COMBINED FORECAST MODEL INVOLVING WAVELET-GROUP METHODS OF DATA HANDLING FOR DROUGHT FORECASTING

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DEDICATION

To my parents, may their souls rest in peace and make them inherit Al-Janatul Firdausi and my family members

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ABSTRACT

Vigorous efforts to improve the effectiveness of drought forecasting models has yet to yield accurate result. The situation gives room on the use of robust forecasting methods that could effectively improve existing methods. The complex nature of time series data does not enable one single method that is suitable in all situations. Thus, a combined model that will provide a better result is then proposed. This study introduces a wavelet and group methods of data handling (GMDH) by integrating discrete wavelet transform (DWT) and GMDH with transfer functions such as sigmoid and radial basis function (RBF) to form three wavelet-GMDH models known as modified W-GMDH (MW-GMDH), sigmoid W-GMDH (SW-GMDH) and RBF W-GMDH. To assess the effectiveness of this approach, these models were applied to rainfall data at four study stations namely Arau and Kuala Krai in Malaysia as well as Badeggi and Duku-Lade in Nigeria. These data were transformed into four Standardized Precipitation Index (SPI) known as SPI3, SPI6, SPI9 and SPI12. The result shows that the integration of DWT improved the performance of the conventional GMDH model. The combination of these models further improved the performance of each model. The proposed model provides efficient, simple, and reliable accuracy when compared with other models. The incorporation of wavelet to the study results in improving performance for all four stations with the Combined W-GMDH (CW-GMDH) and Combined Regression W-GMDH (CRW-GMDH) models. The results show that Duku-Lade station produced the lowest value of 0.0239 and 0.0211 for RMSE and MAE and highest value of 0.9858 for R respectively. In addition, CRW-GMDH model produce the lowest value of 0.0168 and 0.0117, and the highest value of 0.9870 for RMSE MAE, and R respectively. On the percentage improvement, Duku-Lade station shows improvement over other models with the reductions in RMSE and MAE by 42.3% and 80.3% respectively. This indicates that the model is most suitable for the drought forecasting in this station. The results of the comparison among the four stations indicate that the CW-GMDH and CRW-GMDH models are more accurate and perform better than MW-GMDH, SW-GMDH and RBFW-GMDH models. However, the overall performance of the CRW-GMDH model outweigh that of the CW-GMDH model. In conclusion, CRW-GMDH model performs better than other models for drought forecasting and capable of providing a promising alternative to drought forecasting technique.

