INFLUENCE OF CLIMATIC VARIABLES AND SOCIO-ECONOMIC DEFORMS ON MUNICIPAL RESIDENTIAL WATER CONSUMPTION ESTIMATION USING FUZZY-WAVELET APPROACH

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

By

H J SURENDRA

DEPARTMENT OF APPLIED MECHANICS AND HYDRAULICS

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA

SURATHKAL, MANGALORE - 575025

MARCH, 2017

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DECLARATION

(by the Ph.D Research Scholar)

I hereby *declare* that the Research Thesis entitled "**Influence of Climatic variables and Socio-Economic deforms on Municipal Residential Water Consumption Estimation using Fuzzy-Wavelet approach**", which is being submitted to the **National Institute of Technology Karnataka, Surathkal,** in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy in **Civil Engineering**, is a *bonafide report of the work carried out by me*. The material contained in this report has not been submitted to any University or Institution for the award of any degree.

AM12P05 - H.J. SURENDRA

(Register Number, Name and Signature of the student)

Department of Applied Mechanics and Hydraulics

Place: NITK, SURATHKAL

Date: 22/3/2017

CERTIFICATE

This is to *certify* that Synopsis entitled "**Influence of Climatic variables and Socio-Economic deforms on Municipal Residential Water Consumption Estimation using Fuzzy-Wavelet approach**" submitted by **H J SURENDRA** (Register Number: AM12P05) as the record of the research work carried out by him, is *accepted as* research thesis *submission* in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy.

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DEDICATED

TO MY MOTHER AND BROTHER

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H.J SURENDRA

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Date: 22-03-2017

ABSTRACT

The actual level of water consumption is the driving force behind the hydraulic in water distribution system. Consequently it is crucial to estimate the residential water consumption in an urban area as accurately as possible in order to result in reliable simulation models. In this research work, hybrid fuzzy wavelet (denoise and compress) technique has been proposed and used for municipal residential water consumption estimation using climatic variables includes rainfall, maximum temperature, minimum temperature and relative humidity for an urban residential area in a yelahanka city, Bangalore, India. For this purpose historical climatic and water consumption data were collected for a period of ten years. Also field survey is done with questionnaire to collect the information about socio-economic aspects. The developed fuzzy-wavelet denoise and compress models were compared with single fuzzy model. Single Fuzzy model were developed using various membership function, rules criteria with different length of the data set. Also developed single fuzzy models compared with hybrid adaptive neuro fuzzy inference and multiple linear regression models. Denoise and compress process is done after the wavelet transformation using various mother wavelets such as Haar, Daubechies of order 2 to 6 and Discrete Meyer Wavelet for different levels with Shannon entropy. After denoise and compress process, coefficient having useful information is saved and corresponding its statistical properties is transferred to the fuzzy system for better input-output mapping. The performances of the developed models were evaluated using performance evaluation indices, such as RMSE, MAE, CC, PE and BIAS. The result indicates that detecting non-linear aspect and selecting an appropriate normalizing technique were beneficial in improving the estimation accuracy of the fuzzy-wavelet model. It is concluded that, fuzzy wavelet denoise and compress technique has promising potential and applicability in the estimation of municipal water consumption estimation with high accuracy.

Keywords: Climatic variable, Compress, Denoise, Estimation, Fuzzy logic, Fuzzy-Wavelet, Residential water.

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ABBREVIATIONS

Symbol	Descriptions
MLR	Multiple Linear regression
FL	Fuzzy Logic
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro Fuzzy Inference System
FW	Fuzzy Wavelet
FWD	Fuzzy Wavelet Denoised
FWC	Fuzzy Wavelet Compressed
MLD	Million Liters Daily
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
PE	Percentage Error
B	BIAS
CC	Correlation Coefficient
S.D	Standard Deviation
CV	Coefficient of Variation
RH	Relative Humidity
M1	Model 1
MF’s	Membership Function
Tri MF	Triangular Membership Function
Trap MF	Trapezoidal Membership Function

RF	Rainfall
T-Max	Maximum Temperature
T-Min	Minimum Temperature
WC	Water Consumption
DWT	Discrete Wavelet Transform
db1 to db6	Daubechies Wavelet of order 1 to 6
DBMY	Discrete Meyer Wavelet
a1, a2, a3	Approximations
d1, d2, d3	Detailing

CHAPTER 1

INTRODUCTION

1.1 Introduction

Sustainable development of cities depends on availability of water. Uncertainties attached to water consumption are associated with climatic change and other various factors (Khatri K.B. 2009). It is inevitable to study the urbanization process, water availability and water environment changes to understand the interaction of urbanization and water utilities in cities. Accurate estimation of water consumption is a key for urban planning since, it is used as input for proper supply system development and further expansion, especially in the residential areas. To understand the municipal residential water consumption pattern in urban area, various studies were carried out in different climatic condition and in different climatic seasons for effective development plan (Bakker M, 2014).

Water which is utilized for all types of residential activities is treated as residential water. Residential Water Consumption estimation in urban areas is most complex and challenging problems in the developing city. Water supplies vary with days of a particular week, weeks of a particular month and months of a particular year. The Impact of specific days of the week, family size, water supply continuity and seasonal variation (winter and summer) on water consumption were normally considered for estimation. Seasonal variation plays the biggest role in controlling the water consumption factor followed by water supply continuity.

The dynamics aspects of water consumption are very difficult to understand since, it is associated with many parameters which affect the environment in an urban area. Climatic variation could be the one of the factor which influences the water consumption significantly. The Interlinking between climatic variables and water consumption are crucial in arid and semi-arid regions. These climatic variables are time varying in nature and its behavior prediction is one of the challenging tasks to meteorological society all over the world, for proper modeling. To balance the water supply and demand accurate water consumption estimation is necessary, as it can provide a simulated view of future and identify sustainable management alternative.

Most of the research papers addressed the problems of estimating the water consumption using climatic and socio-Economic variables. Babel M.S (2007) developed a model based on the multivariate econometric approach. Randolph.B (2008) discusses the attitude of household to their water consumption. Fox.C (2009) estimate the water demand for a new house, based on physical property characteristics. Sharma, K.D (2010) explored the strategies to improve water management by tracking, anticipating and respond to seasonal to interannual climatic variability and climatic change. Lee, M (2011) presented a projection for water savings specific to different conservation goals. Breyer, B (2012) gives an idea about a complex understanding of how temperature affects the water use pattern.

Municipal Residential water consumption pattern has many nonlinear and complex components which is difficult to explain by a linear relationship. Many researchers have been shown the relationship between water consumption and exogenous parameters are non-linear. However majority of the short term water consumption estimation have treated the water consumption as time series and described the relationship using linear expansion.

Subsequently, for proper understanding of residential water consumption pattern, it is required to identify significant impact of climate variables. The existing literatures indicates that, municipal residential water consumption is dynamic in nature and proper understanding of drivers of residential water demand are very essential in managing water resources and in the region of limited resources. Hence, Residential Water consumption time series in a municipal water distribution system is periodic, time varying and somewhat non-stationary. So, appropriate estimation technique is required in modeling the municipal residential water consumption with higher accuracy.

There are many approaches to water consumption estimation including both mathematical and statistical one. Peng Z (2006) used an approach for short term forecasting of municipal water consumption based on the largest Lyapunov exponent of chaos theory. These conventional time series technique have served the community for a longer time in modeling the water consumption, but suffer from the assumption of stationary and linearity (Kermani & Teshnehlab,2008), hence reasonable accuracy is obtained from the conventional method. Municipal residential water consumption patterns should be model in a better way apart from the physical process of modeling, due to nonlinearity, periodic and time varying nature, for which conventional methods are weak in obtaining the desired accuracy.

To address complex and highly nonlinear type of data, soft computing technique provides an effective approach. Soft computing is a data-driven technique consists of fuzzy logic, neural computing, machine learning and probabilistic reasoning. Soft computing techniques are capable for analyzing stationary and non-stationary series, due to their good tolerance to uncertainty, partial truth and imprecision. The guiding principle of the soft computing is to exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost. Soft computing techniques like fuzzy logic, artificial neural networks and genetic algorithms have been recognized as attractive alternatives to the standard and well established hard computing paradigms.

Soft Computing technique does not need a specific equation like multiple linear regression. But this model need sufficient input and output data, so that it can be continuously re-train and it can conveniently adapt to new data. Many literatures describe the water consumption estimation phenomena using soft computing technique considering both climatic and socio-economic variables. Altunkaynak (2005) applied fuzzy logic approach to predict the water consumption in Istanbul city, using Takagi Sugeno method. Kermani and Teshnehlab (2008) used normalized data for water consumption prediction using Adaptive Neuro Fuzzy Inference method. Sen and Altunkaynak (2009) used Mamdani Fuzzy inference system for modeling of drinking water prediction using different fuzzy sets and rules. Also, there were many reports of using ANN technique in modeling process (Babel and Shinde, 2011: Jain, et al 2001;Firat, et al 2009; Nasseri M. 2011; Pinto, et al 2012; Nayak P.C and Sudheer, K.P, 2004; Nayak P.C. 2012 & 2013; L. Karthikeyan and Nagesh Kumar, D. 2013).

ANFIS is the famous hybrid Neuro-fuzzy for modeling the complex and non-linear systems. ANFIS incorporates the human-like reasoning through linguistic variables consisting of IF–THEN fuzzy rules. ANFIS consist, both the features FL and ANN.

Accuracy of the results is mainly depends upon the proper training due to hybrid composition. If proper training process is not done, the hybrid model results in lower accuracy.

To improve the accuracy of single Fuzzy model, wavelets denoise and compress methods are employed, which decomposes the data set into different scale. This is an alternative technique, based on multiresolution and fuzzy system, called fuzzy-wavelet hybrid technique, which results in significant contribution to enhance the input and output mapping accuracy. After decomposition of the data into different scale, coefficient of wavelet are coupled with fuzzy technique, which result in reduction of error in the model and output obtained will follows the trends of observed one.

In this research work, Discrete Wavelet transform is coupled with fuzzy logic method to improve the accuracy of the estimation. The proposed study involves the development of Wavelet-Fuzzy technique for modeling the urban water consumption estimation. Initially fuzzy logic technique is used with different rules, membership criteria and Fuzzy set. Based on accuracy of the developed model, optimum number of rules and Best membership function is selected. To improve the accuracy of the single Fuzzy model, Wavelets technique (denoised and compressed approach) were coupled with fuzzy logic and results are compared with single Fuzzy model. For this purpose Mat lab software with wavelet tool and Graphical user interface are used. The present research work consist of wavelet-Mamdani fuzzy inference approach to develop the models, based on various input variables like rainfall, maximum temperature, minimum temperature and relative humidity to map the input and output function. The models were trained based on climatic data to a certain period and corresponding estimated models were developed for the same period. This work highlights the importance of wavelet (denoise and compress) technique coupled with fuzzy inference system in modeling the municipal residential water consumption estimation.

In this research work performance of the models were evaluated for different types of inputs and output combinations, length of the data set and for different type of data set. The developed models were evaluated using RMSE, CC, MAE, PE and BIAS. Finally to know the consumer attitudes towards water consumption, field survey was carried out with a proper questionnaire, outcome of the survey work was incorporated in making the rules for Mamdani fuzzy inference system.

1.2 Problem Identification

(i) Water scarcity has become a major concern in Bangalore city as well in many parts of world due to growth of population and urbanization.
(ii) Over extraction of ground water, deficit rainfall, inadequate flow in river and changing climatic conditions plays a major role in controlling the water distribution pattern.

Yelahanka area in Bangalore city facing the problem of inadequate water supply and other consequences mentioned above. This is the main motivation for the selection of this particular topic. Due to increase in the demand of water in recent years, it is necessary to estimate the future requirement of water for managing the resources because irregularity in supply of water, affects most of the activity in a residential areas. Therefore water planners have to give more attention to demand management, as water resources are getting more expensive. To solve this complex problem soft computing techniques were adopted. Soft computing technique such as fuzzy logic is widely used in modeling work, since it does not require more precise and noise-free inputs.

From the literatures it is found that, single artificial Intelligence techniques alone is not sufficient to solve the complex problem which includes missing data, limited data, because those data are noisier. Due to higher nonlinearity, single Fuzzy technique will struck in the local minima results in lower accuracy of the developed model. It is necessary to develop powerful hybrid tool in order to reduce the noise and to improve the accuracy of the model. So, more focus should be given to hybrid approaches to overcome the drawbacks of traditional and single artificial intelligence techniques. To address these complex phenomenon wavelet (denoise and compress) technique were coupled with fuzzy inference system to map the input and output relationship using climatic variables.

1.3 Research Objectives

- Identifying significant Influence of Climatic Variables and socio-Economic deforms for municipal residential water Consumption Estimation.
- Development of Fuzzy model for different membership function, rules criteria with limited data.
- Development of Fuzzy-wavelet hybrid models for various input scenarios based on climatic variables.
- Performance Evaluation of developed hybrid model with other model like ANFIS and selection of best model.

1.4 Scope of the study

Scope of this study is as follows:

- Developing various models to analyze the influence of climatic variables includes rainfall, maximum temperature, minimum temperature and relative humidity on modeling the municipal residential water consumption estimation.
- In the first stage, time series data having more non-linear nature is used to develop various models using fuzzy logic, adaptive neuro fuzzy inference system and multiple linear regression technique.
- In the second stage, data is normalized using wavelet denoise and compress approach with different filter bags.
- Each wavelet component is aggregated to provide single estimated value and it is obtained from fuzzy approach.
- The result of the developed fuzzy-wavelet model is compared with single fuzzy model.
- Performances of various developed models were evaluated and best model is selected.
- To understand the consumer attitude towards water consumption, household survey is carried with a proper questionnaire. Outcome of the survey work is incorporated in the knowledge part of fuzzy set for making the rules combination.

The present work aims to address the problem of modeling the municipal water consumption estimation in the perspective of a developing country like India, in Bangalore city, such as 4th ward of Yelahanka as the case under investigation. In the recent years, Yelahanka city Bangalore has seen unprecedented growth spatially and economically leading to imbalance in supply and demand of municipal water. The present study aims to address the problem of estimating the municipal residential water consumption in an urban area. This research work highlights the importance of hybrid fuzzy-wavelet approach rather than a single approach, in modeling the municipal residential water consumption.

1.5 Organization of the Thesis

This thesis comprises of six chapters as follows:

Chapter 1 Introduction presents the relevant information pertaining to residential water consumption estimation, problem identification, research objective, scope of the study, overview of the conceptual basis for research.

Chapter 2 Literature Review discuss the water consumption estimation modeling, using conventional methods of estimation and soft computing approaches. Also explains the advantage of hybrid approach in modeling residential water consumption. Various literatures discuss the influence of climatic and socio-economic variables in modeling the water consumption.

Chapter 3 Study area and Data set used describes the characteristics of the study area, description of different types of variables used and its characteristics in modeling process, water supply and consumption pattern in the study area.

Chapter 4 Methodology and Model Development explains the methodology adopted in order to achieve the research objectives. This includes the essential background information, description of the structure and terminology of various developed single and hybrid models. Also includes the various performance evaluation indices.

Chapter 5 Result and Discussions describes the method of evaluation and goes on present the analysis of the result obtained from the various developed model for different input scenarios.

Chapter 6 Summary and Conclusions presents the summary of the research work carried out, contribution and conclusion. Further the limitation and future scope of the study are included. At the end, information about the field survey with proper questionnaire is presented in the appendix chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter focus on a review of research carried out in the past considering climatic and socio-economic factors and other various methods applied to estimate the water consumption. It is attempted to make the literature review on traditional and soft computing applications in estimating the water consumption particularly in the following categories.

2.2 Descriptions of the Literature review

2.2.1 Using Traditional method

Aijun A.N (1996) used rough set approach for the discovery of automated rules from a set of given data sample. This method is based statistical information using the above approach. 18 factors which are responsible for affecting the water demand are listed out. Conjunction and disjunction operators are used to compute the decision rules by Boolean expression. The objective is to analyze the training data and generate the decision rules. Decision attributes were divided into ten integers, so the obtain formation has 10 concepts. The present method is capable of deriving the precise part of the rule with many probabilities. When data is incomplete and deterministic, developed method is useful.

Lertpalangsunti N (1999) used intelligent forecasting construction set contains the application of FL, ANN, knowledge based and case based reasoning. Here algorithm is considered to limit the size of the data set. Forecaster used, neural network, knowledge based reasoning, CBR and linear regression to train the data in order to measure the performances. Initially 3-5 neurons are used later it is increased depending upon the previous result. It is found that over fitting of training data set will occur when more neurons are used. Best results were found when three days of previous demand and 5 neurons were applied. Best network was found when 5 hidden neuron, 5 days previous demand and temperature input used. The result obtained is compared with the CBR and LR. They found that, ANN is best compared to the other techniques.

Zhou S.L (2000) formulated time series data to forecast daily water consumption. This paper describe computer mathematical model based on lag demand data and weather condition to estimate consumption for 24 hours lead. Recorded data of water consumption, maximum temperature, precipitation, evaporation (pan) were used to develop the model. Here statistical and graphical parameters were used to compare forecasted and observed of water consumption. The value of the coefficient of determination is close to one, which indicates model can reproduce consumption satisfactorily. From the result it was found that precipitation, antecedent precipitation index, number of days and evaporation are very important.

Fernando A (2003) discussed the main contribution on residential water consumption. This paper gives information about different tariff types and their objectives. Attention is given to many variables, specification model, data set and most common econometric problems.

Surendran S (2005) used chi-square technique to estimate the water consumption of many household. Modeling of water distribution system is done based on the factor of pressure. The peak factor is taken into the consideration and it is coupled with the statistical modeling. The developed network can satisfy any demand and it can be recognized easily.

Durga Rao K.H.V (2005) used scientific approach to determine the present and future water requirement for a domestic type using multi criteria decision analysis. Water demand area has been identified considering various factors. Requirement of water for next two decade is computed and analyzed the condition with present system of supply. Using Incremental method water demand for next two decade has been forecasted. Decision support model was run to produce possible sites of urban expansion. Total domestic requirement was calculated using population data and rate of per capita water consumption. Relative importance of each factor has been prepared using pair wise matrix.

Robert C (2006) examined climatic variability between 1980 and 2004 in the city of Phoenix, Arizons. Multivariate analysis for monthly climatic data indicates, yearly water use is controlled by drought, autumn temperature and summer monsoon precipitation of the state. Model coefficient indicates, temperature, drought condition and precipitation impact the water use.

A.C. Worthington (2006) gives information about survey of empirical residential water demand analysis conducted in last twenty-five years. Due to increase in water demand in urban areas, demand side management has become a considerable debate among economist, water utility managers, regulator, consumer interest groups and policy makers. This paper aims at providing the best practice estimate of price and income elasticity and gauging the impact of nondiscretionary environmental factor affecting residential water demand.

Babel M.S (2007) developed multivariate econometric approach model which consider the factors such as socio-economic, climatic, water policies to manage the water use and demand in domestic areas. Statistical tool is applied to select the influencing variable on water demand. The result highlights that number of connections, pricing of water education level and average rainfall are significant variables. Also it highlights the length of the data on model accuracy.

Gato S (2007) determines the daily water use. Time series technique is employed to find the rainfall and temperature threshold. The performance of the model is evaluated using coefficient of determination and standard error. Model performs is higher for daily data. The model with rainfall and temperature was incorporated in total demand shows strong correlation. The developed model was a time dependent model.

Alvisi S (2007) discussed the issue of control of water distribution. Short term fluctuation is measured by proper monitoring facility. This trend is usually found in time series. Forecast was subjected to sensitivity approach to measure the error in the various components.

Peng, Z (2007) developed Lyapunov exponent of chaos to forecast the municipal water consumption. Time series characteristic was observed and correlation was determined. The developed model is compared with artificial neural network. Developed Chaos theory is better compared to ANN.

Sharma, A.K (2008) presented the water servicing options of water resources and environment for two different townships. Three modeling tools were used to predict the water servicing. Installation of rain water tanks and grey water distribution system and government scheme for rainwater, as a result of this study.

T. Kogest (2008) assessed the influence of socio-economic and demographic parameters on water use. Factor analysis has been used to identify the influences from different types of domestic users. Multiple regression analysis has been applied to estimate age specific per capita unit coefficient as source for forecasting water demand.

Hongwei Z (2009) used system dynamic approach to forecast the water demand in urban area. It was characterized by non-interaction with the elements of system. Model based on Tianjin water supply system. Sensitive analysis is carried out to identify the variables. Model includes population, economic, water pollution control as the subsystem. Finally 15 parameter and 8 variables were used to analyze the effect on the prediction. Result reveals that system dynamic approach is better than other forecasting method.

Fox C (2009) developed water demand forecasting for a new house based on physical property characteristics. Due to increase in population, it is necessary to forecast the water demand for the new houses. This paper deals with classifying the properties based on physical characteristics. Properties are classified based on size (number of bed rooms), architecture type (flat, terraced) and garden present.

Khatri K.B (2009) forecasted the future water demand based on uncertainties, includes, population growth, economic growth, climate change etc. To develop the model time series data is used. It is observed that water demand is governed by socio-economic factor. Climatic factor has less influence in water demand forecasting.

Mohamed M (2010) forecasted the water demand using constant rate, IWR-MAIN Software. The objective of this work is to identify accurate data base. Best data base is used for calibration and result obtained is compared with the actual data. The performance of the model is evaluated using various performance indices. When calibration period is short, difference between the actual and estimated demand is less. From the result, for first data base, model is always underestimating. Error in second data base is less compared to first data base.

Okeloa O.G (2010) estimated the water demand in the developing countries. This paper aims at incorporating the various factors affecting the demand in a particular situation. The model is prepared by considering population as a major variable.

Bhatti A (2010) examined domestic water use in selected cities of Pakistan under changing socio-economic scenarios. The policy-relevant variables, mainly econometric problems and water price are systematically considered and their effect on water demand was appraised. The study concludes that better management coupled with effective policy, awareness.

Cheng, Q (2011) used the system dynamic model to forecast the water demand based on times series and regression approach. It is based on the coupled modeling structure. From the literature review they found many approaches for short and long term demand forecasting. Proposed model was validated using the estimated data and historical data. They have considered many criteria for the analysis. Sensitive analysis improves the reliability of the modeling analysis. The case study using system dynamics modeling was successful.

Chongli, Di (2011) proposed four dimensional systems related to water resources for water-demand supply. It is proved that, this system is chaotic and studied through Lyapunov exponent, bifurcation diagrams. This system is controlled by linear feedback techniques.

Kossay K (2011) determined the actual indoor water consumption of a city. The impact of specific days of the week, family size, water supply continuity and seasonal variation (winter and summer) on water consumption were also considered. It is observed that, daily average water consumption in winter and summer season, the total water consumption for a particular area were determined. Seasonal variation plays a biggest role in controlling the water consumption factor. Also it was found that Family size (negative effect) and specific days (weekends) have an influence on water consumption.

Lee M (2011) presented a projection for water savings specific to different conservation goals. This paper aims to project the water demand in future from the point of demand management.

Grace A (2013) identified various coping strategies that are available during water supply shortages to household in Oke-Ogun, Nigeria. This work also identifies socio-economic factor influence the choice of coping strategies during water supply shortages in local communities. Data were collected by 397 respondent's interviews and focus group discussions. During water scarcity most of the houses combined multiple coping strategies.

Birge O (2013) forecasted urban water consumption using a multi linear regression model with many variables. Variables such as population served, monthly mean temperature and monthly total precipitation were used. Based on climatic change scenarios, urban water demand is forecasted up to 2100.

Slavikovia L (2013) investigates the statistically significant impact of short term climate variables (especially air temperature and rainfall) on residential water consumption at two selected sites in the Czech Republic using daily time series data. The statistical methods used are CART methodology and a decomposition of these time series based on a locally weighted regression method. Apart from this the investigation raises several methodological questions regarding the use of daily data and the scope of analysis based on such data sets.

Chai T (2014) gives information about RMSE and MAE in model performance evaluation. Results reveal that RMSE is better to use when the model error follows a Gaussian distribution and MAE to use, when Model error follows a normal distribution.

Chen J (2014) suggest the integrated time series forecasting framework for forecasting hourly/ quarter-hourly demands in real word, real-time scenarios. This is prototyped with Mat lab software. Framework is applied to real word water demand time series. This framework is applied to additional demand time series to evaluate the forecasting algorithm and compare the water consumption characteristic of different distribution system.

Ouda O (2014) projects the gap between supply-demand under various time scenarios. Future water demand was calculated and corresponding allocation is made in agricultural and industrial sector. Results reveal that, supply-demand gap is difficult to fill and certain demand management measures are required.

Gomes R (2014) addresses the influence of different daily patterns of nodal water demands on the district metered areas (DMA). Design and the benefits yielded by pressure management. The methodology used follows the best practices of water losses management and uses a pressure driven model to predict the hydraulic behavior under different patterns of nodal demands.

2.2.2 Using Soft computing techniques

Kim H (2001) used optimal neural network model to estimate the daily water demand. Here feed forward back propagation algorithm is adopted with one day ahead. Nine set of neural network back propagation are used for training and testing with genetic algorithm. Correlation coefficient relationship indicates that, only water demand and temperature have more influence compared to other factors. Evaluation of the model is done by using various criteria such as absolute mean bias (AMB), RMSE, RRMSE, and MAPE. The nine different model of genetic algorithm is compared with the back propagation. Here comparison of the model is done and found that, the use of genetic algorithm shows better result than feed forward back propagation.

Jain A (2001) used ANN technique to forecast short term water demand. They used time series and regression technique for comparison purpose. The aim is to investigate whether water demand is influenced by air temperature and rainfall occurrence. Here 6 different ANN models, 5 regression models, 2 time series models have been developed. Weekly water consumption, monthly average maximum air temperature and weekly rainfall data were used for the analysis. Among the regressive model 3 are the linear type and 2 are nonlinear type. Back propagation ANN with generalized delta rule as a training algorithm was used for training of all models.

Altunkaynak A (2005) developed Fuzzy model based on Sugeno inference system to predict future water consumption on monthly basis based on antecedent water consumption amounts. Mean square error for all the model is obtained and more effective model is selected. In this prediction only one lag period is considered. Time series is plotted and possible trend is removed. This normalized data set is applied to Sugeno model to obtain efficient configuration of the model. The model consists of three input and single output variable. Out of nine year data set seven year is used for training and two years for testing. Error comparison is done. Results reveal that observed and predicted value is equally scattered around the linear line.

Kermani M (2008) considered Adaptive Neuro fuzzy system containing sugeno inference with different membership function. Outcome of network, compared to an autoregressive approach. Here input data enters into Neuro fuzzy network after normalization. Sugeno inference with product operator was adopted with different membership function. From the result it is found that, Gaussian membership function had better result than triangular membership function and Neuro fuzzy model was better than autoregressive model.

Sen Z (2009) predicted the water consumption rate using fuzzy approach.. Mamdani fuzzy inference is employed for this analysis. Eight fuzzy subsets and 36 fuzzy rule based system were used. Defuzzification is done by centroid method. From the result it is observed that average error is lower than the acceptable error.

Wang C (2009) developed hydrological forecasting model based on past record. Different methods like autoregressive moving-average model (ARMA), ANFIS, GP, and SVM. ANN multilayer feed forward back propagation network with one hidden layer was used with generalized bell shaped membership function. Model performance is evaluated using correlation coefficient (R), coefficient of determination, RMSE, MAPE. From the analysis they found that in training phase ANFIS model obtained best R and RMSE. In validation ANFIS, GP and SVM were good compare to ARMA and ANN model. Finally GP, SVM and ANFIS were found as best models.

Firat M (2009) evaluated various artificial networks to forecast the water consumption from various factors. Several model combinations were studies and best fit parameter is selected. Correlation coefficient between the input-output variables have calculated. Here 8 models were used with one input .Out of 8 models, monthly water bill and average value of temperature was found to be important for the analysis. To determine the accuracy of the model they have used NRMSE and R. the performance of the model in training and testing process stage are compared with observed water consumption. Multiple regression technique is used to train the best fit model. From the result GRNN was found to be best model compared to other models.

Yurdusev M (2009) used ANFIS to forecast the monthly water use. Gradient descent and least square method are used to determine input - output of the model parameters. Selections of the input variable determine the structure of the developed model and determine the performance of the model. Appropriate input variable were selected for analysis using cross correlation between the variable. They have used fuzzy clustering function to establish relationship between the inputs-output variable. They found that among the several model, the model with the monthly water bill and population was best and effective.

Hongwei (2009) used ANFIS method to forecast the water demand. Fuzzy rules are obtained from data sample and appropriate membership function, gained through hybrid-learning algorithm, which contributes to effective and fast forecasting. Four input variables are coupled with many factors together. For this work Mat lab software were used to assist the design of ANFIS, which makes this method easy to master and operate for more users. The results indicated that the predicting precision of this method can satisfy the engineering request.

Firat M (2010) predicted monthly water consumption using ANN technique, including GRNN, CCNN, and FFNN. Performance of the model during training and testing process are compared with observed water consumption. Totally six models were used with different inputs. Finally it is found that out of six models, the five day antecedent values of water consumption are better. They found that NRMSE and AARE of this model is better than other model.

Herrera M (2010) compared many predictive models to forecast hourly water demand. Time series data were used to develop the model. Many techniques includes ANN, support vector machine, were used. Three layered feed forward network is used in ANN. Monte Carlo simulation is used to estimate the predictive performance of the model. From the result it is found that support vector machine coupled with regression model is better.

Mehmet Ali Yurdusev M (2010) predicted the monthly water from socio-economic and climatic factor. The Network contain GRNN is used for this purpose. From the result it is found that, GRNN is capable to predict the water consumption on monthly basis.

Nasseri M (2011) used genetic algorithm and kalman filter to forecast the water demand. The data set is divided into different lag periods from five days to three days as input. Several mathematical operators were used in simulation process. Best model is acceptable as auto regressive approach. It is found that GP operators were more accurate and leads to more efficient model.

