THE ENHANCED GROUP METHOD OF DATA HANDLING MODELS FOR TIME SERIES FORECASTING

RUHAIDAH SAMSUDIN

UNIVERSITI TEKNOLOGI MALAYSIA

THE ENHANCED GROUP METHOD OF DATA HANDLING MODELS FOR TIME SERIES FORECASTING

RUHAIDAH BINTI SAMSUDIN

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ABSTRACT

Time series forecasting is an active research area that has drawn most attention for applications in various fields such as engineering, finance, economic, and science. Despite the numerous time series models available, the research to improve the effectiveness of forecasting models especially for time series forecasting accuracy still continues. Several research of commonly used time series forecasting models had concluded that hybrid forecasts from more than one model often led to improved performance. Recently, one sub-model of neural network, the Group Method of Data Handling (GMDH) and several hybrid models based on GMDH method have been proposed for time series forecasting. They have been successfully applied in diverse applications such as data mining and knowledge discovery, forecasting and systems modeling, optimization and pattern recognition. However, to produce accurate results, these hybrid models require more complex network generating architecture. In addition, several types and parameters of transfer function must be predetermined and modified. Thus, in this study, two enhancements of GMDH models were proposed to alleviate the problems inherent with the GMDH algorithms. The first model was the modification of conventional GMDH method called MGMD. The second model was an enhancement of MGMDH model named HMGMDH, in order to overcome the shortcomings of MGMDH model that did not perform well in uncertainty type of data. The proposed models were then applied to forecast two real data sets (tourism demand and river flow data) and three well-known benchmarked data sets. The statistical performance measurement was utilized to evaluate the performance of the two afore-mentioned models. It was found that average accuracy of MGMDH compared to GMDH in term of R, MAE, and MSE value increased by 1.27 %, 10.96%, and 16.9%, respectively. Similarly, for HMGMDH model, the average accuracy in term of R, MAE, and MSE value also increased by 1.39%, 14.05%, 24.28%, respectively. Hence, these two models provided a simple architecture that led to more accurate results when compared to existing time-series forecasting models. The performance accuracy of these models were also compared with Auto-regressive Integrated Moving Average (ARIMA), Back-Propagation Neural Network (BPNN) and Least Square Support Vector Machine (LSSVM) models. The results of the comparison indicated that the proposed models could be considered as a useful tool and a promising new method for time series forecasting.

ABSTRAK

Peramalan siri masa merupakan satu bidang penyelidikan yang aktif yang telah menarik perhatian di dalam pelbagai bidang aplikasi seperti kejuruteraan, kewangan, ekonomi dan sains. Walaupun telah banyak muncul model-model siri masa, tetapi penyelidikan untuk meningkatkan keberkesanan model-model peramalan terutamanya di dalam ketepatan peramalan siri masa ini tidak pernah berhenti. Pelbagai penyelidikan peramalan siri masa yang biasa digunakan telah merumuskan bahawa ramalan hibrid atau gabungan lebih daripada satu model selalunya mampu meningkatkan prestasi. Kebelakangan ini, satu sub-model rangkaian neural (NN), iaitu, Kaedah Kumpulan Pengendalian Data (GMDH) dan pelbagai model-model hibrid berasaskan kaedah GMDH telah dicadangkan bagi peramalan siri masa ini. Ia telah berjaya digunakan di dalam pelbagai bidang yang besar seperti perlombongan data dan penemuan pengetahuan, sistem peramalan dan permodelan, pengoptimuman dan pengecaman corak. Bagaimanapun, untuk mendapatkan hasil yang tepat, model-model hibrid ini memerlukan penjanaan senibina rangkaian yang lebih kompleks. Di samping itu, pelbagai jenis dan parameter fungsi peralihan dengan memberi kesan kepada hasil kualiti haruslah dikenalpasti dahulu dan diubahsuai. Oleh itu, di dalam kajian ini, dua penambahbaikan terhadap model GMDH telah dicadangkan untuk mengatasi masalah di dalam algoritma GMDH ini. Model pertama adalah pengubahsuaian ke atas kaedah GMDH yang konvensional yang dinamakan sebagai model Modifikasi GMDH (MGMDH). Model kedua adalah penambahbaikan model MGMDH yang dikenali sebagai Hibrid MGMDH (HMGMDH) untuk mengatasi kelemahan model MGMDH yang tidak mampu menangani dengan baik data berjenis ketidak-tentuan. Model-model cadangan ini kemudian digunakan untuk memodelkan dua set data sebenar (data aliran sungai dan data pelancongan) dan tiga set data piawai yang telah dikenali umum. Pengukuran prestasi secara berstatistik adalah digunakan untuk menilai prestasi ketiga-model yang dicadangkan ini. Hasil kajian mendapati bahawa purata ketepatan bagi model MGMDH jika dibandingkan dengan model GMDH melalui pengukuran dari segi nilai R, MAE, dan MSE adalah masing-masing bertambah sebanyak 1.27%, 10.96% dan 16.9%. Begitu juga dengan model HMGMDH, purata ketepatannya juga meningkat sebanyak 1.39%, 14.05% dan 24.28%. Oleh itu, kedua model ini menyediakan satu senibina yang mudah dan mampu memberikan hasil yang lebih tepat berbanding dengan model-model peramalan siri masa sedia ada. Ketepatan prestasi model-model cadangan ini juga turut dibandingkan dengan model *Auto-regressive Integrated Moving Average* (ARIMA), *Back-Propagation Neural Network* (BPNN), dan *Least Square Support Vector Machine* (LSSVM). Hasil dari perbandingan ini juga telah menunjukkan bahwa model-model cadangan ini merupakan satu alat yang berguna dan boleh menjanjikan satu kaedah baru dalam peramalan siri masa.

