Knowing the past and identifying current models of change for the time series
- Giving an idea of the future models, and these models are used by the administration in planning, controlling and forecasting.

Based on the foregoing, it was thought to follow an integrated interconnected methodology, because it represents the link between what is achieved from the accumulation of theoretical and applied knowledge, and the possibility of embodying that accumulation, in reality, present and future. Determining the paths of the methodology depends on what is available from that accumulation, which should be subject to selection and testing, in order to verify the possibility of using it within current and future visions (Ben Baccar, 2019).

3. Components of Time Series Modeling:

Generally, the majority of analysis methods accept, that time series data comprises of the methodical part (commonly including a few parts) and random noise (blunder), which confounds discovery of the normal components. In this way, most of techniques, incorporates distinctive noise filtration methods, to recognize the standard components, or it must be performed during information preprocessing (Ben Baccar, 2019).

A time series overall is impacted by four fundamental components, which can be isolated from the noticed data. These parts are: Trend, Cyclical, Seasonal and Irregular parts. A short portrayal of these four parts is given here. The overall tendency of time series to build, decline or deteriorate throughout an extensive stretch of time is named as Secular Trend or basically Trend. In this way, one might say that pattern is a drawn out development in a period series. For instance, series connecting with populace development, number of houses in a city and so on show up pattern (trend), though descending pattern (trend) can be seen in series connecting with death rates, plagues, and so forth (Adhikari & Agrawal, 2013; Ben Baccar, 2019).

The fluctuation in time series for a year during the season is called seasonal variations. The significant elements causing seasonal varieties are: environment and climate conditions, customs, conventional propensities, and so forth. For instance sales of woolen materials expansion in winter or increasing in the sales of ice cream in winter. Seasonal variety is a significant component for finance managers, retailer and makers for making legitimate future arrangements (Ostashchuk, 2017).

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications (MECSJ)
Issues (52) 2022
ISSN: 2616-9185
www.mecsj.com

The cyclical variety in a time series portrays the medium-term changes in the series, brought about by conditions, which repeat in cycles. The length of a cycle reaches out throughout longer timeframe, normally at least two years. The greater part of the financial and economic time series show some sort of repeating variety. For instance a business cycle comprises of four stages, which are: Prosperity, Decline, Depression and Recovery (Adhikari & Agrawal, 2013).

This buisnees cycle can be displayed schematically as shown in Figure 1 below:

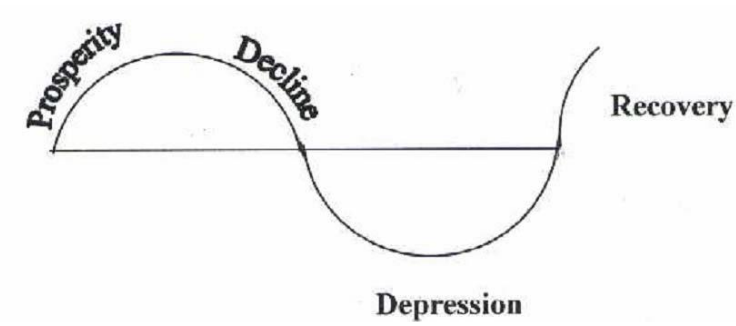

Figure 1: A four phase business cycle (Adhikari & Agrawal, 2013).

Random or irregular varieties in a time series are brought about by capricious impacts, which are not standard and furthermore do not repeat in a specific trend. These varieties are brought about by rates like conflict, strike, tremor, flood, transformation, and so on. There is no characterized factual procedure for estimating irregular changes in a time series (Adhikari & Agrawal, 2013).

The large portion of the standard components of time series has a place with two principle classes. They have a place with either a trend or seasonal part. As mentioned before, the trend is an overall precise straight or non-direct part, which might change after some time. Seasonal part is intermittently repeating part. Both these sorts of standard components are normally introduced in the time series at the same time. For instance, sales might increment from one year to another, however there is a seasonal part, which mirrors the huge development of sales in December and a drop in August for example (Box et al., 2015; Ostashchuk, 2017).