ABSTRAK

Pelbagai usaha untuk meningkatkan keberkesanan model peramalan kemarau masih belum memberikan hasil yang tepat. Situasi ini memberi ruang kepada kaedah ramalan teguh yang dapat meningkatkan keberkesanan kaedah sedia ada. Sifat data siri masa yang kompleks tidak memungkinkan penggunaan satu kaedah tunggal sesuai dalam semua keadaan. Oleh itu, model gabungan yang akan memberikan hasil yang lebih baik telah dicadangkan. Kajian ini memperkenalkan wavelet dan kaedah kumpulan mengendalian data (GMDH) dengan mengintegrasi jelmaah gelombang kecil diskrit (DWT) dan GMDH dengan fungsi pemindahan seperti sigmoid dan fungsi radial basis (RBF), untuk membentuk tiga model gelombang kecil GMDH yang dikenali sebagai W-GMDH terubah suai (MW-GMDH), sigmoid W-GMDH (SW-GMDH) dan RBF W-GMDH. Untuk menilai keberkesanan pendekatan ini, model-model tersebut telah digunakan pada data hujan di empat stesen kajian iaitu Arau dan Kuala Krai di Malaysia, serta Badeggi dan Duku-Lade di Nigeria. Data tersebut telah diubah menjadi empat Indeks Pemendakan piawai (SPI) dikenali sebagai SPI3, SPI6, SPI9 dan SPI12. Hasil menunjukkan gabungan DWT telah meningkatkan prestasi model GMDH konvensional. Kombinasi model ini meningkatkan lagi prestasi setiap model. Model yang dicadang telah memberikan ketepatan yang cekap, sederhana dan boleh dipercayai apabila dibandingkan dengan model lain. Penggabungan gelombang kecil dalam kajian ini telah menghasilkan prestasi yang lebih baik untuk keempat-empat stesen dengan model W-GMDH tergabung (CW-GMDH) dan regresi tergabung W-GMDH (CRW-GMDH). Hasil kajian menunjukkan stesen Duku-Lade menghasilkan nilai terendah 0.0239 dan 0.0211 untuk RMSE dan MAE, serta nilai tertinggi 0.9858 untuk R. Tambahan lagi, model CRW-GMDH menghasilkan nilai terendah 0.0168 dan 0.0117, serta nilai tertinggi 0.9870, masing-masing untuk RMSE, MAE dan R. Mengenai peningkatan peratusan, stesen Duku-Lade menunjukkan peningkatan berbanding model lain dengan pengurangan RMSE dan MAE masing-masing sebanyak 42.3% dan 80.3%. Ini menunjukkan model ini sangat sesuai untuk ramalan musim kemarau di stesen ini. Hasil perbandingan di antara empat stesen menunjukkan model CW-GMDH dan CRW-GMDH adalah lebih tepat dan mempunyai prestasi yang lebih baik daripada model MW-GMDH, SW-GMDH dan RBFW-GMDH. Walau bagaimanapun, prestasi keseluruhan model CRW-GMDH mengatasi prestasi model CW-GMDH. Kesimpulannya, model CRW-GMDH adalah berprestasi lebih baik daripada model peramalan kemarau yang lain dan mampu memberikan alternatif yang menjanjikan kepada teknik ramalan kemarau.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial Neural Networks
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
BIC	Bayesian Information Criterion
CWT	Continuous Wavelet Transform
CW-GMDH	Combine Wavelet-GMDH
DWT	Discrete Wavelet Transform
GMDH	Group Method of Data Handling
FT	Fourier Transform
LR	linear regression
MAE	Mean Absolute Error
MSE	Mean Squared Errors
NGMDH	New Group Method of Data Handling
PD	Partial Descriptions
RMSE	Root Mean Square Error
RW-GMDH	Regression Wavelet-GMDH
PACF	Partial Autocorrelation Function
KS	Kolmogorov Smirnov
R	Correlation Coefficient
RBF	Radial Basis Functions
SPI	Standardized Precipitation Index

CHAPTER 1

INTRODUCTION

1.1 Introduction

Time series forecasting can be defined as a process in which statements are made about the actual outcome of events which are not yet observed. It is a decision-making tool or planning tool used to help the management or many businesses in its attempt to handle the uncertainties of the future, which relies mainly on the data obtained from the present and past. Shijin, (2012) described forecasting which feature as one of the vital research areas in the investigation of the hydrological time series. Similarly, Raicharoen and Lursinsap, (2005) stated that time series forecasting can be known as the act of forecasting the future when the past is understood. Time series forecasting generally applied in many research has become a significant method to drought forecasting (Han et al., 2012).

Group method of data handling (GMDH) which remains the focus of this study stands as a kind of inductive systems for computer-based mathematical modeling of multi-parametric datasets that features entirely on automatic structural and parametric optimization of models. The GMDH method which is also known as the polynomial neural network was initially articulated to solve for complex order regression polynomials principally to solve the modeling and classification problem (Ostertagová, 2014). In modeling techniques, the algorithm of GMDH operates and structured as a computer-oriented and heuristic technique which is capable of learning the relationship between the variables. GMDH is a system of developing nonlinear structures which uses several input variables. The GMDH system was originally discovered and offered by an Ukrainian scientist, Ivakhnenko and his Colleagues in 1968 which bring about mathematical models of complex systems to handle data samples with observations (Ivakhnenko, 1971). The intention was to develop a new way of obtaining another stochastic approximation. GMDH is described as a method which can resist the issue of overfitting. It is widely used in route planning, large data analysis, traffic flow prediction and recently in time series forecasting. Many studies conducted with the application of GMDH have proved its importance in the area of time series forecasting. Some of the results use the combined algorithm the GMDH model to improve the forecasting accuracy of the models (Najafzadeh and Barani, 2013).