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LIST OF ABBREVIATIONS

ACF	-	Auto-Correlation Function
AI	-	Artificial Intelligence
AIC	-	Akaike's Information Criteria
ANN	-	Artificial Neural Network
AR	-	Auto-Regressive
ARIMA	-	Auto-Regressive Integrated Moving Average
CAT	-	Computer Aided Tomography
FIS	-	Fuzzy Inference System
FNNs	-	Fuzzy Neural Networks
FPNN	-	Fuzzy Polynomial Neural Network
GA	-	Genetic Algorithm
GA-PNN		Genetic Algorithm and Polynomial Neural Network
GHFNN	-	Genetically optimized Hybrid Fuzzy Neural Networks
GMDH	-	Group Method of Data Handling
GP	-	Genetic Programming
HMGMDH	-	Hybrid MGMDH
HSOFSPNNs	-	Hybrid Self-Organizing Fuzzy Polynomial Neural Networks
KKN	-	Karush Kuhn Tucker
LSSVM	-	Least Square Support Vector Machine
MA	-	Moving Average
MAE	-	Mean Absolute Error
MAPE	-	Mean Absolute Percentage Error
MGMDH	-	Modified of Group Method of Data Handling
MIA GMDH	-	Multi-Layered Iterative GMDH
MLPs	-	Multi-Layer Perceptrons
MLR	-	Multi Linear Regression
MOGMDH		Multi Objective GMDH
MSE	-	Mean Square Error
PACF	-	Partial Auto-Correlation Function

PDs	-	Partial Descriptions
PWRs	-	Pressurized Water Reactors
R	-	Correlation Coefficient
RBF	-	Radial Basis Function
RMSE	-	Root Mean Square Error
SARIMA	-	Seasonal ARIMA
SVM	-	Support Vector Machine
SVR	-	Support Vector Regression
TF	-	Transfer Function
WLS-SVM	-	Weighted least squares support vector machine

CHAPTER 1

INTRODUCTION

1.1 Overview

Time series prediction or forecasting is an important practical problem with a diverse range of applications in many observational disciplines, such as physics, engineering, finance, economics, meteorology, biology, medicine, hydrology, oceanography and geomorphology. The accuracy of time series forecasting is fundamental for the organization to plan or adopt the necessary policies. Forecasting can assist them to make a better development and decision-making for most of the organization. The identification of highly accurate and reliable time series forecasting models for future time series is an important precondition for successful planning and management for applications in variety of areas.

Generally, time series forecasting models can be grouped into the two main techniques: knowledge-driven modelling and data-driven modelling. The knowledge-driven modelling is so-called physically-based model approachs, which generally use a mathematical framework based on external factors often require economic and demographic data or climatic characteristics such as temperature, humidity and wind characteristics (Jain and Kumar, 2007). As all the external factors have already impacted the generation of the observed time series, it is hypothesized that the forecasts could be improved if external factors variables which affect this time series were to be included. Although incorporating other variables may improve the prediction accuracy, in practice such information is often either not available or difficult to obtain. Moreover, the influence of these variables and many of their combinations in generating external factors especially due to the data collection of multiple inputs and parameters, which vary in space and time and is not understood clearly (Zhang and Govindaraju, 2000).

