A HYBRID GROUP METHOD OF DATA HANDLING WITH DISCRETE WAVELET TRANSFORM FOR RIVER FLOW FORECASTING

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To my beloved father and mother

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ABSTRACT

River flow forecasting is important because it can assist an organization to make better plans and decision makings. One of the major goals in river flow forecasting is to improve the planning, design, operation and management of hydrology and water resources system. This study proposes designing a hybridization model using Group Method of Data Handling (GMDH) and Discrete Wavelet Transform (DWT) for forecasting monthly river flow in three catchment areas in Malaysia. The monthly data of river flow in the form of monthly means are collected from the Department of Irrigation and Drainage, Malaysia. The hybrid model is a GMDH model that uses sub-time series components obtained using DWT on original data. The original data is represented by its features, which term the wavelet coefficients that are then iterated into GMDH model. The individual GMDH is used to forecast the river flow for each single catchment area. The experiments compare the performances of a hybrid model and a single model of Wavelet-Linear Regression (WR), ANN, and conventional GMDH. The results show that the hybrid model performs better than other models for river flow forecasting. It is shown that the proposed model can provide a promising alternative technique in river flow forecasting.

ABSTRAK

Peramalan aliran sungai adalah penting kerana peramalan boleh membantu pengurusan untuk perancangan dan membuat keputusan yang lebih baik. Salah satu matlamat utama dalam peramalan aliran sungai adalah untuk mempertingkatkan pengurusan, rekabentuk, operasi dan pengurusan sumber pengairan. Kajian ini memperkenalkan suatu model hibrid menggunakan Kaedah Kumpulan Pengendalian Data (KKPD) dan Ubahan Wavelet Diskret (UWD) bagi meramal aliran sungai bulanan di tiga kawasan tadahan di Malaysia. Data bulanan aliran sungai dalam bentuk min bulanan diambil dari Jabatan Pengairan dan Saliran, Malaysia. Model hibrid ini adalah model KKPD yang memperolehi sub-komponen siri masa melalui data asal dari UWD. Sifat data asal diwakilkan dan diubah menjadi pembolehubah wavelet, yang kemudiannya disalurkan ke dalam model KKPD. Model KKPD yang dibentuk seterusnya digunakan untuk meramal aliran sungai bagi setiap kawasan tadahan. Eksperimen ini membandingkan pencapaian antara model hibrid dan model-model seperti Wavelet-Regressi Linear (WR), ANN, dan asas KKPD. Keputusan menunjukkan bahawa model hibrid berupaya menghasilkan prestasi yang lebih baik berbanding model lain untuk ramalan aliran sungai. Ini menunjukkan bahawa model yang dicadangkan adalah satu teknik alternatif yang baik dalam ramalan aliran sungai.

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LIST OF SYMBOLS

x	-	Input to the system of the model
M	-	Number of inputs for the model
a	-	Coefficients or weights for the model/
y_t	-	Normalized Data
x_t	-	Original Data
$x_{\max}$	-	The Maximum Values among the Original Data
$\beta_0, \beta_1, \ldots, \beta_p$		The parameters
$x_1, \ldots, x_p$		The predictor variables
y	-	The response
p	-	The associated values on x
ε_p	-	The error term
α	-	The alpha value
H_0	-	Null Hyphothesis
n	-	Independent observations
σ^2	-	Variance,
x_k	-	The input selection variables
N	-	Sample size/Number of observations
i	-	The lagged for each scatter plot

r_k	-	The autocorrelation coefficient at lag, *k*
c_k	-	The autocovariance coefficient at lag *k*
z	-	Prediction variable
$(x_1, x_2, ..., x_M)$		Input vector **X**
$[a_0, a_1, ..., a_5]$		The vector of unknown coefficients
$[y_1, y_2, ..., y_M]^T$		Transpose the vector of output's value
x_t	-	The input at *t* of the model
j	-	The hidden unit neurons
t	-	The number training pattern
$e_j(t)$	-	Error signal at the output of neuron *j* for iteration *t*
$d_j(t)$	-	The desired response for neuron *j*
$y_j(t)$	-	The function signal appearing at the output of neuron *j* at iteration *t*.
$\xi(t)$	-	The instantaneous value
$\xi_{av}(t)$	-	The average squared error
$v_j(t)$	-	The net internal activity level
i	-	Input unit layer in the network
w_{ji}	-	Weight connecting the output of neuron *i* to the input of neuron *j*
$y_i(t)$	-	The function signal appearing at the output of input unit neuron *i* at iteration *t*.
θ_j	-	The threshold
η	-	The rate of learning
$\delta_j(t)$	-	The local gradient for output neuron *j*
$\varphi(.)$	-	Sigmoid transfer function
w_{kj}	-	Weight from output of hidden neuron *j* to the input of output neuron *k*
$\Re$	-	The domain of real numbers
ψ (t)	-	The mother wavelet

b	-	location parameter
a	-	scaling parameter
$f(t)$	-	Time series
$\varphi\ (t)$	-	Set of real valued functions at t
l	-	An integer index
m	-	Valued expansion coefficient
y_t	-	Observed monthly mean river flow at the time t
$\hat{y}_t$	-	Forecasted monthly mean river flow at the time t
x_{mean}	-	The overall mean
S_x,	-	Standard Deviation
C_{sx}	-	Skewness
x_{min}	-	minimum
x_{max}	-	maximum

LIST OF ABBREVATIONS

ACF	-	Autocorrelation Function
AIC		Akaike Information Criterion
ANFIS		Adaptive Neuro-Fuzzy Inference Systems
ANN	–	Artificial Neural Network
AR		Autoregressive
ARMA	–	Autoregressive Moving Average
ARMAX		Autoregressive Moving Average Exogenous Variables
BL		Bilinear
BP	-	Back Propagation
CAT		Computer Aided Tomography
CWT		Continuous Wavelet Transform
Db1		the First Type of Daubechies Wavelet
D		Resolution Levels of Discrete Wavelet Transform
DE		Differential Evolution
DWT		Discrete Wavelet Transform
FFN	-	Feed Forward Network
FPNN		Fuzzy Polynomial Neural Networks
FSPN		Fuzzy Set-based Polynomial Neuron
GA		Genetic Algorithm
GAGMDH		Modified GMDH and GA
GMBA		GMDH and Bayesian classification
GMDH		Group Method of Data Handling
GRNN		Generalized Regression Neural Networks
LR		Linear Regression
MAE	-	Mean Absolute Error
MIA-GMDH		Multilayered Iterative Algorithm
MLP	-	Multilayer Perceptron

MOGMDH		Multi-Objective GMDH
MSE	-	Mean Square Error
PD		Partial Descriptions
PSO		Particle Swarm Optimization
PSS		Prediction Sum of Squares
R	-	Correlation Coefficient
RBF		Radial Basis Functions
RMSE	-	Root Mean Square Error
SVD		Singular Value Decomposition
WGMDH		Wavelet and GMDH
WR		Wavelet-Linear Regression

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CHAPTER 1

INTRODUCTION

1.1 Overview

The hydrology system is a highly complex nonlinear system under the influence of rain bringing the effect for bearing system and underlying surface system (Zhou et al., 2008). The truthful modeling of hydrological process such as rainfall and stream flow can give effective information for city planning, land use, flood and water resources management for a watershed. In need of efficient management, forecasting of future events is required in the many of the activities associated with planning and operation of the components of a water resource system require. Forecasting also plays an important role in the mitigation of impacts of drought on water resources systems. There is a need for both short term and long term forecasts of stream flow events for the hydrologic component in order to optimize the system or to plan for future expansion or reduction. The storage yield sequences are generally related to monthly periods. River flow forecasting is one of the most important components of hydrological processes in water resource management. Forecasting in river flow would solve the problems in designing flood protection works and environmental flows could be preserving too.

Therefore, monthly river flow forecast has a greater importance for water resource system planning.

The government and water authorities can administer and organize water reserves optimally for such water users as hydropower generation, agricultural, domestic and for the maintenance of environmental flows through a dependable and steady river flow forecast. Forecasting river flow is extremely being helpful in the case of multipurpose reservoirs systems. It is essential for forecasting flow in predicting the less amount carried by the river to the reservoirs. Therefore many hydrological models have been proposed in order to inspire this complex process and these models have presented a complete classification. (Nourani et al., 2009).