Babel M (2011) predicted short and long term water demand using ANN technique. Correlation matrix for explanatory variable for short and long term prediction is found out. Finally for short term demand, rainfall, mean temperature and RH were used as variables. For this study multilayer perceptron feed forward network is used. Trails are considered with one, two, three hidden layer to examine the accuracy of water demand prediction. Hyperbolic tangent and sigmoid activation function were used. Model performance was evaluated considering RMSE, AARE and threshold statistic. Different model inputs were selected from the correlation coefficient matrix. Accuracy of the model is checked with different input. It is found that only one lag of historic daily demand is sufficient for short term model development. Prediction accuracy for short and long term model with different input is found to be satisfactory.

Rahmati H (2014) suggests the importance of Neuro Fuzzy system for forecasting water demand in metropolitan cities by comparing with other techniques. It acts as a data preprocessing technique to improve the accuracy of the model.

Adamowski K (2014) develops a hybrid neural–wavelet model to forecast the weekly water consumption with limited data. The result highlights the effectiveness of developed hybrid model to forecast the water demand associated with uncertainties.

2.2.3 Using Wavelet Techniques

Marc Thuillard (2000) used fuzzy wavelet method, in order to transfer the knowledge contained in databank into linguistically interpretable fuzzy rule. Multi resolution technique is adopted based on wavelet estimator. A multiresolution fuzzy technique known as fuzzy-wavelet technique helps to transfer the knowledge.

Engin K (2005) applied two different network containing Fuzzy and discrete wavelet transform. In the beginning process the translation part are fixed and in the second stage, Discrete Wavelet were used completely. Result indicates that Fuzzy wavelet achieve higher accuracy of the model.

G. Ghodrati (2009) examined an approach and a new method for processing the ground motion, which is modeled as a non-stationary process both in amplitude and frequency. This technique uses the best algorithm with wavelet packets. In this approach, the signal is expressed as a linear combination of time frequency atoms which are obtained by dilations of the analyzing functions and organized into dictionaries as wavelet packets. Several numerical examples are given to verify the developed models.

Nassim H (2011) developed a fusion model for forecasting stock price by combining wavelet with fuzzy logic and ANFIS From the experiments it is found that fusion model achieve better forecasting accuracy.

Jower R (2012) used hybrid wavelet- neural network method to forecast the municipal water demand. The model consists of discrete wavelet transforms (DWT) with multilayer perceptron neural network. In the developed model Daubechies wavelet function with different orders and level of resolution were used in the decomposing process of time series. Fourteen years of daily and monthly data were used for the analysis. From the result it is found that hybrid wavelet-ANN approach provides accurate daily and monthly forecast as measured using a validation period of 5, 10, and 15 for daily data and 24 months for monthly data. Recording MAPE value equal to 1.029 and R^2 value 0.967.

Pinto (2012) used artificial neural network to solve the problem of water demand in an urban area by back propagation network with wavelet-denoising approach. The developed model is compared with ANN and regression model. The main aim is to develop a model which is readily use for water budgeting. This paper explores the importance of wavelet-ANN technique. For this work five different wavelet filter banks were used on a single neural network. The empirical result shows that neural network coupled with Haar and Daubechies filter-banks of type db2 and db3 outperformed for all other models.

Longqin Xu (2013) used combined wavelet-neural network to predict the water quality. The developed models have high learning and high predict accuracy. From the result it is found that, developed model can predict the water quality in a better way.

P.C.Nayak (2013) demonstrates the potential use of wavelet neural network (WNN) for river flow modeling daily data of rainfall; discharge and evaporation for 21 years have been used for modeling. In the modeling original model, inputs have been decomposed by wavelets and decomposed sub-series were taken as input to ANN. Optimum architectures of the WNN models are selected according to the obtained evaluation criteria in terms of Nash–Sutcliffe efficiency coefficient and root mean squared error. The results of this study indicate that the WNN model performs better compared to an ANN and other models.

Zhang F (2014) proposed wavelet transform particle swarm optimization support vector machine (WT-PSO-SVM) model for stream flow prediction for time series data. Initially data were decomposed into various details and approximation, at three resolution levels (21-22-23) using Daubechies (db3) discrete wavelet. The test results indicate that developed model is better than single SVM type.

Mirbagheri S (2014) highlights the importance of Neuro fuzzy coupled with wavelet analysis for sediment load concentration. Followed by different models were developed. Neuro fuzzy with wavelet analysis performed better compared to other three models.

Zhang J (2015) combines the advantage of wavelet analysis, multiple criteria decision making, and artificial neural network. Forecasting extreme monthly maximum temperature of Miyun reservoir has been conducted to examine the performance of WNMCDM model. Compared with nearest neighbor boot strapping regression (NNBR), the probability of relative error smaller than 10% increases from 65.79% to 84.21%

(forecast period T = 1) and from 51.35% to 91.89% (T = 2) by WNMCDM model. Therefore, WNMCDM model is superior to NNBR model in forecasting temperature time series

2.3 Summary of the Literature Review

Based on the Literature review, on Fuzzy-Wavelet application in water consumption, it is observed that some of the grey area appears as mentioned below:

- A major concern for several researchers experienced in any estimation technique is the lack of quality and quantity of the data.
- The effect of combined and individual parameter analysis for modeling water consumption has not been studied so far in a comprehensive manner.
- Proper methodology to improve the accuracy of the fuzzy technique, when the data are nonlinear and non-stationary is very few. So, there is a wide scope to improve the accuracy of the fuzzy technique.
- Developments of Fuzzy wavelet (denoise and compress) hybrid model for estimating water consumption has not been addressed in a detailed manner.
- Utilizing socio-economic parameters for modeling water consumption estimation using fuzzy approaches are very few.
- Addressing the problem of selecting best performance evaluation indices in any water consumption estimation modeling has not been discussed.
- Field survey approach to understand the influence of socio-economic factors for modeling the water consumption has not discussed in a comprehensive manner.

To address above limitation, it is necessary to provide a powerful tool in order to reduce the noise in the data and to improve the accuracy of the model. From the literature review it is highlighted the applications of fuzzy logic technique with wavelet transform (denoise and compression) for estimating the municipal residential water consumption using climatic variables are limited. This research work signifies the importance of developing new hybrid fuzzy-wavelet technique rather than single fuzzy technique.

CHAPTER 3

STUDY AREA AND DATA SET

3.1 Introduction

Study area covers the fourth ward of yelahanka city, shown in the figure 3.1.1, which is a suburban of Bangalore in the state of Karnataka, India. The city is at a height of about 915m above mean sea level. The city is lush green and has pleasant weather throughout the year. Summer season starts from the beginning of the March month and lasts until the end of May, with a temperature in the range 20^0C to 35^0C results in higher water consumption. At the end of May, the monsoon season starts and lasts until the end of September. Annual rainfall of city is 1140mm. Yelahanka is served by both south west and south east monsoon. Winters are mild and start from the mid of November to the end of February, with a temperature in the range 14^0 C to 24^0C.

City has most of the water from their ground sources in addition to municipal supply. There is an irregularity in water supply due to increase in demand, so it is necessary for managing the water resources. Water planners have to pay more attention to demand management, since water resources are getting more expensive. Water consumption data were collected from Bangalore water supply and sewerage board (BWSSB) on monthly basis for a period of ten years. Climatic data includes rainfall, maximum temperature, minimum temperature and relative humidity are collected from Disaster management cell Yelahanka for the same period. The variation of monthly rainfall, maximum temperature, minimum temperature, relative humidity and water consumption data were shown in the figure 3.1.2, 3.1.3, 3.1.4 and 3.1.5. The Variation of rainfall in different climatic seasons such as summer, winter and monsoon are shown in the figure 3.1.6. The variation of rainfall in different climatic seasons such as summer, winter and monsoon are shown in the figure 3.1.6. The Variation of temperature in different climatic seasons are shown in the figure 3.1.7. The Variation of relative humidity in different climatic seasons are shown in the figure 3.1.8. The Variation of water consumption in different climatic seasons is shown in the figure 3.1.9. From the figures it is observed that, variations are nonlinear, non-stationary, time varying. As summer season starts, the depletion in both surface as well as ground water observed regularly. Hence estimation of water consumption during this period with higher accuracy is very essential which needs sophisticated technique in the problem domain. Variation of rainfall in the two different years 2012 and 2013 is shown in the figure 3.1.10. The rate of water supply to Bangalore city is represented in the figure 3.1.11. The rate of water supply to Yelahanka city is represented in the figure 3.1.12. The rate of water supply to fourth ward of yelahanka city is shown in the 3.1.13.

Figure 3.1.1 Location of Study Area

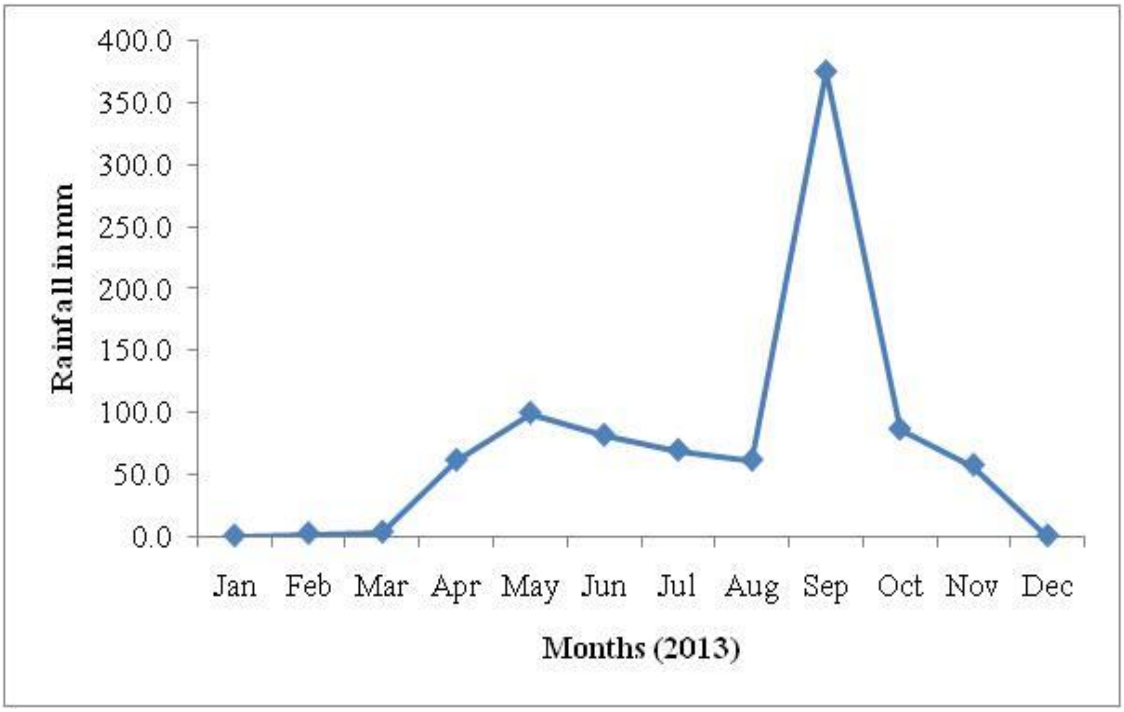


Figure 3.1.2 Variation of Rainfall

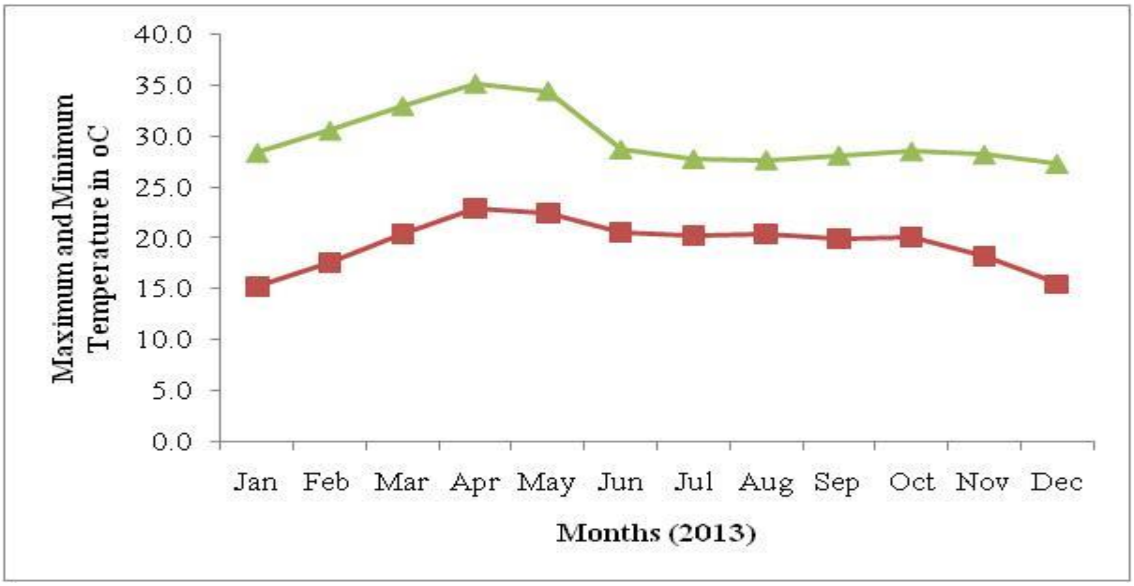


Figure 3.1.3 Variation of Maximum and Minimum Temperature

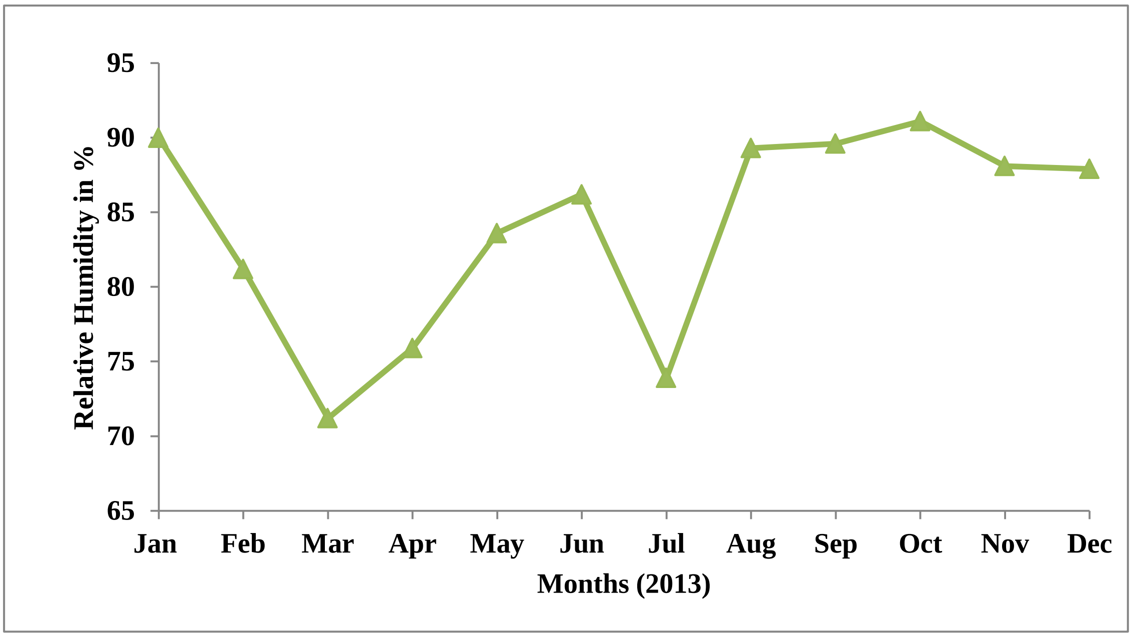


Figure 3.1.4 Variation of Relative Humidity

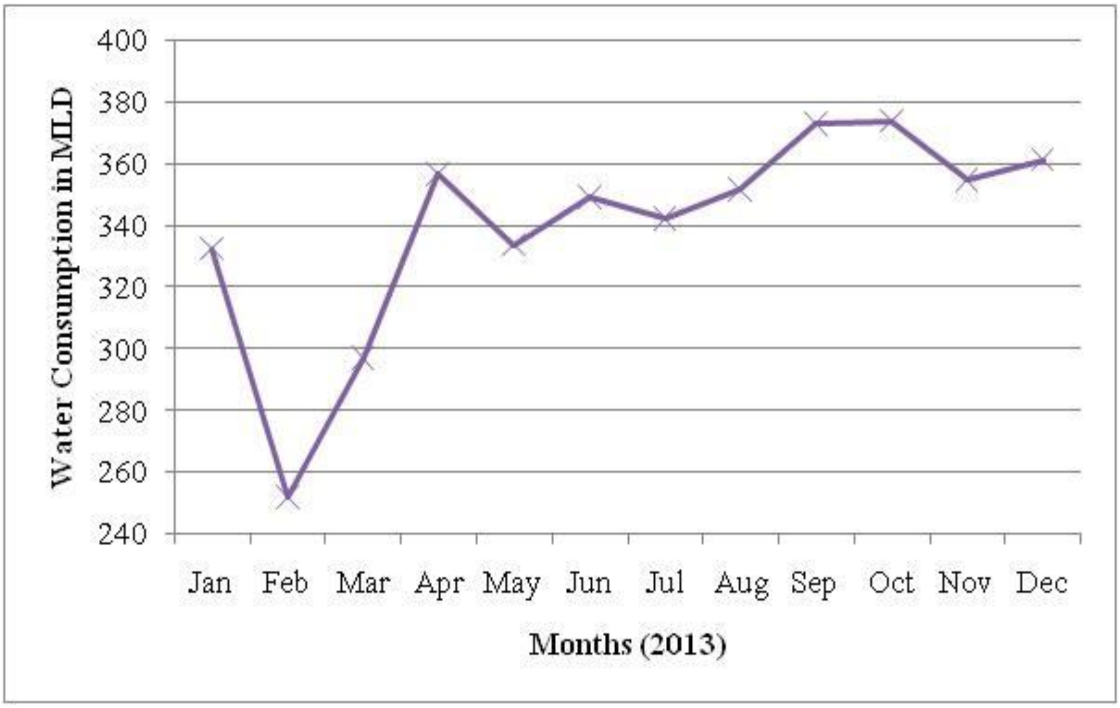


Figure 3.1.5 Variation of Monthly Water Consumption

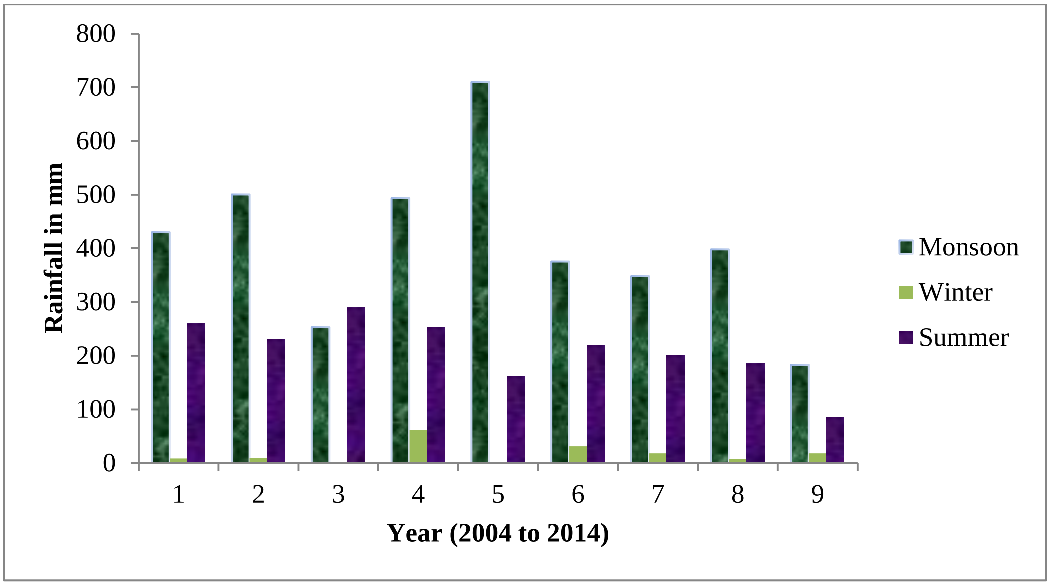


Figure 3.1.6 Rainfall variation in different seasons

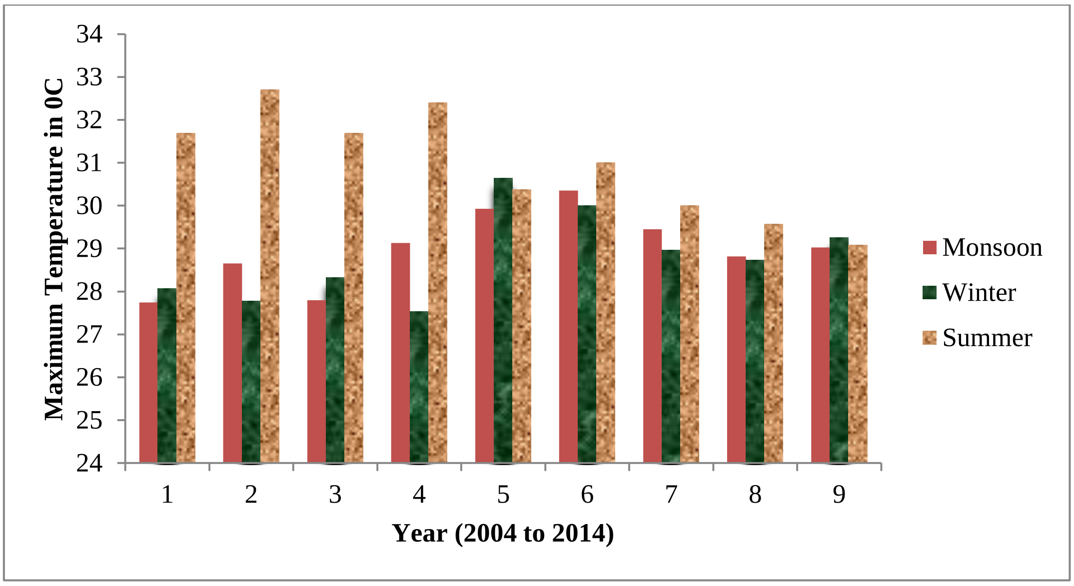


Figure 3.1.7 Temperature variation in different seasons

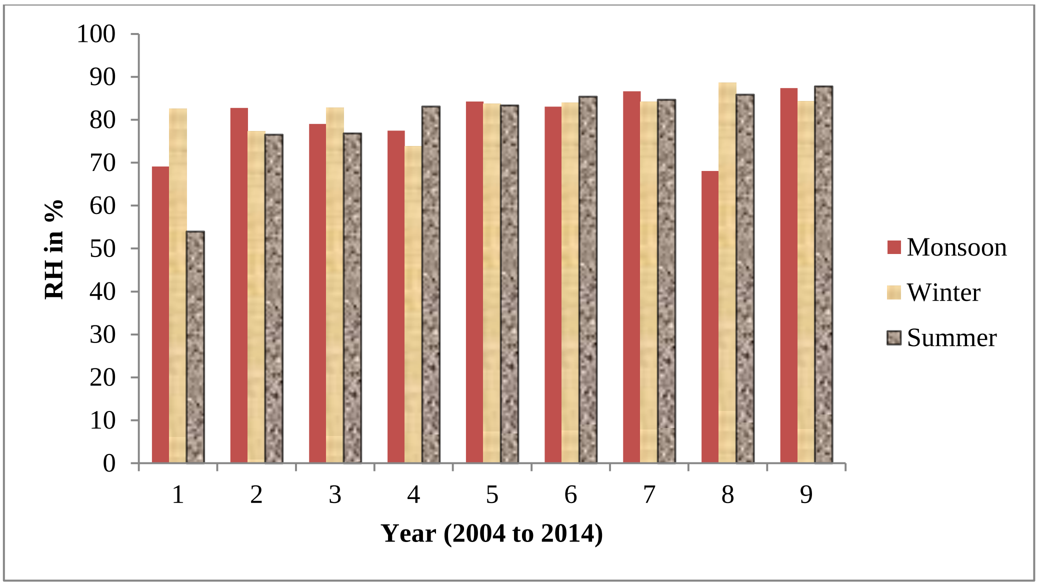


Figure 3.1.8 RH variation in different seasons

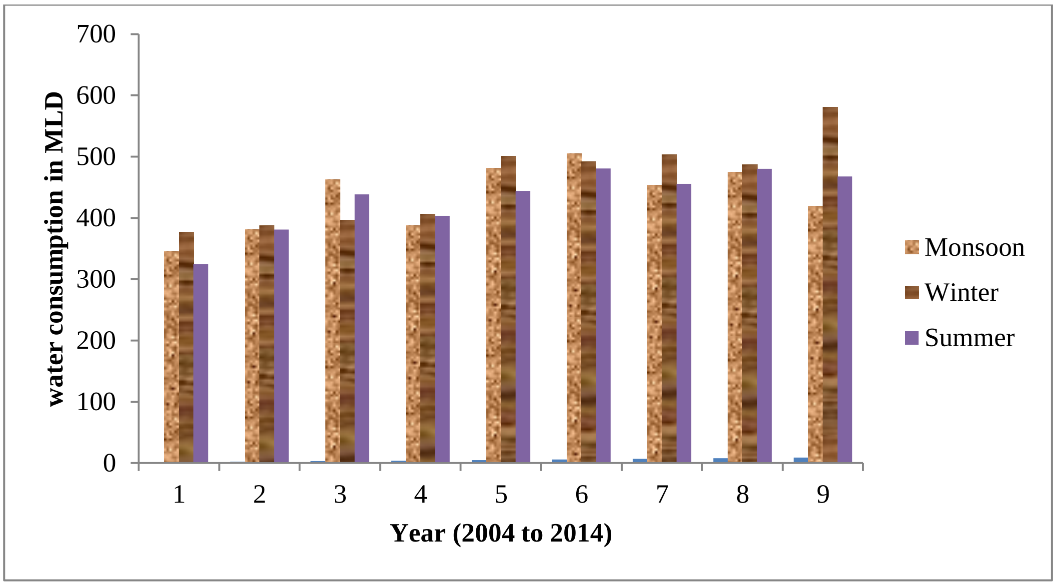


Figure 3.1.9 Water Consumption variation in different Seasons

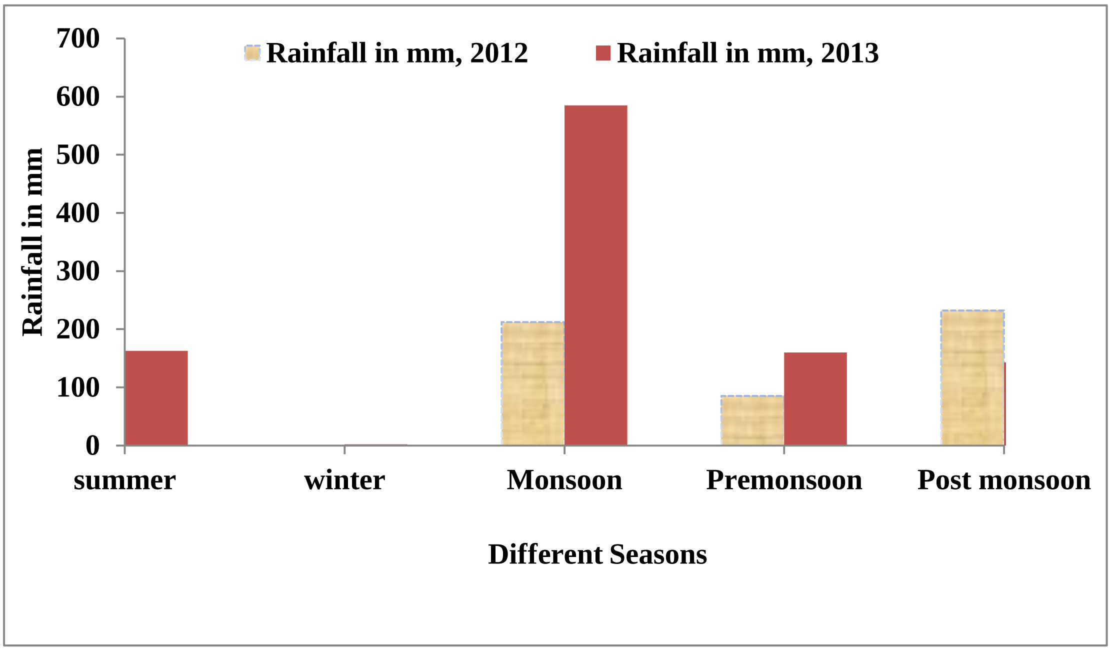


Figure 3.1.10 Variation of Rainfall in the year 2012 and 2013 at Different seasons