Drought forecasting is an essential tool used to implement appropriate moderation actions to reduce undesirable impacts on the socioeconomic events of man in a location. The presence of drought forecasting indices for a particular site or a particular area is capable of assisting in improving the decision-making course for drought mitigation because the appropriate actions can be chosen which can be based on the danger connected with the likely evaluation of existing drought conditions. Drought is a most damaging among all the natural hazards (Pulwarty and Sivakumar, 2014) and it is the least understood of the natural disasters. The negative effect of drought becomes noticeable through its effect on a region (Wilhite et al., 2000). The actual end of the drought is difficult to predict (Payus et al., 2020) and what made up of drought differs from one region to another (Sherval and Mcguirk, 2014). With the drought forecasting, the likelihood of drought occurring can be predicted using scientific models by using precipitation indices like the standardized precipitation index (SPI) data series. The drought can create significant economic and social problems in the areas of its occurrence. Insufficient rain can lead to a loss in the crops, diseases in the land and even unemployment due to the declines on human production.

If there is a reduction of water in rivers and lakes, this can lead to the problems on the side of users such as man and animals. The problem of drought on the environment is also an issue on the inhabitants which includes plants other vegetations and human beings. When drought takes place their means of survival on food supply will reduce which can equally lead to the damage of their habitat. Among the negative effects of drought are anxiety, economic losses, conflicts when there is an absence of enough water and loss of human life. Generally, the drought forecasting has not been given the desired attention it deserves in order give room for drought preparedness and the timely notice as mentioned earlier. As a result of this, the emphasis on crisis management, various people have generally moved from one tragedy to another tragedy without any drop in risk which they are likely to encounter (Hayes et al, 1996).

1.2 Background of the Study

Generally, forecasting methods widely used in time series applications can be categorized into two. These are statistical methods and Artificial Intelligence (AI) methods. Statistical methods include simple moving average (SMA), exponential smoothening (ES) and auto-regressive integrated moving average (ARIMA) while AI techniques are Artificial neural networks (ANN), support vector machine (SVM), fuzzy logic, among others. Statistical methods have been used successfully and extensively in time series forecasting for many years in the past (Deb et. al, 2017). These methods are simple and easy to interpret, but not without its limitations. One of the major limitations of this method is its merely described as a linear. It is desirable to fit the data with the available data and the prior knowledge about the relations between the inputs and outputs before modeling process is determined.

The linear modeling which uses the univariate time series modeling approach is based on extracting and by means of information which is implicitly contained in the past data without directly taken into consideration the external factors are becoming increasingly popular because of their rapid development in times together with little requirement of information (Adamowski, 2008; Pai *et al.,* 2010; Chen *et al.*, 2013; Chau and Wu, 2010 and Nourani *et al.*, 2011). Of recent the application of data-driven models is proved to provide accurate prediction with little knowledge of the behavior and criteria of the geographical, hydrological, and physical process (Moosavi et al., 2013).

Nonetheless, the use of only the past time series data having the same variable is analyzed to develop a model. The development of the underlining relationship can reduce the data dimensionality for a given problem being modeled which improves the generalization and forecasting performance. This modeling approach is useful when little knowledge is available on the data generating process or when satisfactory explanatory model which is related to the prediction variable to obtain the explanatory variables are not available. The goal of forecasting time series data is to obtain information about the data to be able to predict future values. Over the years, many efforts have been devoted to the development and improvement of univariate time series forecasting models. One of the popular and extensively used forecasting model is the auto-regressive integrated moving average (ARIMA) model. The popularity of the ARIMA model is due to its statistical properties and the famous Box-Jenkins methodology in the model building process. (Saleh, 2018) and (Al-Douri et al, 2018).

In addition, ARIMA model provides a comprehensive statistical modeling methodology for the input and output processes. It covers a wide range of patterns, which ranges from stationary to nonstationary time series, and has been used widely in the past work (Shabri and Samsudin, 2014b)which has been adopted successfully in many fields such as sciences, engineering, methodology, hydrology and financial studies. ARIMA models originated from the auto-regressive models (AR), the moving average (MA) which gives the combination as ARMA models. However, integrated (I) is added and it becomes ARIMA models. ARIMA model has been highly successful in both areas of academic research and numerous areas of applications during the past four decades. It assumes that the future values of a time series have a linear relationship with the current and past values, hence, approximations by the model may not be adequate for complex nonlinear real-world problems. This is because real-world systems are often nonlinear (Guoqiang et al,. 1998), therefore, it may be unreasonable to assume a realization of a given time series is generated by a linear process.