The accuracy of time series forecasting is fundamental to many decisions processes and thus the research has never been refrained for improving the effectiveness of forecasting models (Zhang, 2003). Traditionally, the class of autoregressive moving average (ARMA) models has been statistical method most widely used for modeling water resources time series (Maier and Dandy, 1996). Time series models are used to describe the stochastic structure of the time sequence of river flows and precipitation values measured over time in river flow forecasting. The only information they incorporate is present in past flows and therefore it inflicted the limitation of time series models river flow forecasting. Many of the available techniques for time series analysis assume linear relationships among variables. In the real world, however temporal variations in data do not exhibit simple regularities and are difficult to analyze and predict. It seems necessary that nonlinear models such as Artificial Neural Network (ANN) be used for the analysis of real world temporal data which ANN is very much suited to complex nonlinear problems (Kisi et al., 2005). ANN showing the differences from the traditional approaches in synthetic hydrology in the sense that they belong to a class of data-driven approaches.

Recently, wavelet transform analysis has become a popular analysis tool due to its ability to explain simultaneously both spectral and temporal information within the signal. This overcomes the basic shortcoming of Fourier analysis, which is that the Fourier spectrum contains only globally averaged information. Therefore, the time series can decompose data into its subcomponents using wavelet transform analysis. The wavelet transformed data can be improve the ability of a forecasting model when wavelet transforms provide useful decompositions of main time series by capturing useful information on various resolution levels. The wavelet decomposition of non stationary time series into different scales provides an interpretation of the series structure and extracts the significant information about its history using few coefficients. Currently, it was reported that a hybrid system in prediction and classification could produce a higher performance level against the traditional system (Min, et *al*, 2006; Chang and Chang, 2006; Lekakos and Giaglis, 2007; Kim and Shin, 2007). The application of hybridization between ANN method and the wavelet transform for river flow forecasting has been widely implemented in recent years (Wang et al., 2006; Kisi et al., 2009). It is due of reason that, ANN are nonlinear data driven methods thus, it suit well to nonlinear input-output mapping techniques. ANNs have black box properties thus, it does not require a prior knowledge of the process (Nourani et al., 2009). Sometimes there is a shortage when signal from original data are highly non stationary and physical hydrologic process operates under a large range of scales varying from one day to several decades in spite, of suitable flexibility of ANN in modeling hydrologic time series, (Hsu et al., 1995; Zhang and Dong, 2001).

Kisi (2009) had proposed by combining the wavelet transform and regression since the hybrid model is much easier to interpret as an alternative to ANN for monthly stream flow forecasting. However, the disadvantage of regression analysis is its amplifying frequency noise in the data when differencing (Wang et al., 2009). Consequently, lots of researches had tried to apply the artificial intelligent techniques to improve the accuracy of the time series forecasting issues named Group Method of Data

Handling (GMDH: Kalantary et *al*, 2009; Wongseree et *al*., 2007; Onwubolu, 2008). The GMDH algorithm had been widely applied in time series forecasting because of its self organizing and adaptive learning. Furthermore, GMDH produce minimum value of external criterion and require less time to run the algorithm than ANN itself.

Thus, in improving the performance of GMDH algorithm, the combination between GMDH algorithm and wavelet analysis is exploring in this study.

1.2 Background of the Problem

There exits some linear and nonlinear patterns in time series simultaneously because of the effect from the world that is complex. There were many research on hybridization between the wavelet transform and ANN (Cannas et al., 2006; Wang and Ding, 2003; Kim and Valdes, 2003) because ANN is a self learning network and also functional as self adaptive approximate function. ANN has shown great ability in modeling and forecasting nonlinear hydrological time series. However, in such situation, ANN has problem which the algorithm is slow in converging and may not be able to cope with non stationary data if pre processing of the input and output data is not performed. Kisi (2009) had presented the combination between the wavelet transform and linear regression model in order to solve the problem on ANN. In spite of proposing a new solution, threshold regression model is developed by setting restrictions on variables and therefore, the regression model cannot fully explain many complex hydrological data sets. To solve the problems, one of the first approaches along the line of a systematic design of nonlinear relationships between system’s inputs and outputs comes under the name of a group method of data handling (GMDH) (Ivakhnenko et al., 1971).

Recently the group method of data handling (GMDH) algorithm has been successfully used to deal with uncertainty, linear or nonlinearity of systems in a wide range of disciplines such as economy, ecology, medical diagnostics, signal processing, hydrology and control systems (Oh and Pedrycz, 2002; Nariman-Zadeh et al., 2002; Delivopoulos et al., 2004; Kondo, T et al., 2005, 2006; Onwubolu, 2009). The prediction accuracy was surprising successful for researchers who used the GMDH in modeling. The GMDH algorithm can be devoted to developing polynomial structure for modeling highly nonlinear systems with large number of inputs. The GMDH models are layered structures that exhibit a number of significant advantages as contrasted to other nonlinear modeling techniques.

The GMDH algorithms are self organizing networks developed in a layer by layer basis, following a systematic expansion procedure. The performance of GMDH can be determined by controlling the network depth. Accordingly, by combining successively the low order regressions in layers to achieve higher order polynomials until the system's dynamics is captured to an adequate level of accuracy in controlling the network depth (Ivakhnenko et al., 1971).

However, owing to its limited generic structure, GMDH tends to generate an overly complex polynomial when it is applied to estimate highly nonlinear systems (Oh *et al*., 2003). The main characteristics of GMDH are that it is self-organizing and provides an automated selection of essential input variables without using prior information on the relationship among input-output variables. The output of each node in GMDH structure is obtained using several types high-order polynomial such as linear of quadratic of input variables. GMDH have fewer nodes than Artificial Neural Networks (ANNs), but the nodes are more flexible.

The GMDH algorithms consists the structural parameters such as the number of neurons in each layer, the number of layers and the useful input variables are automatically determined so as to minimize the prediction error criterion. In this study, in addressing the problems with the conventional GMDH based on quadratic polynomial, we propose that the combination GMDH with wavelet decomposition. The modified GMDH also will be tested using application data and compared to the conventional GMDH. The accuracy of outcome from the forecasting models can improve by hybridizing between the forecasting models distinctly compared with single forecast models (Liu and Wang, 2009).

There have been variants devised from different perspectives to realize more competitive networks and to alleviate the problems inherent with the GMDH algorithms. It includes hybridize the GMDH with intelligent model such as Genetic Algorithms and Fuzzy Logic (Oh et al., 2002; Nariman-Zadeh et al., 2002). Kim et al., (2009) proposed neuro-fuzzy GMDH algorithm and Shinohara et al., (1999) introduced the hybridized between Akaike Information Criterion (AIC) and the GMDH algorithm. Xiao et al., (2009) presented combination GMDH and Bayesian classification then named as GMBA. This study will carry out on hybridized wavelet decomposition and GMDH algorithm. The main motivation of using wavelet decomposition is the easy analysis of the obtained series (Soltani et al., 2002). To the writer’s knowledge, there is not any published work indicating the input output mapping capability of the combination wavelet decomposition and GMDH algorithm in forecasting of monthly mean river flow in Malaysia.

1.3 Problem Statement

The GMDH algorithm is a heuristic and computer oriented method which provides the foundation for the construction of high order regression models of complex system. The basic building block of GMDH is a quadratic polynomial of two 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 certain selection.

The algorithm can automatically organize the modified GMDH fitting the complexity of the nonlinear system and structural parameters such as the number of neurons in each layer, the number of layers and the useful input variables are automatically determined so as to minimize the error criterion (Kondo and Pandya et al., 2007). Moreover, the modified GMDH can generate different nonlinear combinations of input and select useful combinations so that the high-order effects of input suiting the complexity of the nonlinear system.

Hybridization of existing competitive modeling methodologies is now an active area of research. For example, Oh et al. (2003) proposed and investigated a new category of neurofuzzy networks- Fuzzy Polynomial Neural Networks (FPNN) endowed with fuzzy set-based polynomial neurons (FSPNs) in which they developed a comprehensive design methodology involving mechanisms of genetic optimization, and Genetic Algorithms (GAs) in particular. Nariman-Zadeh et al.(2002) applied GA and singular value decomposition (SVD) in the topology design of GMDH to reduce the size of search space for evolutionary design of GMDH. Onwubolu et al.(2009) introduced a hybrid of GMDH and differential evolution (DE) to predict burr types formed during face milling. Also Ruhaidah et al. (2009) proposed combining based on the modified GMDH and GA then called GAGMDH to improve the forecasting capability of the model compared with optimal simple combining forecasting methods and neural networks combining forecasting methods.