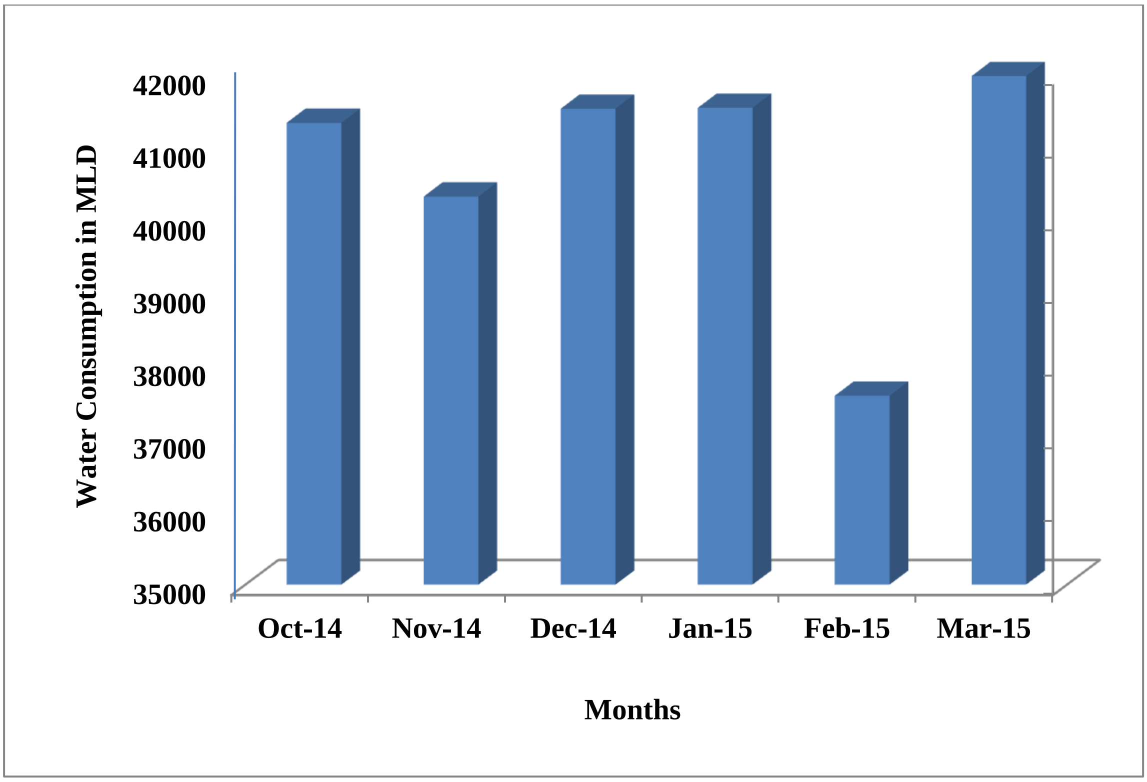


Figure 3.1.11 Rate of Water Supply to Bangalore City

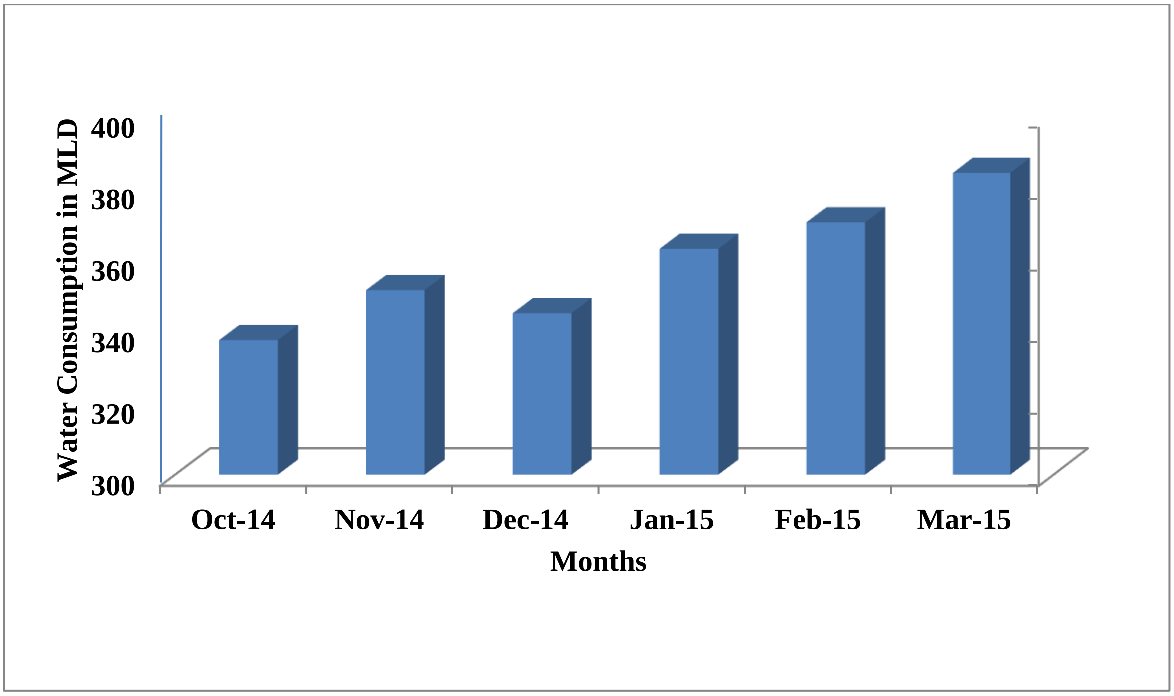


Figure 3.1.12 Rate of Water Supply to Yelahanka City

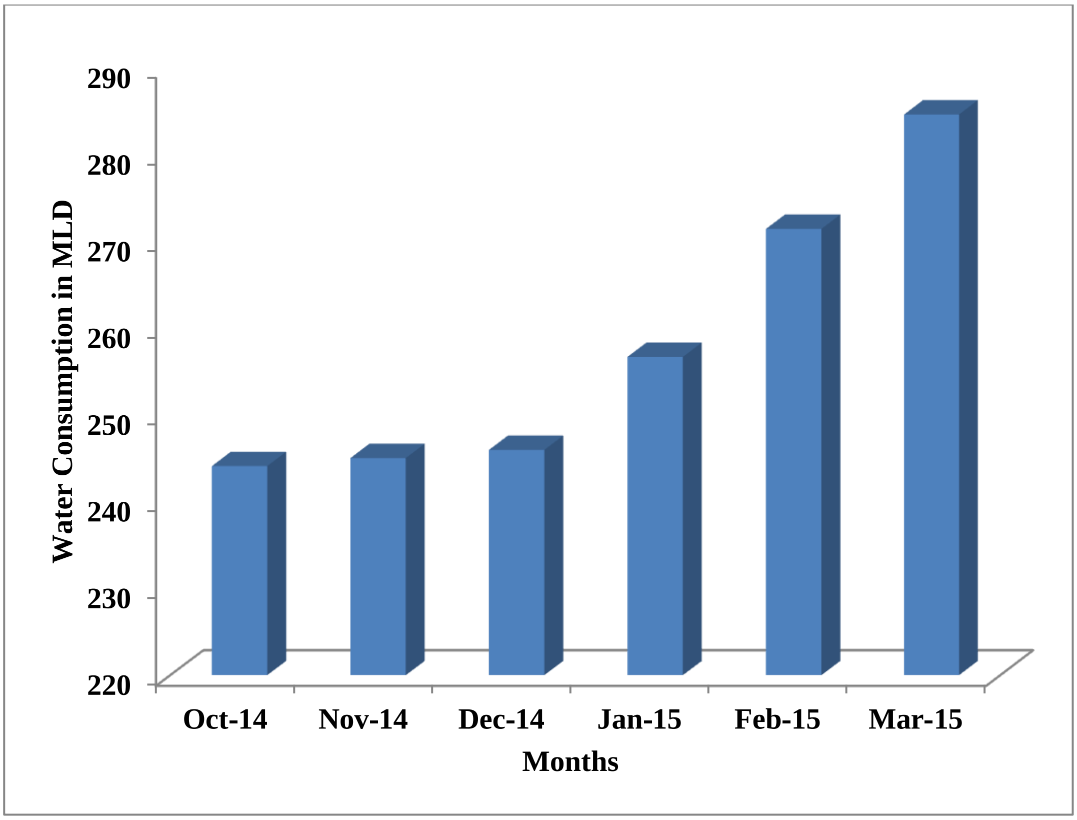


Figure 3.1.13 Rate of Water Supply to Fourth Ward (yelahanka)

3.2 Characteristics of Data Set

Climate data such as rainfall, maximum temperature, minimum temperature and relative humidity are collected on monthly basis from Karnataka state disaster management cell, yelahanka. Similarly water consumption data were collected from Bangalore water supply and sewage board (BWSSB) for a period of 10 years from 2004 to 2014. The influence of climatic factors on water demand is selected based on importance due to potential change in temperature, reduced rainfall and more humidity in the past and as well as in future as a result of the changing climate.

To build any water consumption model 10 years of data set is not sufficient. Water consumption data for a larger period were not maintained. To overcome this problem soft computing technique was adopted which address the problem of limited data. The monthly data set consist of 120 data points out of which 108 data points were used for training and 12 data points were used for testing. From the figure 3.1.1, it is observed that rainfall is not uniform, indicating the high rainfall in the month of September. The value of rainfall in the city varies from 0 to 800mm. Similarly maximum temperature value varies in the range of 25^0c to 35^0c, minimum temperature in the range of 11^0c to 24^0c, relative humidity in the range of 55 to 90%. Comparing the climatic conditions in different seasons indicates that, water consumption fluctuation is not depend on the seasons, irrespective of the seasons water consumption variation will takes place. Comparing the rainfall in two different years, in different seasons, it is observed that rainfall is not uniform. Figure 3.1.11, 3.1.12 and 3.1.13 indicates variation of water consumption for Bangalore, yelahanka and fourth ward. From these figure it is observed that water consumption increases as a result of climatic, demographic and socio-economic changes.

CHAPTER 4

METHODOLOGY AND MODEL DEVELOPMENT

4.1 Introduction

The Methodology adopted to identify the best technique in modeling the water consumption is shown in the figure 4.1. Initially single fuzzy technique is used to build various models. To explore the various options in fuzzy technique (GUI tool box), various models were developed using Mamdani fuzzy inference system for different membership function, rules criteria and with limited data. Developed fuzzy model were compared with ANFIS and multiple linear regression models for different input scenarios. Since data is nonlinear, noisy in nature, to improve the performance of the model, fuzzy technique is combined with wavelet in a improved framework called fuzzy wavelet approach. Discrete wavelet transform is coupled with fuzzy system to develop fuzzy wavelet model. Various models were developed using Haar, Daubechies (db2 to db6) and Discrete Meyer wavelet of level 1 to level 6 with Shannon entropy. In the hybrid approaches, fuzzy wavelet Denoise (FWD) and fuzzy wavelet Compress (FWC) were used to estimate the residential water consumption. The developed FWD and FWC model were compared with the single fuzzy model. Performances of various developed models were assessed using different performance evaluation indices and best model were selected.

Also for better understand of water consumption pattern in the proposed study area and to frame the rule in fuzzy system, field survey was carried out with a prepared questionnaire. Questionnaire is handed over to the interested people participated in the household interview asking to fill the information containing various factors influencing the water consumption using climatic as well as socio-economic variables. This information was considered in framing the rules for Fuzzy modeling. Field survey includes 260 houses of single and attached type. Survey data were divided on the basis of single, attached houses, number of members in family, age group, water bill, maximum usage of water per day.

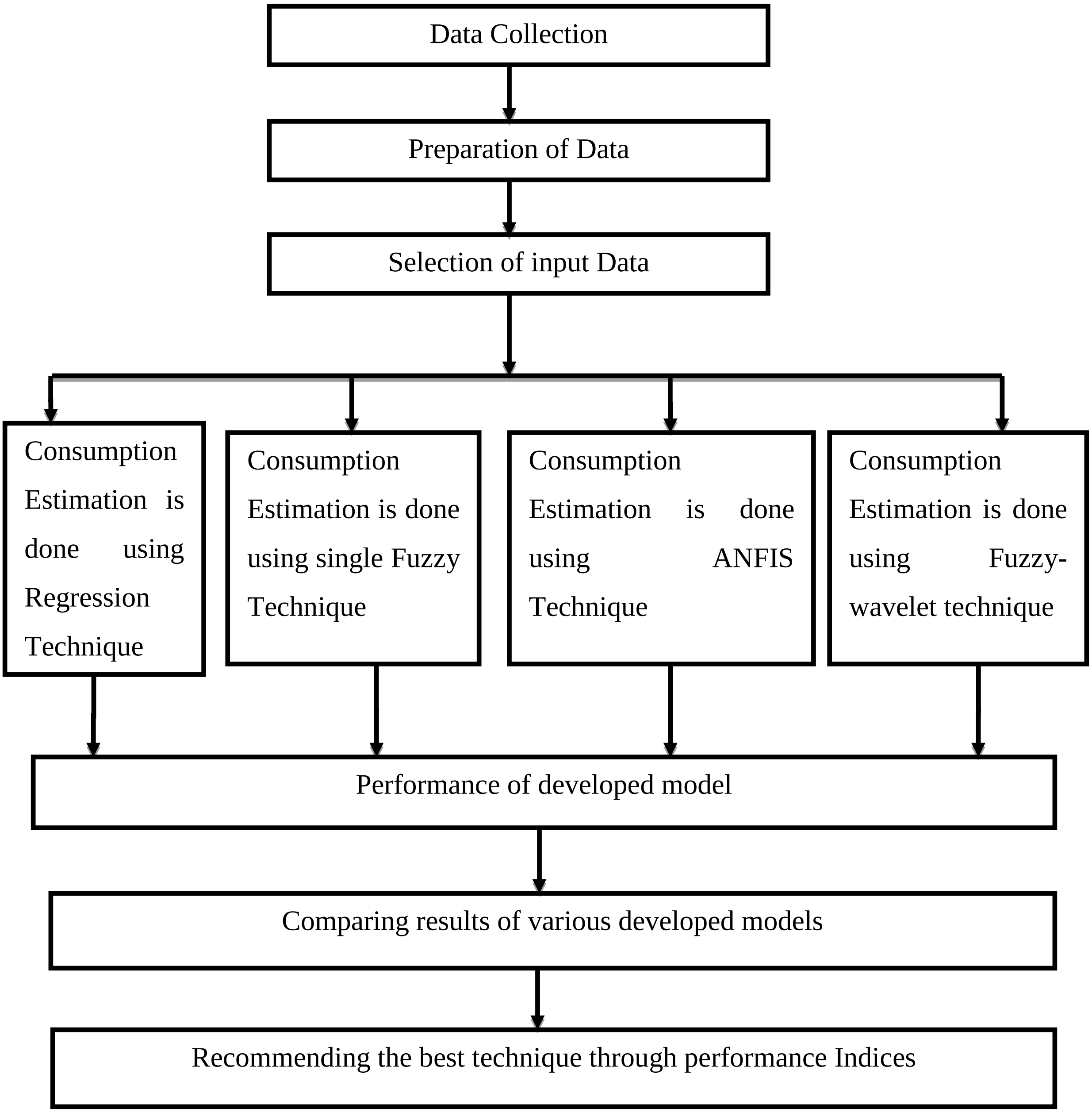


Figure 4.1 Methodology adopted for the present work

4.2 Development of Various Models

The most important step in developing a satisfactory estimation model is the selection of proper input variables, since these variables determine the model structure and affect the accuracy of the model. Selection of proper input variables is done using the correlation coefficient between the variables. For modeling the residential water consumption, rainfall, maximum temperature, minimum temperature, and relative humidity data were collected on monthly basis and it is divided into two parts namely training and testing part. Correlation coefficients of all the variables used for the analysis were represented in the table 4.2.1. From the table it is observed that rainfall and relative humidity having high correlation compared to other variables. Similarly maximum and minim temperature having good correlation To map the given input and output parameter, it is necessary to study the statistical properties of all the input-output variables. Statistical parameter helps identify the lowest, average and highest value of all the variables, which is very useful in modeling process. Statistical properties of all the variables during training and testing period were represented in the table 4.2.2. From the table it is observed that rainfall having larger difference between the maximum and minimum value during training and testing process. Similarly relative humidity and minimum temperature is high during training and testing process. To develop hybrid fuzzy wavelet approach, climatic data were collected from disaster management cell (yelahanka, Bangalore) on monthly basis for a period of ten years from 2004 to 2014. Similarly water consumption data were collected from water supply authority for the same period. Data preparation is done using training and testing process, 70% of the data is used for training process and 30% of the data is used for testing purpose in the case of limited data. 90% and 10% combination is used for ten years data set, which includes 108 data point for training and 12 data for testing.

Table 4.2.1 Correlation Coefficient of all the variables

CC	RF(mm)	T-Max (^{o}C)	T-Min (^{O}C)	RH (%)	WC (MLD)
RF	1.00	0.09	0.05	0.34	0.16
T-Max	0.09	1.00	0.42	0.09	0.24
T-Min	0.05	0.42	1.00	0.16	0.66
RH	0.34	0.09	0.16	1.00	0.04
WC	0.16	0.24	0.66	-0.04	1.00

Table 4.2.2 Statistical Properties of Climatic Variables

Data	Type	RF(mm)	T-Max (^oC)	T-Min (^OC)	RH (%)	WC (MLD)
Training	Maximum	605.60	33.30	23.30	91.60	184.30
	Minimum	0.00	25.60	11.50	16.80	109.20
	Mean	95.00	29.30	20.70	60.10	145.90
	SD	98.40	1.70	2.40	10.00	18.90
	CV	1.00	17.60	8.50	6.00	7.70
	Skewness	2.00	0.40	1.10	0.10	0.30
Testing	Maximum	374.00	35.10	22.90	91.60	215.20
	Minimum	0.00	27.30	15.10	55.00	182.80
	Mean	74.40	29.80	19.40	60.50	201.90
	SD	101.20	2.80	2.40	10.20	10.00
	CV	0.70	10.70	8.00	5.90	20.20
	Skewness	2.70	1.20	0.60	3.00	0.60

4.3 Model Developed using Fuzzy Logic Technique (FL)

Fuzzy Logic is one of the soft computing technique having a wide range of applications covering the entire field. Fuzzy technique works on user defined rules and handles imprecise data. It proves to be advantageous to solve many control problems. Fuzzy systems are rule-based systems, works on the basis of linguistic function to represent the system with better accuracy. Linguistic variables are defined through their membership function, to map the input and output variables in the range of 0 to 1. Commonly two fuzzy inference system are used, includes Mamdani fuzzy inference and Sugeno fuzzy inference. Mamdani fuzzy inference system expects the output value of the membership functions as fuzzy sets. To enhance the efficiency of the fuzzy system, defuzzification process is done. Structure of the Mamdani fuzzy inference used to develop various models is shown in the figure 4.3.1

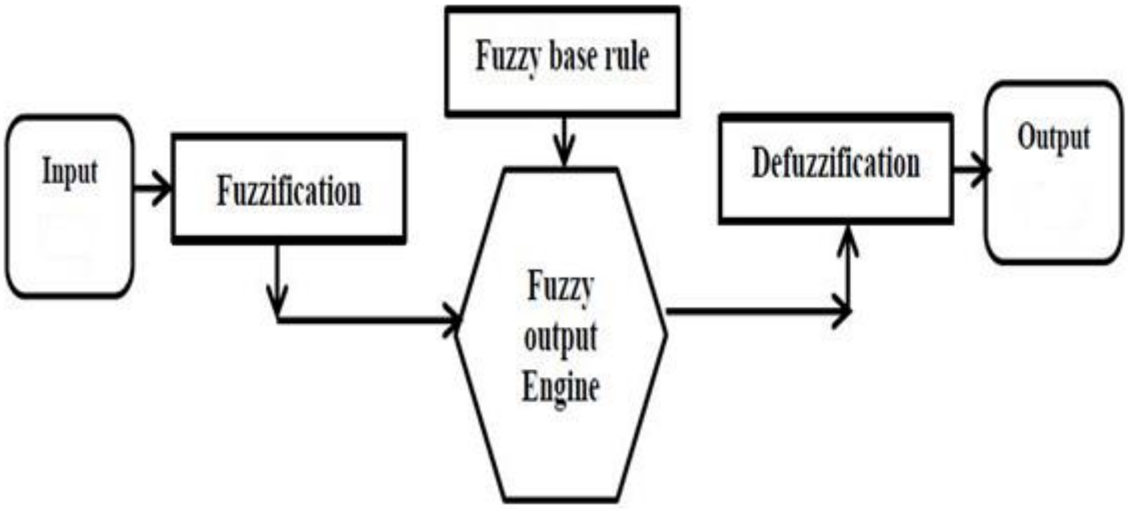


Figure 4.3.1 Mamdani Fuzzy Inference structure

Fuzzy logic provides a simple way of approaching the problems to obtain definite conclusion based on imprecise and noisy type data. Mapping from given input to output variables will be done based on membership function and rules criteria. Once it is mapped then finally defuzzification is carried out to convert linguistic variables into crisp variables, which is an exact opposition of fuzzification process. In the present work, Centroid Defuzzification is used to develop various fuzzy model.

Fuzzy logic is capable of modeling vagueness, handling uncertainty, and supporting human type reasoning, estimates the function without any mathematical equation and learns from experience of training process. Fuzzy Technique starts with the concept of fuzzy set, without crisp and clearly defined boundary. Fuzzy set concept provides a proper procedure to perform numerical computations by using linguistic variables related to membership functions. The fuzzy technique based on linguistic variable expressions includes uncertainty rather than statistical approaches. The basis of fuzzy technique is to consider the system in the form of fuzzy sets, each of which is named with linguistic words such as high, medium and low etc. A fuzzy set element has varying degree of membership in a given set. A small number of fuzzy set result in unrepresentative estimation, where as a large number leads to over estimation (Altunkaynak et al 2005). Structure of Input and output combination with membership function is shown in the figure 4.3.2

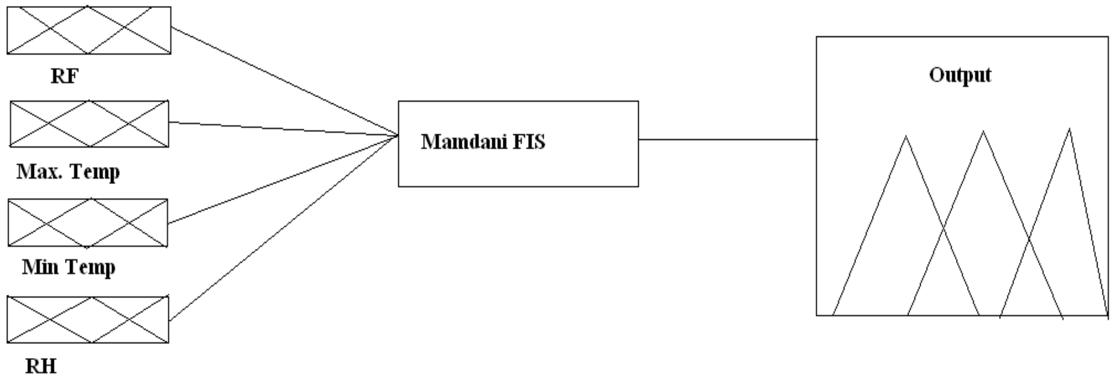


Figure 4.3.2 Input and output combination with Membership Function

Fuzzy systems are constructed from a collection of linguistic rules which represents any system with accuracy. The rule-based Fuzzy system uses linguistic variables as its antecedents and consequents parts, where antecedent defines the inference process, which should be satisfied to the higher extent and consequents part is the output. The rule-based system of Fuzzy Logic is based on IF–THEN rule system, where IF is the antecedent, THEN is the consequent. Fuzzy operations were based on the concept of fuzzy sets where the input data is defined as fuzzy sets with a membership value one.

Fuzzy sets are defined through their membership values, which map the given parameter in the range of 0 to 1. The value 0 indicates non-membership and 1 represents the complete membership. If the value is in between 0 to 1, represents the partial membership value. Depending on the if–then rule structure, Mamdani and Sugeno models were identified. The different types of Fuzzy reasoning used to develop the model is shown in the figure 4.3.3.

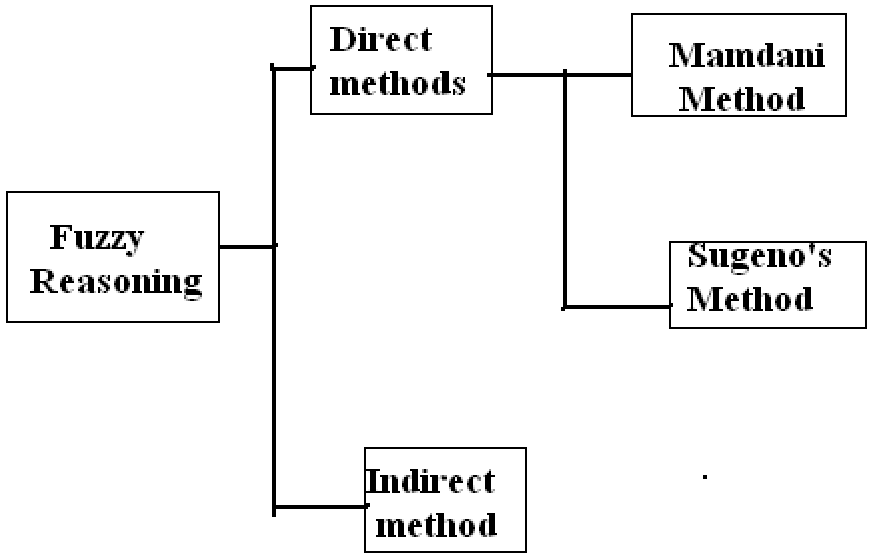


Figure 4.3.3 Different Types of Fuzzy Inference method

Formulating the mapping process from given input to output represent the inference process. Inference process helps to make decision. Mamdani Inferences commonly adopted for complex and decision making process, expects the output membership value to be fuzzy sets. After the process of aggregation, defuzzification is needed for the fuzzy set for each output variables. In Mamdani method, the antecedent and the consequent part are fuzzy propositions.

- Conversion of crisp data into fuzzy data through the process of fuzzification.
- Membership functions with defined rules are connected through inference process to obtain the fuzzy output.
- The opposite of fuzzification process called defuzzification which determines the each associated output.

In fuzzy inference process, input and output measurements sets are provided to the fuzzy system and it learns to transform the inputs to the corresponding outputs. Fuzzy logic does not provide a defined way for developing rules, which is done through many ways.

Developed Fuzzy models are trained by changing different input scenarios, different membership function like triangular, trapezoidal, different rules criteria, and different fuzzy sets like two, three and four to identify optimum number of rules and fuzzy sets with appropriate membership function using centroid defuzzification method.

Results of testing data were compared with the observed value of water consumption, to find the accuracy model. Best fuzzy model is selected which satisfies all the performances criteria includes rules, membership function. The different fuzzy set employed for developing the fuzzy model is shown in the table 4.3.1. Input and output combination used in the modeling process is represented in the table 4.3.2. The different rules criteria used in the fuzzy logic technique is shown in the table 4.3.1. Rules are framed considering the information obtained in field survey. The structure of trapezoidal membership function and triangular membership used to develop various model is shown in the figure 4.3.4 and 4.3.5.

Table 4.3.1 Fuzzy set used in Fuzzy logic analysis

Membership Function	**Number of Fuzzy set**	**Types of Fuzzy Set (Linguistic variables)**
Triangular	Three	Low, Medium , High
Trapezoidal	Four	Low, Medium , High, very high

Table 4.3.2 Input and output model combination

Sl.no	**Input**	**Output**
Input 1	Rainfall (RF)	Water Consumption (WC)
Input 2	Maximum Temperature (T max)	
Input 3	Maximum Temperature (T max)	
Input 4	Relative Humidity (RH)	

Table 4.3.3 Rules criteria used in Fuzzy Model

No. of Rules	Different rules used to develop the models
R1	If (input1 is high) and (input2 is low) and (input3 is medium) and (input4 is high) then (output1 is medium)
R2	If (input1 is high) and (input2 is low) and (input3 is medium) and (input4 is high) then (output1 is high)
R3	If (input1 is medium) and (input2 is low) and (input3 is medium) and (input4 is medium) then (output1 is medium)
R4	If (input1 is medium) and (input2 is low) and (input3 is medium) and (input4 is medium) then (output1 is high)
R5	If (input1 is low) and (input2 is medium) and (input3 is high) and (input4 is medium) then (output1 is medium)
R6	If (input1 is low) and (input2 is medium) and (input3 is high) and (input4 is medium) then (output1 is high)
R7	If (input1 is low) and (input2 is medium) and (input3 is high) and (input4 is high) then (output1 is medium)
R8	If (input1 is low) and (input2 is medium) and (input3 is high) and (input4 is high) then (output1 is high)
R9	If (input1 is medium) and (input2 is low) and (input3 is medium) and (input4 is medium) then (output1 is low)
R10	If (input1 is high) and (input2 is low) and (input3 is medium) and (input4 is low) then (output1 is low)
R11	If (input1 is high) and (input2 is low) and (input3 is low) and (input4 is low) then (output1 is medium)
R12	If (input1 is high) and (input2 is medium) and (input3 is medium) and (input4 is high) then (output1 is high)

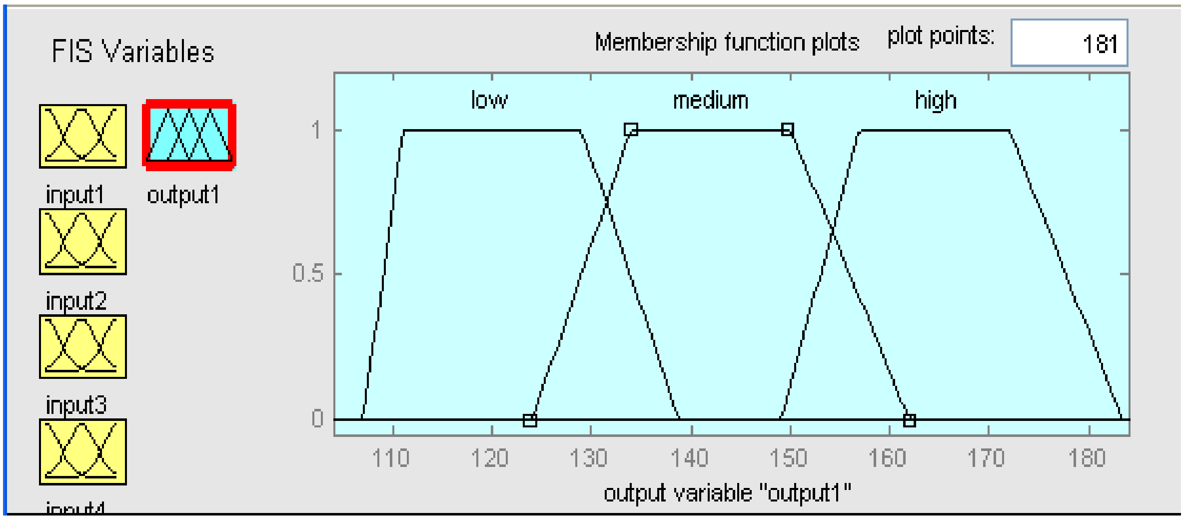


Figure 4.3.4 Structure of trapezoidal membership function

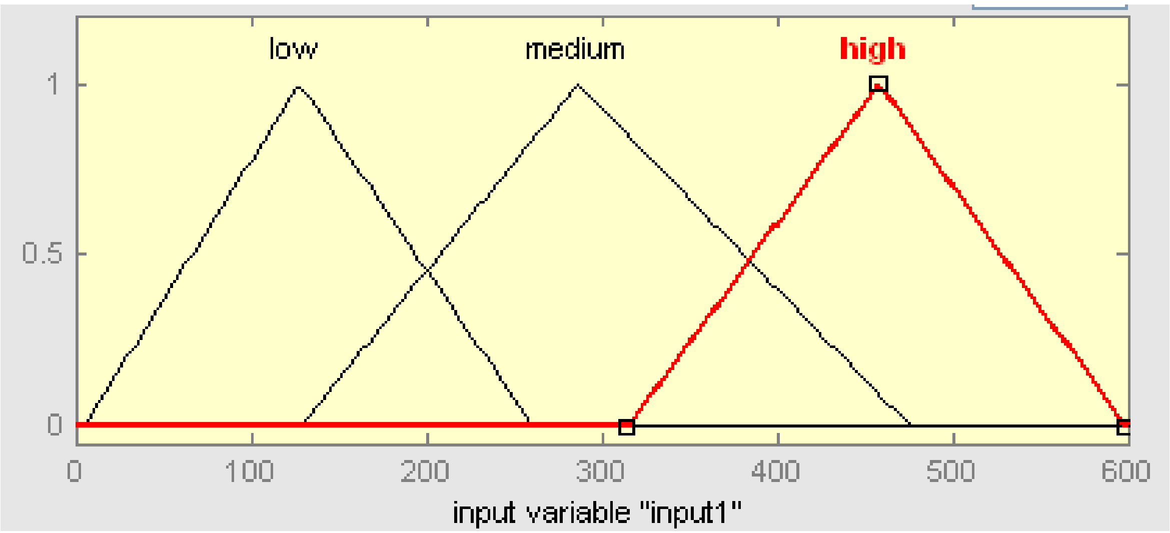


Figure 4.3.5 Structure of triangular membership function

4.4 Multiple Linear Regression Technique

The relationship between dependent and two or more independent variables were determined using multiple relation regression Technique by fitting a linear equation to training data. Each value of the independent variables is connected with the value of the dependent variables.

