A Review of Forecasting Techniques

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Abstract - *This work examines recent publications in forecasting in various fields, these include: wind power forecasting; electricity load forecasting; crude oil price forecasting; gold price forecasting energy price forecasting etc. In this review, categorization of the processes involve in forecasting are divided into four major steps namely: input features selection; data pre-processing; forecast model development and performance evaluation. The various methods involve are discussed in order to provide the overall view about possible options for development of forecasting system. It is intended that the classification of the steps into small categories with definitions of terms and discussion of evolving techniques will provide guidance for future forecasting sytem designers.*

Keywords: Forecasting; Prediction; Feature selection; Modeling; Performance evaluation

1 Introduction

This paper gives a brief overview of forecasting techniques published in the last ten years. An attempt has been made in categorizing relevant published work into series of steps needed for understanding forecasting techniques.

Forecasting involve predicting future behavior or value of certain phenomena. Forecasting has been applied in various fields such as wind power [1,2] ; electricity load consumption [1] ; energy price forecast in power systems [1,2,3] ; gold price forecasting[4] ; price spike prediction [5] ; financial sequence prediction [6] ; fatigue life prediction [7] ; car fuel consumption forecasting [8] and so on.

Generally, forecasting activity can be divided into three relevant classes, namely short term, medium term and long term forecasting. Short term forecast activity concentrates on predicting unknown values of price for a short period of time. These periods include few minutes, hours, or days. Monthly forecast activity falls into medium term while long term forecast activity may cover period of one to few years. Short term forecast is informative for profit maximization [1, 2] while medium term price forecast is useful for negotiations of bilateral contract between suppliers and consumers. Long term forecast is a valuable tool for assets expansion [1].

The first difficulty associated with forecasting activity is the linearity of data. Forecast activity becomes easier when dealing with linear historical data [3]. Linear data normally undergo linear changes such as linearly increasing or linearly decreasing over certain period of time. On the other hand, forecasting activity become very challenging issues when dealing with non-linear data [9]. External influence has been identified as one of the reasons responsible for non-linearity nature of data. Electricity power system, load and demand system, crude oil and gold price prediction are some of the sectors known for having non-linear data.

Lots of forecasting models and techniques have been proposed in literature with each achieving various degree of success. Among the reported methods are Moving Average (MA), Linear Prediction (LPC), Auto-Regressive Moving Average (ARMA) and the Box-Jenkins approach based on Auto-Regressive Integrated Moving Average (ARIMA). These methods are preferred by some researchers when dealing with linear data [5,10].

The remaining part of this paper is organized as follows: Section II describes the common methodology used for forecasting while the last section provides a list of commonly used performance metrics.

2 Review of forecasting techniques

Extensive study of various forecasting techniques have shown four major steps; namely, input features selection, data pre-processing, Modelling cum data training and performances evaluation. Modelling and data training have been the major areas of focus in the literature. Model represent the forecast system since it is to receive input data, analyse it and produce output called predicted value. Most forecasting models are based on assumption of relationship between inputs (historical time series data) and outputs (future values). A typical forecasting block diagram is shown in Fig. 1.

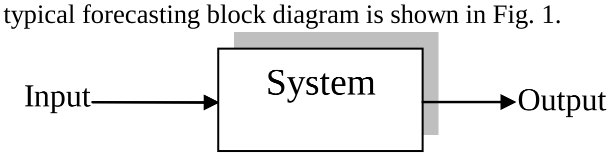

Figure 1: Block diagram of system

The overall review done in this paper based on the forecasting steps consist of (i) Input features selection (ii) Data Preprocessing step (iii) Forecasting models development step and (iv) Performance evaluation step and their components in each step are shown in Fig. 2. The details of each components are subsequently discussed.