However, there is no further research investigating the GMDH algorithm combined with the wavelet decomposition thus far. Hence, this research will provide further investigation on the hybridizing GMDH to improve the performance of the standard GMDH approach. The wavelet is applied to the data while GMDH iterates the filtered data through in order to find the best function that maps the input to output.

1.4 Objectives of the Study

The objectives of this study are:

1. To explore the hybridized wavelet decomposition into the GMDH (WGMDH) model in order to achieve better accuracy in the performance of the standard GMDH approach
2. To compare the performance of the combination GMDH model with the conventional GMDH and the benchmarked individual model, ANN.

1.5 Scope of the study

In this research, the data were collected from Department of Irrigation and Drainage, Ministry of Natural Resources and Environment, Malaysia. These data is used to validate the WGMDH algorithm for 1-month-ahead mean river flow forecasting modeling. The results are compared with those the Wavelet-Linear Regression (WR), ANN and GMDH. These time series come from different locations and have different statistical characteristics.

In this study, the mean monthly river flow data of Jeniang Station, Muda River in Kedah, Jam SKC Station, Bernam River in Selangor and Rahang Station, Linggi River in Negeri Sembilan of Malaysia are used. The drainage area at Jeniang Station is 1710 km^2. The observed data is 48 years long with an observation period between 1961 and 1988 for Jeniang station. The drainage area at Jam SKC Station is 1090 km^2. The observed data is 43 years long with an observation period between 1966 and 2008 for Jam SKC station. The drainage area at Rahang Station is 523 km^2. The observed data is 11 years long with an observation period between 1961 and 1971 for Rahang station.

The performance measurement for accuracy prediction is based on the standard statistical performance evaluation such as mean absolute percentage error (MAE), root mean squared error (RMSE) and correlation coefficient. RMSE and MAE are the most widely used performance evaluation criteria and will be used in this research.

1.6 Significance of the Study

This research is expected to contribute towards the fulfillment of needs to produce a new architecture 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 and superb predictive capability in comparison to some previous models available in the literature.

REFERENCES

Abbod., M and Deshpande, M. (2008). Using Intelligent Optimization Methods to Improve the Group Method of Data Handling in Time Series Prediction. *Berlin:Springer*. 16-25.

Adamowski, J.F. (2008). River Flow Forecasting using Wavelet and Cross-Wavelet Transform Models. *Hydrological Process*. 22, 4877-4891.

Addison, P.S., Murrary, K.B., and Watson, J.N. (2001). Wavelet Transform Analysis of Open Channel Wake Flows. *Journal Engineering Mechanical*. 127(1), 58-70.

Addison, P.S. (2002). *The Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science, Engineering, Medicine and Finance*. (First Edition). Taylor and Francis Group,LLC:NY.

Anctil, F., and Tape, D.G. (2004). An Exploration of Artificial Neural Network Rainfall-Runoff Forecasting Combined with Wavelet Decomposition. *Journal Environment Engineering Science*. 3, 5121-5128.

Antar, M. A., Elassiouti, I., and Allam, M.N. (2006). Rainfall-Runoff Modeling using Artificial Neural Networks Technique: A Blue Nile Catchment Case Study. *Hydrology Process*. 20, 1201-1216.

Aussem, J.C.A. and Murtagh, F. (1998). Wavelet-based feature extraction and decomposition strategies for financial forecasting. *Journal of Computational Intelligence in Finance*, 6,5-12.

Aussem, A. and Murtagh, F. (1997). Combining Neural Network Forecasts on Wavelet Transformed Time Series. *Connection Science,* 9, 113-122.

Aussem, A. and Murtagh,F. (1998). A Neuro-Wavelet Strategy for Web Traffic Forecasting. *Journal Official Statistics*. 1,65-87.

Aussem, A. and Murtagh,F.(2001). Web Traffic Demand Forecasting using Wavelet-based Multiscale Decomposition. *International Journal Computer Intelligence System*. 16,215-236.

Barron, A., and Baron, A. (1988). Statistical Learning Networks: a Unifying View. *Proceeding 20th Symp. Interface*. 192-203.

Bayazit, M., and Aksoy, H. (2001). Using Wavelets for Data Generation. *Journal Applied Statistics*. 28(2), 157-166.

Bayazit, M., Onoz, B., and Aksoy, H. (2001). Nonparametric Streamflow Simulation by Wavelet or Fourier Analysis. *Hydrology Science Journal*. 46(4), 623-634.

Bernouda, D., Murtagh, F., Renaud,O. and Starck J.L. (2006). Wavelet based Nonlinear Multiscale Decomposition Model for Electricity Load Forecasting. *Neurocomputing*, 70(1-3),139-154. Elsevier Science B.V.

Brockwell, P. and Davis, A. (2002). *Time Series: Theory and Methods*. (Second Edition). Springer Series in Statistics: New York.

Burrus, C.S., Gopinath,R.A., and Guo, H. (1998). *Introduction to Wavelets and Wavelet Transforms*. (First Edition). Upper Saddle River, NJ: Prentice Hall-Inc.

Buryan, P., and Onwubolu, G.C. (2008). Design of Enhanced MIA-GMDH Learning Networks. *International Journal System Science.*

Cannas, B., Fanni, A., Sias, G., Tronei, S., and Zedda, M.K. (2005). River Flow Forecasting using Neural Networks and Wavelet Analysis. *E.G.U, European Geosciences Union, Vienna: Austria*, 24-29.

Cannas, B., Fanni, A., See, L., and Sias, G. (2006). Data preprocessing for River Flow Forecasting using Neural Networks, Wavelet Transforms and Data Partitioning. *Physics Chemical Earth*, 31(18), 1164-1171.

Chan, K.P., and Fu, A.W.C. (1999). Efficient Time Series Matching by Wavelets. *Data Engineering, Proceedings 15th International Conference on IEEE*. 126-133.

Chang, F.J., and Hwang, Y.Y. (1999). A Self-Organization Algorithm for Real-Time Flood Forecast. *Hydrological Processess*. 13,123-138.

Chang, F.J., and Chen, Y.C. (2001). A counterpropagation Fuzzy-Neural Network Modeling Approach to Real Time Streamflow Prediction. *Journal Hydrology*. 245, 153-164.

Chau, K.W., Wu, C.L., and Li, Y.S. (2005). Comparison of Several Flood Forecasting Models in Yangtze River. *Journal Hydrology Engineering*. 10(6), 485-491.

Chau, K.W. (2006). Particle Swarm Optimization Training Algorithm for ANNs in Stage Prediction of Shing Mun River. *Journal Hydrology*. 329 (3-4), 363-367.

Chen, T.P., and Chen, H. (1995). Approximation Capability to Functions of Several Variables Nonlinear Functionals and Operators by Radial Basis Function Neural Network. *IEEE Transactions Neural Network*. 6(4), 904-910.

Chen, S.Y., Wang, W., and Qu, G.F. (2004). Combining Wavelet Transform and Markov Model to Forecast Traffic Volume. *International: Proceedings of the Third International Conference on Machine Learning and Cybernatics, Shanghai*. 2815-2818.

Chen, Y., Yang, B. and Dong, J. (2006). Time Series Prediction using a Local Linear Wavelet Neural Network. *Neurocomputing*, 69 (6), 449-465. Elsevier Science B.V.

Cheng, C.T., and Chau, K.W. (2001). Fuzzy Iteration Methodology for Reservoir Flood Control Operation. *Journal Am. Water Resource Association*. 37(5), 1381-1388.

Cheng, C.T., Lin, J.Y., Sun, Y.G., and Chau, K.W. (2005). Long-Term Prediction of Discharges in Manwan Hydropower using Adaptive-Network-Based Fuzzy Inference Systems Models. *Lectures Notes Computing Science*. 3612, 1152-1161.

Chou, C.M., and Wang, R.Y. (2002). On-line Estimation of Unit Hydrogaphs using the Wavelet-based LMS Algorithm. *Hydrological Sciences Journal.* 47(4), 721-738.

Chou, C.M., and Wang, R.Y. (2004). Application of Wavelet Based Multi Model Kalman Filters to Real Time Flood Forecasting. *Hydrology Process*. 18, 987-1008.