Based on Linear interval combination, less independent variable can be determined. The Multiple linear regression used to develop the model is shown in the equation below.

$$\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 = Y \qquad (1)$$

Models were developed using four input and single output combination with limited data, including four years and ten years. In the above equation, Y denotes the target strength and x_1, x_2, x_3 and x_4 represents the independent variables. The above equation is a linear function of unknown parameters, called partial regression coefficient.

Assumptions Used

Several Assumptions were made while developing the multiple linear regression models. These Assumptions satisfied the estimators in an optimal manner in the sense that they are unbiased, consistency, and effectiveness. If the expected value equal to the true value, then it is called unbiased. If the estimated value has small variation compared to observed value, then it Is called efficient. If the bias value of the variable approaches to zero, then it is called consistent.

a. **Linearity**: Multiple Linear regression models applied to linear relationship. Scatter plot must be used to identify the possible departure from the linearity. If the data is highly non-linear, transfer the data to make linear. Otherwise use any other statistical model.
b. **Non Stochastic:** The error is encountered with the individual predictors. This assumption is checked in residual analysis with scatter plot of the residual against individual predictors. Violation of the assumption might suggest a transformation of the predictors.
c. **Zero mean**: Residual must have the expected value as zero. The least squares method of estimating the regression, guarantees the mean value as zero.

d. **Constant Variance:** The residual variance is constant. Generally in time series analysis violation of this assumption is, indicated by dependence of the residuals on time.

e. **Non-auto regression**: The residual were uncorrelated with respect to time. This type of assumption also violated in time series analysis.

f. **Normality:** The error must be normally distributed. This assumption must be satisfied through conventional test and other statistics. This assumption is least crucial compare to all other assumption**.**

Uses of Multiple Linear regressions technique

1**.** To study the simultaneous effect of a number of input variables on an output.

2. To estimate a value of an outcome, from the given inputs.

4.5 Adaptive Neuro Fuzzy Inference system (ANFIS) Technique

Adaptive Neuro Fuzzy Inference system (ANFIS) is the famous hybrid approach for modeling the complex non-linear systems, which combines the features of both fuzzy and neural network. The ANFIS having a learning algorithm composed of least square and back propagation method called hybrid learning algorithm.

The integration of Fuzzy Logic and neural network has given the path for new hybrid approach. There is no systematic procedure to define the membership functional parameters in fuzzy logic. To construct the fuzzy rule the definition of premises and consequences as fuzzy set is necessary. On the other side artificial neural network has the ability to learn from input and output combination and adapt to it in a better manner. The basic problem in fuzzy system includes, defining the membership function and fuzzy rules is eliminated by using ANFIS. Due to effectively learning capability of artificial neural network, automatic fuzzy rule generation and parameter optimization will be in a better way. (yurdusev & Firat, 2009). Adaptive neuro fuzzy inference system has a greater potential to capture the advantage of both neural network and fuzzy logic in a single frame work.

ANFIS Architecture used to Develop the Model

If ANFIS contains two fuzzy rules (If-Then), then architecture can be written as follows. ANFIS structure along with fuzzy reasoning is shown in Fig. 4.5.1 and 4.6.2. (Source: Yurdusev & Firat, 2009, Liu Hongbo, 2009)

A1, A2, B1 and B2 are membership function for the inputs X and Y respectively. P1,q1,r1 and p2,q2,r2 are the parameters of the output function. W1 and W2 are the weights corresponding to the rule. F1 and f2 represents the output for the given input. 'f' represents the final output of whole system in the linear combination of consequent parameter.

Rule 1: IF x is A1 and y is B1, THEN f1 = p1x + q1y + r1. (2)

Rule 2: IF x is A2 and y is B2, THEN f2 = p2x + q2y + r2. (3)

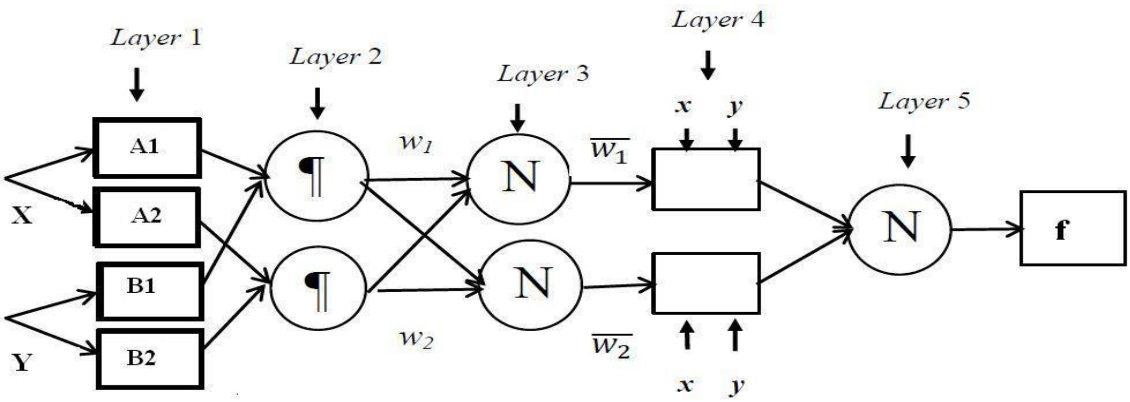


Figure 4.5.1 ANFIS structure used for the analysis

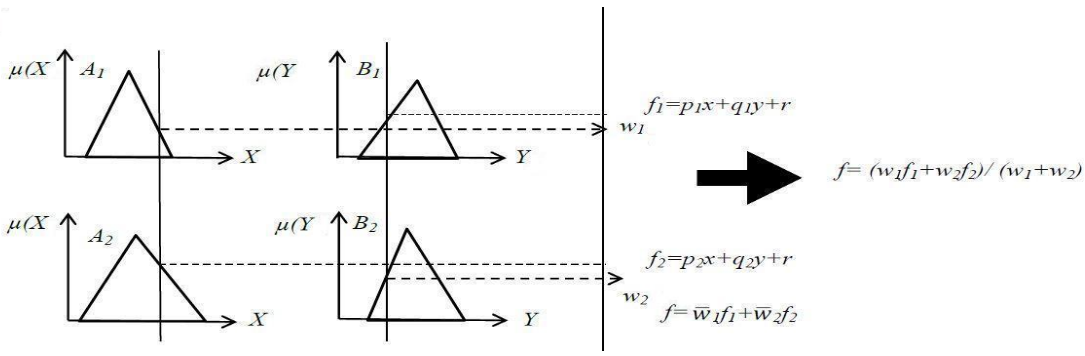


Figure 4.5.2 Fuzzy reasoning scheme for the ANFIS structure

The node function description in each layer is as follows:

- In the first layer each node is adjustable, indicated by square node, with node function.
- In the second layer, node is fixed, indicated by circle node, with node function to be multiplied by the input signal to get output signal.
- In the third layer, node is fixed type indicated by circle node. To normalize the firing strength, each node firing strength must be calculated to the sum of the firing strength.
- In the fourth layer, node is adjustable, indicated by square node.
- In the fifth layer, node is fixed type indicated by circle mode to compute the overall output.

4.6 Wavelet

Time frequency resolution information for a given data is obtained from a mathematical function that analyze the data into different component of frequency and each component is studied with a resolution matching to its scale called wavelet. These wavelet functions were developed independently from the application, being studied largely in the many fields including mathematics, engineering and having a wide range of application.

Wavelet refers to the broken information present in the data. It utilizes the shorter interval for high frequency and longer interval for Low frequency. Several mother wavelets have their own advantages and disadvantage. Selection of particular wavelet plays an important role. Example continuous wavelet function requires more computational time and data. To avoid the drawbacks, in this study discrete wavelet transform is employed. Decomposition of the signal is uniform in wavelet transform and the problem of basis selection not exists. But in the case of the wavelet packet transformer composition of the signal are not unique and attention is paid to best basis selection. The present method is more suitable for individual signal not for group of signal due to the process of denoising and compression. In this research work, wavelet denoising and wavelet compression technique is adopted to reduce the degree of non-linearity present in the data. Denoise and compress operation is done after the wavelet transform process. Compression of the data set is very important in data processing. In the same way when more noise presents in the data it is necessary to remove the noise by filtering process. Wavelet denoising technique removes the smaller coefficients which are not having significant information in the signal. Those noises can be removed without losing the information. Decomposition results in the coefficient with the same number as in the case of original signal, whereas the denoise results in reducing the coefficient which produces the noise.

Compress and denoise operation is done for various mother wavelet includes Haar, Daubechies of order 2,3,4,5,6 and Discrete Meyer wavelet with various level. Initially, wavelet transformation is applied to the indivisible data for a threshold basis function, using Mat lab, wavelet one dimension tool box. In the further stage, to perform the compress and denoise operation, wavelet packet transform were used. Selection of mother wavelet and entropy plays an important role during denoise and compress operation. Hence various models were developed using two different entropy, such as Shannon entropy and log energy entropy. After the denoise and compress operation, the selected entropy plays a prominent role to spread over the coefficient containing the larger information. Hence denoise and compress technique plays a prominent role in reducing the degree of non-linearity present in the data. After denoise and compress operation, coefficient will be given to the fuzzy system for better input and output mapping. Due to lesser degree of variation in the data set, developed fuzzy model may give better result. Hence, combining the wavelet technique with fuzzy may enhance the model accuracy,

4.6.1 Discrete wavelet Transform (DWT)

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other way, this wavelet transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT). Different mother wavelets such as Haar, Daubechies (2, 3, 4, 5 and 6) are used in the filter optimization steps. Since Discrete wavelet transform (DWT) requires less data and time for computations, it is used to denoise and compress the data. After the denoise operation, Shannon entropy will capture the coefficient having higher information The discrete wavelet transform is given by an equation mentioned below.

$$\Psi_{j,k}(x) = 2^{j/2} \psi\, j,k\,(2^{j}_{x}-k) \quad (4)$$

$\Psi_{j,k}$ (x) = Approximate coefficient signal, which is Dilated by j and Translated by k.

Haar Wavelet

Haar wavelet is the first and simplest form of the wavelet. The Haar wavelet represents the same wavelet of Daubechies order 1, It is discontinuous, and resembles a step function. Shape of Haar wavelet is shown in the figure 4.6.1.a

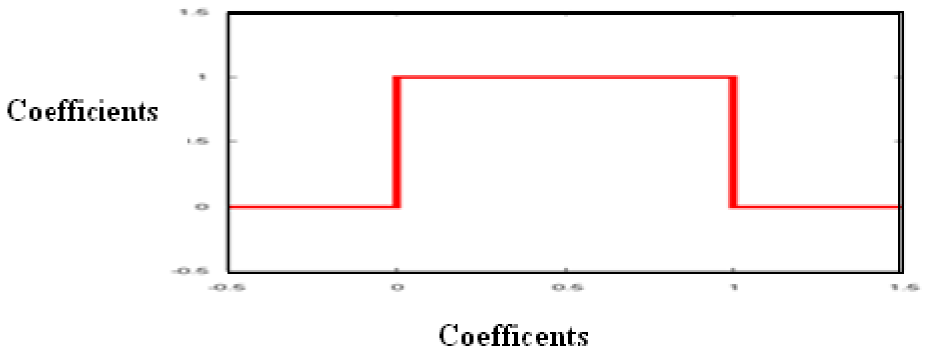


Figure 4.6.1.a Shape of Haar wavelet

Daubechies Wavelet (db)

The names of the Daubechies family wavelets are written dbN, where N represents the order and db represents the surname. The db1 wavelet, as mentioned above, is the same as Haar wavelet. Shape of the Daubechies wavelet group from db2 to db6 is shown in the figure 4.6.1.b. The structure of the wavelet tree for Daubechies wavelet is shown in the figure 4.6.1.c

Figure 4.6.1.b Daubechies Wavelet family from db2 to db6

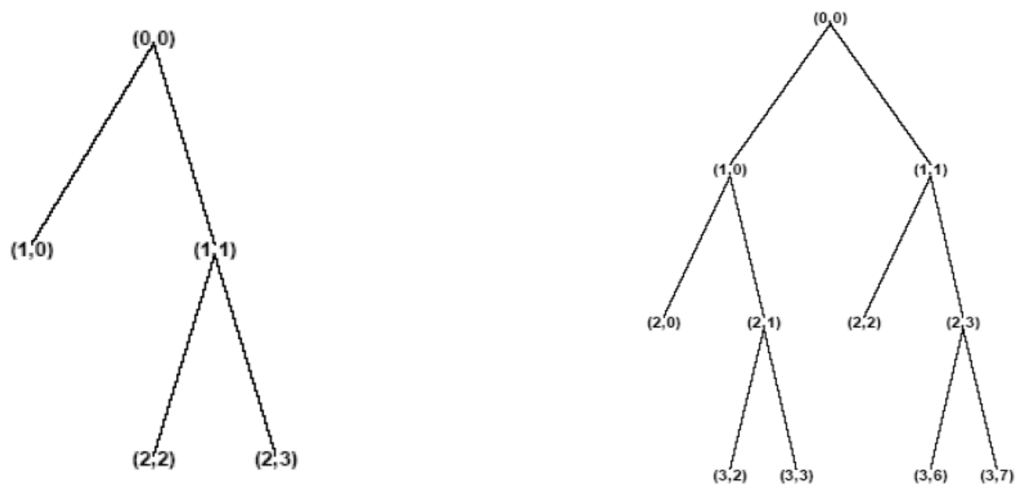


Figure 4.6.1.c Wavelet tree for different Daubechies group

Discrete Meyer Wavelet

The Discrete Meyer wavelet and its scaling function are defined in the frequency domain. The structure of Meyer wavelet is shown in the figure 4.6.1.d.

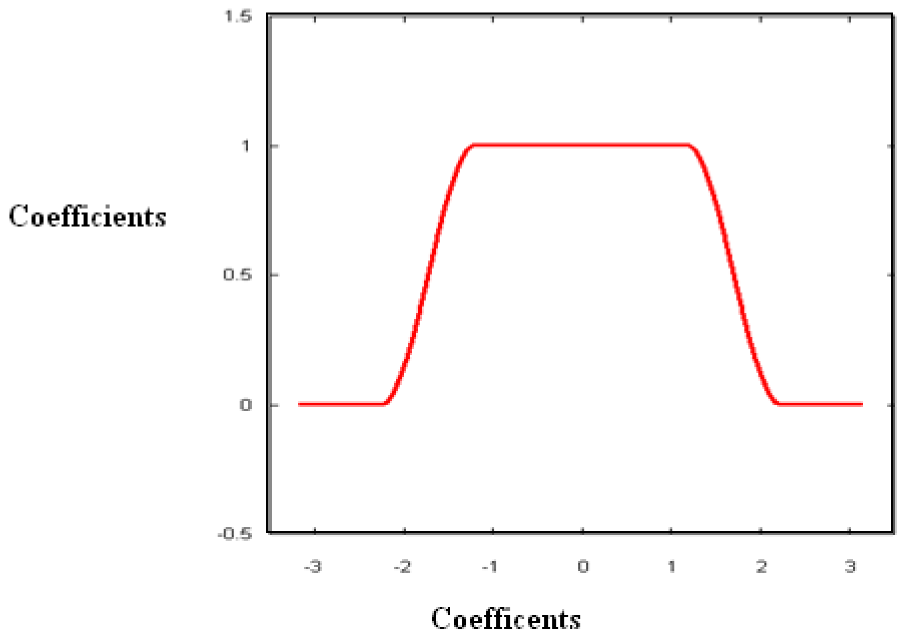


Figure 4.6.1.d   Shape of Discrete Meyer wavelet

4.6.2   Fuzzy –Wavelet Compressed (FWC)

It is necessary to reduce the degree of non-linearity in the data set to improve the model accuracy. One of the methods to reduce the degree of non-linearity is by compressing the data. Hence compress process act as a data normalizing technique. Compress method will not remove any coefficient, but it will compress the signal having lesser information. After wavelet transformation, signal can be compressed easily because the information is concentrated on few coefficients. Hence degree of non-linearity will be reduced. For this process various mother wavelets were used such as Haar, Daubechies of order 2 to 6 and Discrete Meyer wavelet of different level. The obtained coefficient which contains the information is saved and corresponding statistical properties were obtained and applied to Fuzzy Logic method. So the consequent parts of the Fuzzy rules are able to trigger the output function in a better way. Process of denoise operation used in the mat lab tool is shown in the figure 4.6.2.a. Data before and after compression is shown in the figure 4.6.2.b.

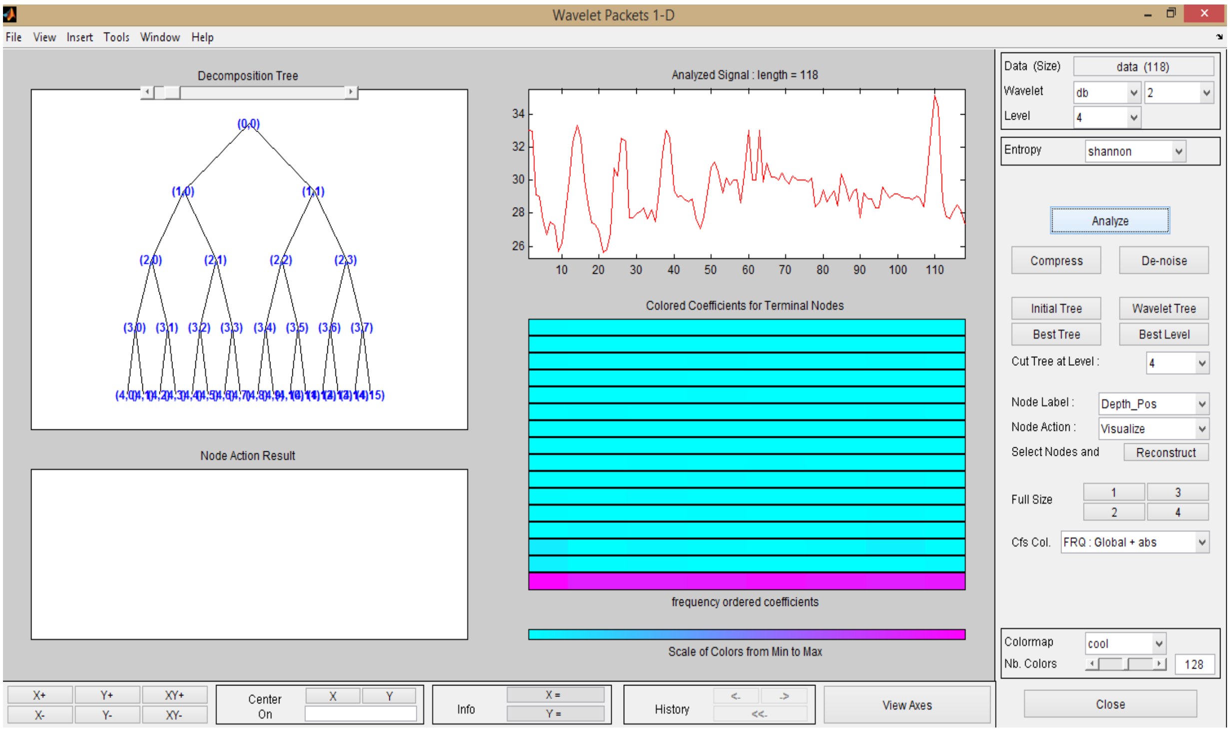


Figure 4.6.2.a Fuzzy-wavelet in Mat-lab tool

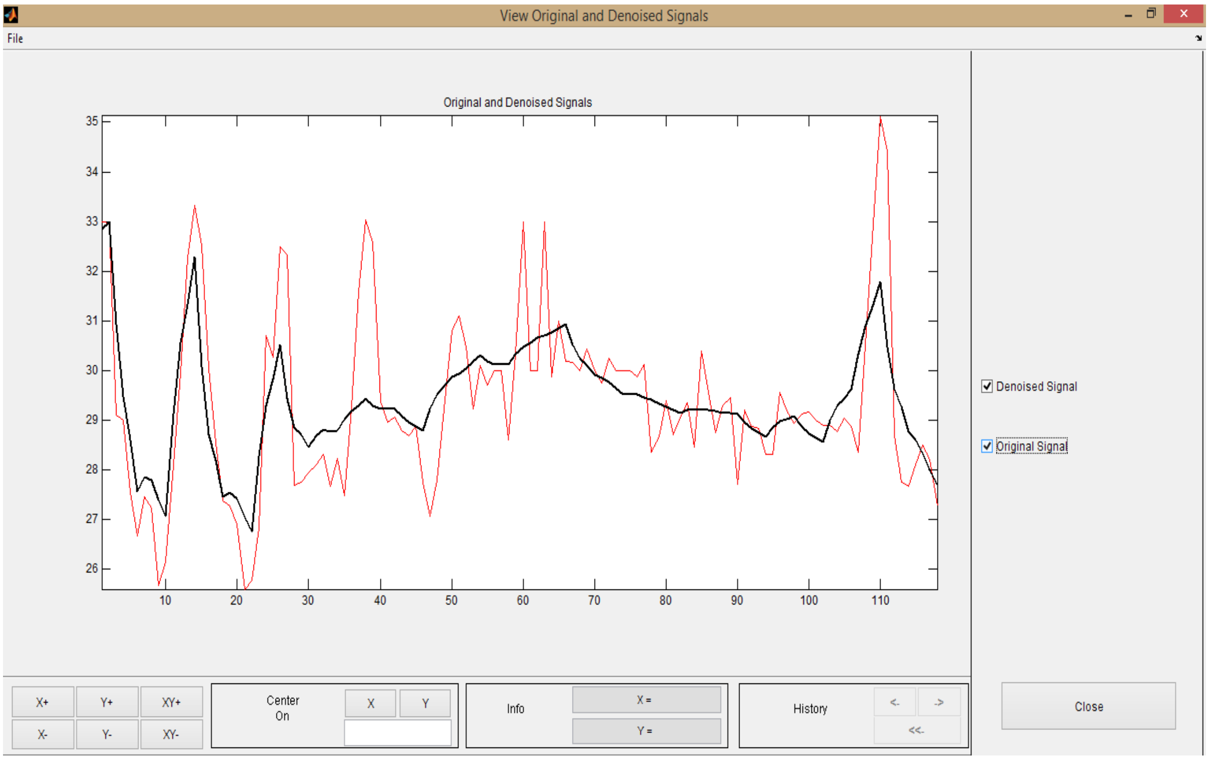


Figure 4.6.2.b Data before and after the compression operation

4.6.3 Fuzzy –Wavelet Denoise Technique (FWD)

It is proposed to reduce the error in the model by removing the noise in the data. Denoise is one of the method to reduce the degree of non-linearity in the data. Denoised approach reduces the unwanted signal which contains lesser information, these are referred as Noise. By removing noise, only the coefficient which contains more information with respect to time-frequency domain will be retained. This performance is done for different types of wavelets such as Haar, Daubechies of different order db2 to db6 and Discrete Meyer Wavelet. The obtained coefficient which contains the information is saved and corresponding statistical properties were studies and then applied to Fuzzy Logic method. So the consequent parts of the fuzzy rules are able to trigger same desired output. Denoised and compress method is done using Shannon entropy. Which spread over the wavelet after denoise and compress operation, so more information will be collected. The input-output combination used to develop fuzzy wavelet model were presented in the table 4.6.3.

. **Denoise procedure**

- Apply wavelet transform to the noisy data to produce the noisy wavelet coefficients
- Select appropriate threshold limit and threshold method to remove the noises.

Table 4.6.3 Input- output combination for Fuzzy Wavelet model (denoise and compresses)

Model Type	Inputs	Output
Fuzzy Model	Rainfall	WC
	Maximum Temperature	WC
	Minimum Temperature	WC
	Relative Humidity	WC
Fuzzy wavelet denoised (FWD) Including Haar, Daubechies family group of 1 to 6 levels, Discrete Meyer.	Rainfall	WC
	Maximum Temperature	WC
	Minimum Temperature	WC
	Relative Humidity	WC
Fuzzy wavelet compression (FWC) Including Haar, Daubechies family group of 1 to 6 levels, Discrete Meyer.	Rainfall	WC
	Maximum Temperature	WC
	Minimum Temperature	WC
	Relative Humidity	WC

4.7 Performance Evaluation Indices

To evaluate the accuracy of the developed single fuzzy model, hybrid Fuzzy wavelet denoise model and Fuzzy wavelet compress model, various performance evaluation indices were used, which includes, RMSE, CC, MAE, PE and Bias. The description of each performance evaluation indices is given below.

a) Correlation Coefficient (CC)

Strength of the linear relationship between two variables is measured using CC. It is defined as the ratio between coefficients of variation divided by the standard deviation. If CC value is near to 1, model is treated as better one. Equation for correlation coefficient is represented in the equation number 5.

$$\sum(x-x')(y-y')/\sqrt{(x-x')(y-y')2} \quad (5)$$

Where,

n= number of data present, x= observed values, y= estimated values, $x' =$ Mean of the observed values, $y' =$ Mean of the estimated values.

b) Mean Absolute error (MAE)

Smaller the MAE value better will the model result. It is defined as the ratio between the differences of observed and estimated value by number of observation. Lower value of MAE is better one. MAE is shown in the equation number 6.

$$\text{MAE} = \frac{\textit{observed values} - \textit{estimated values}}{\textit{Number of test observation}} \quad (6)$$

c) Percentage Error (PE)

If the value is close to zero then the model is treated as best one. It is defined as the ratio between the differences of estimated and observed value by number of observation percentage error is given in the equation number 7. It is expressed in %.

$$\mathbf{P.E} = \frac{\textbf{Estimated values} - \textbf{observed values}}{\textbf{observed values}} \times \mathbf{100} \qquad (7)$$

If percentage error is close to zero then model is good one.

d) Root mean square error (RMSE)

It is used to measure the estimation accuracy between the observed and estimated value in a model. For Lower value of RMSE, model performance is better. It is given in the equation number 8.

$$\sqrt{\sum(observed - Estimated)^2/N} \qquad (8)$$

Where, X = observed values, Y = Estimated values, N= Number of observation

e) BIAS

It is defined as the ratio between estimated and observed value. If the value of BIAS close to 1, model performance is better. BIAS is presented in the equation number 9.

i.e. BIAS= estimated / observed (9)

Chapter 5

RESULTS AND DISCUSSIONS

5.1 Introduction

This research work highlight the importance of developing Fuzzy wavelet (denoise and compress) approach for modeling the municipal residential water consumption estimation using rainfall, maximum temperature, minimum temperature and relative humidity as input variable. The results of developed fuzzy wavelet models were compared with the single fuzzy model for different length of data and different input and output combination. An attempt is made to focus the strength of hybrid soft computing technique in modeling the non-linear type of data, by comparing with single fuzzy, ANFIS and multiple linear regressions techniques.

In the first stage, multiple linear regression models were developed using partial linear regression coefficient. Performances of the developed regression model for two different lengths of the data were analyzed separately for a period of four years and ten years using four input climatic variables. From the result it is found that for a larger length of data, accuracy of the model decreases.

In the second stage, performance of the single fuzzy model is analyzed using trapezoidal membership function and six rules criteria. Due to self-rule framing and mapping of input and output data, developed fuzzy model performed better, compared to multiple regression model using four combined input and single output combination. Further performance of the fuzzy model for individual variables, studied separately using trapezoidal membership function and six rules criteria. The results obtained reveals that, developed fuzzy model is weak in mapping the input and output parameter for individual variables due to high non-linearity nature. To overcome the problem of parameter adjustment, hybrid adaptive neuro fuzzy inference system is adopted, since it adjust all the membership parameter from a given input and output data using back propagation algorithm. For individual input combination, the developed hybrid approach shows better result compared to single fuzzy and multiple linear regression model. This opens the platform for developing the model using hybrid approaches.