To address the drawbacks of this linear models, Artificial neural networks (ANN) model is one of the nonlinear models which is often considered in many researches. ANN models have received a global attention in the fields of science and engineering. It represents a class of nonlinear models which is capable of learning from the data itself. It has been used in many areas where statistical methods such as ARIMA are traditionally employed. They have been applied in areas such as pattern recognition, classification, forecast and process control. ANN is being applied in the areas of forecast and classification, where regression and other related statistical methods have been conventionally used(Gunn, 1998). Forecasting, in time series is a common issue. Using statistical approach, Box and Jenkins,(Saleh, 2018)have developed ARIMA methodology for fitting a class of linear time series models.

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Among the studies that has been undertaken using artificial intelligent techniques to improve the accuracy of the time series forecasting problems like Artificial Neural Network (ANN) are contained in the works of(Wei et al., 2016); (Zhang, 2003) and(Chen and Zhu, 2007), GMDH (Kordnaeij et al., 2015); (Kondo et al., 2013) and(Onwubolu et al., 2008).

One sub-model neural networks (NN) are a group method of data handling (GMDH) algorithm which were initially developed by (Ivakhnenko, 1971)for modeling and identification of complex systems. The GMDH model is known as a self-organizing heuristic (experimental) modeling technique. The goal of GMDH is to build an analytical function in a feed-forward network based on a quadratic node transfer function whose coefficients are obtained by using a regression method. The GMDH has the ability of self-selecting the number of layers and self-selecting useful input variables (Yen, 2016).The method offers the advantages of improved performance of forecasting (Adhikari*et al.*, 2013) and (Misra et al., 2009). This model has been successfully used to deal with uncertainty, linear and nonlinear in different disciplines most especially in engineering, science, medical applications, signal processing and control systems (Voss*et al.*, 1999); (Onwubolu et al., 2008); (Kondo et al., 2013) and(Ivakhnenko and Ivakhnenko, 2000).

Most application of GMDH model only implements a second order polynomial since it is a nonlinear model. Such polynomial is referred to as a partial decision (PD) of the GMDH algorithm (Teng et al., 2017a). The PD describes a nonlinear system where it is the transfer function for the GMDH model which consists of only two variables. In 2002, Zadeh et al., presented three different approaches of structural identification of GMDH model for modeling. In the study by Zadeh et al., (2002) indicated that GMDH model with the error driven approach is better than other existing methods. In error driven approach, the number of layers and the number of neurons in each layer is determined according to a threshold value before the GMDH process started and the best performing neuron is combined with previous input variable for the new layer.

To alleviate the problems associated with the GMDH model, many modified methods have been undertaken such as work of (Kondo et al., 2013) modified GMDH model by the introduction of various types of neuron or transfer functions such as sigmoid, RBF function, the high order polynomial, and the linear function. Since these modifications can still be improved upon, the combined forecasting models were considered to further resolve these problems. In achieving this, various models were considered. Among these models, the ones that produces results in terms of measures of performances were combined and compared with the individual models in which the combined models are expected to improve the previous results.

1.3 Challenges of Drought Forecasting

There has been considerable research on modelling various aspects of drought such as identification and prediction or forecasting of its duration and severity. The term severity has various connotations in drought literature such as in hydrological drought, where it is defined as the cumulative shortage or the deficit sum with reference to a pre-specified truncation level. In meteorological drought, the severity has rather been defined in the form of indices such as the Palmer drought severity index. There exist a variety of techniques and methods to analyse the duration and severity of meteorological and hydrological droughts through probability characterization of low flows, time series methods, synthetic data generation, theory of runs, multiple regression, group theory, pattern recognition and neural network methods. Agricultural droughts are analyzed based on soil moisture modelling concepts with crop yield considerations and using multiple linear regression techniques. The prediction or forecasting aspects of drought duration are developed better than the drought severity aspects. Drought means scarcity of water, which adversely affects various sectors of human society, e.g., agriculture, hydropower generation, water supply, industry (Panu and Sharma, 2002).