Accordingly, it can be said that overall model of time series generally contains different components: trend part T(t), irregular (random noise) part R(t), seasonal part S(t), and cyclical part C(t). The contrast among seasonal and cyclical parts is, that seasonal parts addresses a customary occasional periodicity, however cyclically part has a more drawn out enduring impact and may shift from one cycle to another. Frequently, cyclical part is incorporated into one trend part T(t) (Ben Baccar, 2019; Ostashchuk, 2017). Figure 2 exhibit an illustration of time series components decomposition.

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ISSN: 2616-9185
www.mecsj.com

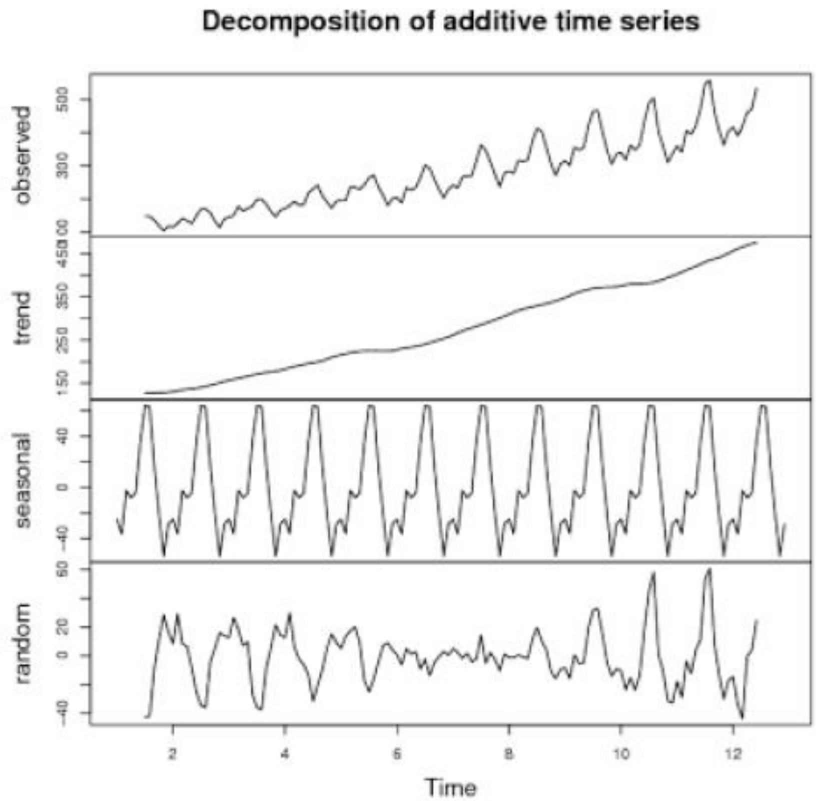

Figure 2: Time Series components (Ostashchuk, 2017)

It is also important, after identifying these components, to describe how they interact with each other mathematically, in order to form a time series. Each type of time series has a specific method or specific type of concrete functional relationship. However, there are two main models for how they interact with each other (Ben Baccar, 2019; Ostashchuk, 2017):

- Additive model

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ISSN: 2616-9185
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$$Z(t) = T(t) + C(t) + S(t) + R(t)$$

- Multiplicative model

$$Z(t) = T(t) \times C(t) \times S(t) \times R(t)$$

The growth rate is the main contrast between the previous multiplication and addition models. The additive model assumes that the four components (seasonal, trend, cyclical and irregular) are independent of each other, however, the multiplicative model assume that the four components of a time series are not essentially independent and can influence each other (Falk et al., 2012).

4. Types of Time Series Modeling:

Time series analysis is defined as a way of depicting the intrinsic nature of data over time, and utilizing it to anticipate the future (Al-Ghamdi, 1995).

There are numerous different time series groupings dependent on explicit measures. The main classifier standard of series types are: stationarity, memory and the length of the time step (Ostashchuk, 2017).