Owing to the complexity of this process, most conventional approaches are often unable to provide sufficiently accurate and reliable forecasts (Firat and Turan, 2010).

The data-driven modelling which use the univariate time series modelling approach is based on extracting and re-using information that is implicitly contained in past data without directly taking into account the external factors are becoming increasingly popular due to their rapid development times and minimum information requirements (Adamowski and Sun, 2010, Atiya *et al.*, 1999; Lin et al., 2006; Wang *et al*. 2006; Wu *et al*., 2009; Firat and Güngör,, 2007; Kisi, 2008, 2009; Wang *et al*., 2009). Moreover, using only the past time series of the same variable are analyzed to develop a model describing the underlying relationship can reduce the data dimensionality for the problem being modeled, which improves generalization and forecasting performance. This modeling approach is particularly useful when little knowledge is available on the underlying data generating process or when there is no satisfactory explanatory model that relates the prediction variable to other explanatory variables (Zhang, 2003). The ultimate goal of time series forecasting is to be able to obtain some information about the series in order to predict future values.

Generally, there are two main types of forecasting methods that are widely used in time series problem: statistical methods and Artificial Intelligence (AI) methods (Sallehuddin *et al*., 2007). The example of Statistical method includes Box-Jenkins method, Multiple Regressions and Exponential Smoothing while methods under AI technique are neural networks, genetic algorithm, fuzzy logic, etc. Statistical methods have been used successfully in time series forecasting for several decades. Despite being simple and easy to interpret, statistical methods have several limitations. One of the major limitations of statistical methods is it is merely depicted as a linear model, also known as model driven approach. It is desirable to fit the data with the available data and the prior knowledge about the relationships between the inputs and outputs before modeling process is conducted (Zhang, 2000).

Over the past several decades, much effort has been devoted to the development and improvement of univariate time series forecasting models. Time series analysis and prediction refers to the branch of statistics where observations are collected sequentially in time, usually (but not necessarily) at equally-spaced time points, and the analysis relies, at least in part, on understanding or exploiting the dependence among the observations. Because of the importance of time series analysis, many works can be found in the literature, especially those based on statistical models. One of the most popular and extensively used seasonal time series forecasting models is the auto-regressive integrated moving average (ARIMA) model. The popularity of the ARIMA model is due to its statistical properties as well as the well-known Box–Jenkins methodology in the model building process. In addition, ARIMA model provides a comprehensive statistical modelling methodology for input and output processes. It covers a wide variety of patterns, ranging from stationary to non-stationary and seasonal (periodic) time series, and has been used extensively in the literature (M´elard and Pasteels, 2000; Valenzuela *et al*., 2008) and has been successfully adopted in numerous fields such in social, economic, engineering, foreign exchange, stock and hydrological problems (Goh and Law, 2002; Huang and Min, 2002; Navarro-Esbri *et al.*, 2002). ARIMA models have been originated from the autoregressive models (AR), the moving average models (MA) and the combination of the AR and MA, the ARMA models. Although the ARIMA model has been highly successful in both academic research and variety areas of applications during the past three decades, their major limitation is the pre-assumed linear form of the model. ARIMA models assume that future values of a time series have a linear relationship with current and past values as well as with white noise, so approximations by ARIMA models may not be adequate for complex nonlinear real-world problems. However, real world systems are often nonlinear (Zhang *et al*., 1998), thus, it is unreasonable to assume that a particular realization of a given time series is generated by a linear process.