A useful index for drought forecasting, based only on monthly precipitation, is the Standardized Precipitation Index (SPI); By applying an appropriate forecast method to the precipitation time series and then computing the SPI, it is possible to forecast future drought occurrences (Bordi et al., 2005 and Bordi et al., 2000). On the time scales of droughts, the most commonly used time scale in drought analysis is the year followed by the month (Bonacci, 2018). A major challenge of drought research is to develop suitable methods and techniques for forecasting the onset and termination points of droughts. An equally challenging task is the dissemination of drought research results for practical usage and wider applications.

1.4 Challenges of GMDH Model in Time Series Forecasting

The major goal of time series forecasting is to achieve the best accuracy to be able to make a good decision for any organization. There are limitations to the GMDH model, in cases where it tends to produce a complex polynomial network despite having a reasonably simple input data for the network (Onwubolu et al., 2008). Park *et al.*, (2004) points out whether there sufficiently large number of input variables and data points, GMDH model tends to produce more complex neurons. The complexity of GMDH model increases at each training stage and a selection of a new layer, because of the addition of new input variables. Furthermore, the GMDH model just employ the same quadratic polynomial in each layer.(Park et al., 2004) also introduced a modified GMDH algorithm referred to as self-organizing polynomial neural network (SOPNN) model. The architectures of this model are like feed-forward NN whose neurons are replaced by polynomial nodes. Many types of high-order polynomial called partial decisions (PDs) such as linear quadratic and modified quadratic of variables were used in SOPNN structure. Although the SPNN is structured by a systematic design procedure, it has some drawbacks to be solved. With the availability of small number of input variables, SOPNN does not give good performance (Park et al., 2004).

Having discussed various challenges of drought forecasting and GMDH methods and their drawbacks particularly GMDH model, this research, therefore, focuses on efforts to improve the forecasting accuracy of GMDH model by proposing a Combine GMDH models with wavelet method and further combine GMDH model with regression and compare the results with the existing GMDH and Wavelet-GMDH models for drought forecasting. There are two types of wavelet methods, namely, discrete wavelet transform (DWT) and continues wavelet transform (CWT), the former is simple and easy to compute while the latter is difficult and complex (Heil and Walnut, 1989). This study will focus on the use of DWT.

1.5 Problem Statement

Various researchers have used different methods for drought forecasting such as Mokhtarzad, (2017) used ANN, ANFIS, and SVM. The researchers that used ARIMA for drought forecasting includes Karavitis et al., (2015); Bazrafshan et al., (2015); Mossad and Alazba, (2015); (Han et al., (2012) and Durdu (2010). Those that used hybrid methods such as ANFIS, ARIMA, and wavelet includes Shabri, (2014); Deo, et al., (2016); Belayneh, et al, (2013).So far and to the best knowledge of the researcher, there seems to be no research carried out aimed at using combine wavelet-GMDH model in drought forecasting. However, various works have been done using GMDH in areas such as forecasting rice yields (Ruhaidah et al., 2010); flood forecasting (Badyalina and Shabri, 2015); crude palm oil price (Belayneh et al., 2014) and (Basheer and Khamis, 2017); Runoff forecasting (Moosavi et al., 2017); China's energy consumption forecasting (Liang and Liang, 2017); streamflow forecasting

(Badyalina, 2014), river flow forecasting (Samsudin et al., 2011) time series forecasting (Zhang et al., 2012) and (Shabri and Samsudin, 2014b).

The problems associated with these models that are visible in the literatures include the fact that they could not delve into a large volume of standardized precipitation index (SPI) data which can be overcome by the combined wavelet-GMDH in addressing drought forecasting. Therefore, this current effort is expected to address the issues which are associated SPI which is usually used for drought forecasting. In this aspect previous forecasting models could not address this, hence, the focus on combined wavelet-GMDH model since no study has used the combined wavelet-GMDH model for drought forecasting using SPI. Consequently, the combined wavelet-GMDH forecasting model is expected to address these issues and produce a better result which will improve the forecasting performance when compared with the individual models. Combining forecast models from two or more forecasting models is capable of serving as an alternative to using an individual model (Winkler, 1983).