According to the distance between recorded vales, time series data modeling are grouped into (Ostashchuk, 2017):

- Equidistant time series
- Non-equidistant time series

Equidistant time series are shaped, when its values are recorded intermittently with a consistent period length. A ton of physical or natural cycles are depicted by this sort of time series. Non-equidistant time series are those time series, which do not keep the steady distance between perceptions. Econometric pointers, similar to stock costs are excessive performed inside normal time spans, they are controlled by a substantial organic market rates on the particular market. Hence, this sort of series appropriately exhibits a non-equidistant time series model (Ostashchuk, 2017). As indicated by the pace of reliance between recently noticed values and its predecessors, time series are separated into (Ostashchuk, 2017):

- Long memory time series
- Short memory time series

Time series with long memory are those, for which the autocorrelation work diminishes gradually (Box et al., 2015).This sort of time series generally portrays processes, which do not have quick turnovers. Electric energy utilization, traffic congestion, distinctive physical or meteorological pointers, similar to air temperature estimations, this large number of cycles are normally portrayed by long memory time

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Issues (52) 2022
ISSN: 2616-9185

series. Short memory time series are those, for which autocorrelation work is diminishing all the more quickly. Typical models contain processes from the econometric area (Box et al., 2015; Ostashchuk, 2017).

One more classification of time series depends on their stationarity (Box et al., 2015):

- Fixed time series
- Non-fixed time series

Fixed time series are time series, for which factual properties like mean or variance values, are consistent over the long run. These time series stay in relative balance comparable to its comparing mean values. Other time series have a place with non-fixed time series. In industry, exchanging or economy, time series all the more often has a place with the non-fixed class. To manage the estimating task, non-fixed time series are generally changed to the fixed ones, by the fitting preprocessing strategies (Box et al., 2015; Ostashchuk, 2017).

The cause-and-effect time series approach and the self-projecting time series approach are the two fundamental ways to deal with anticipating time series data. The latter uses just the time series data for predicting while the former depends on the intrinsic series expected to result in the pattern of the original series. The self-projection time-series approach also has the advantage of being cheaper to implement, dependent on less data and works better for long- and short-term forecasting (Sanusi et al., 2016).

Time forecast exponential smoothing (ES), autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) models are among the most prominent models used by scientists and researchers for forecasting, and the following is a brief summary of each (Lemke, 2010; Ben Baccar, 2019; Shah, 2020):

4.1 Exponential Smoothing

Exponential smoothing strategies apply weights that rot dramatically with time and hence depend with the understanding that later perceptions are probably going to be more significant for a figure than those lying further previously. Smoothing strategies started in the 1950's and 1960's, with the techniques for Brown, Holt Winter actually being of extensive significance today as summed up and referred to in Makridakis et al. (2008). The apparently just initially new smoothing technique since the classic methodologies was presented by Taylor (2003), who recommended utilizing a damped multiplicative pattern.

A scientific classification of exponential smoothing techniques has first been introduced by Pegels (1969), recognizing nine models with various seasonal impacts and patterns, which can be added

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Issues (52) 2022
ISSN: 2616-9185
www.mecsj.com

substance, multiplicative or non-existent. Gardner (1985) expanded this characterization by including damped patterns, expanding the quantity of models to twelve (Lemke, 2010).

Abraham and Ledolter (1986) showed that some exponential smoothing strategies emerge as extraordinary instances of ARIMA models. Aside from this, these strategies have been deficient with regards to a sound statistical establishment for quite a while, which forestalled a uniform way to deal with computation of forecast intervals, probability and model determination standards. Consequently, numerous publications were worried about exploring the stochastical system of the exponential smoothing strategies. The most intensive work in this setting has been published by Hyndman et al. (2002), who fitted every one of the twelve models of Gardner (1985) into a state space structure, giving state space conditions for every one of them utilizing both an added substance and a multiplicative mistake approach. They besides fit a model determination technique to the system to take into consideration automatic forecasting (Lemke, 2010.

One of the variety models has drawn scientists' consideration is the Theta-model proposed by Assimakopoulos and Nikolopoulos (2000). It breaks down seasonally changed series into short and long haul parts by applying a coefficient θ to the second order diffferences of the time series, in this way adjusting its curve. Hyndman and Billah (2003) show that this strategy is comparable to single exponential smoothing with drift.