Chu, K.W., Lam, S.K., and Wong, M.H. (1999). An Efficient Hash-based Algorithm for Sequence Data Searching. *The Computer Journal*.

Cigizoglu, H.K., Melcalfe, A., and Adamson, P.T. (2002). Bivariate Stochastic Modeling of Ephemeral Streamflow. *Hydrology Processing*. 16(7), 1451-1465.

Cigizoglu, H.K. (2003). Estimation, Forecasting and Extrapolation of Flow Data by Artificial Neural Networks. *Hydrology Science Journal*. 48(3), 349-361.

Cigizoglu, H.K. (2005). Application of Generalized Regression Neural Networks to Intermittent Flow Forecasting and Estimation. *Journal Hydrology Engineering*. 10(4), 336-341.

Cigizoglu, H.K., and Kisi, O. (2005). Flow Prediction by Three Back Propagation Techniques using K-Fold Partitioning of Neural Network Training Data. *Nord. Hydrology*. 36(1), 49-64.

Coulibaly, P., Anctil, F., and Bobee, B. (2000). Daily reservoir Inflow Forecasting using Artificial Neural Networks with Stopped Training Approach. *Journal of Hydrology*. 230, 244-257.

Coulibaly, P., and Burn, H.D. (2004). Wavelet Analysis of Variability in Annual Canadian Streamflows. *Water Resource Research*. 40(3), 1-14.

Coulibaly, P., and Evora, N.D. (2007). Comparison of Neural Network Methods for Infilling Missing Daily Weather Records. *Journal Hydrology*. 341, 27-41.

Cristea, P., Tuduce, R., and Cristea, A. (2000). Time Series Prediction with Wavelet Neural Networks. *Fifth Seminar on Neural Network Applications in Electrical Engineering*. 5-10.

Daliakopoulos, I.N., Coulibaly, P., and Tsanis, I.K. (2005). Groundwater Level Forecasting using Artificial Neural Networks. *Journal Hydrology*. 309,229-240.

Dash, P.K., Nayak, M. and Senapati, M.R. (2007). Mining for Similarities in Time Series Data using Wavelet based Feature Vectors and Neural Networks. *Engineering Applications of Artificial Intelligence*, 20 (2), 185-201. Elsevier Ltd.

Dash, P.K., Panigrahi, B.K. and Panda, G. (2003). Power Quality Analysis using S-transform. *IEEE Transactions on Power Delivery*. 18(2), 406-411.

Daubechies,I. (1988). Orthonormal bases of Compactly Supported Wavelets.*Communication Pure Application Maths XLI*,909-996.

Daubechies, I. (1992). *Ten Lectures Of Wavelets*. SIAM Press,357.

Daubechies, I. (1990). The Wavelet Transform, Time Frequency Localization and Signal Analysis. *IEEE Transactions on Information Theory*. 36(5),961-1005,September.

Drago, A.F. and Boxall, S.R. (2002). Use of the Wavelet Transform on Hydro Meteorological Data. *Physics and Chemistry of the Earth* 27,1387-1399.Elsevier Science Ltd.

Drago, A.F. (1999). *A Study on the Sea Level Variations and the Milghuba Phenomenon in the Coastal Waters of the Maltese Islands*. Doctor Philosophy. University of Southampton.

Faloutsos, C., Ranganathan, M., and Manolopoulos, Y. (1994). Fast Subsequence Matching in Time-Series Databases. *Proceedings of the ACM SIGMOID Conference on Management of Data.* 419-429.

Feng,G. (1998). A Method for Simulation of Periodic Hydrologic Time Series using Wavelet Transform. Stochastic Models for Hydrological Processes and Their Applications to Problems of Environmental Preservation. *Proceedings NATO Advanced Research Workshop*. Novermber 23-27, Moscow, Rusia.

Foufoulla-Georgiou, E. and Kumar,P. (1995). *Wavelets in Geophysics*. Academic Press,373.

Frand, H., Jane, B.G., and Hui, M. (2001). Consolidation of Human Memory over Decades Revealed by Functional Magnetic Resonance Imaging. *Nature Neuroscience*. 4(11). 1139-1145.

Fryzlewics, P.Z. (2003). *Wavelet Techniques for Time Series and Poisson Data*. Doctor Philosophy. University of Bristol.

Fu, Y.X. and Liu,Z.Q. (2003). Analytic Method and Application about Chaotic Slope Deformation Destruction Time Series. *Journal of Wuhan University of Technology (Transportation Science and Engineering),* 27(4),473-476.

Gabor, D. (1946). Theory of Communication. *Journal of the Institute of Electrical Engineers*. 93(22).429-457.

Galvao, R.K.H., Takshi, Y., and Tania, N.R. (1999). Signal Representation by Adaptive Biased Wavelet Expansions. *Digital Signal Processing*. 9(4), 225-240.

Gaouda, A.M., Salama, M.M.A., Sultan, M.R. and Chikhani, A.Y. (1996). Power Quality Detection and Classification using Wavelet Multiresolution Signal Decomposition. *IEEE Transactions on Power Delivery.* 14,1469-1476.

Gaouda, A.M., Salama, M.M.A., Sultan, M.R. and Chikhani, A.Y. (2000). Wavelet-based Intelligent System for Monitoring Non Stationary Disturbances. *Proceedings of the International Conference on Electric Utility Deregulation and Restructing and Power Technologies*. 84-89.

Haofei, Z., Guoping, X., Fangting, Y., and Han, Y. (2007). A Neural Network Model based on the Multistage Optimization Approach for Short Term Food Price Forecasting in China. *Expert Systems with Applications*. 33,347-356.

Haykin, S. (1994). *Neural Networks: A Comprehensive Foundation*. (First Edition). Maxwell Macmillan N.Y: Macmillan College Publishing Company.

Hocking, R.R. (2003). *Methods and Applications of Linear Models: Regression and the Analysis* of Variance. (Second Edition). Wiley Series in Probability and Statistics, New Jersey: John Wiley and Sons Inc.

Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer Feedforward Networks are Universal Approximators. *Neural Networks 2*. 2,359-366.

Hsu, K., Gupta, H.V., and Sorooshian, S. (1995). Artificial Neural Network Modeling of Rainfall-Runoff Process. *Water Resource Research*. 31, 2517-2530.

Huang, S.J., and Shih, K.J. (2002). Application of a Fuzzy Model for Short-Term Load Forecast with Group Method of Data Handling Enhancement. *Electrical Power and Energy Systems*. 24, 631-638.

Huang, Z.X., and Wu, F.P. (2003). Present Development of China's Insurance and the Calculation of Its Fee Scale. *Forecasting*. 22(2).

Huang, W., Xu, B., and Hilton, A.C. (2004). Forecasting Flows in Apalachicola River using Neural Networks. *Hydrological Process*. 18(13), 2545-2564.

Huang, Z.Q. and Fan, J.L. (2005). A Prediction Method of Chaotic Time Series for Slope Deformation. *Journal of Engineering Geology*,13(2),252-256.

Huang, W., Wang, Y., Xu, R., and Xie, H. (2006). Research on Fan Fault Forecasting based on Wavelet Analysis and Support Vector Machine. *Metal Machine*. 358, 55-58.

Hwang, C. and Chen,S. (2000). Fourier and Wavelet Analysis of Topex/Poseidon Derived Sea Level Anomaly over the South China Sea: a Contribution to the South China Sea Monsoon Experiment. *Journal Geology Research*.105 (C12), 28785-28804.

Ikeda, S., Ochiai, M., and Sawaragi, Y. (1976). Sequential GMDH Algorithm and Its Application to River Flow Prediction. *IEEE Transaction on Systems, Manufacturing and Cybernatics.*

Ivakhnenko, A.G. (1971). Polynomial Theory of Complex Systems. *IEEE Transcations System Manufactured Cybern*. 1,364-378.

Ivakhnenko, A.G., and Ivakhnenko, N.A. (1974). Long Rand Prediction of Random

Processes by GMDH algortithms using the unbiasedness Criterion and Balance of Variables Criterion. *Automatyka Soviet Automatic Control*. 4,52-58.

Ivakhnenko, A.G. (1979). Development of Models of Optimal Complexity using Self-Organization Theory. *International Journal Computing Information Science*. 8(2), 12-21.