In the third stage, further to explore the option of fuzzy Logic, various fuzzy models were developed using different membership function, rules criteria and fuzzy set, to select the best membership function and optimum number of rules in modeling the water consumption estimation. For this purpose, triangular and trapezoidal membership functions were used using three, six, nine and twelve rules criteria. The developed fuzzy model shows improved performance for triangular membership function with twelve rules criteria. Further using triangular membership function, fuzzy models were developed for individual variables. The selected best membership function shows improved result compared to trapezoidal membership function. Both triangular and trapezoidal fuzzy model performance for individual variables reveals that, rainfall and maximum temperature variables having higher value of RMSE and higher response in the error magnitude. Hence rainfall and maximum temperature is treated as most important variables which affect the model accuracy.

Although developed hybrid ANFIS model performed better, it required higher number of rules for computation and increasing the number of rules leads to slow convergence results in lower performance in accuracy of the model. Hence developed single fuzzy and ANFIS models, may not get the higher accuracy in the case of highly nonlinear data.

Further, to improve the efficiency of model, wavelets were used in modeling complex nonlinear processes. In this research work, fuzzy wavelet (denoise and compression) techniques were employed to estimate the residential water consumption for indivisible climatic variables. Denoise and compression methods reduces the degree of nonlinearity of the input data, so the consequent part of fuzzy system provide better input and output mapping, results in enhancing the model accuracy. Discrete wavelet transform function with various mother wavelet such as Haar , Daubechies of order db2, db3, db4, db5, db6 of different levels and Discrete Meyer wavelet were used to develop fuzzy wavelet model. The coefficients obtained after denoised and compress process were given to the consequent part of the fuzzy set with optimum rules and memberships function to get the desired output. Denoise and compress operation of the wavelet make the signal smoother reducing the risk in framing the rules for fuzzy system. In this research work, performance of entropy in improving the model performance is examined. Also efficiency of different performance evaluation indices in selecting the best model is analyzed. Overall performance of the model reveals that, hybrid fuzzy-wavelet denoise and compress technique found to be effective in modeling the complex nonlinear processes. The results of all the developed models were discussed below.

5.2 Results of Developed Regression model

Table 5.2.1 represents the results of regression technique, for a period of four years from January 2004 to December 2008 with limited data. For the developed model, regression coefficients were obtained by fitting the training data using the equation, with two independent variables and one dependent variable. Due to limited data, error for the developed model is found less. From the result it is found that percentage error is 25.8 and correlation coefficient is 0.69. Further analysis is carried out using ten years of data for four inputs and single output combination. Due to increase in the length of the data having more non-linear nature, error obtained is very high, compared to limited data. Results of regression technique for ten years of data were presented in the table 5.4.1. From the overall performance it is found that as the data length increases, degree of nonlinearity also increases. Hence developed regression model is capable for linear nature of the data. The observed and estimated value of water consumption using regression technique is shown in the figure 5.2.1.

Table 5.2.1 Results of Regression Techniques for limited data (4 years)

Input	Output	CC	PE (%)	RMSE (MLD)
RF, T-Max , T-Min, and RH	WC	0.69	25.8	21.50

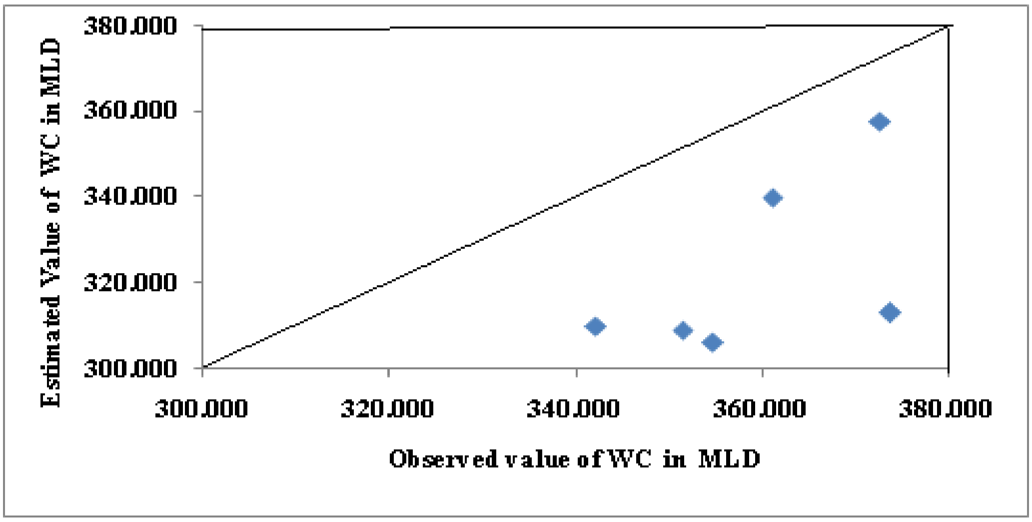


Figure 5.2.1 Observed and estimated values of water consumption using regression technique

Figure 5.2.1 shows the observed and estimated value of water consumption using regression technique. Due to higher degree of non-linearity, the developed regression model shows weak performance having CC value 0.49, percentage error 74 and RMSE value 83.22, shown in the table 5.4.1. The developed regression model shows under prediction.

5.3 Results of Developed Fuzzy models

For highly nonlinear data, developed regression model has more error, discussed in the section 5.2. Further analysis is carried out using Fuzzy logic method. For this purpose, trapezoidal membership function with six rules criteria is adopted using Mamdani Fuzzy Inference system. The result of developed fuzzy model for four combined inputs and single output combination were presented in the table 5.4.1. From the result, it is found that, developed fuzzy model shows better performance compared to regression model. The observed and estimated value of water consumption using fuzzy approach is shown in the figure 5.3.1.

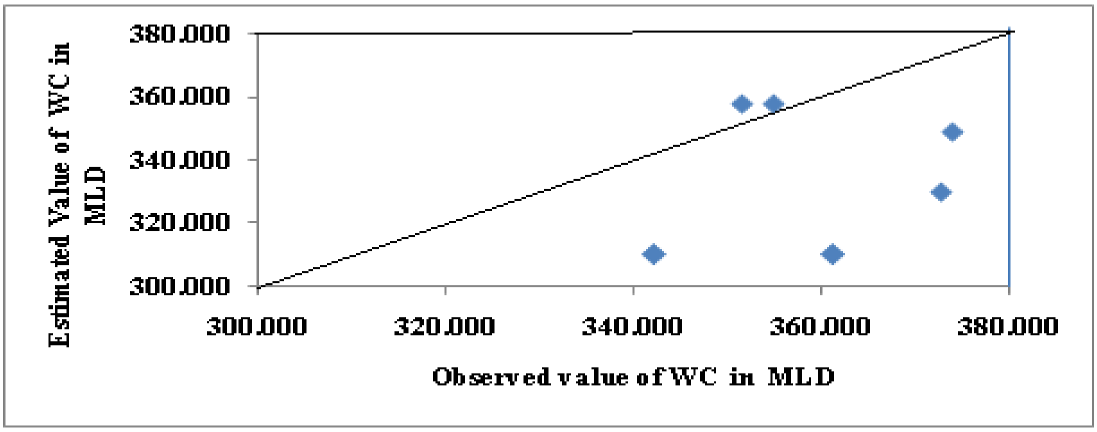


Figure 5.3.1 Observed and Estimated values of water consumption using fuzzy approach

Figure 5.3.1 shows the results of fuzzy model having CC value 0.57, percentage error 14.50 and RMSE value 53.39, shown in the table 5.4.1. Developed fuzzy model shows better performance compared to regression model, due to rule base creation of the fuzzy system and mapping of input and output function. Although the obtained model showed improved result, but weak in handling the degree of non-linearity. Hence the result obtained is slightly accurate than regression technique.

5.4 Results of developed ANFIS models

To improve the model accuracy, by increasing the rate of convergence, adaptive neuro fuzzy inference system is used for four combined input and single output combination. Due to self-rule framing criteria and self-learning criteria of ANFIS, rate of convergence will improve, results in better mapping of input-output combination. Model having 243 fuzzy rules were created by grid partition and fuzzy inference system trained by hybrid network. The results obtained were compared with the observed values to find out performance of the models. Table 5.4.1, shows the results of ANFIS model. From the overall performance it is found that soft computing methods such as Fuzzy logic and ANFIS shows improved result compared to regression technique. Hybrid ANFIS model perform better compared to single fuzzy model. The results of all the developed models using various techniques for four combined input and single output combination were presented in the table 5.4.1. Observed and estimated value of water consumption is shown in the figure 5.4.1. Comparative results of all the technique for four input and single output combination is shown in the figure 5.4.2.

Table 5.4.1 results of developed model of all the techniques (Four inputs and one output)

Type	Regression	Fuzzy Logic	ANFIS
Correlation Coefficient (CC)	0.49	0.57	0.97
Percentage Error (PE) in %	74.00	14.50	11.00
RMSE (MLD)	83.22	53.39	12.95

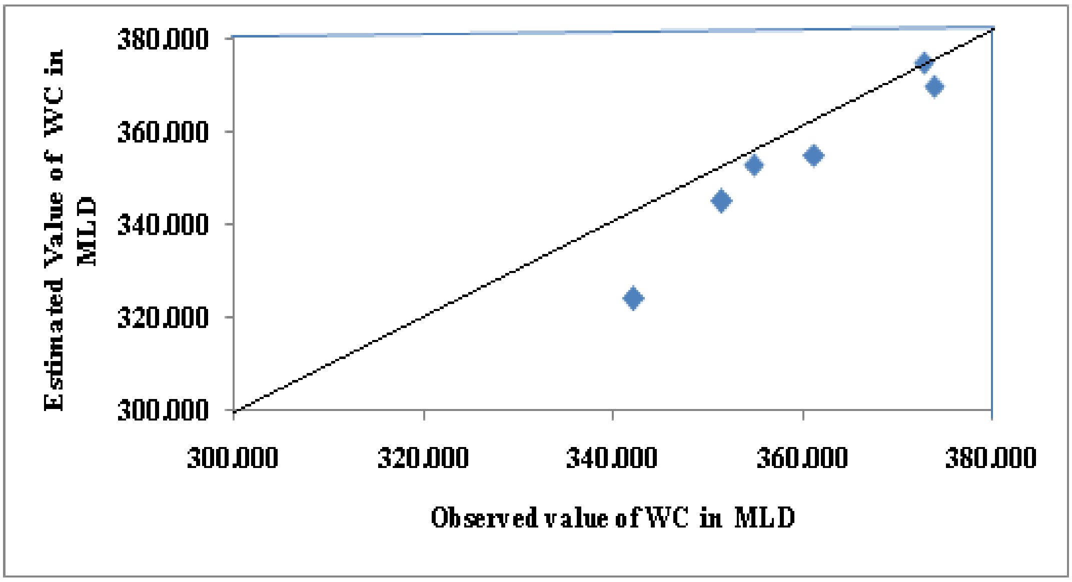
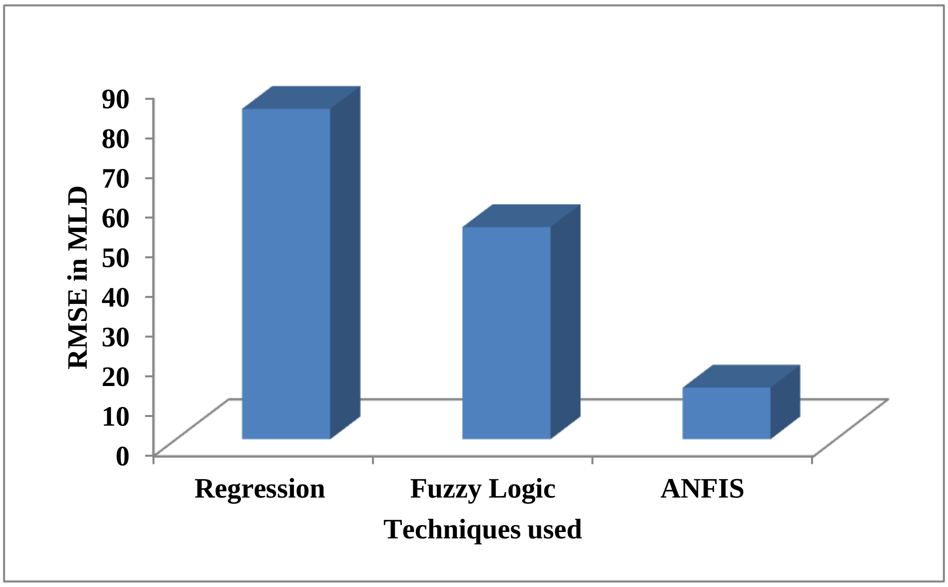


Figure 5.4.1 Observed and Estimated values of Water Consumption using ANFIS

Figure 5.4.1 shows the results of adaptive neuro fuzzy inference model for four input and single output combination. The develop model having CC value 0.97, percentage error 11 and RMSE value 12.95. Model performance is found to be better compared to regression and single fuzzy approach, due to self-rule framing and learning criteria. Due to increase in the rate of convergence, estimated values are closer to observed value.



5.4.2 Comparative results of all the Techniques

Figure 5.4.2 shows the comparative result of developed regression, fuzzy and neuro fuzzy model for four input and single output combination using climatic variables. The value of RMSE for the developed regression model is found to be very high compared to single fuzzy and neuro fuzzy model. From the figure, it is observed that hybrid approach handles the complex non-linear data better way compared to single fuzzy and traditional model.

5.5 Results of Developed Fuzzy model for Individual variables

To identify the significant influence of climatic variables in modeling the water consumption, further analysis is carried out using triangular membership function with proper rules and fuzzy set. The input variables such as rainfall, maximum temperature, minimum temperature and relative humidity were used separately rather than combined input approach. Table 5.5.1 represents the results of developed fuzzy model for individual variables. From the result it is found that, in mapping the input and output relationship rainfall and maximum temperature shows higher response in the variation of error, whereas minimum temperature and relative humidity, error variation is less. rainfall and maximum temperature are the two variables which affect the modeling process. Hence these two are significant in reducing the model accuracy. Similarly minimum temperature and relative humidity are treated as best variables influencing the model accuracy. The results of individual variables used for the analysis is represented in the table 5.5.1. Comparative results of individual variables analysis using fuzzy approach is shown in the figure 5.5.1.

Table 5.5.1 Results of fuzzy models for individual variables

Models	Input	Output	RMSE (MLD)
F1	RF	WC	81.46
F2	T-MAX	WC	62.77
F3	T-MIN	WC	49.79
F4	RH	WC	54.39

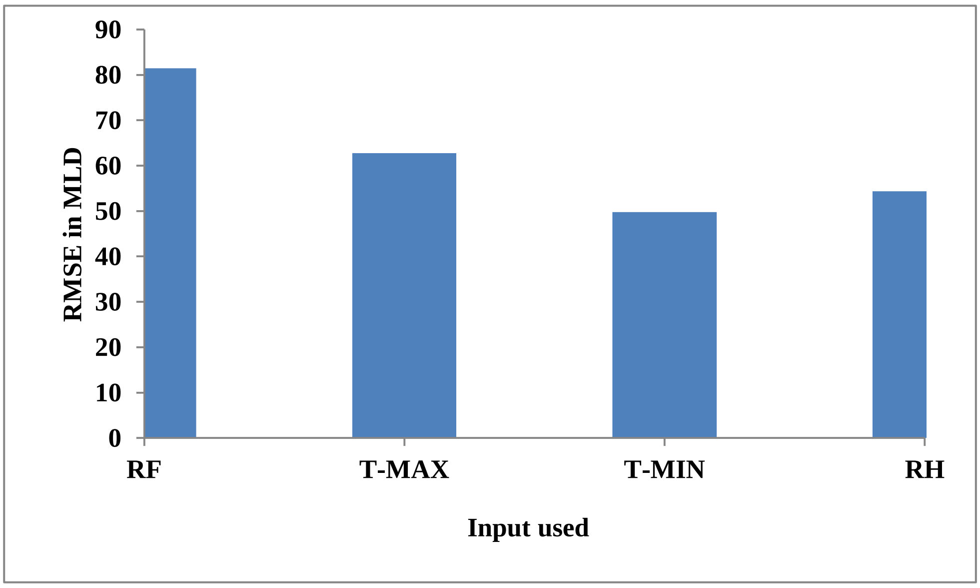


Figure 5.5.1 Comparative results of fuzzy approach for individual variables

Figure 5.5.1 shows the comparative results of fuzzy model for individual variables using trapezoidal membership function. Larger length of the data makes the fuzzy structure complex in defining the rule base, result in slow convergence. RMSE value of the developed fuzzy model for rainfall and maximum temperature is 81.46 MLD and 62.77MLD. For minimum temperature and relative humidity input combination, RMSE is 49.79 MLD and 54.49 MLD.

Further to improve accuracy of the model by enhancing the rate of convergence, it is necessary to frame optimum number of rules, proper membership function with appropriate number of fuzzy set. Hence various fuzzy models were developed using triangular and trapezoidal membership function for different rules criteria include three rules, six rules, nine rules and twelve rules with three fuzzy set such as low, medium and high. Rainfall, maximum temperature, minimum temperature and relative humidity were used to map the input and output. The results of triangular membership function for different rules criteria were represented in the table 5.5.2. From the results, it is found that, developed model using twelve rules criteria with three fuzzy set, shows less error in terms of RMSE compared to other rules criteria. Twelve rules were found effective in mapping the input output relationship. Consequent part of the data set were closer to the observed one, if the optimum number of rule were used, which acts as a firing rules in modeling water consumption. Hence error in the model is less. Triangular membership function with three fuzzy set for twelve rules criteria improve the rate of convergence.

Table 5.5.2 represents the results of trapezoidal membership function used for the analysis. From the results it is found that trapezoidal membership function performance is much lesser compared to triangular membership function. Since the mapping of input variables struck in the local minima due to its trapezoidal shape. From the overall performance triangular membership function with twelve rules criteria and three linguistic variables (fuzzy set) found to be better. The overall performances of different membership function and rules criteria were presented in the table 5.5.2. The improved result of fuzzy model for twelve rules and triangular membership function for individual variables were presented in the table 5.5.3. The observed and estimated value of water consumption using fuzzy approach for triangular membership function is shown in the figure 5.5.2. Comparative results of RMSE for different membership functions and rules criteria is shown in the figure 5.5.3. Comparative results of improves fuzzy model for individual variables is shown in the figure 5.5.4.

Table 5.5.2 Results of fuzzy model for different membership and rules criteria

Membership Type	Type	Three rules	Six rules	Nine rules	Twelve rules
Trapezoidal	RMSE (MLD)	14.69	25.08	15.27	12.38
	MAE (MLD)	4.24	7.24	4.40	3.57
Triangular	RMSE (MLD)	14.40	12.67	14.40	10.30
	MAE (MLD)	4.15	3.65	4.15	2.99

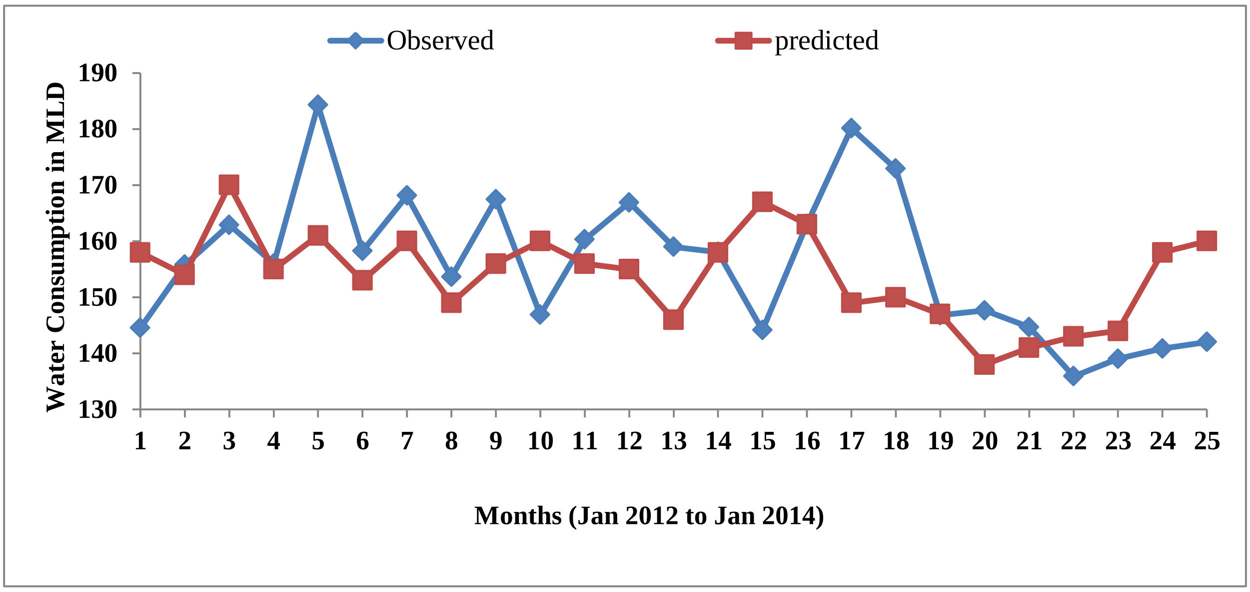


Figure 5.5.2 Observed and Estimated values of water consumption using fuzzy approach

Figure 5.5.2 shows the observed and estimated value of water consumption for fuzzy approach using triangular membership function. Fuzzy models were developed for period of two years from January 2012 to January 2014. Due to limitation of rule base creation, model performs both under and over estimation. In the 5th month, observed value is high compared to estimated value and in the 17th month estimated value is high compared to observed value. These inevitable character are due to improper rule framing criteria, result in slow convergence in mapping the input- output characteristics.

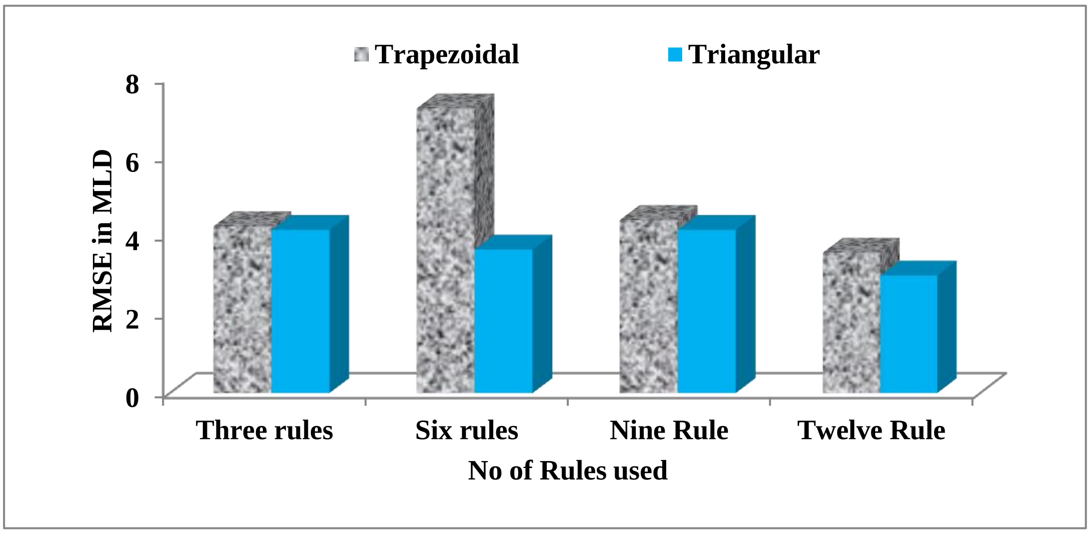


Figure 5.5.3 Membership function Performance for different rules criteria

Figure 5.5.3 shows the result of Mamdani fuzzy inference model for triangular and trapezoidal membership function with three rules, six rules, nine rules and twelve rules criteria. From the figure it is found that both triangle and trapezoidal membership function performance is better for twelve rules, having the RMSE value 12.38 MLD and 10.30 MLD compared to other rule structure. Similarly, the developed model having higher value of RMSE 25.08 MLD for nine rule trapezoidal membership function. From the overall performance triangular membership function shows improved result compared to trapezoidal membership function. Due to triangular membership shape, the defined fuzzy sets along with framed rules were able to map the input-output function effectively. From the overall performance it is found that, triangular membership function with twelve rules criteria is found to be better.

Table 5.5.3 Results of improved fuzzy model for individual variables analysis

Models	Input	Output	RMSE (MLD)
F1	RF	WC	44.17
F2	T-MAX	WC	21.44
F3	T-MIN	WC	13.04
F4	RH	WC	13.13

Table 5.5.3 shows the result of fuzzy model for individual variables. The models were developed using triangular membership function with three fuzzy set. After incorporating the proper membership function, rule base and fuzzy set, the developed fuzzy model shows improved result compared to trapezoidal membership function as shown in the table 5.5.1. The improved performance of the model using triangular membership function is presented were the table 5.5.3, shows higher RMSE value of 81.46 MLD and 62.77 MLD for rainfall and maximum temperature input. After incorporating the triangular membership function error reduces to 44.17 MLD and 21.44 MLD for the same input criteria. Hence selection of optimum rules and membership function play an important role in modeling phenomenon. Result of both cases, shown in the table 5.5.1 and table 5.5.3. Higher error variation for rainfall and maximum temperature data set.

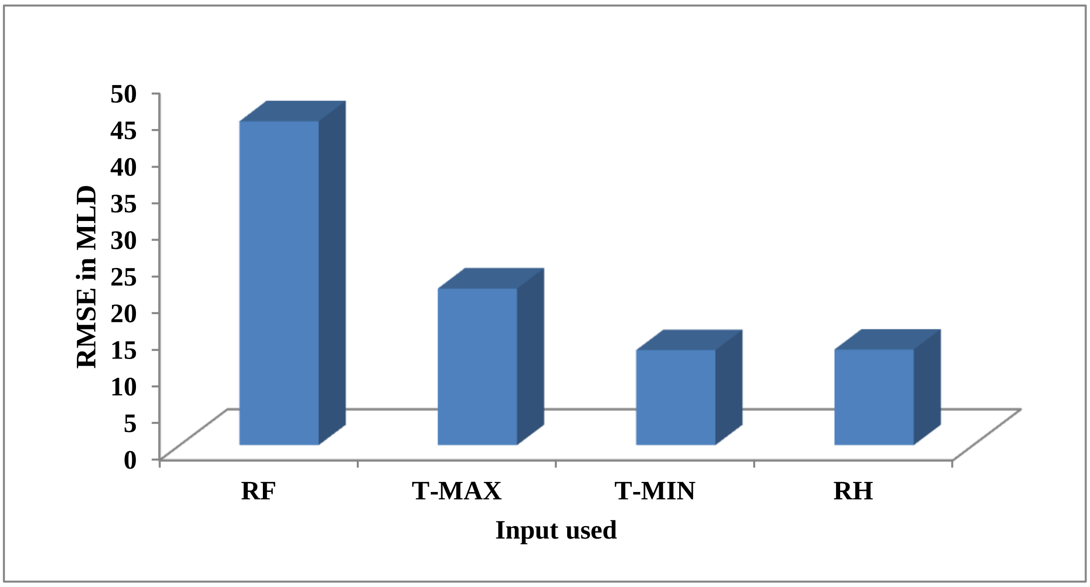


Figure 5.5.4 Results of improved fuzzy model for individual variable analysis

Figure 5.5.4 shows the improved result after incorporating triangular membership function. From the figure it is observed, that rainfall and maximum temperature having higher value of RMSE 44.17 MLD and 21.44 MLD, compared to minimum temperature and relative humidity.