The strength of combine forecasting model involves its capability to address the pitfalls of individual models since it considered multiple models for its result while as the individual model only considers single model. Robert and Clemen (1989) said whatever method are used, combined forecasting models produce more accurate result compared with individual model. therefore, forecasts accuracy can be improved substantially through the combination of two or more single forecasting models. among the strength of the combined models include its reliability since it involves more forecasting models. if the best model results are selected for combination, it produces are more accurate result and the involvement of multiple models make it a good representation. A combined forecasting model is capable of minimizing the shortcomings of each individual models and allow them to complement each other.

GMDH has shown an improvement when combined with other models. Zadeh et al (2002) combined GMDH model with individual value decomposition and it indicates significant improvement over GMDH model alone. Ruhaidah et al., (2009) proposed combined model with LSSVM and obtained a significantly improved result in the forecast. Of recent wavelet transform has gained popularity since it can produce an encouraging result in the time series. Although GMDH is useful as a statistical tool in many fields but not often in hydrology particularly in drought forecasting. Discrete Wavelet Transform (DWT) has been widely used to improve the forecasting performance for time series models (Wang and Ding, 2003; Kisi and Jala 2010; Kisi and Cimen, 2011 and Salahaldeen *et al.*, 2019).The DWT has several levels of decomposition. There are still lack of methods to determine which decomposition level is suitable for a specific data. GMDH similarly show a significant improvement when combine with genetic algorithm and fuzzy logic (Park *et al.*, 2004 and Ahmadi *et al.*, 2015).

Improving the forecasting accuracy is fundamental and yet it is one of the more difficult tasks faced by the decision-makers in many areas. However, using combine models have become a common practice to improve the forecasting accuracy. Many studies have shown that the combine models can be an effective means to the improvement of the forecasting accuracy when compared with the individual models(Qin *et al.*, 2017 and Wei *et al.*, 2016). The combined method of modeling has improved the performance of traditional models. (Shiri and Kisi, 2010) has proposed the combination of the wavelet transform and linear regression since it is easier to interpret for monthly stream flow forecasting.

The combined model is expected to improve the individual models which is as a result of involvement of more than one model. Panopoulou and Vrontos (2015) in applying combined model is of the opinion that it outperformed the individual forecasting model. The combined forecasting models can reduce errors arising from faulty assumption, bias or mistakes made in the data (Armstrong, 2001). One of the drawbacks of the individual forecasting model is its limitation to only one single model as opposed to the consideration of more models in the combined model.

Accurate and reliable forecasts are extremely important in diversity of applications in any organization in the area of planning and management. The best way to achieve this goal is in the area of selecting the forecasting methods that suites the situation. Having studied the various methods adopted by the different researchers, one of which is the use of the conventional GMDH, the present effort is aimed proposing a more accurate and reliable combine wavelet-GMDH model as a tool for the drought forecasting. This is expected to improve the forecasting potential of the existing models.

Consequently, this study attempts to investigate the accuracy of combining discrete wavelet transform (DWT) and GMDH model and Combine Regression with wavelet-GMDH using the SPI data set. The combination of wavelet and GMDH is to enhance the forecasting accuracy of wavelet-GMDH model. This approach is expected to improve the forecasting ability of the existing GMDH and Wavelet-GMDH models and to reduce the errors.

1.6 Research Questions

This study is driven by three research questions as stated below:

(a) How can the Wavelet-GMDH model enhance drought forecasting?

(b) Can the Combined wavelet-GMDH model contribute to the improvement of drought forecasting?

(c) What is the strength and role of the combined wavelet-GMDH model in relation to the individual models?

The study, therefore, propose a Combined Wavelet-GMDH forecasting modeling procedure with the SPI data series in forecasting drought. The outcome is expected to improve the power of drought forecasting with better performance accuracy.

1.7 Research Objectives

This study is aimed at proposing a Combine Wavelet-GMDH for drought forecasting with traditional ARIMA and conventional GMDH models as benchmark. Specifically, the objectives of the study are:

(a) To develop various Wavelet-GMDH models for drought forecasting

(b) To propose the combination of the Wavelet-GMDH models developed which combines decomposition, data pre-processing and forecasting techniques and its application for drought forecasting with SPI datasets.