Ivakhnenko, A.G., and Ivakhnenko, G.A. (2000). Problems of Further Development of the Group Method of Data Handling Algorithms. *Part 1, Pattern Recognition and Image Analysis*. 110,187-194.

Jiang, X.Q., Blunt, L., and Stout, K.J. (2001). Application of the Lifting Wavelet to Rough Surface. *Precis Engineering*. 25(2), 83-89.

Jin, J.L., and Yang, X.H. (2000). Application of the Time Series Decomposable Model in Medium and Long Term Hydrologic Forecasting. *Hydrology*. 21(1), 21-24.

Jin, J.L., Wei, Y.M., and Din, J. (2002). Application of Projection Pursuit Threshold Regressive Model for Predicting Annual Runoff. *Scientia Geographica Sinica*. 22(2), 171-175.

Ju, Q., Yu, Z., Ha, Z., She, C., Ou, G., and Liu, D. (2008). Streamflow Simulation with an Integrated Approach of Wavelet Analysis and Artificial Neural Networks. *IEEE Computer Society: Fourth International Conference on Natural Computation.*

Kaboudan, M. (2005). Extended Daily Recharge Rates Forecasts using Wavelet Temporal Resolutions. *New Mathematics and Natural Computation*. 1(1), 79-107.

Karananithi, N., Grenney, W.J., Whitley, D., and Bovee, K. (1994). Neural Networks for River Flow Prediction. *Journal of Computing in Civil Engineering*. 8(1), 201-220.

Kim, T.W., and Valdes, J.B. (2003). Nonlinear Model for Drought Forecasting Based on a Conjuction of Wavelet Transforms and Neural Networks. *Journal Hydrology Engineering.* 8(6), 319-328.

Kim, D., and Park, G.T. (2005). GMDH-Type Neural Network Modeling in Evolutionary Optimization. *Springer-Verlag Berlin Heidelberg*. 563-570.

Kim, D., Seo, S.J., and Park, G.T. (2009). Hybrid GMDH-type Modeling for Nonlinear Systems: Synergism to Intelligent Identification. *Advances in Engineering Software*. 40,1087-1094.

Kisi, O. (2004). River Flow Modeling using Artificial Neural Networks. *Journal*

Hydrology Engineering. 9(1), 60-63.

Kisi, O. (2005). Daily River Flow Forecasting using Artificial Neural Networks and Auto Regressive Models. *Turkish Journal Engineering Environment Science*. 29, 9-20.

Kisi, O. (2005). Suspended Sediment Estimation using Neuro-Fuzzy and Neural Network Approaches. *Hydrology Science Journal*. 50(4), 683-696.

Kisi, O. (2007). Streamflow Forecasting using Different Artificial Neural Network Algorithms. *Journal Hydrology Engineering*. 12(5), 532-539.

Kisi, O., and Cigizoglu, H.K. (2007). Comparison of Different ANN Techniques in River Flow Prediction. *Civil Engineering Environment System*. 24(3), 211-231.

Kisi, O. (2008). Stremaflow Forecasting using Neuro-Wavelet Technique. *Hydrology Process*. 22(20), 4142-4152.

Kisi, O. (2008). River Flow Foecasting and Estimation using Different Artificial Neural Network Techniques. *Hydrology Research*. 39(1), 27-40.

Kisi, O. (2009). Neural Networks and Wavelet Conjunction Model for Intermittent Streamflow Forecasting. *Journal of Hydrologic Engineering.* 14(8), 773-782.

Kisi, O. (2009). Wavelet Regression Model as an Alternative to Neural Networks for Monthly Streamflow Forecasting. *Hydrological Processess*. 23, 3583-3597.

Kolehmainen, M., Martikainen, H., and Ruuskanen, J. (2001). Neural Networks and Peridoic Components used in Air Quality Forecasting. *Atmospheric Environment*. 35,815-825.

Kondo, T., and Pandya, A.S. (2004). Identification of the Multi-Layered Neural Networks by Revised GMDH-Type Neural Network Algorithm with PSS Criterion. *Springer-Verlag Berlin Heidelberg*. 1051-1059.

Kondo, T., Ueno, J., and Kondo, K.(2005). Revised GMDH type Neural Networks Using AIC or PSS Criterion and Their Application to Medical Image Recognition. *Journal of Advanced Computational Intelligence and Intelligent Informatics*. 9(3),257-266.

Kondo,T., and Ueno,J.(2006). Logistic GMDH-Type Neural Network and its Application to Identification of X-Ray Film Characteristic Curve. *Journal of Advanced Computational Intelligence and Intelligent Informatics.*11(3).

Kondo, T., Pandya, A.S., and Nagashino, H. (2007). GMDH-type neural network algorithm with a feedback loop for structural identification of RBF neural network. *International Journal of Knowledge-Based and Intelligent Engineering Systems.* 11,157-168

Kondo, T., Ueno, J., and Pandya, A.S. (2007). Multilayered GMDH-Type Neural Network with Radial Basis Functions and its Application to 3-Dimensional Medical Image Recognition of the Liver. *Journal of Advanced Computational Intelligence and Intelligent Informatics*. 11(1), 96-104.

Kong, Y., Yuan, J., Yang, F., and Shi, Y. (2008). Online Prediction of Time Series using Incremental Wavelet Decomposition and Support Vector Machine. *Electric Utility Deregulation and Restructuring and Power Technologies, 2008. DRPT 2008. Third International Conference on IEEE.* 6-9 April, Nanjing, China. 2390-2402.

Kulkarni, J.R. (2000). Wavelet Analysis of the Association between the Southern Oscillation and the Indian Summer Monsoon. *International Journal of Climatology*. 20,89-104.

Kumar, P., and Foufoula-Georgiou, E. (1993). A Multicomponent Decomposition of Spatial Rainfall Fields. *Water Resources Research*. 29(8), 2515-2532.

Kutner, M.H., Nachtsheim, C.J., and Neter, J. (2004). *Applied Linear Regression Models*. (Fourth Edition). McGraw-Hill, NY: The McGraw-Hill Companies, Inc.

Kwak, J.S., and Ha, M.K. (2004). Detection of Dressing Time using the Grinding Force Signal Based on the Discrete Wavelet Decomposition. *International Journal Advances Manufactures Technology*. 23, 87-92.

Labat, D., Ababou, R., and Mangin, A. (1999). Wavelet Analysis in Karstic Hydrology 2nd Part: Rainfall-Runoff Cross-Wavelet Analysis. *Comptes Rendus de I'Academie Des Sciences Series IIA. Earth Planet Science Lett*. 329, 881-887.

Labat, D., Ababou, R., and Mangin, A. (2000). Rainfall-Runoff Relation for Karstic Spring. Part 2: Continuous Wavelet and Discrete Orthogonal Multi Resolution Analyses. *Journal Hydrology*. 238, 149-178.

Labat, D., Rocnhail, J., and Guyot, J.L. (2005). Recent Advances in Wavelet Analyses: Part 2-Amazon, Parana, Orinoco and Congo Discharges Time Scale Variability. *Journal of Hydrology*. 314(1-4), 289-311.

Lang, M., Guo, H., Odegard, J.E., Burrus, C.S., and Wells Jr, R.O. (1996). Noise Reduction using an Undecimated Discrete Wavelet Transform. *IEEE Signal Processing Letters*. 3(1), 10-12.

Lee, B.Y., and Tarng, Y.S. (2000). Drill Facture Detection by the Discrete Wavelet Transform. *Journal Material Process Technology*. 99(3), 250-254.

Lee, I.W.C. and Dash, P.K. (2002). An S-transform Based Neural Pattern Classifier for Non Stationary Signals. *Proceedings of the Sixth International Conference on Signal Processing*. August 26-30, Beijing, China.

Lee, I.W.C. and Dash,P.K. (2003). S-transform Based Intelligent System for Classification of Power Quality Disturbance Signals. *IEEE Transactions on Industrial Electronics*. 50(4), 800-806.

Lee, S., Cho, S. and Wong, P.M. (1998). Rainfall Prediction using Artificial Neural Networks. *Journal of Geographic Information and Decision Analysis*. 2,233-242.

Li, B.L., and Wu, H.I. (1995). Wavelet Transformation of Chaotic Biological Signals. *Biomedical Engineering Conference. Proceedings of the 1995 Fourteenth Southern.* 185-188.