In fact, the drawbacks of these linear methods, the artificial neural networks (ANNs) are one of the most important types of nonparametric nonlinear time series or Artificial Intelligence (AI) models, which have been proposed and examined for time series forecasting, have led to the development of alternative solutions using nonlinear modelling. Since the 1990s, ANN, based on the understanding of the brain and nervous systems, was gradually used in time series forecasting. ANNs represent an important class of nonlinear prediction models that has generated a lot of interests in the forecasting community over the past decade (Adya and Collopy, 1998; Alves da Silva *et al.*, 2008; Balkin and Ord, 2000; Ter¨asvirta, *et al*., 2006; Zhang et al., 1998). ANNs are one of the most accurate and widely used forecasting models that have enjoyed fruitful applications in forecasting social, economic, engineering, foreign exchange, stock problems, hydrology etc. Given the advantages of artificial neural networks, it is not surprising that this methodology has attracted overwhelming attention in time series forecasting. One of the main reasons that ANN performs better than the statistical method is due to its influential feature in handling nonlinear time series data. In addition, ANN has also been shown to be effective way with can handle noise or without noise data in modeling and forecasting nonlinear time series. Besides that, ANN also does not require any knowledge about systems of interest. Although ANNs have the advantages of accurate forecasting, their performance in some specific situation is inconsistent. In the literature, several papers have shown ANNs are significantly better than the conventional linear models and their forecast considerably and consistently more accurately, some other studies have reported inconsistent results. Moreover, there are some disadvantages of ANN due its network structure which is hard to determine and usually established by using a trial-and-error approach (Kisi, 2004).

Over the last few years, kernel methods (Scholkopf and Smola, 2001) have proved capable of forecasting more accurately than other techniques such as neural networks, neuro-fuzzy systems or linear models (ARIMA), in terms of various different evaluation measures during both the validation and test phases (Hong and Pai, 2006; Wang *et al*., 2009; Xu *et al*., 2006). Kernel methods are defined by operations over the kernel function values for the data, ignoring the structure of the input data and avoiding the curse of dimensionality problem (Bellman, 1966). The main motivation for using kernel methods in the field of time series prediction is their ability to forecast time series data accurately when the model could be non-linear, non-stationary and not defined a priori (Sapankevych and Sankar, 2009). The two most promising kernel methods for time series prediction are Support Vector Machines (SVM) (Misra *et al.*, 2009; Sapankevych and Sankar, 2009; Zhou *et al*., 2008) and Least Square Support Vector Machines (LSSVM) (Van Gestel *et al*., 2001; Xu and Bian, 2005).

Support Vector Machine (SVM) is proposed by Vapnik and his co-workers in 1995 through statistical learning theory have become a key machine learning technique (Quan et al. 2010). Originally, SVM has been developed to solve pattern recognition problems. However, with the introduction of Vapnik's ε-insensitive loss function, SVM has been extended to solve nonlinear regression estimation problems, such as new techniques known as support vector machines for regression, which have been shown to exhibit excellent performance (Vapnik *et al*., 1997). The SVM is a powerful methodology and has become a hot topic of intensive study due to its successful employed to solve most non-linear regression and time series problem and becoming increasingly in the modeling and forecasting of chaotic processes, water resources engineering (Lau and Wu, 2008). The standard SVM is solved by using quadratic programming methods. However, this method is often time consuming and has a higher computational burden due to the requisite constrained optimization programming, and is only found to be useful for the classification and prediction of small sample cases (Vapnik, 1999).

Least squares support vector machines (LSSVM), as a modification of SVM was introduced by Suykens in 1999. Both SVM and LSSVM have been applied to time series prediction with promising results, as can be seen in the work of Tay and Cao (2001) and Thiessen and Van Brakel (2003) for Support Vector Regression (SVR) and Van Gestel *et al.* (2001) and Xu and Bian (2005) for LSSVM. The LSSVM has a similar advantage to that of the SVM, but its additional advantage is that it only requires the solving of set linear equations, which is much easier and computationally more simples. The method uses equality constraints instead of inequality constraints and adopts the least squares linear system as its loss function, which is computationally attractive. LSSVM also has good convergence and high precision. Hence, this method is easier to use than quadratic programming solvers in SVM method. Extensive empirical studies have shown that LSSVM is comparable to SVM in terms of generalization performance (Wang and Hu, 2005). The major advantage of LS-SVM is that it is computationally very cheap while it still possesses some important properties of the SVM. Recently, LSSVM has been successfully applied to chaotic time series forecasting, for example, see Mei-Ying and Xiau-Dong (2004), Herrera et al. (2007), Wang *et al*. (2005), Liu and Wang (2008), Rubio *et al.* (2011), Du (2009), and Quan *et al*. (2010).