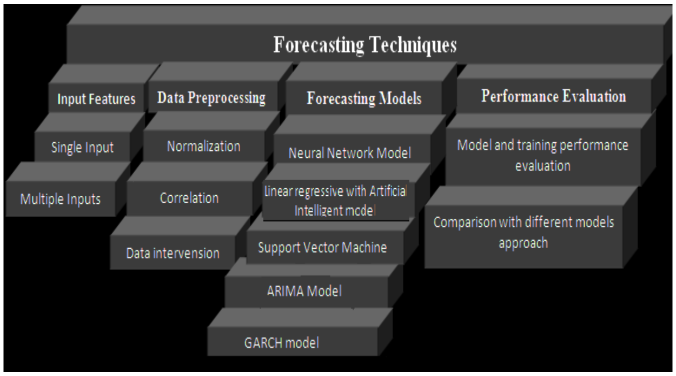

Figure 2: Major steps for forecasting

2.1 Input features selection

Input data in forecasting consist of collection of historical information that used to forecast the future values. Input data are fed into forecasting model for analysis in order to determine future output value. Input data can be developed through collection of various information that influence the data. Therefore, proper selection of input data is of utmost importance. Adequate input may give enough information to forecasting model to analyze the future trend of data accurately, whereas insufficient features in the input data may lead to serious error in forecast. Time series historical data is mainly used in forecasting system. However, in some forecasting field, time series data alone is inadequate to accurately forecast the future trends of data. Therefore, utilization of historical information base on other features may be used to enhance the forecast output. The utilization of both types of data is discussed as follows.

2.1.1 Time series historical data

Information from historical time series data is very useful for forecasting models to learn the trend of future data. Generally, time series data can be obtained from historical documents. The trend of a time series historical data is normally assumed to shows certain repetitive pattern. List of the time series data were used in lituretures such as Market Clearing Price (MCP) for forecasting electricity demand[14, 15], and previous time electricity price and load price data to forecast a day ahead electricity price [16]. In addition, utilization of previous three months data in forecasting monthly price was reported in [17] and previous hours data were used to forecast next hour data in [18].

2.1.2 Combination of time series with other features data

Multiple features input utilization have been reported in [19, 20, 25]. Seasonal factors and weather conditions were included as additional as input besides time series data for electricity demand forecasting model [19]. Ignoring the external factors may lead to inadequate training to the forecasting model which may lead to forecast error. For example, daily whether information is unignorable in electricity forcasting field since people will definitely use more electricity during hot days as compare to cold weather[19]. Other factors such as added value and number of customer were also incorporated as input features in [20], while total number of weeks, yearly number of weeks, world events impact factor and global demand were used as input features in [9,51]. Similarly, market clearing price (MCP) and other influence factors such as previous competitive load, competitive generating capacity, system running style, previous market have also been considered in forecasting electricity price [22].

2.2 Data pre-processing

The second stage in forecasting is data pre-processing stage. The objective of data pre-processing step is to remove abnormalities in the data such as noise. Besides that, data pre-processing technique is used to regulate the input and output range of data. Through this step, original historical data will be altered in order to produce new set of input data. Some of the known data pre-processing techniques are (i) Normalization, (ii) Correlation and (iii) Data intervention. Each of the preprocessing techniques is discussed as follows.

2.2.1 Normalization

Normalization is the most popular data preprocessing technique reported in literature as part of forecasting technique [9, 19, 24, 25, and 34]. Data normalization reduces data range into smaller scale such as in the range from 0 to 1. In other word, normalization process helps to rescale the huge number of data to lie between the scaling ranges.

2.2.2 Correlation

The purpose of correlation is to detect non randomness in time series data [26]. Informally, correlation technique is used to find the similarity between different observations in a given time series data. Furthermore, correlation is used for features selection from large size of data. Autocorrelation analysishas been used for feature selection process by removing irrelevant and redundant features and selecting a small set of informative features that are necessary and sufficient for good forecasting [27,28].

2.2.3 Data intervention technique

Data intervention technique function is to improve forecasting result. This technique removes intervention effects such as changes of whether condition or political instability that may produce spike to time series data. In [29], sudden high peak in the data is removed from input data since it is considered as intervention effect [29].

2.3 Forecast Model Development

The third stage in forecasting is the development of the forecast model. This is the art of the whole process and lots of efforts are usually expended in the development of such a model. Some of the reported forecast models include:

i. Artificial Intelligence model.
ii. Linear regressive with Artificial Intelligence mathematical model.
ii. Support Vector Machine (SVM) approach.
iv. Autoregressive Integrated Moving Average (ARIMA) model.
v. Generalized Autoregressive Conditional Heteroskedastic (GARCH) model.