<u>Results of Developed Fuzzy model for Normalized data</u>

To understand the behavior of the data set in modeling work further analysis is carried out for normalized data. The data normalization is done using an equation shown below. Totally 12 models were developed using different input and output combination for both time series and normalized data set. The result of entire model were presented in the table 5.5.4. Comparative result of the entire model is shown in the figure 5.5.5. From the overall performance, it is observed that model having minimum temperature and relative humidity as input, found less effective for normalized data. For the remaining model, normalized data shows better result.

$$Xnormalized = (\frac{(XRaw - Xmaximum)}{Xmaximum - Xminimum})$$

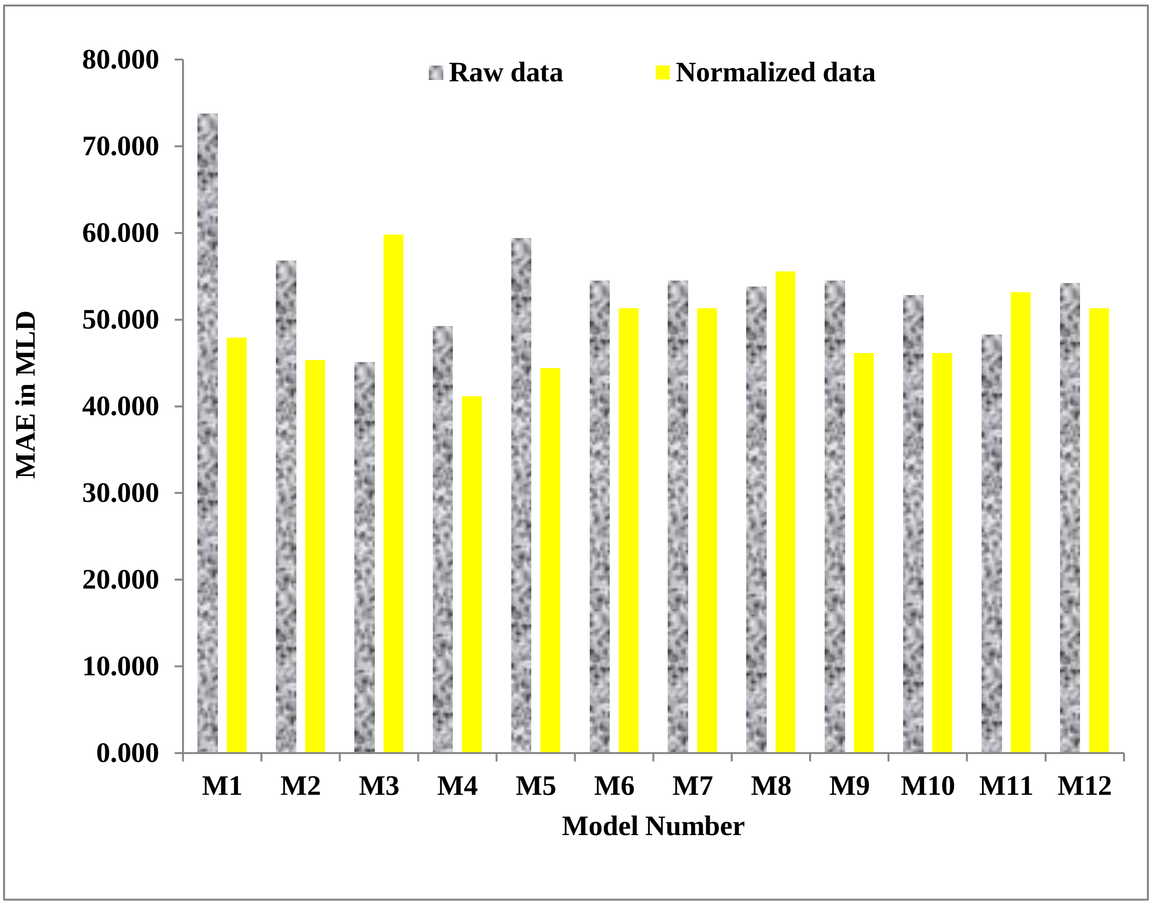


Figure 5.5.5 Results of fuzzy models for normalized data

Figure 5.5.5 shows the results of fuzzy model for different input and output combination using triangular membership function. Developed M1 to M4 Model having single input-output combination, compared to all other model combination. These models were developed using time series and normalized data. From the figure it is observed that, most of the developed model performances were found to be better for normalized due to reduction in the degree of non-linearity. The model 3, model 8 and model 11 shows reverse performance, due to the combination of minimum temperature and relative humidity variables. Minimum temperature and relative humidity variables having lower variation, when these variables are subjected to normalization, the normalized data are almost closer for all the data point, for which fuzzy system becomes complex in mapping the input-output function. Hence model 3, model 8 and model 11, having higher value of RMSE compared to time series data. From the overall performance of the model present in the table 5.5.4, it is observed that, normalized data found effective for modeling process. This opens the issue of developing proper data preprocessing technique in modeling the water consumption.

Table 5.5.4 Results of fuzzy model for normalized data

Model No	Inputs	Output	Evaluation Type	Fuzzy logic Method	
				Raw Data	Normalized Data
M1	RF	WC	PE (%)	37	24
			MAE (MLD)	73.74	47.91
			RMSE (MLD)	81.46	52.92
M2	Tmax	WC	PE (%)	28	22
			MAE (MLD)	56.82	45.32
			RMSE (MLD)	62.77	50.07
M3	Tmin	WC	PE (%)	22	30
			MAE (MLD)	45.07	59.82
			RMSE (MLD)	49.79	66.08
M4	RH	WC	PE (%)	24	20
			MAE (MLD)	49.24	41.16
			RMSE (MLD)	54.39	45.46
M5	RF, Tmax	WC	PE (%)	29	22
			MAE (MLD)	59.41	44.41
			RMSE (MLD)	65.62	49.05
M6	RF, Tmax, Tmin	WC	PE (%)	27	25
			MAE (MLD)	54.49	51.32
			RMSE (MLD)	60.19	56.69
M7	RF, Tmax, Tmin, RH	WC	PE (%)	27	25
			MAE (MLD)	54.49	51.32
			RMSE (MLD)	60.19	56.69

M8	Tmax, Tmin	WC	PE (%)	27	28
			MAE (MLD)	53.82	55.57
			RMSE (MLD)	59.45	61.39
M9	RF, RH	WC	PE (%)	27	23
			MAE (MLD)	54.49	46.16
			RMSE (MLD)	60.19	50.99
M10	Tmax, RH	WC	PE (%)	26	23
			MAE (MLD)	52.82	46.16
			RMSE (MLD)	58.38	50.99
M11	Tmin, RH	WC	PE (%)	24	26
			MAE (MLD)	48.24	53.16
			RMSE (MLD)	53.29	58.72
M12	RF, Tmin	WC	PE (%)	27	25
			MAE (MLD)	54.24	51.32
			RMSE (MLD)	59.92	56.69

Table 5.5.4 represents the result of different kind of data set. Total 12 models were developed using triangular membership function. Model performances were evaluated using RMSE, MAE and percentage error. RMSE value of the M1 model having rainfall and water consumption combination is 81.46 MLD and 52.92 MLD for time series and normalized data. The values of RMSE, MAE and percentage error of the entire developed model were presented in the table 5.5.7. Out of developed 12 models, 9 model performances is found better for normalized data, due to mapping of input-output function by a fuzzy system. whereas model 3, model 8 and model 11 results in higher error compared to time series data, as discussed in the figure 5.5.5. From the overall performance, it is found that normalized data were effective in modeling the water consumption.

<u>Results of Developed Fuzzy and ANFIS model for seasonal values of Climatic variables</u>

Behavior of the model performance in different climatic condition is examined using rainfall and maximum temperature as input variables. Due to extreme variation of climatic variables, the data shows the nonlinear trend. Even in this condition, single fuzzy approach is found weak to map the input output relationship. The results of single fuzzy model and hybrid ANFIS model performance were highlighted in the table 5.5.5. Comparative results of RMSE for developed fuzzy and ANFIS model is shown in the figure 5.5.6.

Table 5.5.5 Results of all the models considering seasonal variations

Model	CC		RMSE in MLD	
	FL	ANFIS	FL	ANFIS
M1	0.91	0.99	61.14	5.71
M2	0.88	0.98	7.27	1.20

Table 5.5.5 represents the result of fuzzy and ANFIS model for two input and single output combination. M1 represent the rainfall and water consumption combination for monsoon season and M2 model represent maximum temperature and water consumption combination for summer season. CC values for model 1 (one input) is 0.91 and for model 2 (two input) is 0.88 for fuzzy approach. Similarly CC values for model 1 is 0.99 and for model 2 is 0.98 for ANFIS approach. Performance of developed fuzzy model is found less, due to higher degree of nonlinearity in different climatic condition. Developed fuzzy model were weak to map the membership function, during these extreme seasonal condition compared to ANFIS model. Hence it is necessary to develop hybrid approach to provide better mapping of input and outputs.

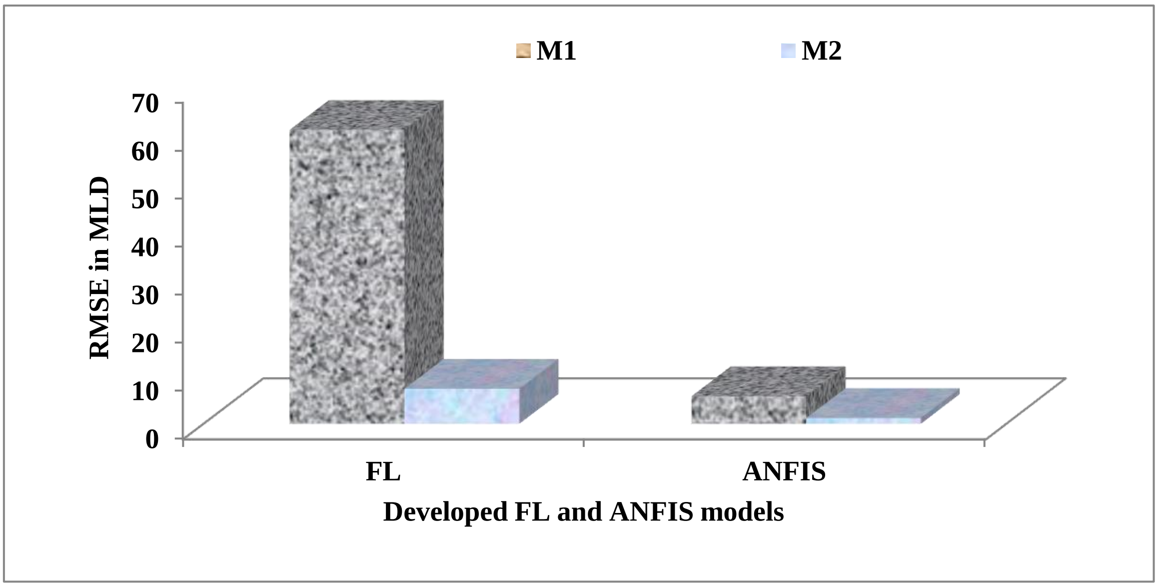


Figure 5.5.6 Results of RMSE Fuzzy model for different climatic seasons

Figure 5.5.6 shows, comparative result of Fuzzy and ANFIS model for two different seasonal values. From the figure it is observed that, ANFIS model having lower value of RMSE compared to fuzzy model, due to self-adjusting rules and training process. Hence the developed hybrid model handle the degree of non-linearity in a better way compared to fuzzy model.

5.6 Results of Developed Fuzzy wavelet model for denoised approach

In the section 5.5, results reveals the scope for hybrid approach. Further analysis is carried out to develop fuzzy wavelet hybrid models with climatic variables. Denoise approach is adopted to reduce the degree of nonlinearity. Denoise is the process, removes noise present in the data. The performance of the model were examined for three different wavelet namely Haar, Daubechies of order 2 to 6 and Discrete Meyer Wavelet for level 1 to Level 6. Initial stage, models were developed using threshold based wavelet for individual variables without any denoising process. Decomposition level is fixed depending upon the frequency of information in each level, and best level is selected. The result of the developed model were represented in the table 5.6.1. Later stage, denoise operation is performed using wavelet packet transform in the mat lab tool box. After the denoise operation, the coefficient which contain more information will be retained and the corresponding statistical properties of the data were studied and these data used further for fuzzy system to map the input and output function. Also the performance of the developed fuzzy-wavelet model were checked for different entropy. The best model were selected based on RMSE indicator.

The results obtained reveals that denoised based fuzzy wavelet approach model have less error compared to single fuzzy model. That is consequent parts of the fuzzy rules are able to trigger the firing rules, which produce the same desired output. Hence denoised fuzzy-wavelet technique found better.

Results of the Denoised fuzzy wavelet model for different wavelet and for different level were represented in the Table 5.6.2. The decomposition level including detailing and approximation information for rainfall, maximum temperature, minimum temperature and relative humidity were shown in the figure 5.6.1, 5.6.2, 5.6.3 and 5.6.4. Smoothing of the signal after denoise operation for rainfall, maximum temperature, minimum temperature and relative humidity data were shown in the figure 5.6.5, 5.6.6, 5.6.7, and 5.6.8. the observed and estimated value of water consumption using denoised fuzzy wavelet is shown in the figure 5.6.9.

Table 5.6.1 Results of threshold base wavelet (without denoise)

Level	Three Rules (RMSE)				Four rules (RMSE)			
	RF	T-Max	T-Min	RH	RF	T-Max	T-Min	RH
Level 1	25.11	12.32	15.36	17.82	29.81	33.88	12.44	15.91
Level 2	19.52	13.99	19.62	21.74	21.16	21.73	18.64	17.40
Level 3	12.44	13.86	17.60	17.60	26.41	28.83	28.09	27.25
Level 4	15.19	17.40	18.41	18.41	23.64	23.86	25.70	19.61

Table 5.6.1 represents the result of threshold base wavelet technique. These models were developed without any denoise operation using wavelet transform one-dimensional tool in the mat lab software. The developed model reveals that, degree of non-linearity reduction is not in a better way, due to improper selection of threshold value. Hence, it is necessary to use the denoise approach to reduce the higher degree of non-linearity.

Figure 5.6.1 shows the decomposition level of rainfall data, having the original time series data at the top. Decomposition level shows the freqence of information present at each level. Level 1 shows higher frequency component, hence signal are non-linear, as the decomposition level increses, degreee of non-lineraity decreses. In the level 4, signal shows almost linear variation. This helps to select the best level to perform the wavelet operation.

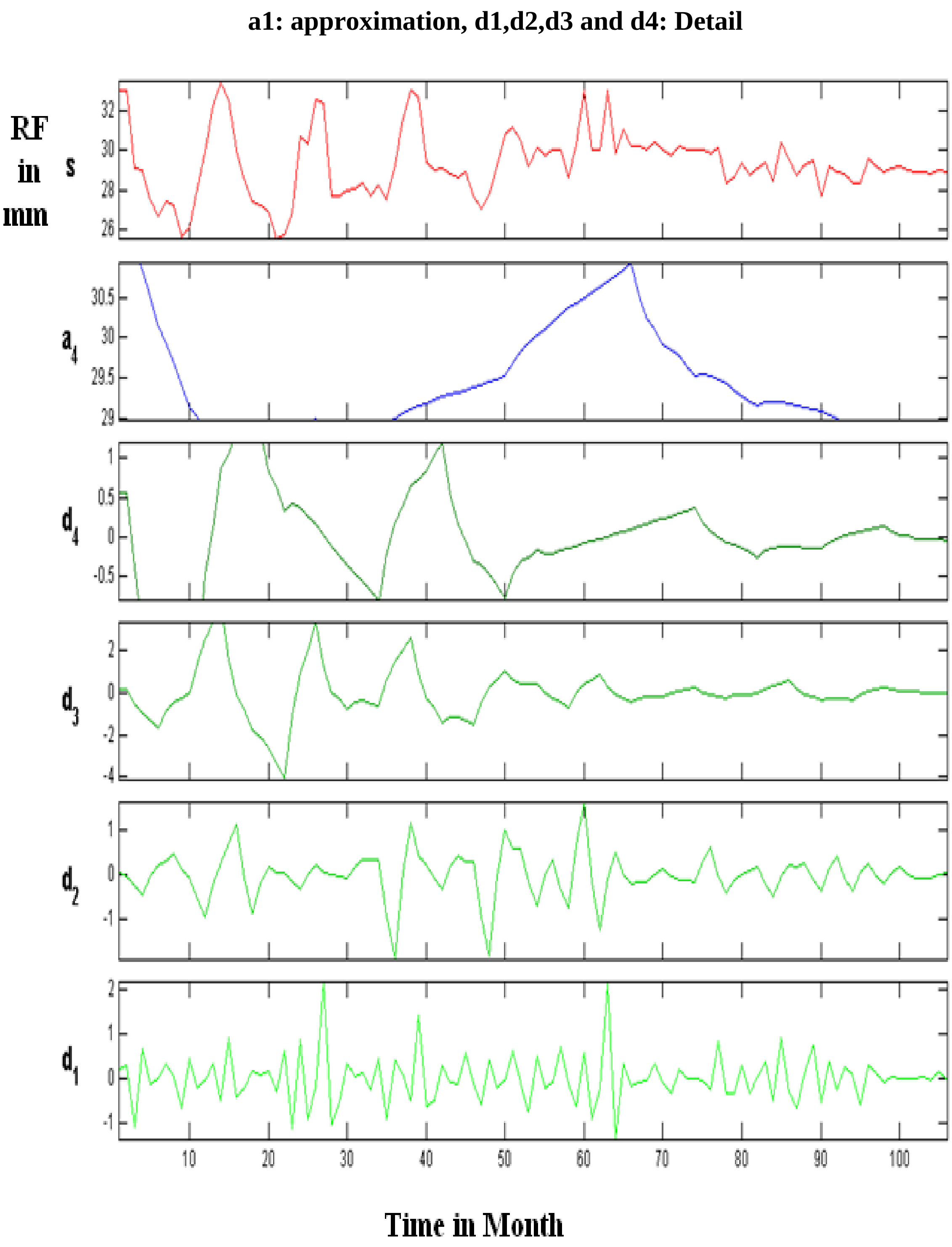


Figure 5.6.1 Decomposition level of rainfall data

a1: approximation, d1,d2,d3 and d4: Detail

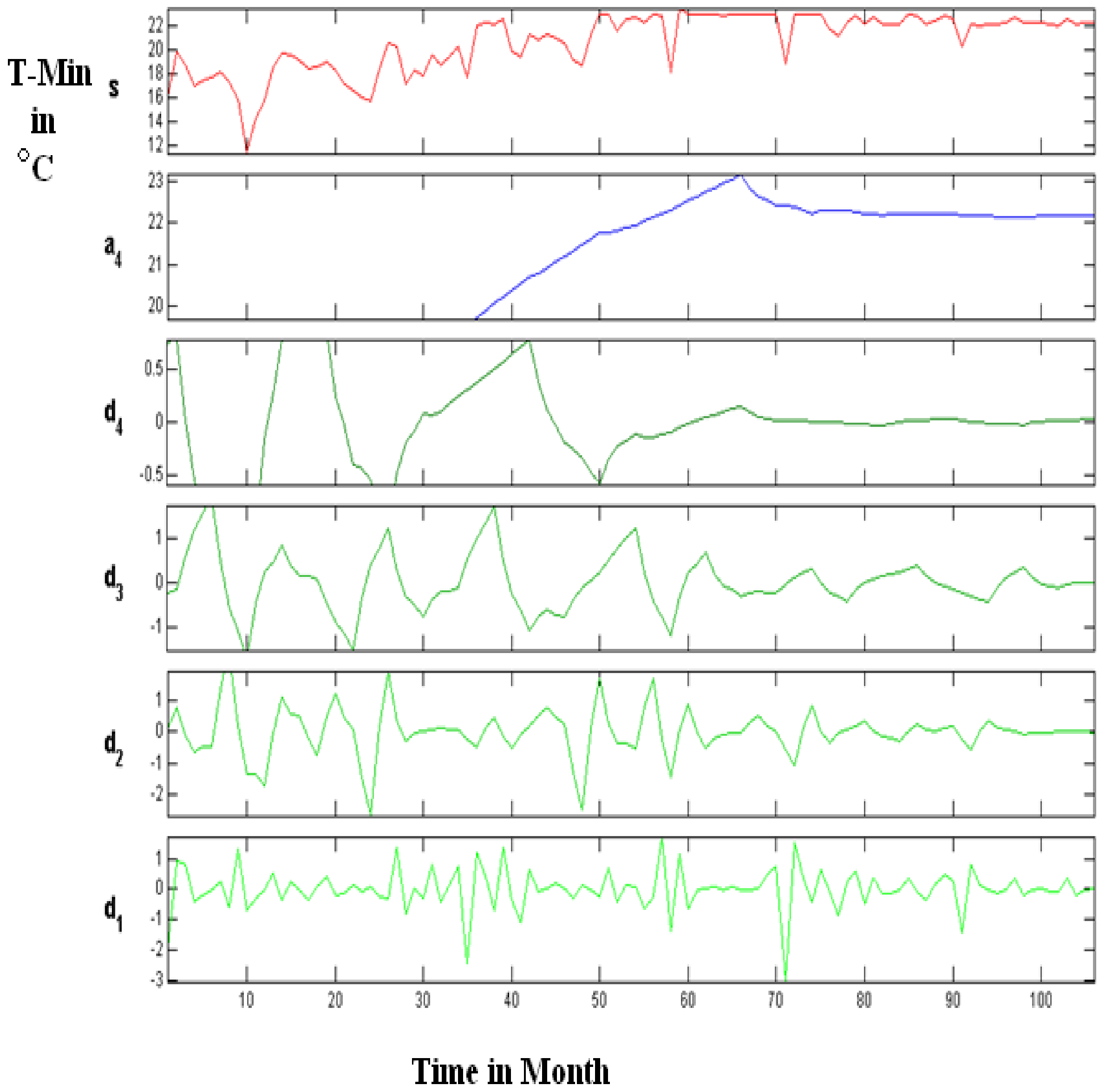


Figure 5.6.2 Decomposition level of minimum temperature data

Figure 5.6.2 shows the decomposition level of minimum temperature data. The original time series data is shown at the top. Detailing part of signal at each stage is shown in the above section. It indicates the frequencey of information occurred in particular level of decomposition. In the first decomosition level, higher frequency of information is present for minimum temperature data. Further in the level 2 , level 3 and level 4, degreee of non-linearity reduces , hence variation of minimum temperature is less.

a1: approximation, d1,d2,d3 and d4: Detail

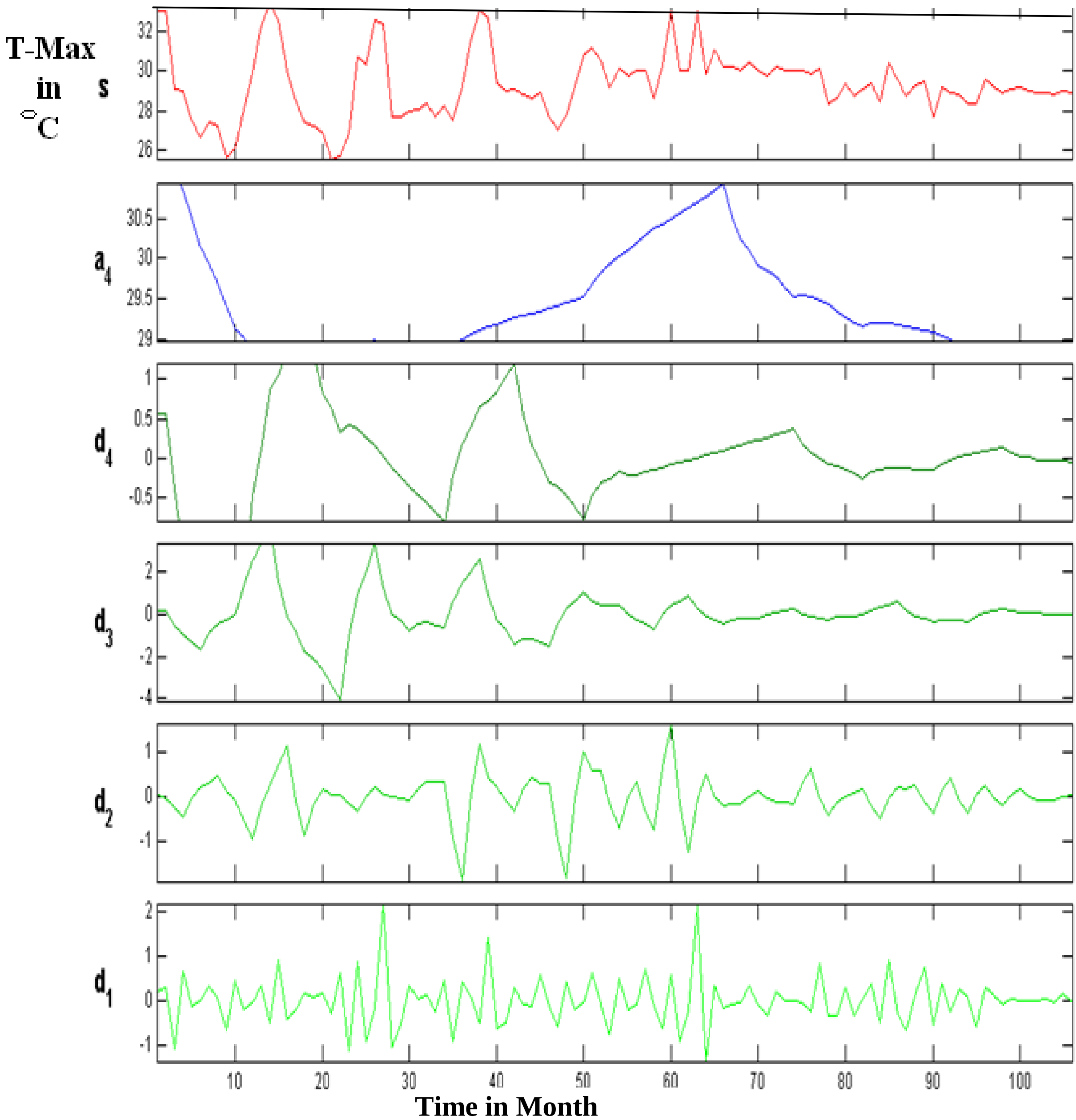


Figure 5.6.3 Decomposition level information for maximum temperatuire data

Figure 5.6.3 shows the decomposition level of maximum temperature data. The original time series data is shown at the top. Detailed part of the signal at each level of decomposition is shown in the above section. In the first level, signal shows more non-linear trend compared to other level. As decomposition level increses, frequency of information present will be less, hence data is linear.

a1: approximation, d1,d2,d3 and d4: Detail,

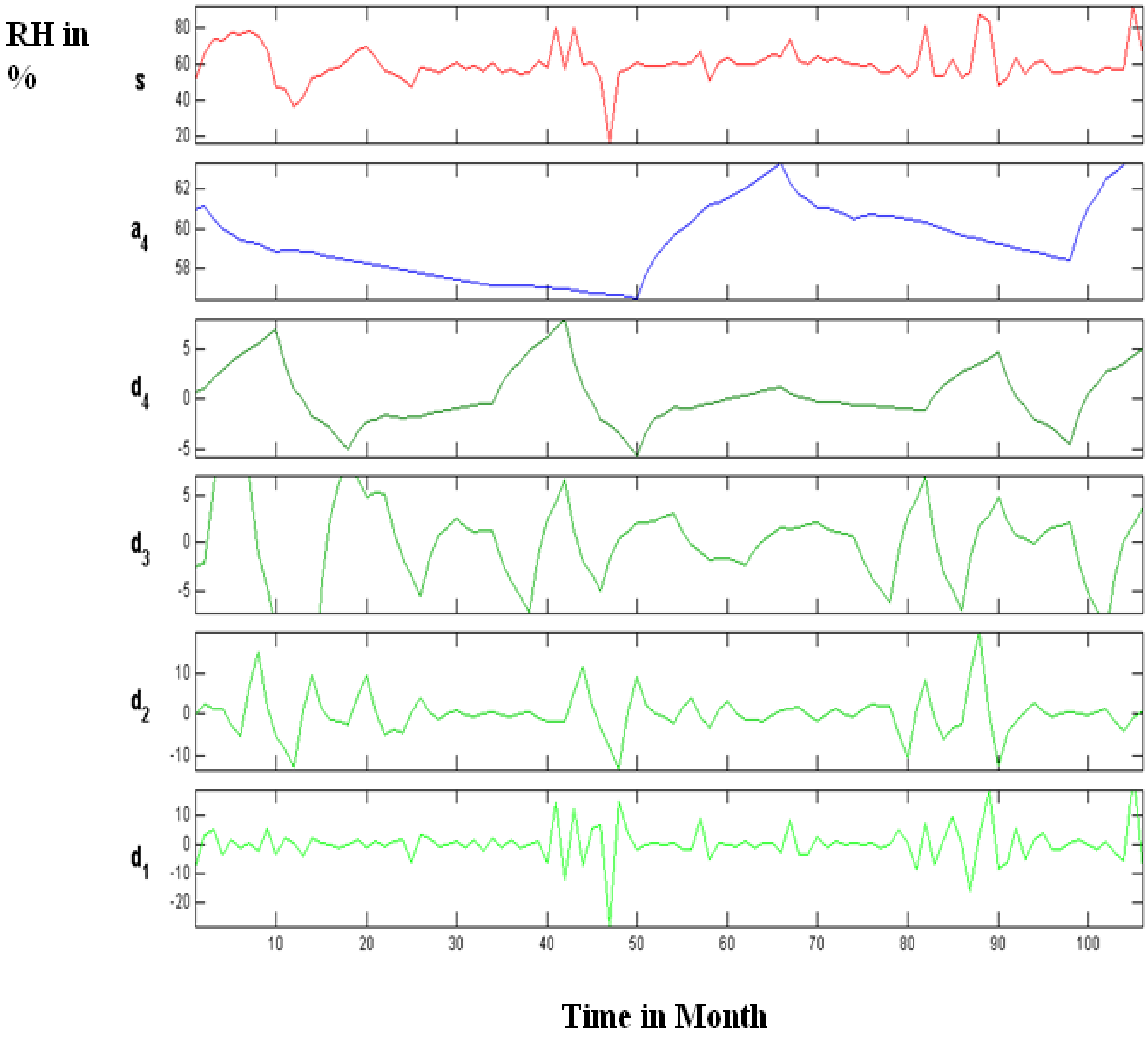


Figure 5.6.4 Decomposition level information for relative humidity data

Figure 5.6.4 shows the decomposition level of relative humidity data. The original time series data is shown at the top. Signal frequency at each detailed part of decomposition is shown in the above section. Proper selection of decomposition level, help to choose ectreme lower or extremme higher value of relative humidity. Higher frequency is found in the level 1, where as due to lesser frequency of information, data shows a linear trend in the level 4.