Exponential smoothing techniques have a standing of performing astoundingly well for their straightforwardness as summed up in De Gooijer and Hyndman (2006). In a broad contest directed by Makridakis and Hibon (2000), the researchers suggest Taylor's exponential smoothing strategy with hosed pattern as a technique that is exceptionally simple to execute and gives powerful execution. Chatfield et al. (2001) contend that the hearty idea of these models is because of the way that they are the most ideal decision for a huge class of issues. Hyndman (2001) gets on that and adds that complex models are dependent upon performance instabilities caused by a more complex model selection and parameter estimation process, which exponential smoothing models do not experience those effects of to this degree (Ben Baccar, 2019).

4.2 ARIMA Modeling

ARIMA is one of the most common time series methods that belongs to self-projecting time-series prediction method which is the univariate version of the Box-Jenkins method, where most studies including (Stellwagen & Tashman, 2013; Hassouna & Tubaileh, 2020; Hassouna et al., 2020) have adopted it into analyzing and modeling.

Time series models that are built using Box-Jenkins method are often called ARIMA models (a term that refers to an auto-regression integrated moving average) (Al-Ghamdi, 1995). In general, prediction based on ARIMA models consists of three distinct steps: identification, estimation, and diagnostic examination. These three fundamental steps are repeated over and over until an appropriate data model is obtained (Box et al., 2015). In other words, the Box and Jenkins method is an iterative procedure that requires a good understanding of time series technique, a certain amount of judgment as well as several rounds of trials (Wu, 2013).

The ARIMA model has three components, each of which helps in designing a specific type of pattern. The 'AR' or auto-regression component attempts to calculate patents between any one time period and previous periods (Hassouna et al., 2020).

The “MA” or moving average component (better understood as the error feedback term) measures the conditioning of new forecast errors. The “I” or integrative component indicates another “integrative” trend or process in the data (Stellwagen & Tashman, 2013). Three different parameters are implied in the ARIMA model, which are p: the number of ordinary autoregressive, d: the number of non-seasonal differences needed for stationarity and q: the number of lagged forecast errors. As such, the p is the quantity of critical lags of the autocorrelation function

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Issues (52) 2022
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www.mecsj.com

(ACF), q is the quantity of critical lags of the partial autocorrelation function (PACF) and d is the diverse order expected to eliminate the conventional non-stationarity in the mean of error terms (Hyndman & Athanasopoulos, 2018).

All the more explicitly, the ARIMA technique incorporates (Paul et al., 2013):

1) Autoregressive Process, each value in this process is a linear function of the previous value in the series (for instance, in the second-order autoregressive series two previous values are utilized as a function of the current value);

(2) Differencing measure, which is a general basic process that includes computing successive changes in data series' values;

(3) Moving average process, which is utilized to streamline short-term fluctuation, in this way featuring longer-term cycles or patterns.

Selection of an appropriate model can be done judgmentally. A strategy mainly based on examining (partial) autocorrelation values can be found in Makridakis et al. (2008). Alternatives have been suggested, for example using information criteria like Akaike's information criterion (AIC)[2] introduced in Akaike (1973) and Bayes information criterion (BIC)[3] introduced in Raftery (1986).

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4.3 Artificial Neural Network Modeling

By reviewing the domain of computational intelligence models, it is neural networks that have most often and effectively been utilized for time series estimating purposes. Neural networks address a nonlinear information driven strategy and can, as all inclusive approximators, approximate any continuous function to any necessary accuracy without the need of wide knowledge on the fundamental data generation process or displaying connections unequivocally. They truly do anyway accompany the notable risks of overfitting, over-parametrisation and the issue of picking an ideal typology (Adhikari & Agrawal, 2013).

ANNs work in a similar way of human brain working, where it attempt to perceive patterns and normalities in the input data, gain from experience and afterward give summed up outcomes dependent on their known past knowledge. Though the improvement of ANNs was for the most part organically roused, however subsequently they have been applied in various regions, particularly for classification and forecasting purposes (Kihoro et al., 2004; Adhikari & Agrawal, 2013). The following text represent some striking features of ANNs, which make them very top choice for time series forecasting and modelling.

In the first place, ANNs are information driven and self-versatile in nature. There is no compelling reason to determine a specific model structure or to make any deduced supposition about statistical distribution of the data; the ideal model is adaptively developed dependent on the characteristics of the data (Tealab, 2018).