Li, X.B., Ding, J., and Li, H.Q. (1999). Combing Neural Network Models Based on Wavelet Transform. *Journal Hydrology Engineering*. 2,1-4.

Li, J.P., Yan, S.A., and Tang, Y.Y. (2001). The Application of Wavelet Analysis Method to Civil Infrastructure Health Monitoring. *Lecture Notes in Computer Science, Springer-Verlag GmbH*. 2251,393-401.

Liang, H., and Lin, Z. (2002). Stimulus Artifact Cancellation in the Serosal Recordings of Gastric Myoelectric Activity using Wavelet Transforms. *IEEE Trans. Biomedical Engineering*. 49,681-688.

Liang,H., Lin, Q., and Chen, J.D.Z. (2005). Application of Empirical Mode Decomposition to the Analysis of Esophageal Manometric Data in Gastroesophageal Reflux Disease. *IEEE Trans. Biomedical Engineering.* 52(10), 1692-1701.

Lin, Z.S., Liu. J. and He, X.D. (1994). The Self Organizing Methods of Long Term Forecasting-GMDH and GMPSC Model. *Meteorology and Atmospheric Physics*. 53,155-160.

Liu, H.M., Qi, H., and Cai, Z.Q. (2003). Nonlinear Chaotic Model of Landslide Forecasting. *Chinese Journal of Rock Mechanics and Engineering*. 22(3), 434-437.

Liu, M.C. (2005). *Wavelet Analysis and its Application*. Tsinghua University Press, Beijing.

Liu, X., Zeng, X.H. and Liu, Y.C. (2005). Research on Artificial Neural Network Time Series Analysis of Slope Nonlinear Displacement. *Chinese Journal of Rock Mechanics and Engineering*, 4 (19), 3499-3504.

Liu, M., Liu, X., and Rong, G. (2006). Short Term Load Forecasting using Wavelet

Transform and SVM based on Similar Days. *Transaction of China Electrotechnical Society*. 21, 59-64.

Liu, F., Zhou, J.Z., Qiu, F.P., and Yang, J.J. (2006). Biased Wavelet Neural Network and Its Application to Streamflow Forecast. *Springer-Verlag Berlin*. 880-888.

Liu, S., Pu, J., Zhang, H., and Zhao, L. (2009). Dynamic Analysis of Functional Magnetic Resonance Images Time Series based on Wavelet Decomposition. *Proceedings of the 2009 IEEE International Conference on Mechatronics and Automation*. August 9-12, Changchun, China. 4765-4769.

Liu, B.S., and Wang, Z.J. (2009). A Forecast Method of Economic Data and Its Application. *Proceedings-International Conference on Management and Service Science, MASS 2009*. No 5301751.

Loh, R.H. (2003). *Time Series Forecast With Neural Network and Wavelet Techniques.* Bachelor Degree. University of Queensland.

Lu, R.Y. (2002). Decomposition of Interdecadal and Iinterannual Components for North China Rainfall in Rainy Season. *China Journal Atmosphere*. 26,611-624.

Ma, P.Y. (2006). *A Fresh Engineering Approach for the Forecast of Financial Index Volatility and Hedging Strategies*. Doctor Philosophy, Quebec University, Montreal, Canada.

Ma, S.W., Chen, L., Kou, C.H., and Wang, A.P. (2009). Application of Group Method of Data Handling to Stream Way Transition. *International Joint Conference on Artificial Intelligence.*

Maier, H.R., and Dandy, G.C. (1996). Use of Artificial Neural Networks for Prediction of Water Quality Parameters. *Water Resource Research*. 32(4), 1013-1022.

Maier, H.R., and Dandy, G.C. (2000). Neural Networks for the Prediction and Forecasting of Water Resources Variables: a Review of Modeling Issues and Applications. *Environmental Modeling Software.* 15, 101-124.

Mallat, S.G. (1989). A theory for multiresolution signal decomposition: the wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence,*
11,674-693.

Mallat, S.G., and Falzon, F. (1998). Analysis of Low Bit Rate Image Transform Coding. *IEEE Transactions on Signal Processing.* 46, 1027-1042.

Mary Sue, Y. (1985). *A First Course In Linear Regression*. (Second Edition). PWS Publishers.

Masters, T.(1995). *Neural Novel and Hybrid Algorithms for Time Series Prediction*. Wiley New York.

Mendenhall, W., Beaver, R.J., and Beaver, B.M. (2002). *A Brief Introduction to Probability and Statistics.* (First Edition). Duxbury, Thomas Learning, CA, USA: Thomas Learning, Inc.

Misiti, M., Misiti, Y., Oppenheim, G. and Poggi, J.M. (2007). Daubechies Wavelets: dbN. *Wavelets and Their Applications*. (Page: 93-96). London: ISTE Ltd.

Montgomery, D.C., Jennings, C.L. and Kulahci, M. (2008). *Introduction to Time Series Analysis and Forecasting.* John Wiley and Sons.

Morabito, F.C. (2002). Wavelet Neural Network Processing of Urban Air Pollution. Proceedings of the 2002, *International Journal Conference Neural Networks*, IJCNN '02.

Moreno-Baron, L., Cartas, R., Merkoci, A., Alegret, S., Del Valle, M., Leija, L., Hernandez, P.R. and Munoz, R. (2006). Application of the Wavelet Transform Coupled with Artificial Neural Networks for Quantification Purposes in a Voltammetric Electronic Tongue. *Sensors and Actuators B*. 113,487-499. Elsevier B.V.

Muller, B., Reinhardt, J., and Strickland, M.T. (1995). *Neural Networks: An*

Introduction. New York: Springer-Verlag, 52-62.

Murray,M.T. (1964). A General Method for the Analysis of Hourly Heights of the Tide. *International Hydrographic Revolution*. 41(2),91-101.

Murtagh, J., Starch, L., and Renaud, O. (2004). On Neuron Wavelet Modeling. *Decision Support Systems.* 37.475-484.

Najmabadi, M., Devabhaktuni, V.K., Sawan, M., and Fallone, C.A. (2007). Wavelet Decomposition for the Analysis of Esophageal Manometric Data in the Study of Gastroesophageal Reflux Disease. *Biomedical Circuits and Systems Conference,* IEEE. 207-210.

Nariman-Zadeh, N., Darvideh, A., Felezi, M.A., and Gharababaei, H. (2002). Polynomial modelling of explosive compaction process of metallic powders using GMDH- type neural networks and singular value decomposition. *Modelling Simulation Material Science Engineering* 10,727-744

Nariman-Zadeh, N., Darvizeh, A., and Ahmad-Zadeh, G.R. (2003). Hybrid Genetic Design of GMDH-type Neural Networks using Singular Value Decomposition for Modeling and Predicting of the Explosive Cutting Process. *Proceedings Institute Mechinical Engineering*. 217(B), 779-790.

Nariman-Zadeh, N., Darvizeh, A., Jamali, A., and Moeini, A. (2005). Evolutionary

Design of Generalized Polynomial Neural Networks for Modeling and Prediction of Explosive Forming Process. Journal of Materials Processing Technology. 164-165, 1561-1571.

Nason, G.P., and Von Sachs, R. (1999). Wavelets in Time Series Analysis. *Philosophical Transactions of the Royal Society of London*. 357, 2511-2526.

Nayak, P.C., Rao, Y.R.S., and Sudheer, K.P. (2006). Groundwater Level Forecasting in a Shallow Aquifer using Artificial Neural Network Approach. *Water Resource Management*. 20,77-90.

Nourani, V., Komasi, M., and Mano, A. (2009). A Multivariate ANN-Wavelet Approach for Rainfall-Runoff Modeling. *Water Resource Manage*. 23, 2877-2894.

Ochoa-Rivera, J.C., Garcia-Bartual, R., and ANdreu, J. (2002). Multivariate Synthetic Streamflow Generation using a Hybrid Model based on Artificial Neural Networks. *Journal Hydrology Earth Science.* 6,641-654.

Oh, S.K., and Pedrycz, W. (2002). The Design of Self Organizing Polynomial Neural Networks. *Inf. Science*. 141, 237-258.

Oh, S.K., Pedrycz, W., and Park, B. (2003). Polynomial neural networks architecture; analysis and design. *Computers and Electrical Engineering*. 29,703-725

Oh, S.K., and Pedrycz, W. (2004). Self-Organizing Polynomial Neural Networks based on Polynomial and Fuzzy Polynomial Neurons: Analysis and Design. *Fuzzy Sets System*. 142,163-198.