One sub-model of neural network is a group method of data handling (GMDH) algorithm which was first developed by Ivakhnenko (1971) for modeling and identification of complex systems (Kim and Park, 2005). GMDH is a heuristic self-organizing modeling method. The main idea of GMDH is to build an analytical function in a feed-forward network based on a quadratic node transfer function whose coefficients obtained by using a regression technique. The GMDH model has the ability of self-selecting such the number of layers, the number of neurons in hidden layers and self-selecting useful input variables (Hwang, 2006). The method offers the advantages of improved forecasting performance (Abdel-Aal, 2004; Abdek-Aal *et al*., 2009), faster model development requiring little or no user intervention, faster convergence during model synthesis without the problems of getting stuck in local minima, automatic selection of relevant input variables, and automatic configuration of model structures (Ravisankar and Ravi, 2010). This model has been successfully used to deal with uncertainty, linear, nonlinearity or chaotic of systems in a wide range of disciplines such as engineering, science, economy, medical applications, signal processing and control systems (Tamura and Kondo, 1980; Ivakhnenko and Ivakhnenko, 1995; Voss and Feng, 2002, Lin *et al*. 1994, Onwubolu, 2008).

1.2 Challenges of GMDH Model in time series forecasting

The major goal of time series forecasting is to get the best accuracy model in order to make a good decision for the organization. As mentioned above, artificial intelligence techniques have been extensively studied and a lot of attention has been directed to developing advance technique in time series forecasting. Neural networks, fuzzy systems and machine learning techniques have been widely used and have been investigated by many authors. The approximation capability of neural networks, such as multilayer perceptrons, radial basis function (RBF) networks, or dynamic recurrent neural networks has been investigated by many authors (Chen and Chen, 1995; Li, 1992). On the other hand, fuzzy systems have been proved to be able to approximate nonlinear functions with arbitrary accuracy (Wang and Mendel, 1992). But the resultant neural network representation is very complex and difficult to understand and fuzzy systems require too many fuzzy rules for accurate function approximation. As another method, there is a Group Method of Data Handling (GMDH)- type algorithms which was introduced by Ivakhnenko in the early 1970’s (Ivakhnenko, 1971; Ivakhnenko and Ivakhnenko, 1975). GMDH-type algorithms have been extensively used since the mid-1970’s for prediction and modelling complex nonlinear processes. Recently the GMDH has been successfully applied in a great variety of areas for data mining and knowledge discovery, forecasting and systems modelling, optimization and pattern recognition. The main characteristics of GMDH is that it is a self-organizing and provides an automated selection of essential input variables without using a prior information on the relationship among input-output variables (Farlow, 1984). This research is focusing on the efforts of improving the accuracy of forecasting methods based on GMDH model.

1.3 Background of the problem

The GMDH algorithm is a heuristic method which provides the foundation for the construction of high-order regression models of complex systems. The basic building block of GMDH is a quadratic polynomial of two variables. The GMDH algorithm generates an optimal structure of the model through successive generations of partial descriptions of data (PD) by using quadratic regression polynomials of two input variables.

GMDH usually consists of many "layers", each layer consists of a bank of quadratic polynomial functions that requires input from the previous layer after having passed a selection criteria. Each layer consists of nodes (PD) for which the number of input variables could be same as in the previous layers or may differ across the network depend on the selection criteria. Although the GMDH is structured by a systematic design procedure, it has some drawbacks to be solved. In the standard GMDH, the issues to address are how to determine the optimal number of input variables and how to determine which input variables are chosen. If a small number of input variables are available, GMDH tends to generate more complex polynomials even for relatively simple systems as in experimental data. On the other hand, if there are sufficiently large numbers of input variables and data points, GMDH algorithm has a tendency to produce more complex networks (Oh and Pedrycs, 2002). Furthermore, the method of GMDH is difficult to follow its network architecture, required advanced knowledge of the final network structure, and require a large amount of time to train. Moreover, the performances of GMDH depend strongly on the number of input variables and types or order in each PD. They must be chosen in advance before the architecture of GMDH is constructed. In most cases, they are determined by the trial and error method with a heavy computational burden and low efficiency.

In order to alleviate the problems associated with the GMDH, many modified methods have been proposed. For example, Oh and Pedrycz (2002) introduced a family of multi-layer self organizing neural networks (PNN), the Self-Organizing Fuzzy Polynomial Neural Networks (SOFPNN) and the hybrid Self-Organizing Fuzzy Polynomial Neural Networks. The design procedure of multi-layer self-organizing neural networks exhibits some tendency to produce more complex networks as well as comes with a repetitive computation load caused by the trial and error method being a part of the development process.