This modeling technique is very helpful for some useful circumstances, where no hypothetical direction is accessible for a fitting information generation process. Second, ANNs are intrinsically non-linear, which makes them more functional and precise in developing models for complex data, rather than different conventional linear methodologies, for example, ARIMA strategies. There are many examples, which propose that ANNs have much better analyzing and predicting performance over different linear models (Kuo & Huang, 2018; Tkáč & Verner, 2016).

At long last, as recommended by Feng and Zhang (2014), ANNs are widespread practical approximators. They have shown that a network can approximate any continuous function to any ideal exactness. ANNs utilize parallel processing of the data to approximate an enormous class of functions with a high level of exactness. Further, they can manage circumstance, where input data are incorrect, inadequate or fuzzy (Adhikari & Agrawal, 2013).

The most generally involved ANNs in anticipating and forecasting issues are multi-linear perceptions (MLPs), which a single hidden layer feed forward network (FNN).The model is portrayed by a network of three layers, which are input, hidden and output layers that are connected through neurons (acyclic links) (Adhikari & Agrawal, 2013; Tealab, 2018).

The network can be made up of more than hidden layer, however Goodfellow et al. (2017) found and proved that MLP with one hidden layer can approximate any function that is required if given enough hidden units (nodes) in the layer. The nodes in different layers are otherwise called processing components. The three-layer feed forward design of ANN models can be diagrammatically portrayed as underneath:

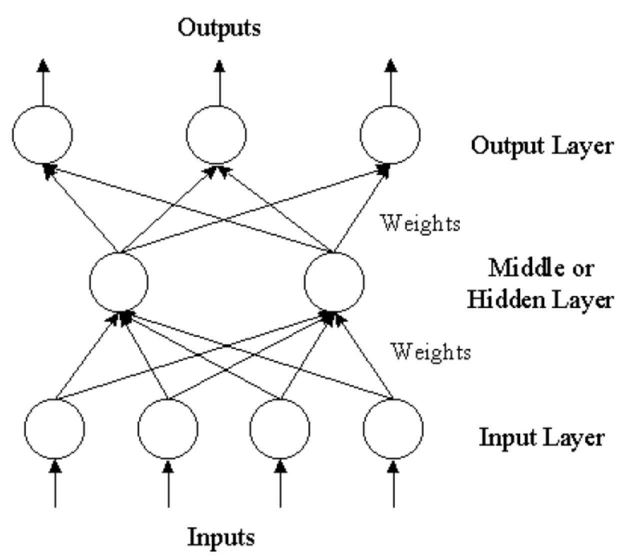

Figure 3: The three-layer feed forward ANN architecture (Adhikari & Agrawal, 2013)

5. Conclusion:

Time series is a typical numerical articulation that can be oftentimes seen in different texts about measurements, signal handling or econometrics. Consistently, papers contain business areas, which report every day stock costs, unfamiliar cash trade rates or month to month paces of joblessness. Meteorology records typically comprises of hourly wind speeds, every day greatest and least temperatures or yearly precipitation. Geophysics are constantly noticing processes like shaking or earthquakes of the earth, to foresee potentially approaching seismic tremors. Every one of these and unquestionably numerous different models could be referenced to depict the job of time series in our general public.

There are many types of forecasting methods, and using forecasts from a method that is not applicable to the given time series may result in inaccurate forecasts. Accordingly, the forecaster must be careful in choosing a forecasting method that is suitable for the investigated situation.

It was found that there are different types of prediction models that are classified according to three characteristics: stationarity (Fixed & Non-fixed), memory (Long memory time series & Short memory time series) and the length of the time step (Equidistant time series & Non-equidistant time series); each has different uses and features from the other. It was concluded that there are three commonly used models in forecasting and widely used by researchers, namely: ARIMA, ES and ANN.

By comparing those three models, it was concluded that ANNs are an alternative to traditional methods, which are often limited by stringent assumptions such as residuals normality, variables linearity, and variables multicollinearity. ANNs' ability to process various relationships enables users to develop the required model quickly and relatively easily. ANNs offer certain advantages such as less statistical training is required; compound nonlinear relationships between dependent and independent variables can be detected implicitly, all possible interactions between predictor variables can be identified, and multiple training algorithms are available.

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