Oh, S.K., Park, B., Pedrycz, W., and Ahn, T.C. (2005). Genetically Optimized Hybrid Fuzzy Neural Networks based on Simplified Fuzzy Inference Rules and Polynomial Neurons. *LNCS*. 3514,798-803.

Oh, S.K., Pedrycz, W., and Park, B. (2006). Multilayer Hybrid Fuzzy Neural Networks: Synthesis via Technologies of Advanced Computational Intelligence. *IEEE Transactions Circular System 1*. 53,688-703.

Onwubolu, G.C. (2009). Prediction of Burr Formation during Face Miling using a Hybrid GMDH Network Model with Optimized Cutting Conditions. *Journal Advances Manufactured Technology*. 44,1083-1093.

Oppenheim, A.V., and Schafer, R.W. (1975). *Digital Signal Processing*. Prentice Hall.

Osowski, S., and Garanty, K. (2007). Forecasting of the Daily Meteorological Pollution using Wavelets and Support Vector Machine. *Engineering Application Artificial Intelligent*. 20,745-755.

Palani, S., Liong, S.Y., and Tkalich, P. (2008). An ANN Application for Water Quality

Forecasting. *Marine Pollution Bulletin*. 56, 1586-1597.

Partal, T., and Kucuk, M. (2006). Long-Term Trend Analysis Using Discrete Wavelet Components of Annual Precipitations Measurements in Marmara Region (Turkey). *Physics Chemical Earth, Part A Solid Earth Geod*. 31, 1189-1200.

Partal, T., and Cigizoglu, H.K. (2008). Estimation and Forecasting of Daily Suspended Sediment Data using Wavelet-Neural Networks. *Journal Hydrology*. 358(3-4), 246-255.

Pasquini, A., and Depetris, P. Discharge Trends and Flow Dynamics of South American Rivers Draining the Southern Atlantic Seaboard: an Overview. *Journal Hydrology*. 333,385-399.

Phusakulkajorn, W., Lursinsap, C., and Asavanant, J. (2009). Wavelet-Transform Based Artificial Neural Network for Daily Rainfall Prediction in Southern Thailand. *International Symposium on Communications and Information Technologies 2009*, ISCIT 2009.

Qiao, W., Sun, H.H., Chey, W.Y., and Lee, K.Y. (1996). Continuous Wavelet Analysis as an aid in the Representation and Interpretation of Electrogastrographic Signals. *Proceeding IEEE Biomedical Engineering Conference., Dayton, Ohio.* March, 140-141.

Rajaee, T., Mirbagheri, S.A., Zounemat-Kermani, M., and Nourani, V. (2009). Daily Suspended Sediment Concentration Simulation using ANN and Neuro-Fuzzy Models. *Science Total Environment.* 407, 4916-4927.

Rajaee, T. (2010). Wavelet and Neuro-Fuzzy Conjuction Approach for Suspended Sediment Prediction. Clean-Soli, Air, Water. 38(3), 275-286.

Raman, H. (1995). Multivariate Modeling of Water Resources Time Series using Artificial Neural Network. *Hydrology Science Journal*. 40(2),145-163.

Rao, M., Raghuveer and Bopardikar, A.S. (1998). *Wavelet Transforms Introduction to Theory and Applications*. Addison-Wesley,Reading,MA.

Renaud, O., Starck, J.L. and Murtagh, F. (2002). *Wavelet based Forecasting of Short and Long Memory Time Series.* Departement d' econometrie, Universite de Geneve. from http://www.unige.ch/ses/metri/.

Renaud, O., Starck, J.L. and Murtagh, F. (2005). Wavelet-based Combined Signal Filtering and Prediction. *IEEE Transaction on System, Man and Cybernatics*. 35(6).

Resnikoff, H.L. and Wells, R.O. (1998). *Wavelet Analysis: The Scalable Structure of Information.* (First Edition). Springer-Verlag New York, Inc.

Robinson, C. (1998). *Multi-Objective Optimization of Polynomial models for Time Series Prediction using Genetic Algorithms and Neural Networks*. Doctor Philosophy. University of Sheffield, UK.

Roussas, G. (2003). *Introduction to Probability and Statistical Inference.* (First Edition). Academic Press, USA: Elsevier Science.

Ruch, D.K. and Van Fleet, P.J. (2009). *Wavelet Theory: An Elementary Approach with Applications*. (First Edition). John Wiley and Sons, Inc:NJ.

Rumelhart, D.E., Durbin, R., Golden, R., and Chauvin, Y. (1995). *Backpropagation the Basic Theory*. New Jersey: Lawrence Eribaum Associates.

Saco, P., and Kumar, P. (2000). Coherent Modes in Multiscale Variability of Streamflow over the United States. *Water Resources Research*. 36, 1049-1068.

Sahoo, G.B., and Ray, C. (2006). Flow Forecasting for a Hawaii Stream using Rating Curves and Neural Networks. *Journal Hydrology*. 317,63-80.

Sakaguchi, A., and Yamamoto, T. (2003). A Study on System Identification using GA and GMDH Network. *IEEE.*

Samsudin,R., Saad, P., and Sabri., A. (2009). Combination of Forecasting using Modified GMDH and Genetic Algorithm. *International Journal of Computer Information Systems and Industrial Management Applications*. 170-176.

Sayer, A.M., Walsh, R.P.D., and Bidin, K. (2006). Pipe Flow Suspended Sediment Dynamics and Their Contribution to Stream Sediment Budgets in Small Rainforest Catchments, Sabah, Malaysia. *For Ecology Manage*. 224,119-130.

Seber, G.A.F. and Lee, A.J. (2003). *Linear Regression Analysis.* (Second Edition). Wiley Series in Probability and Statistics, N.J: A John Wiley and Sons Publication.

Sfetsos, A., and Coonick, A.H. (2000). Univariate and Multivariate Forecasting of Hourly Solar Radiation with Artificial Intelligent Techniques. *Solar Energy*. 68(2), 169-178.

Sforna, M. (1995). Searching for the Electric Load-Weather Temperature Function by using the Group Method of Data Handling. *Electric Power Systems Research*. 32, 1-9.

Sivakumar, B., (2000). Chaos Theory in Hydrology: Important Issues and Interpretations. Journal of Hydrology. 227, 1-20.

Sivakumar, B., Jayawardena, A.W., and Fernando, T.M.K.G. (2002). River Flow

Forecasting: Use of Phase Space Reconstruction and Artificial Neural Networks Approaches. *Journal Hydrology*. 265, 225-245.

Shamseldin, A.Y. (1997). Application of a Neural Network Technique to Rainfall-Runoff Modeling. *Journal Hydrology*. 199, 272-294.

Shinohara, Y., Dohi, T., and Osaki, S. (1999). Predictive Evaluation for Software Tetsing Progress via GMDH Networks. *Electronics and Communications in Japan*. 82(5), 1982-1988.

Smith, J., and Eli, R.N. (1995). Neural Network Models of Rainfall-Runoff Process. *Journal Water Resource Planning Management*. 121(6), 499-508.

Smith, L.C., Turcotte, D.L., and Isacks, B. (1998). Streamflow Characterization and Feature Detection using a Discrete Wavelet Transform. *Hydrology Process*. 12, 233-249.

Soltani, S. (2002). On the Use of the Wavelet Decomposition for Time Series Prediction. *Neurocomputing*, 48, 267-277. Elsevier Science B.V.

Soltani, S., Boichu, D., Simard, P. and Canu, S. (2000). The Long Term Memory Prediction by Multiscale Decomposition. *Signal processing*, 80. 2195-2205.

Soman, K.P., and Ramachandran, K.I. (2005). *Insight into Wavelets-From Theory to Practice.* (Second Edition). New Delhi: Prentice-Hall of India Private Limited.

Starck, J.L., Murtagh, F., and Bijaoui, A. (1995). Multiresolution Support Applied to Image Filtering and Restoration. Graphical Modes and Image Processing. 57,450-431.

Starck, J.L. and Murtagh, F. (2002). *Astronomical Image and Data Analysis*. Springer-Berlin.

Stockwell, R.G. (1999). *S-transform Analysis of Gravity Wave Activity from a Small Scale Network of Airglow Imagers*. Doctor Philosophy. University of Western Ontario.