Kondo and Euno (2006, 2007) modified GMDH model by introducing many types of neurons or transfer function such as the sigmoid function, the radial basis function, the high order polynomial and the linear function. The structural parameters such as the number of the layers, and the number of the neurons in the hidden layers, the useful input variables etc. are automatically determined so as to minimize the error criterion defined as Akaike's information criterion (AIC) and stepwise regression (SW). Although AIC and SW criterions are suitable to find the optimal number of neurons and layers of the modified GMDH networks, this criterion is not always satisfactory. Some time such regularization takes into account just the complexity of GMDH network and the outputs from neurons in a layer can be highly correlated.

Zadeh *et al.* (2002) introduced a modified GMDH algorithm called the error-driven approach. In this approach, the number of layers as well as the number of neurons in each layer is determined according to a threshold value before the algorithm even begins developing the network. The single best neuron out of each layer which gives the smallest of such as mean square error (MSE) the data set is combined with the previous input variables. The model are used for simultaneous determination of structure of input variables identification and tested for the modelling of explosive cutting process of plates using shaped charges. In their study shown that this model is easy to understand, simple to use and has been successfully used for modelling of very complex process of explosive cutting of plates by shaped charges. However, in this model, unlike the basic GMDH algorithm, the effect of the basic input variables in the first layer can be included in the subsequent layers and the model obtained at each layer is progressively more complex than the model at the preceding layers. The inherent computational cost of this approach can be significant and the need for a less iterative method is obvious. Furthermore, the basic building blocks of this model consist of polynomials. If the time series or the system is very complex, it does not guarantee to obtain a good prediction accuracy by using the conventional polynomial function type neural network.

In practice it is quite common that one forecasting model performs well in certain periods while other models perform better in other periods. It is difficult to find a forecast model that outperforms all competing models. Several researchers have argued that the forecast model performance can be improved when using hybrid models.

Hybridization of existing competitive modelling methodologies is now an active area of research. The basic idea of this multi-model approach is the use of each component model's unique capability to better capture different patterns in the data. Bates and Granger (1969), Newbold and Granger (1974), Granger and Newbold (1986), Granger and Jeon (2004) and Yang (2004) show that forecast hybridization model can improve forecast accuracy over a single model.

The hybridization forecast model is a process which gives the results of several individual forecasting models different weights. The hybrid models are then the weighted average of the forecasts provided by the individual models in order to obtain a better result. A simpler way is to use the equal weights (simple mean). This becomes a common strategy when the models are of similar quality or because their relative performance is unknown or unstable over time. Simple mean only makes sense if the class of models under consideration is reasonable. The other hybridizing models are the regression based methods (Granger and Ramanathan (1984), the weighted average method (Shamseldin *et al.* ,1997; Gao *et al.* (2000)), the mean squared error and mean absolute error (Zhang and Joung, 1999). However, the application of these hybridization forecast models have many limitations. One of the main problems in one of the above-mentioned forecasts methods is the choice of the optimal weight obtained between the forecast models.

Several hybridization model involved GMDH algorithm are introduced and modified to alleviate the problems inherent with the GMDH algorithms. It includes combining the GMDH with intelligent model such as Genetic Algorithms (Zadeh *et al.*, 2002), GMDH and Fuzzy Logic (Oh et al., 2005); GMDH and differential evolution (Onwubolu 2008), neuro-fuzzy and GMDH algorithm (Kim *et al.*, 2009) and GMDH and Bayesian (Xiao *et al.*, 2009), GMDH and ANN (Kim *et al.*, 2009). However, to get the high level of accuracy, the issues here are, these hybridization models tend to generate more complex architecture and several types and parameters of transfer function should be predetermined and amended. This requires a diverse set of heuristic settings to be devised and for each case the building process is repeatedly applied until an optimal hybridization is found. This leads to model with large number of parameters and high computational burden.

1.4 Problem Statement

Accurate forecasts are extremely important in diverse applications in any organizations. However, each organization must select the forecasting methods that help their particular situation. This forecasting dilemma is further complicated by the fact that most time series conditions are constantly changing.