2.3.1 Artificial Intelligence model

Artificial intelligence (AI) model in forecasting field has received favourable success in the last few years. Among the AI techniques reported in literature are fuzzy inference[11], fuzzy-neural models[12] and Artificial Neural Network (ANN) [13]. The application of ANN approach for nonlinear data, such as load forecasting in power system has received much attention in recent years, since ANN has the ability to learn complex and nonlinear relationships [5].

Modeling using Artificial Neural Network (ANN) plays the important role in forecasting field because of its capability to learn both linear and nonlinear relationship from a given input data during training process. Different types of learning algorithms for training this model has been proposed in literature. A list of studies have used Gradient Descent learning rule with momentum [19,30,31], Levenberg-Marquardt (LM) algorithm [15][18], conjugate gradient (SCG) algorithm [15] and multi ELM training algorithm [16]. Levenberg-Marquardt (LM) algorithm and scaled conjugate gradient (SCG) algorithm are proposed to overcome slow convergence of BP algorithm. Genetic Algorithm has been used as an alternative training rules to BP algorithm in order to overcome local minima problem associated with BP algorithm[14]. Combination of Levenberg-Marquardt back-propagation algorithm(LM-BP) and evolutional algorithm approach to train their MLN model was proposed in [18]. Similarly, LM-BP and Particle Swarm Optimization is reported in [18].

Radial Basis Network(FBN) is another type of feed forward network used as an alternative to Multi Layer Network in forecasting model [25]. RBN use Euclidean distance as activation function for hidden layer instead of linear activation function that used in Multi Layer Network (MLN). Elman neural network forecasting model with BP learning algorithm was reported in [17]. Elman neural network or Elman regression neural network (ERN) has an additional of one layer compared to MLN, which is the context layer. In other words, ERN developed with 4 layers; namely, input layer, hidden layer, context layer and output layer. The outputs data from hidden layer are stored in the context layer (also called accepter layer) before sending it to output layer. Therefore, ERN offers the system the capability to adapt the time variability by its dynamic character mapping function supported via internal status memory [17]. Artificial Neural Networks- Quantitative (ANN-Q) Model has been introduced in [23]. Hybrid of ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) has also been proposed to accomplish the forecast purpose in [31]. These two model are combined (in series) in such a way that one of forecasted data will be fed into ANFIS network.

2.3.2 Linear regressive with artificial intelligent mathematical model

The objective of regression analysis is to develop mathematical model that can forecast the values of dependent variables (e.g. *y* plane in the data graph) by using independent variables (e.g. *x* plane in the data graph) as input. In the case of daily gold price forecasting, the price of the gold will be dependent variables, while the date of that price occur will be independent variables. The general form of linear regressive model is :

$$y = mx + c \qquad (1)$$

Where y is the forecast value, m is the slope of 'best fit' line, x is prediction date and c is intercept point of best fit line to y axis. In the classical method, the 'best fit' line is considered as linear line that follows the trend of data as illustrated in the Fig. 3.

Figure 3: 'Best fit line' across historical data of gold price data

The best fit line is drawn in the way that it not bias to any points. However, in case of nonlinear relationship between input and output, straight linear line unable to follow the trend of graph closely. Consequently, classical linear regressive model is not suitable for forecasting non linear data because it has tendency to produce high error in forecast value. Therefore, Artificial Intelligent technique is used to find the *m* variable, to be substitute in the linear regressive model for forecasting non-linear data. For example, in [32], Genetic Algorithm is used to find five 'best fit' coefficients for four independent variables. Similarly, Particle Swarm Optimization (PSO) algorithm has been used for tuning linear algorithm coefficients from electricity consumption data for electric consumption forecasting model of the following year [20].

2.3.3 Support Vector Machine approach (SVM)

SVM's is a supervised learner that used to analyse and recognize the patterns of data. SVM is used to constructs set of hyperplanes (gap between different classes) in a high or infinite- dimensional space in order to classify data. SVM has the advantage of reducing the problem of over-fitting or local minima because its learning algorithm is based on the structural risk minimization principle compared to ANN, which use learning algorithm based on the empirical risk minimization principle. The four basic kernel types in SVM include Linear Kernel, Polynomial Kernel, Radial, Basis Function Kernel (RBF) and Sigmoid Kernel. Kernel is used to compute dot product in terms of the variables in the original space. SVM with RBF kernel function has also been developed for forecast purpose in [9].