Stockwell, R.G., Mansinha, L. and Lowe,R.P. (1996). Localization of the Complex Spectrum: the S-transform. *IEEE Transactions on Signal Processing*. 44(4), 998-1001.

Sudheer, K.P., Gosain A.K., and Ramasastri, K.S. (2002). A Data Driven Algorithm for Constructing Artificial Neural Network Rainfall-Runoff Models. *Hydrology Processes*. 16,1325-1330.

Sudheer, K.P., and Jain, S.K. (2003). Radial Basis Function Neural Network for Modeling Rating Curves. *Journal Hydrology Engineering*, 8(3), 161-164.

Swee, E.G.T., and Elangovan, S. (1999). Applications of Symmlets for Denoising and Load Forecasting. *Proceedings of the IEEE Signal Processing Workshop on Higher-Order Statistics*. 165-169.

Talebizadeh, M., and Moridnejad, A. (2011). Uncertainty Analysis for the Forecast of Lake Level Fluctuations using Ensembles of ANN and ANFIS Models. *Expert Systems with Applications*. 38,4126-4135.

Tamura, H., and Halfon, E. (1980). Identification of a Dynamic Lake Model by the Group Method of Data Handling: an Application to Lake Ontario. *Ecological Modeling*. 11, 81-100.

Tang, Y.Y., Yang, L.H., Liu, J., and Ma, H. (2000). *Wavelet Theory and Its Application to Pattern Recognition*. (First Edition). Farrer Road, Singapore: World Scientific Publishing Co.Pte.Ltd.

Tantanee, S., Patamatammakul, S., Oki, T., Sriboonlue, V., and Prempree, T. (2005). Coupled Wavelet-Autoregressive Model for Annual Rainfall Prediction. *Journal of Environmental Hydrology*. 13.

Tokar, A.S., and Johnson, P.A. (1999). Rainfall-Runoff Modeling using Artificial Neural Networks. *Journal Hydrology Engineering*. 4(3), 232-239.

Tong, X.H., Kuang, J.C., Wang, X.Y., and Qi, T.X. (1996). Setting Up Prediction Model of Gas Well Prediction Rate by Various Methods. *Natural Gas Industry*. 16(6), 49-53.

Torrence, C., and Compo, G.P. (1998). A Practical Guide to Wavelet Analysis. *Bulletin Amplitude Meteology Society*. 79(1), 61-78.

Vaziri, M. (1997). Predicting Caspian Sea Surface Water Level by ANN and ARIMA Models. *Ocean Engineering*. 123(4), 158-162.

Venugopal, V., and Foufoula-Georgiou, E. (1996). Energy Decomposition of Rainfall in the Time Frequency Scale Domain using Wavelet Packets. *Journal of Hydrology*. 187, 3-27.

Walczak, B. and Massart,D.L. (1997). Noise Suppression and Signal Compression using the Wavelet Packet Transform. *Chemometer Intelligence Lab. System*. 36,81-94.

Walter, G.G. (1994). *Wavelets and Other Orthogonal Systems with Applications*. (First Edition). Florida, USA: CRC Press, Inc.

Wang, Z., Massimo, C.D., Tham, M.T., and Morris, A.J. (1994). A Procedure for Determining the Topology of Multilayer Feed Forward Neural Networks. *Neural Networks.* 7,291-300.

Wang, W.S.(1999). *Nonparametric Stichastic Simulation and its Application.* Doctor Philosophy. Sichuan University.

Wang,L., Koblinsky,C.J. and Howden,S. (2000). Mesoscale Variability in the South China Sea from the Topex/Poseidon Altimetry Data. *Deep-Sea Research, Part 1*,47(4), 681-708.

Wang, W., and Ding, S. (2003). Wavelet Network Model and Its Application to the Predication of Hydrology. *Nature and Science*. 1(1), 67-71.

Wang, Y., Zhou, J., Xu, H., Dong, Y., and Liu, X. (2007). An Adaptive Forecasting Method for Time Series Data Streams. *Automatica Sinica*. 33, 197-201.

Wang, W.S., Jin, J.L., and Li, Y.Q. (2009). Prediction of Inflow at Three Gorges Dam in Yangtze River with Wavelet Network Model. *Water Resource Manage*. 23,2791-2803.

Wang, W., Hu, S., and Li, Y. (2010). Wavelet Transform Method for Synthetic Generation of Daily Streamflow. *Water Resource Management.*

Wu, D., Agrawal, D., Abbadi, A.E., Singh, A., and Smith, T.R. (1996). Efficient Retrieval for Browsing Large Image Databases. *Proceedings Conference on Information and Knowledge Management.*

Wu, Q., Liu, W., and Yang, Y. (2007). Time Series Online Prediction Algorithm based on Least Squares Support Vector Machine. *Central South University of Technology*. 14, 442-446.

Xiao, J., He, C., and Jiang, X. (2009). Structure Identification of Bayesian Classifiers based on GMDH. *Knowledge-Based Systems*. 22,461-470.

Xingang, D., Ping, W., and Jifan, C. (2003). Multiscale Characteristics of the Rainy Season Rainfall and Interdecadal Decaying of Summer Monsoon in North China. *China Science Bulletin.* 48, 2730-2734.

Xizheng, K., Licheng, J., Tinggao, Y., and Zhensen, W. (1999). Wavelet Model for the Time Scale. *Proceedings of the 1999 Joint Meeting of the European Frequancy and Time Forum*. 1,177-181.

Xu, J. and Ma, F. (2008). Application of Nonlinear Time Series Analysis in Slope Deformation Analysis and Forecast. *Geotechnical Engineering for Disaster Mitigation and Rehabilitation.* Science Press Beijing and Springer-Verlag GmbH Berlin Heidelberg.

Yang, J., Zhai, Y., Dongfeng, W., and Xu, D. (2005). Time Series Prediction based on Support Vector Regression. *Proceedings of the CSEE*. 25, 110-114.

Zealand, C.M., Burn, D.H., and Simonovic, S.P. (1999). Short Term Streamflow Forecasting using Artificial Neural Networks. *Journal Hydrology*. 214, 32-48.

Zhang, B.L., and Dong, Z.Y. (2001). An Adaptive Neural Wavelet Model for Short Term Load Forecasting. *Electrical Power System Research*. 59, 121-129.

Zhang, G.P. (1998). Forecasting with Artificial Neural Networks: The State of the Art. *International Journal of Forecasting*. 14(1), 35-62.

Zhang, G.P., Patuwo, B.E., and Hu, M.Y. (1998). Forecasting with Artificial Neural Networks:the State of the Art. *International Journal of Forecasting*. 14,93-105.

Zhang,G.P. (2003). Time Series Forecasting using a Hybrid ARIMA and Neural Network Model, *Neurocomputing*,50,159-175.

Zhang, W.S., and Wang, Y.T. (2003). Study of Mid Long Term Hydrological Forecasting Based on Weather Factors. *Water Resources and Power*. 21(3), 3-5.

Zhang, L., Liu, X., and Yin, H. (2004). Application of Support Vector Machine based on Time Sequence in Power System Load Forecasting. *Power System Technology*. 28,38-41.

Zheng, G., Starck,J.L., Campbell,J.G. and Murtagh,F. (1999). Multiscale Transforms for

Filtering Financial Data Streams. *Journal Computer Intelligence Finance*. 7,18-35.

Zhou, B., Shi, A.G., Cai, F., and Zhang, Y.S. (2004). Wavelet Neural Networks for Nonlinear Time Series Analysis. Lectures Notes in Computer Science, Volume 3174. *Springer-Verlag, Berlin Heidelberg New York*. 430435.

Zhou, H.C., Peng, Y., and Liang, G.H. (2008). The Research of Monthly Discharge Predictor-Corrector Model Based on Wavelet Decomposition. *Water Resource Management*. 22, 217-227.

Zhu, Y.M., Lu, X.X., and Zhou, Y. (2007). Suspended Sediment Flux Modeling with Artificial Neural Network: an Example of the Longchuanjiang River in the Upper Yangtze Catchment, China. *Geomorphology*. 84,111-125.

Zhu, Y., Qian, J., Fan, Q., Wan, D. and Li, S. (2009). Study on Hydrology Time Series Prediction Based on Wavelet Neural Networks. *Proceedings of the 2009 8th IEEE ACIS International Conference on Computer and Information Science, ICIS 2009*. 411-415.