Many research efforts have been expended to use of GMDH methods as effective tools for time series forecasting. Among these methodologies, the GMDH was developed by Zadeh *et al.* (2002) as a multi-variate analysis method are successfully used for modelling the explosive cutting process of plates by shaped charges. This research will concentrate on extension of the GMDH model proposed by Zadeh *et al.* (2002) by modifying and hybridizing this model in order to improve the existing model in time series forecasting. The GMDH model established by Zadeh *et al*. (2002) is chosen because the algorithm of this model has self organizing of termination network and simple structures that lead to work well in modelling. These improved methods expand the capabilities of combined forecast models enabling them to become more practical and effective. This study describes improvements to this effective forecasting method.

The problem statement can be dictated as follows:

“ Given time series data, the challenge is to enhance GMDH model that can produce a simple, accurate, and robust forecasting for time series data.”

In order to find the best prediction model, the following issues will be need to be considered:

i. Many GMDH methods are developed using polynomial equations that are not able to detect complex problems and are limited to the very specific uses for which they were designed. The first issue relates to GMDH model is how to modify GMDH model in order to improve the prediction accuracy. The goal is to ensure the forecasting model will achieve better accuracy after the modification model is performed.

ii. Many researchers have demonstrated that hybridizing of several models frequently results in higher forecasting accuracy than that of the individual models. However, in the development of the hybridizing model between two or more forecasting models, the problems is how to determine the optimal weights for the network in order to improve the capability of time series forecasting.

1.5 Research Goal

The goal of this research is to develop an enhanced GMDH model that is capable of forecasting diverse types of time series data.

1.6 Research Objectives

The main objectives of this research are:

1. To propose a new modification of conventional GMDH model that outperform conventional model in time series forecasting in term of statistical performance measurement.

2. To further enhance the modified GMDH model by hybridizing the conventional GMDH with modified GMDH models in order to improve the performance accuracy of modified GMDH model.

1.7 Research Scope

1. The proposed model is based on the GMDH model proposed by Zadeh et al. (2002) by modifying and hybridizing this model in order to improve of existing model in time series forecasting.

2. Four models namely are ARIMA, ANN, original GMDH and LSSVM models were used to test and validate the performance of these proposed models.
3. Two type of data set will be used. The first data sets are the monthly stream flow of Selangor river of Selangor and monthly of tourism in Johor. The second data set is the benchmarked data. These are three well-known data sets - the international airline passengers, the Canadian Lynx data and the gas furnace data. These data are utilized to forecast through an application aimed to handle real life time series.

4. The performance measurement for accuracy prediction is based on the standard statistical performance evaluation such as the sum of square error (SSE), mean square error (MSE), mean absolute percentage error (MAPE), root mean squared error (RMSE), and correlation coefficient (R). MSE, MAE and R is used in this study due to its different statistical characteristics. In addition, these measurements are the most widely used in time series forecasting.

1.8 Justification of the Research

This thesis presents a new algorithm by modifying and combining models based on GMDH. The new updated and refined GMDH is based on GMDH algorithm and its variation proposed by Zadeh *et al*. (2002). This research is expected to contribute towards the fulfilment of needs to produce a new model of the GMDH model which is more flexible as well as robust than the conventional GMDH, and the obtained results demonstrate the proposed model exhibits higher accuracy in comparison to some previous models available in the literature.

1.9 Organization of Report

This thesis is organized into six chapters. A brief description on the content of each chapter is given below:

(i) Chapter 1 defines the challenges, problems, objectives, scopes and significance of the study.

(ii) Chapter 2 reviews the main subjects of interest, which are time series forecasting model, traditional time series forecasting model such as ARIMA model and artificial intelligence model such as GMDH model, LSSVM model, and ANN model.

(iii) Chapter 3 presents the design of the computational method that supports the objectives of the study. This includes performance measurement, data sources and instrumentations.

(iv) Chapter 4 shows the development of the first proposed model, MGMDH. This chapter describes the steps of the development process for this proposed model. Comparison with previous individual models also implemented to evaluate the performance of this model. The two real data sets and three bench mark data sets are employed to validate this model.

(v) Chapter 5 describes the development of the enhancement of MGMDH model which hybridize MGMDH with GMDH namely, HMGHDH model. This chapter describes the steps of the development process for this hybrid HMGMDH model. Comparison with previous individual models and previous literature models also implemented to evaluate the performance of this model. The two real data sets and three bench mark data sets are employed to validate this model.

(vi) Chapter 6 draws general conclusions of the accomplished results and presents the contributions of the study as well as recommends the potential enhancements for future study.

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