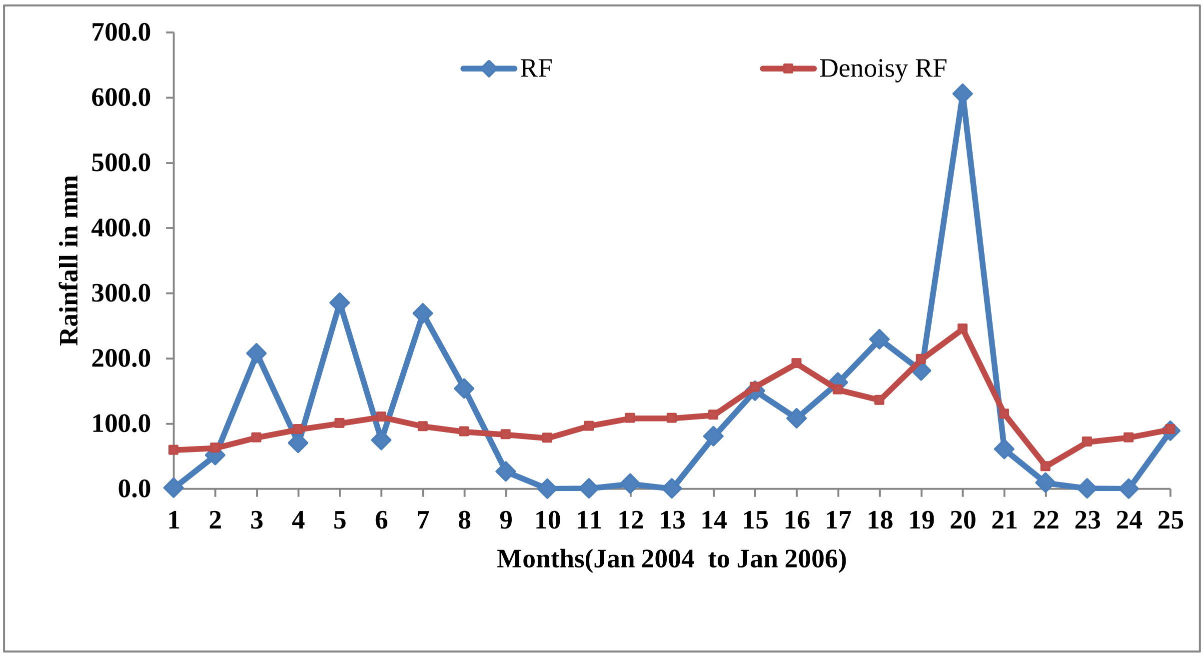


Figure 5.6.5 Variation of rainfall before and after denoising

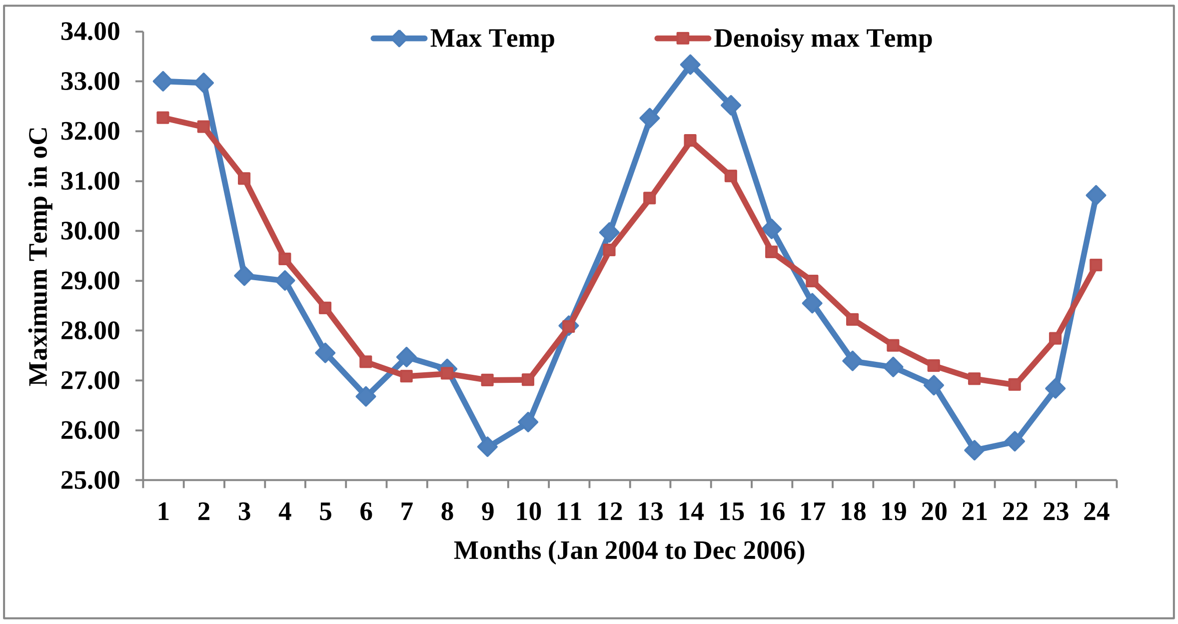


Fig 5.6.6 Variation of maximum temperature before and after denoising

Figure 5.6.5 shows the variation of rainfall before and after the denoising operation. To perform denoise operation rainfall data is considered for a period of 25 months from January 2004 to January 2006. Initially Time series rainfall data having higher degree of variation, observed in the 4th month, 5th month and 7th month and 20th month. After performing the denoising operation using Daubechies wavelet of second order fourth level, the noise in the data reduced in the above mentioned month. Due to reduction in non-linearity, from the figure it is observed that, denoised time series rainfall having less variation.

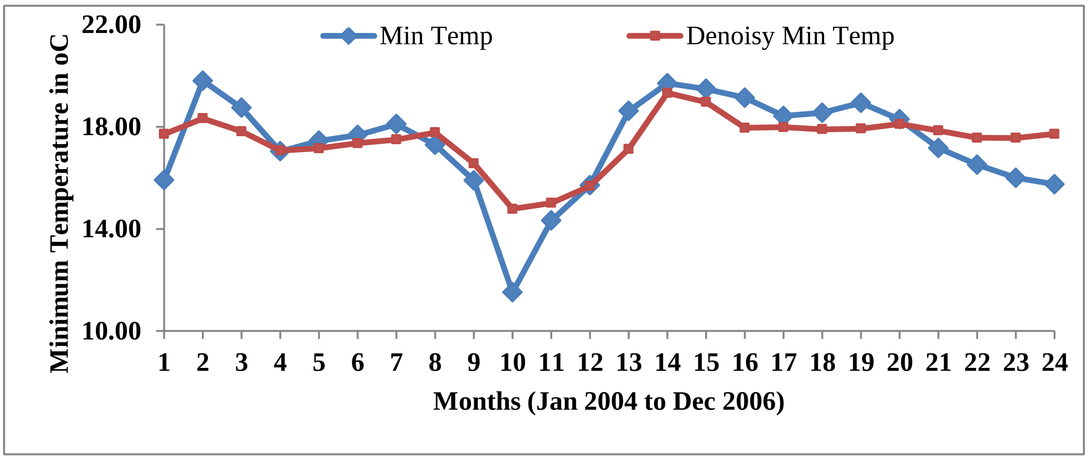


Fig 5.6.7 Variation of minimum temperature before and after denoising

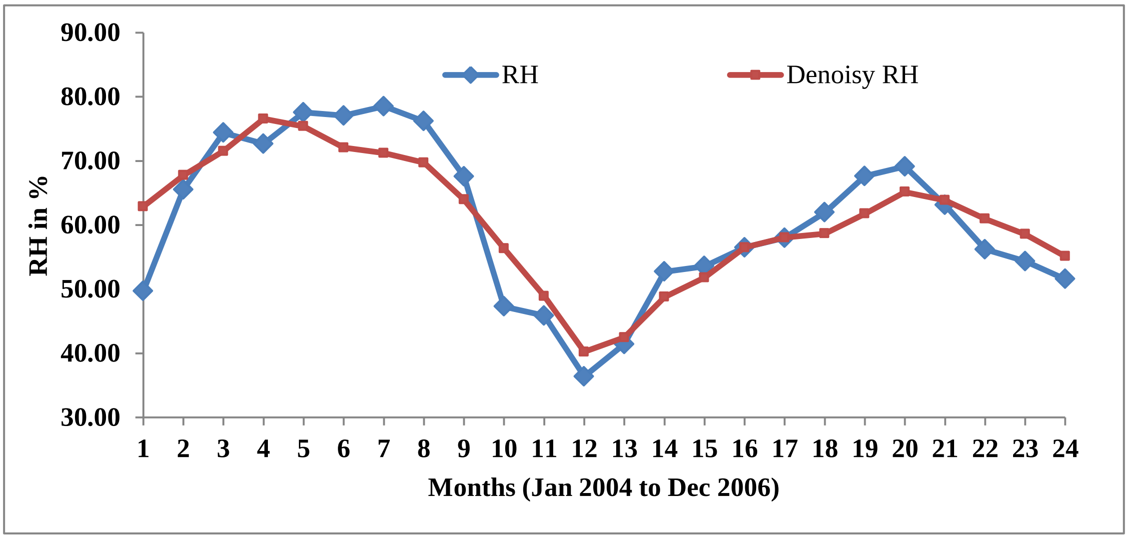


Fig 5.6.8 Variation of relative humidity before and after denoising

Figure 5.6.6 shows the variation of maximum temperature before and after the denoising operation. To perform denoise operation maximum temperature data were considered for a period of 24 months, from January 2004 to December 2006. Initially time series maximum temperature data having higher degree of variation, observed in the 1st month, 14th month, 24th month. After performing the denoising operation using Daubechies wavelet of second order fourth level, the noise in the data reduced in the above mentioned month. Due to reduction in non-linearity, from the figure it is observed that, denoised time series maximum temperature data have lesser variation.. The peak value in the 14th month is reduced in a greater way.

Figure 5.6.7 shows the variation of minimum temperature before and after the denoising operation. To perform denoise operation minimum temperature data were considered for a period of 24 months from January 2004 to December 2006. Initially time series maximum temperature data having higher degree of variation, observed in the 2nd month, 10th month and 19th month. After performing the denoising operation using Daubechies wavelet of second order fourth level, the noise in the data reduced in the above mentioned month. Due to less non-linearity, from the figure it is observed that, denoised minimum temperature have less variation.

Figure 5.6.8 shows the variation of relative humidity before and after the denoising operation. To perform denoise operation relative humidity data were considered for a period of 24 months from January 2004 to December 2006. Initially, time series maximum temperature data having higher degree of variation, observed in the 7th month and 20th month. After performing the denoising operation using Daubechies wavelet of second order fourth level, the noise in the data reduced in the above mentioned month. Due to reduction of degree of non-linearity, from the figure it is observed that, denoised time series relative humidty data has less variation.

Table 5.6.2 Results of RMSE (MLD) for fuzzy-wavelet denoised Models (db1 to db6)

Wavelet	Input	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
db 1	RF	39.80	38.31	34.05	36.66	36.72	32.31
	T.Max	70.35	59.17	58.08	57.27	60.75	57.48
	T.Min	81.21	80.95	71.53	70.70	74.26	71.39
	RH	69.89	69.27	66.60	63.84	67.60	68.44
db 2	RF	29.47	28.64	33.62	7.28	8.21	9.13
	T.Max	13.34	11.34	10.02	8.83	9.85	10.22
	T.Min	12.25	10.43	8.56	7.74	8.76	9.77
	RH	11.06	4.82	7.92	6.55	7.57	9.04
db 3	RF	22.50	24.78	23.06	15.12	19.09	19.59
	T.Max	13.56	15.20	16.30	11.10	11.33	9.64
	T.Min	11.82	11.91	13.65	10.92	11.24	9.64
	RH	11.46	11.09	14.84	12.10	12.33	10.55
db4	RF	76.21	73.96	74.87	75.89	68.81	71.40
	T.Max	42.70	46.94	38.35	38.09	51.00	43.65
	T.Min	34.49	39.91	35.70	39.46	43.15	43.65
	RH	41.52	40.92	39.63	41.65	42.70	39.91
db5	RF	58.30	57.16	59.13	56.27	58.83	55.41
	T.Max	36.85	35.89	33.48	26.61	37.56	29.94
	T.Min	42.34	35.28	47.79	51.67	60.18	52.03
	RH	43.71	45.87	44.68	43.82	44.48	43.09
db6	RF	61.41	61.98	64.45	58.44	60.64	59.96
	T.Max	55.75	49.66	48.02	52.05	55.98	54.94
	T.Min	43.98	47.56	44.19	51.23	55.25	62.79
	RH	42.42	44.18	45.56	41.01	42.75	42.43

Table 5.6.2 represents the result of Fuzzy-wavelet denoised technique for Haar Wavelet and Daubechies wavelet of order 2 to order 6, with six different levels. Denoising operation is performed for single input variables. After denoise operation, the coefficient obtained were transferred to the fuzzy system to map the input-output function. From the table it is observed that Haar wavelet having the RMSE value 32.31 MLD for sixth level, which is slightly lower compared to other level in the case of rainfall as input variable. Maximum temperature having RMSE Value 57.27 MLD, for fourth level found less compared other level. Minimum temperature having RMSE Value 70.70 MLD for fourth level is less than other level. Relative humidity having RMSE Value 63.84 MLD for fourth level is less than other level. Hence, in the case of Haar wavelet fourth level found better during denoising operation.

Similarly Daubechies wavelet of order 2 having the RMSE value 7.28 MLD for fourth level, is low compared to other level in the case of rainfall as input variable. Maximum temperature having RMSE Value 8.83MLD for fourth level is less than other level. Minimum temperature having RMSE Value 7.74MLD for fourth level is less than other level. Relative humidity having RMSE Value 6.55MLD for fourth level is less than other level. Hence, in the case of Daubechies wavelet of second order, fourth level found effective during denoising operation.

Daubechies wavelet of order 3 having the RMSE value 15.12 MLD for fourth level, is low compared to other level in the case of rainfall as input variable. Maximum temperature having RMSE Value 9.64 MLD for sixth level is less than other level. Minimum temperature having RMSE Value 9.64 MLD for sixth level is less than other level. Relative humidity having RMSE Value 10.33MLD for sixth level is less than other level. Hence in the case of Daubechies wavelet of second order, sixth level found effective during denoising operation.

Although performance of the model is evaluated up to six level using Haar and Daubechies wavelet, but from the table 5.6.1, it is found that db4, db5 and db6 having higher value of RMSE compared to db1 , db2 and db3. From the overall result, it is found that Daubechies wavelet of order 2 performed better for fourth level.

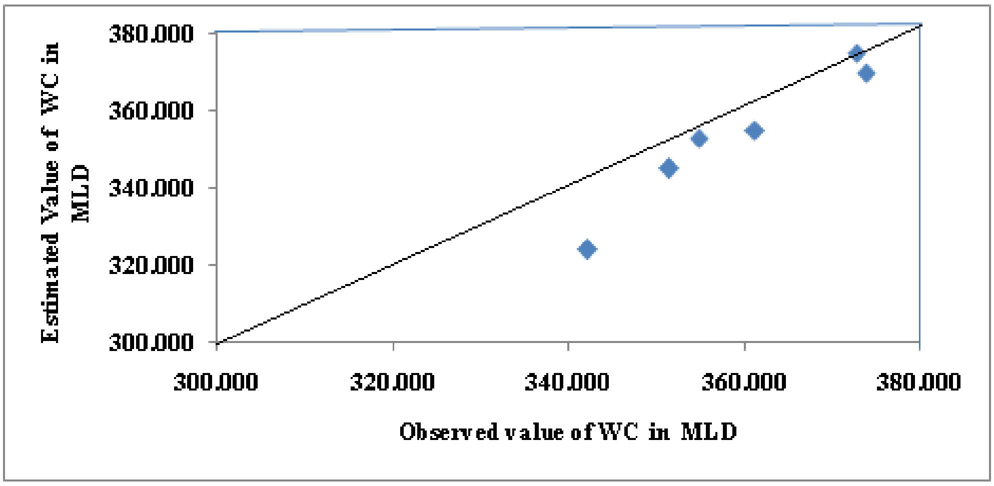


Figure 5.6.9 observed and estimated values of water consumption for denoised approach

Figure 5.6.9 shows the observed and estimated value of water consumption using denoised Fuzzy-wavelet approach. Developed fuzzy-wavelet model found better compared to single fuzzy model, presented in the table 5.7.1. Due to reduction in the degree of nonlinearity, Fuzzy system able to map the input-output function in a better way. Hence model performance is improved in a greater way, showing the estimated value closer to the observed one.

Table 5.6.10 represents the denoised results of Discrete Meyer wavelet for indusial variables. From the results it is found that, performance of discrete Meyer wavelet is low compared to daubechies wavelet. Comparative results of denoised technique for Daubechies group (db 1 to db6) for rainfall and water consumption combination, maximum temperature and WC combination, minimum temperature and WC, RH and WC combination, were shown in the figure 5.6.10, figure 5.6.11, figure 5.6.12 and figure 5.6.13.

Table 5.6.3 Results of RMSE for Discrete Meyer wavelet

Wavelet	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
	68.15	73.57	70.49	70.13	69.97	69.95
	51.81	43.81	43.93	39.37	47.24	43.38
	32.64	36.87	39	41.11	34.92	23.85
DBMY	36.83	35.6	36.81	36.91	37.2	35.9

Table 5.6.3 represents the result of Discrete Meyer wavelet with single input and output combination of the climatic variables. Daubechies wavelet of order 4, 5 and 6 shows higher value of RMSE, further model investigation is done using Discrete Meyer wavelet. Results reveal that Discrete Meyer wavelet able to reduce the noise of Minimum temperature and relative humidity data in a better way. Due to lesser time series variation, higher order of Daubechies wavelet for denoising purpose may not be suitable. From the table it is found that, Discrete Meyer wavelet shows better result compared to Daubechies wavelet of order 4, 5 and 6.

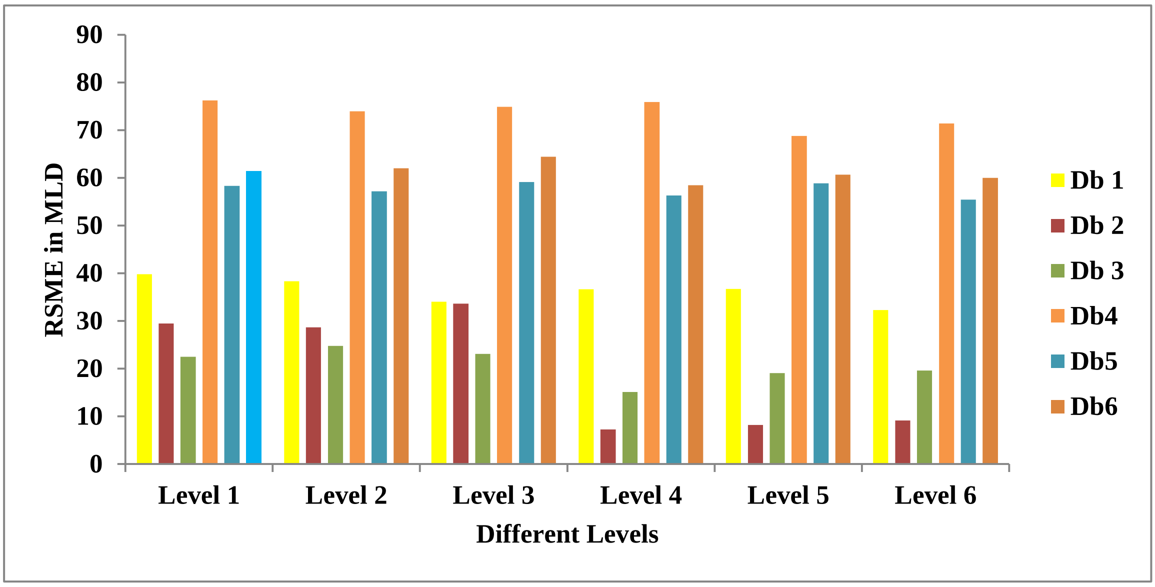


Figure 5.6.10 db1 to db6 model Performance for RF and WC combination

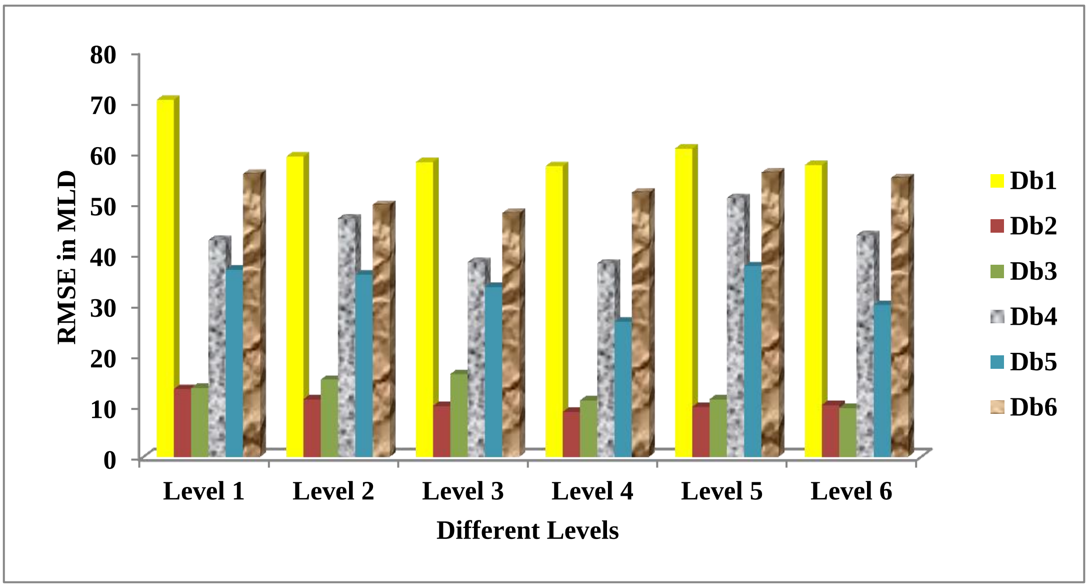


Figure 5.6.11 db 1 to db6 model performance for T-max and WC combination

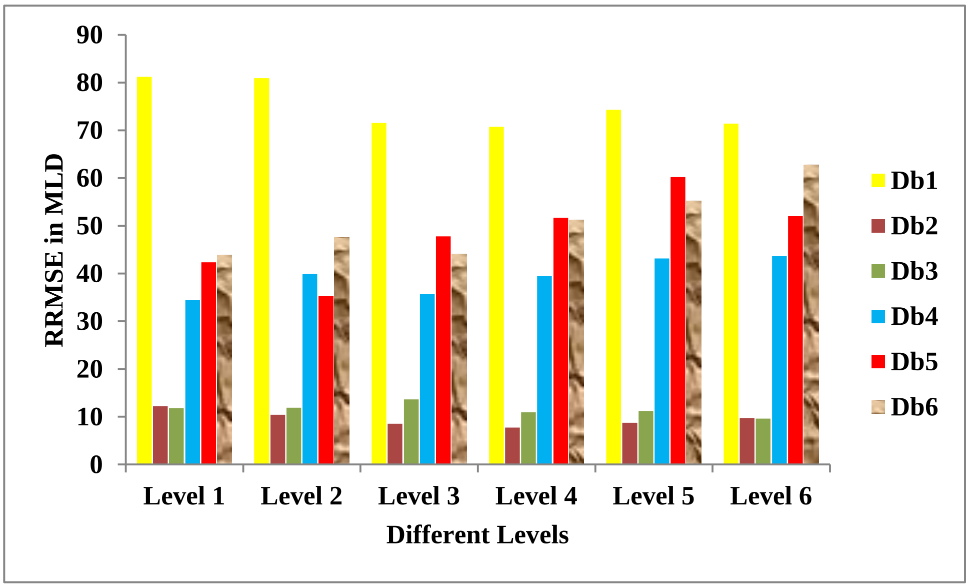


Figure 5.6.12 db 1 to db6 model performance for T-Min and WC combination

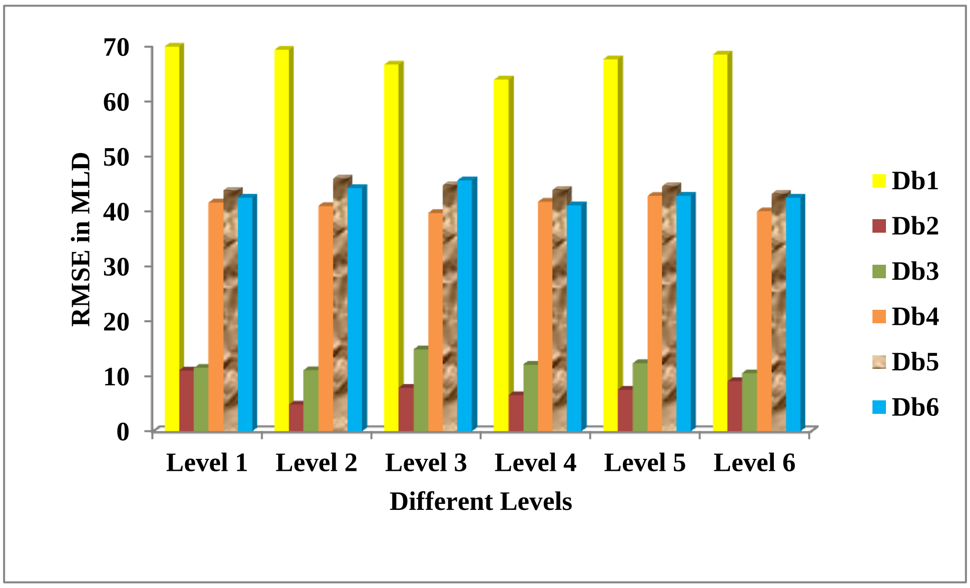


Figure 5.6.13 db 1 to db 6 model performances for RH and WC combination

Figure 5.6.10 shows the comparative result of denoised fuzzy-wavelet approach for rainfall and water consumption combination. From the figure it is found that, db2 and db3 having lower value of RMSE for all the levels compared to other order. The value of RMSE for db4 is almost high for all the level. Similarly db5 and db6 having higher value of RMSE for all the levels. From the overall results it is found that db2 and db3 models were effective.

Figure 5.6.11 shows the comparative result of denoised Fuzzy-wavelet approach for maximum temperature and water consumption combination. From the figure it is observed that, db2 and db3 having lower value of RMSE for all the levels compared to other order. The value of RMSE for db1 is almost high for all the level. From the overall results it is found that db2 and db3 models were better

Figure 5.6.12 shows the comparative result of denoised Fuzzy-wavelet model for minimum temperature and water consumption combination. From the figure it is observed that, db2 and db3 having lower value of RMSE for all the levels compared to other order. The value of RMSE for db1 is almost high for all the level. Similarly db4, db5 and db6 having higher value of RMSE compared to other levels. From the overall result, it is observed that db2 and db3 models were better.

Figure 5.6.13 shows the comparative result of denoised fuzzy-wavelet approach for relative humidity and water consumption combination. From the figure it is observed that, db2 and db3 having lower value of RMSE for all the levels compared to other order. The value of RMSE for db1 is almost high for all the level. Similarly db4, db5 and db6 having higher value of RMSE for all the levels. From the overall results it is found that, db2 and db3 model were better.

5.7 Results of Developed Fuzzy wavelet Compressed approach

In the same way as denoised technique, another method called compression which play an important role in reducing the degree of non-linearity in the data set. Compression technique is applied after the wavelet transform. The coefficient obtained during wavelet transform operation is compressed easily, because the information is concentrated on a few coefficients, these coefficients are coded to the entropy. Hence selection of Entropy play an important role for proper distribution of the coefficient. Compression technique is employed for the data having periodic variation. Compression is the method which will not remove any coefficient, coefficient will be same as original data set. Shannon based entropy is used to spread over the compressed data, this will act as Data preprocessing. To perform the individual compression, wavelet packet is better. From the compressed data statistical information is obtained and it is used in the consequent part of the fuzzy set. Result reveals that compressed fuzzy wavelet model performance found to be better compared to single fuzzy model. Hence fuzzy-wavelet compressed method is more reliable. To perform the wavelet transform operation, Haar, Daubechies of order 2 to 6 and Discrete Meyer wavelet were used. Compressed operation for rainfall, maximum temperature, minimum temperature and relative humidity data were shown in the figure 5.7.1, figure 5.7.2, figure 5.7.3 and figure 5.7.4. Comparative results of single fuzzy model, fuzzy wavelet denoised and Fuzzy-wavelet compression technique were represented in the table 5.7.1. Results of the entire compressed model for Haar and Daubechies wavelet of order 2 to 6 were represented in the table 5.7.2. Results of Discrete Meyer wavelet is shown in the table 5.7.3. Comparative results of all the developed model is shown in the figure 5.7.5. The observed and estimated value of water consumption for compressed technique is shown in the figure 5.7.6. Comparative results of Daubechies (1 to 6) group for RF, T-Max, T-Min and RH combination is shown in the figure 5.7.7, Figure 5.7.8, figure 5.7.9, figure 5.7.10.