2.3.4 Autoregressive Integrated Moving Average (ARIMA) model

ARIMA model can be used to get better understanding of time series data and forecast the future points. ARIMA model consist of three parts : namely, an autoregressive part of order p, moving average part of order q and the first derivative of the time series of order d, known as the integrated part. Thus, the model is generally referred to as an ARIMA(p,d,q). ARIMA model can be called an Autoregressive model (AR(p)) whenever the order d and q becomes zero (e.g *ARIMA(1,0,0)).* Similarly, the model may be regarded as ARMA model when only the d term is set to zero. SARIMA model is developed with addition of seasonal component to this model. In [28], two ARIMA models was proposed to forecast hourly prices in the electricity markets. Furthermore, a model called seasonal autoregressive integrated moving Average (SARIMA) was developed to forecast electricity price [29].

2.3.5 Generalized Autoregressive Conditional Heteroskedastic (GARCH) model

The GARCH time series model was introduced in [29]. It overcomes the ARIMA and linear regression models that have limitation to deal with non linear data. This model determine the explicit relationship of the nonlinear data series. In order to get acceptable accuracy, the formulation of non linear model is developed to capture the entire important features in the historical data.

2.4 Performance evaluation

Performance evaluation is the crucial part to test the performance of the newly developed model. Normally, the performance of forecasting model is evaluated by using standard performance evaluation formula. Once the performance of the model is satisfied, the scope of evaluation is expanded to compare this newly developed model with other existing models. In the following subsections, both methods of evaluating the results obtained from the model are discussed herewith.

2.4.1 Modeling and training performance evaluation

In order to evaluate the forecast results, the facts or empirical results are normally presented. In forecast issue, standard performance evaluation metrics include mean square error (FMSE)[24], RMS error[16], [23], [33], mean absolute percentage error (MAPE) [15], [18], [30], [31], Relative absolute error (RAE) [27] and correctly forecasted percentage error[9],[16]. MAPE evaluation metric are among of the frequently used performance metric. MAPE was used as the fitness function for measuring the evolutionary algorithm optimization in [15], [18], [30], [31]. Percentage error and RMS error are used to compare performance between two or more forecast models. These metrics are calculated using (2)-(5) :

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(actual - forecast)^2} \tag{2}$$

$$FMSE = \frac{1}{N}\sum_{i=1}^{N}(actual - forecast)^2 \tag{3}$$

$$MAE = \frac{1}{N}(\sum_{i=1}^{N}[\left|\frac{actual - forecast}{actual}\right|] \tag{4}$$

$$MAPE = \frac{1}{N}(\sum_{i=1}^{N}[\left|\frac{actual - forecast}{actual}\right| \times 100\%] \tag{5}$$

where N is the data length.

Combination of more than one performance metrics have been used in some literature. Combination of MAE, RAE and MAPE was proposed in [27] while the combination of RMSE and NMSE was used in [23]. *Dstat* is used to evaluate the forecasted price movement.

2.4.2 Performance comparison of different methodology

The main objective of forecast research nowadays is to develop the best and reliable forecast model that will give minimal error between the forecasted value and actual value. Methodology comparison in term of performance metrics is a mean for evaluating any new model performance in order to compare the result among existing models. For example, RBF performance was compared with autoregressive forecasting model in [25]. Similarly, ARIMA and linear regression technique performance was compared in [32]. In [10], it was shown that ANN method leads to better prediction than time series ARIMA method, while GA performance is better than linear regression technique model. The performance of SVM and BPNN is compared in [9]. In another study, ANN performance was compared with similar day (SD) forecast approach[19].

3 Conclusion

This paper contains review of some of the forecasting techniques that have been published in the last ten years. The steps associated with forecasting are categorized into four primary steps: namely, of input features selection (step one) ; data preprocessing (step two); forecast model development (step three) and performance evaluation (step four). The various methodology proposed in each step are highlighted and discussed.

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