(c) To compare the performance of various individual forecasting models with the proposed Combined Wavelet-GMDH forecasting models as a potential application for drought forecasting.

1.8 The Scope of the Study

In this study, the data used were obtained from four distinct irrigation stations in Malaysian and in Nigeria. The stations in Malaysia are Arau and Kuala Krai from Kelantan and Perlis states respectively. From Arau station, 624 datasets for a period of January 1956 and December 2008 were collected. From Kuala Krai station, 384 datasets for a period of January 1975 and December 2008 were collected. Stations in Nigeria are Badeggi and Duku-Lade from Niger and Kwara states respectively. From Badeggi station, 600 observations for a period of January 1968 and December 2018 were collected and from Duku-Lade station, 580 observations were obtained for a period of January 1992 and December 2016, were collected. The study used these data which are mainly from the rainfall in mm and converted to standardized precipitation index SPI) data series used to build the models and used as a tool for the drought forecasting at the four stations.

In this thesis, the wavelet GMDH model is based on the traditional GMDH model which is combined with the wavelet. The comparison models are ARIMA, W-ARIMA, GMDH, W-GMDH, Modify GMDH, Modify W-GMDH, Sigmoid GMDH, Sigmoid W-GMDH, RBF GMDH and RBF W-GMDH. Lastly, the combination of the best three models (MW-GMDH, Sigmoid W-GMDH and RBF W-GMDH) was done to produce the combined model. Further to that a regression was carried out to obtain the overall best model.

1.9 Significance of the Study

Although several studies have been conducted on drought forecasting, but so far to the best knowledge of the researcher, very few has worked using the combine wavelet-GMDH and Combine Regression Wavelet-GMDH model for drought forecasting using SPI data. Therefore, the present effort attempts to develop various wavelet-GMDH models with their transfer functions obtained as a tool for drought forecasting. To achieve this, the various SPI data series will be used in building the combined wavelet-GMDH forecasting models. In the final analysis, three best models were combined to obtain the Combined forecasting model using SPI data sets. The results obtained are expected to demonstrate a higher accuracy and improvement when compared with the individual models. The combined wavelet-GMDH forecasting model is more effective in drought forecasting because of the involvement of multiple individual models which makes it a good representation to obtain the proposed combined model.

1.10 Organization of Thesis

The thesis is made up of six chapters which were discussed accordingly, followed by references and then appendices.

Chapter 1 defines the background, challenges, problems, research questions, research objectives, the scope, the significance and lastly, thesis organization.

Chapter 2 reviews the main subjects of the study, these include the forecasting models, time series forecasting, SPI data and drought forecasting.

Chapter 3 discusses the research methodology used in the study. These include the design of the computational techniques that support the objectives of the study. Other areas such as performance evaluation measures, source of data and instrumentation are discussed.

Chapter 4 gave the description of the study areas and the collected data both in Malaysia and Nigeria.

Chapter 5 contains the analysis and comparison of the model results for the four study stations involving SPI datasets. The results are compared based on models and the stations.

Chapter6 presents the summary, conclusion, contribution, and recommendation which includes the suggestions for future work with regards to the continuation of the research in the area of this Group Method of Data Handling (GMDH) methodology. And finally, the references and appendix of the thesis.

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LIST OF PUBLICATIONS

Journal Publications

1. Mohammed Salisu Alfa, Ani Bin Shabri, Muhammad Akram Shaari (2019). A Wavelet-ARIMA Model for Drought Forecasting using SPI Data. International Journal of Emerging Technology and Advanced Engineering Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 9, Issue 10.

2. Mohammed Salisu Alfa, Ani Bin Shabri, Muhammad Akram Shaari (2019). Drought Forecasting using Wavelet-GMDH Model with Standardized Precipitation Index International. Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-4.

3. Mohammed Salisu Alfa and Ani Bin Shabri, (2019). Forecasting Drought with ARIMA model and Standardized Precipitation Index (SPI). Science Proceedings Series (SPS) www.readersinsight.net/SPS

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