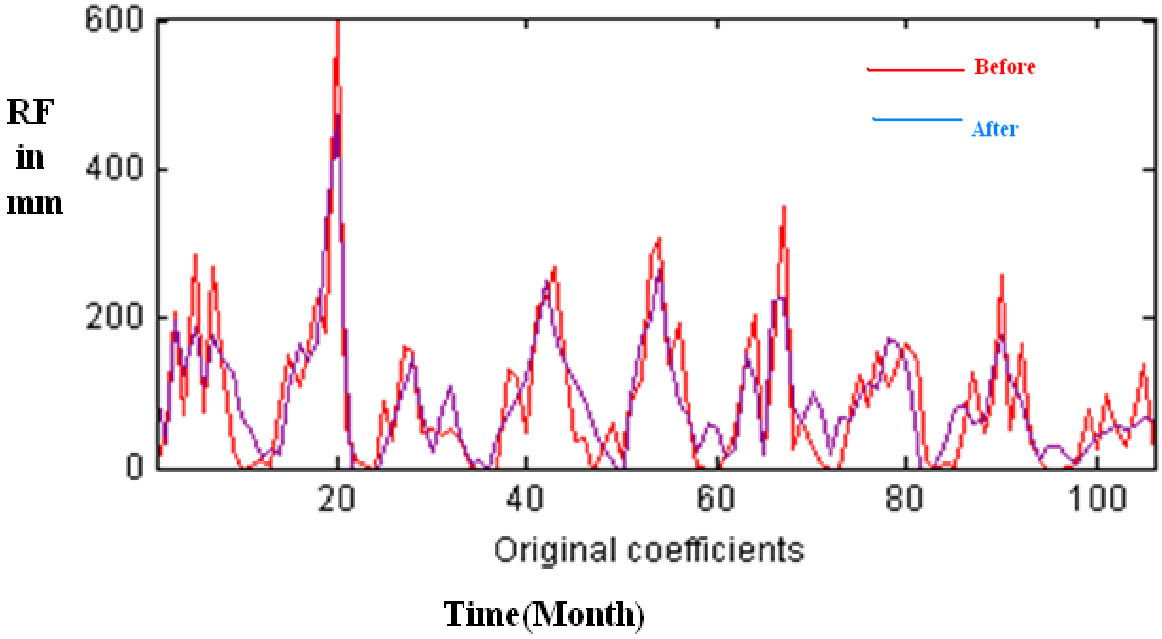


Figure 5.7.1 Variation of rainfall before and after compression

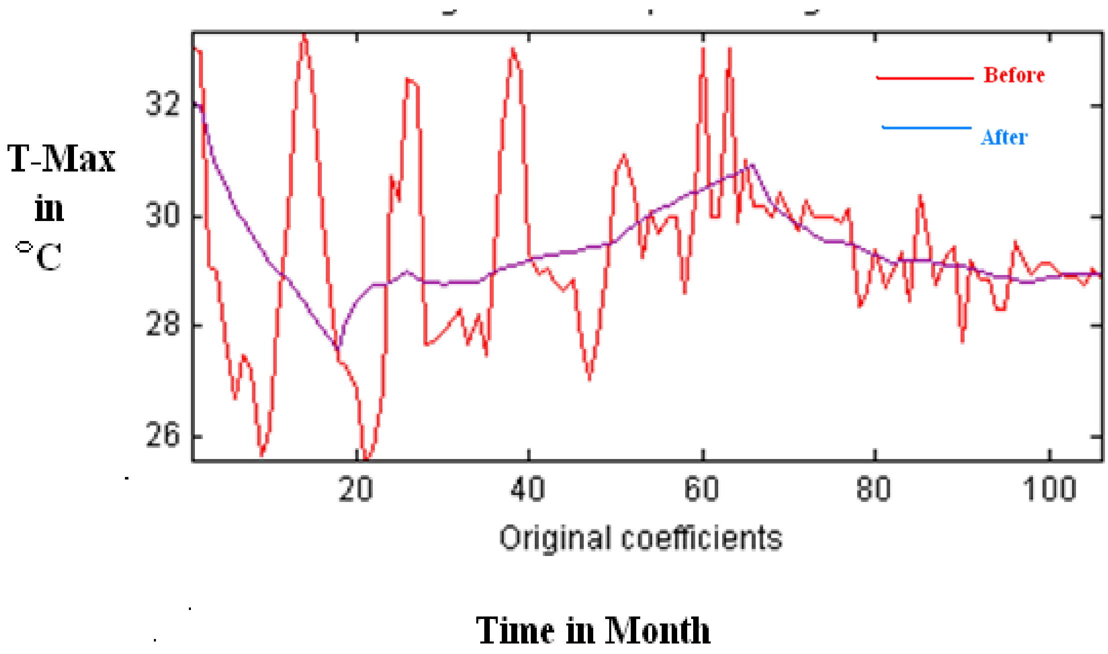


Figure 5.7.2 Variation of maximum temperature before and after compression

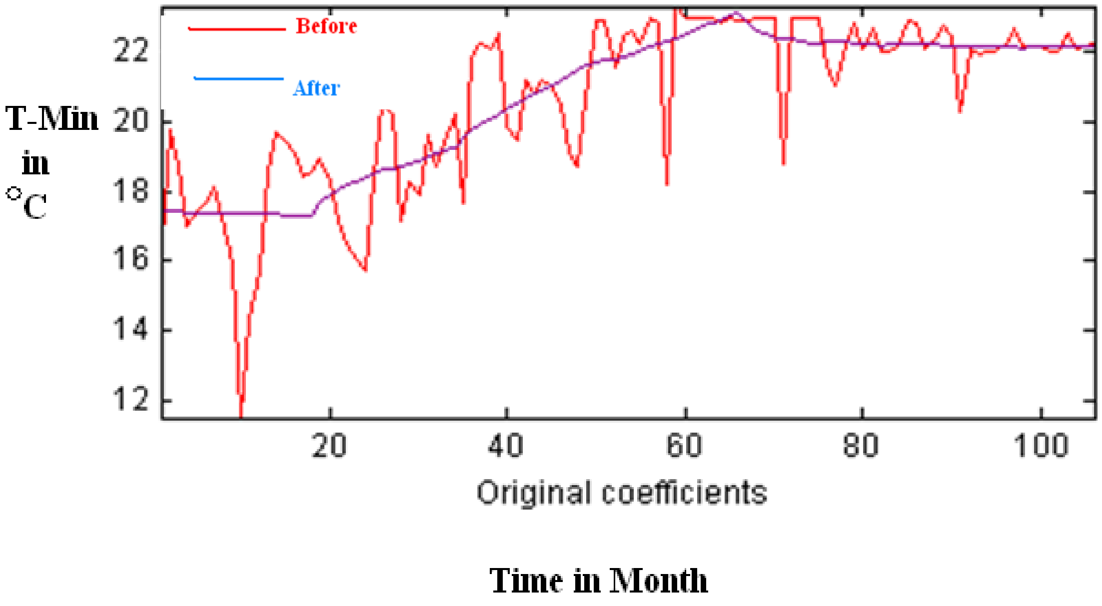


Figure 5.7.3 Variation of minimum temperature before and after compression

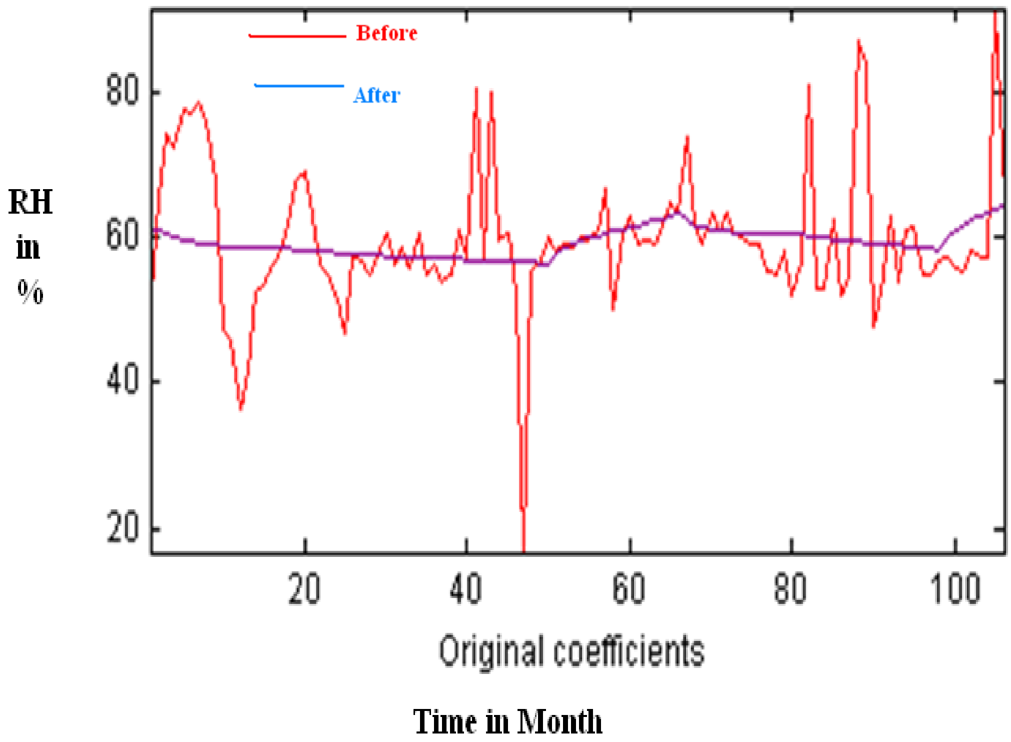


Figure 5.7.4 Variation of relative humidity before and after compression

Figure 5.7.1 shows the variation of rainfall data before and after the compression process. From the figure it is observed that, variation of rainfall is highly non-linear, after wavelet transform operation, data concentrated on few coefficient compressed. But in the case of rainfall data, coefficient is not at a statistical point. Hence, rainfall data shows the slightly lesser variation compared to original time series data.

Figure 5.7.2 shows the variation of maximum temperature data before and after the compress process. From the figure it is observed that, variation of maximum temperature is high. After, wavelet transform operation, information concentrated on few coefficients will be compressed, hence it appears the linear trend at the end of the signal.

Figure 5.7.3 shows the variation of minimum temperature data before and after the compress process. From the figure it is observed that, after wavelet transform operation, information is more at the middle portion of the signal, Coefficient concentrated on these statistical points will be compressed, hence, data follows a linear trend for half of the portion.

Figure 5.7.4 shows the variation of relative humidity data before and after the compress process. From the figure it is observed that, after wavelet transforms operation, information is more between 40 to 60%. Hence these coefficients will be compressed, resulting in the smoothing of variation.

Table 5.7.1 Comparative results of single fuzzy and hybrid fuzzy wavelet models

		RMSE (MLD)		
Input	**Output**	**FL**	**FWD**	**FWC**
RF	WC	44.17	7.28	0.98
Tmax	WC	21.44	8.83	1.35
Tmin	WC	13.04	7.74	5.13
RH	WC	13.13	4.82	0.12

Table 5.7.1 represents the comparative result of single fuzzy, fuzzy wavelet denoise and fuzzy wavelet compress approach using single climatic variables as input. From the table it is found that, due to higher degree of non-linearity, developed fuzzy model shows higher value of RMSE compared to FWD and FWC approach. RMSE value for RF and WC combination is 44.17 MLD for fuzzy approach, 7.28 MLD for FWD approach and 0.98 for FWC approach. Similarly for T-max and WC combination RMSE value is 21.44 MLD for Fuzzy model, 8.83 MLD for FWD model and 1.35 MLD for FWC model. For T-min and WC Combination, RMSE value is 13.04 MLD for Fuzzy model, 7.74 MLD for FWD model 5.13 MLD for FWC model. For RH and WC combination RMSE is 13.13 MLD for Fuzzy model, 4.82 MLD for FWD model and 0.12 for FWC model. Overall result reveals that combined fuzzy-wavelet approach found better. Among denoise and compress technique, compressed approach is effective in modeling the water consumption.

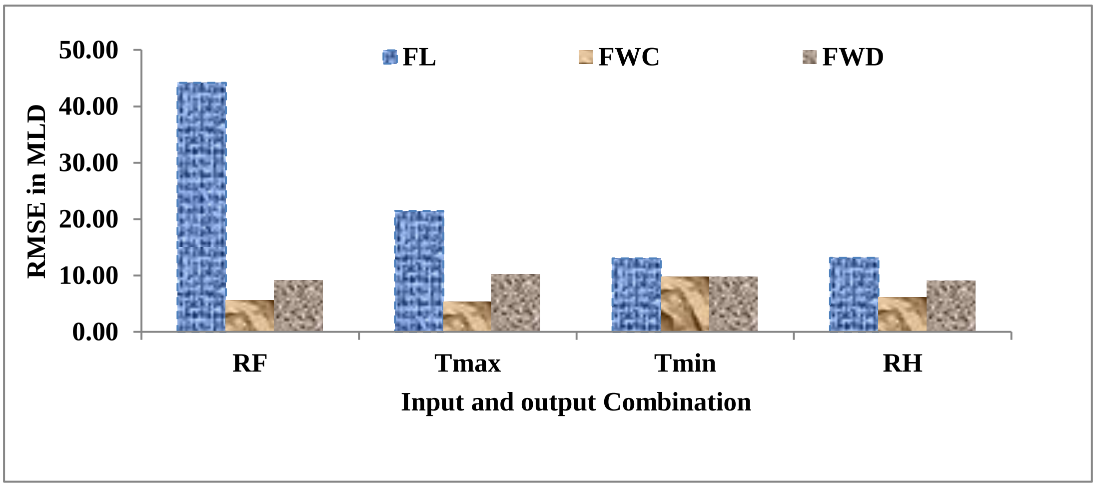


Figure 5.7.5 Results of single fuzzy, FWD and FWC technique

Figure 5.7.5 shows the comparative of fuzzy, FWD and FWC approach. From the figure it is found that, rainfall as input variable, FWC approach shows better performance. For maximum temperature input, FWC shows better result. For minimum temperature input FWC shows better result and RH input variable FWC shows better result. Hence FWC approaches were found better compared to FWD and single fuzzy model.

Table 5.7.2 Results of RMSE (MLD) for fuzzy-wavelet compressed models (db1 to db6)

Wavelet	Input	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
db 1	RF	34.35	21.56	19.40	4.61	25.73	15.93
	T.Max	57.32	49.79	43.06	22.92	32.39	7.75
	T.Min	68.76	61.07	41.74	22.75	35.68	57.59
	RH	65.15	56.63	61.46	40.06	44.44	26.99
db 2	RF	8.31	1.26	2.99	0.98	9.81	5.65
	T.Max	13.23	1.35	1.90	1.62	1.51	5.38
	T.Min	12.25	10.43	8.56	7.74	8.76	9.77
	RH	11.14	0.26	3.08	0.12	9.27	6.11
db 3	RF	18.79	16.46	15.33	7.23	10.05	14.99
	T.Max	12.31	14.82	13.41	5.32	6.95	13.90
	T.Min	11.12	11.53	13.13	5.23	6.95	5.13
	RH	12.68	15.18	14.23	6.32	7.04	14.63
db4	RF	69.32	61.43	64.21	44.85	52.17	40.94
	T.Max	55.48	44.66	3.08	17.83	59.01	34.55
	T.Min	32.44	36.88	30.80	31.62	52.44	28.34
	RH	41.93	39.98	42.12	28.42	17.93	19.22
db5	RF	59.41	67.19	69.16	58.66	50.52	47.64
	T.Max	48.37	43.55	41.05	35.93	61.93	42.62
	T.Min	33.92	34.49	43.13	45.64	48.76	34.69
	RH	42.07	58.25	45.15	40.22	16.92	36.14
db6	RF	54.92	68.58	67.01	49.90	44.93	45.28
	T.Max	53.73	49.77	42.27	49.62	47.49	49.11
	T.Min	42.70	51.85	46.74	61.55	60.27	60.60
	RH	39.03	46.58	54.05	19.13	14.90	15.25

Table 5.7.2 represents the result of fuzzy-wavelet compressed technique for Haar and Daubechies wavelet of order 2 to 6, for six different levels. Compress operation is performed for single input variables. After compress operation, the coefficient obtained is transferred to the fuzzy system to map the input-output function. From the table it is observed that Haar wavelet having the RMSE value 4.61 MLD for fourth level, is low compared to other level in the case of rainfall as input variable. Maximum temperature having RMSE Value 7.75MLD, for sixth level is less than other level. Minimum temperature having RMSE Value 22.75MLD for fourth level, is less than other level. Relative humidity having RMSE Value 26.99 MLD for sixth level, is less than other level. Hence, in the case of Haar wavelet sixth level found better during compress operation.

Similarly Daubechies wavelet of order 2 having the RMSE value 0.98 MLD for fourth level, is low compared to other level in the case of rainfall as input variable. Maximum temperature having RMSE Value 1.35MLD for second level is less than other level. Minimum temperature having RMSE Value 7.74 MLD for fourth level is less than other level. Relative humidity having RMSE Value 0.12MLD for fourth level is less than other level. Hence, in the case of Daubechies wavelet of second order, fourth level found better during compress operation.

Daubechies wavelet of order 3 having the RMSE value 7.23 MLD for fourth level, which is low compared to other level in the case of rainfall as input variable. Maximum temperature having RMSE Value 5.23 MLD for sixth level, is less than other level. Minimum temperature having RMSE Value 5.13 MLD for sixth level, is less than other level. Relative humidity having RMSE Value 6.32 MLD for fourth level is less than other level. Hence, in the case of Daubechies wavelet of order three, fourth level found better during compress operation.

Although performance of the model were evaluated using Daubechies wavelet up to the order 6, but from the table 5.7.2, it is found that db4, db5 and db6 having higher value of RMSE compared to db1, db2 and db3. Hence from the overall result it is found that Daubechies wavelet of order 2, fourth level performed better.

Table 5.7.3 Results of RMSE for Discrete Meyer Wavelet for compressed approach

Wavelet	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
	65.58	69.09	67.03	67.29	53.79	35.86
	55.63	45.44	45.21	52.96	28.78	29.47
	35.09	39.42	40.01	49.76	28.6	11.85
DBMY	38.74	43.98	46.22	37.53	17.1	20.89

Table 5.7.3 represents the result of Discrete Meyer wavelet using single input and output combination of the climatic variables for compressed approach. Since Daubechies wavelet of order 4, 5 and 6 shows higher value of RMSE, further model investigation is done using Discrete Meyer Wavelet. Results reveal that Discrete Meyer wavelet performance is less for compressed signal compared to db4, db5 and db6. Overall it is found that Discrete Meyer wavelet performance is better for denoised signal compared to compress signal.

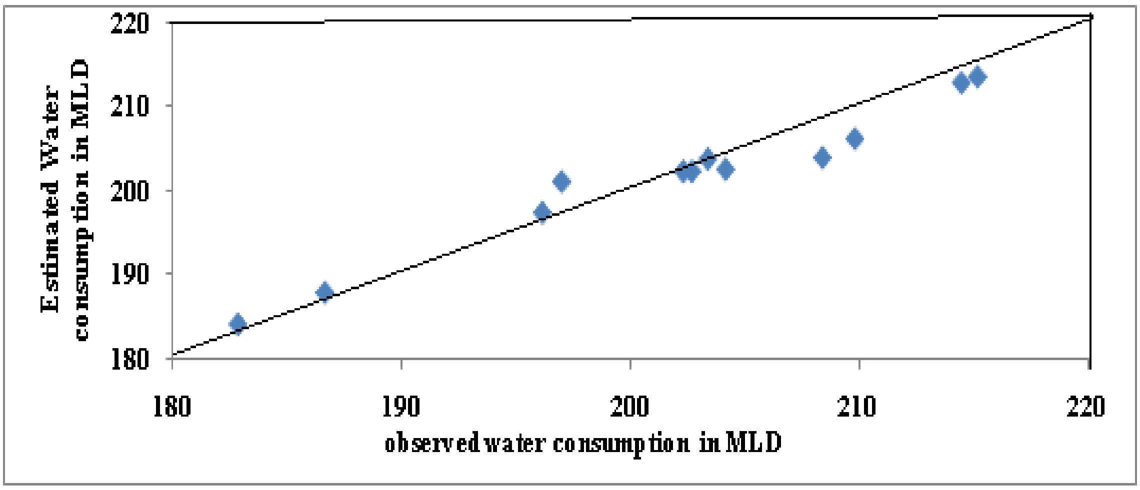


Figure 5.7.6 Observed and estimated value of water consumption (Compressed)

Figure 5.7.6 shows the observed and estimated value of water consumption using compressed Fuzzy-wavelet approach. The developed compress fuzzy-wavelet model found better compared to single fuzzy model, presented in the table 5.7.1. Due to reduction in the degree of nonlinearity, fuzzy system able to map the input-output function in a better way. Hence model performance were improved in a great way. From the figure it is observed that, estimated value of water consumption is almost close to the observed value.

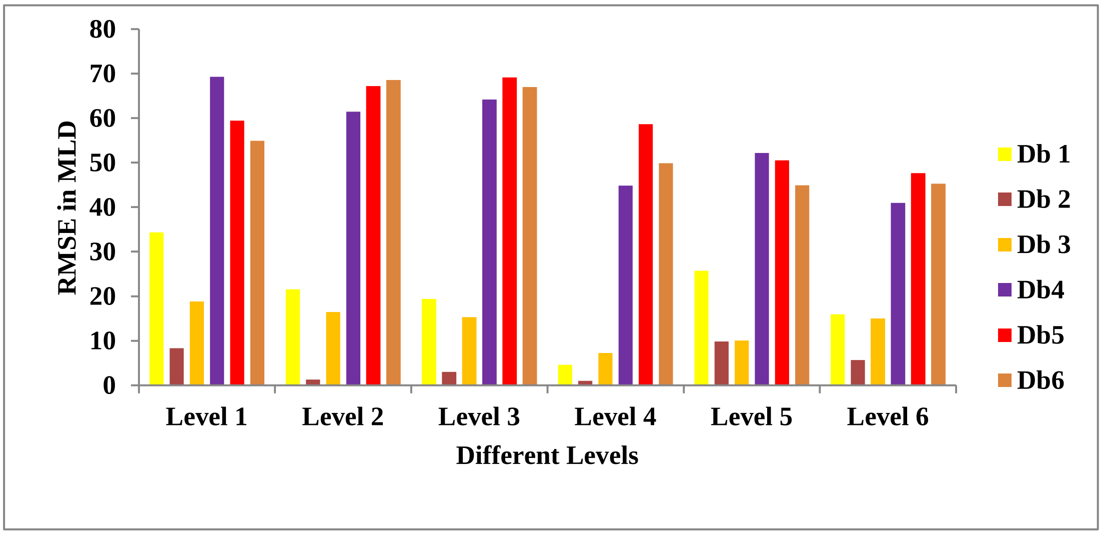


Figure 5.7.7 Results of db (1 to 6) for RF and WC combination

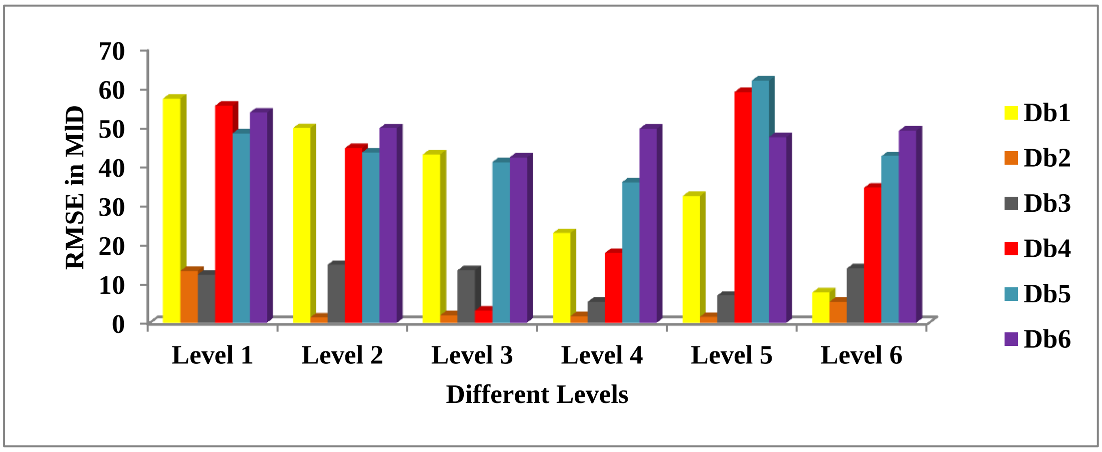


Figure 5.7.8 Results of db (1 to 6) for T-MAX and WC combination

Figure 5.7.7 shows the comparative result of compress fuzzy-wavelet approach for RF and WC combination. From the figure it is observed that, db2, having lower value of RMSE for all the levels compared to other order. But in the level 4 and 6, Value of RMSE is low for db1 wavelet. The value of RMSE for db6 is almost high for all the level. Similarly level 5 and level 6 having lower value of RMSE compare to level 1, 2, 3 and 4. Overall it is found that db2 and db3 were better for Rainfall and water consumption input combination.

Figure 5.7.8 shows the comparative result of compress fuzzy-wavelet approach for T-max and WC combination. From the figure it is observed that, db2, and db3 having lower value of RMSE for all the levels compared to other order. But in the level 3, Value of RMSE is low for db4 wavelet. The value of RMSE for db5 and db6 is almost high for all the level. Overall it is found that db2 and db3 were better for T-max and water consumption input combination.

Figure 5.7.9 shows the comparative result of compress fuzzy-wavelet approach for T-min and WC combination. From the figure it can be observed that, db2, and db3 having lower value of RMSE for all the levels compared to other order. The value of RMSE for db4, db5 and db6 is almost high for all the level. Overall it is found that db2 and db3 were better for T-min and water consumption input combination.

Figure 5.7.10 shows the comparative result of compress fuzzy-wavelet approach for RH and WC combination. From the figure it can be observed that, db2, and db3 having lower value of RMSE for all the levels compared to other order. The value of RMSE for db1, db4, db5 and db6 is almost high for level 1, 2 and 3. Overall it is found that db2 and db3 were better for RH and water consumption input combination.

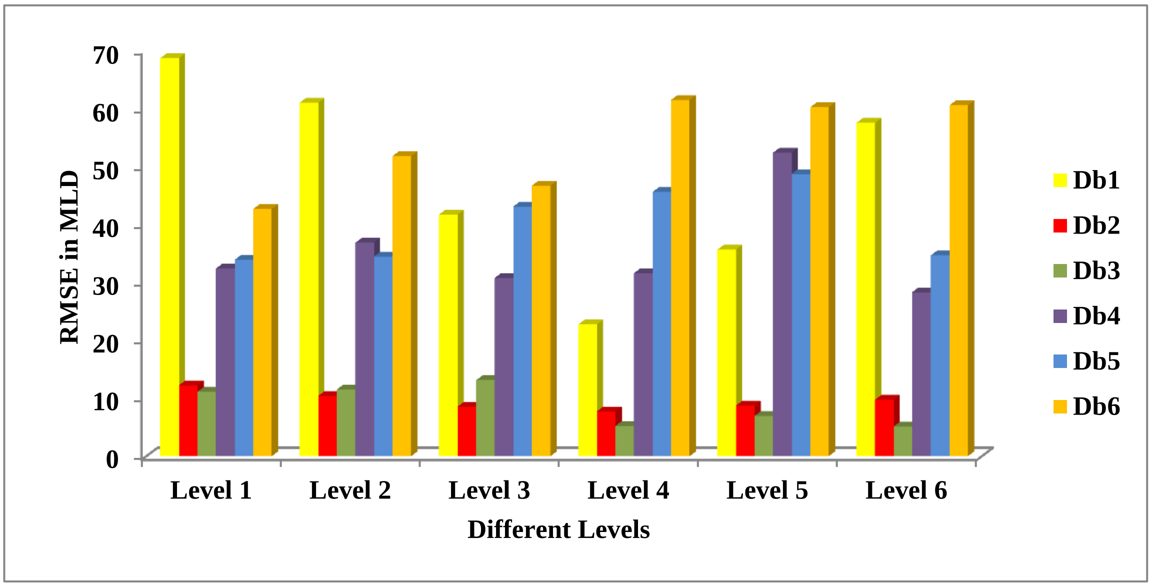


Figure 5.7.9 Results of db (1 to 6) for T-min and WC combination

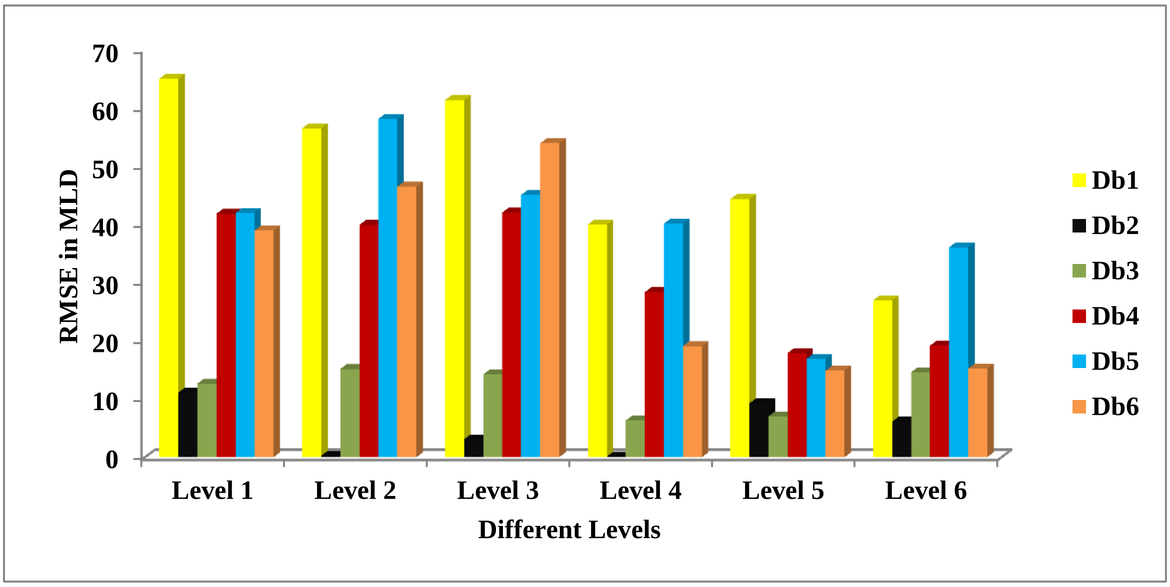


Figure 5.7.10 Results of db (1 to 6) for RH and WC combination

5.8 Results of Developed models for different entropy

In Fuzzy-wavelet modeling work, various mother wavelets such as Haar, Daubechies of different group db2, db3, db4, db5, db6 and Discrete Meyer wavelet at different level were used with different entropy such as Shannon and Log energy. Results revealed that Shannon entropy performed better compared to Log energy Entropy for Daubechies group. Shannon entropy gives useful information over a probabilistic distribution. Log energy is useful for narrow information. It spreads the wavelet to measure a particular domain (Time-Frequency), hence Shannon Entropy shows better results compare to Log energy**.** Results of different entropy used for compressed and denoised signal were represented in the table 5.8.1 and table 5.8.2. The comparative results of log energy entropy and Shannon entropy used for the compressed and denoised approach is shown in the figure 5.8.1 and Figure 5.8.2.

Table 5.8.1 Results of RMSE (MLD) for different entropy used (compressed)

Wavelet (db2)	Input	Output	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Log Energy Entropy	RF	WC	64.39	73.65	71.77	68.01	64.15	64.77
	T.Max	WC	50.14	47.85	36.01	43.91	61.03	75.99
	T.Min	WC	34.80	40.18	38.84	52.77	68.61	60.93
	RH	WC	42.20	48.67	35.56	35.79	55.92	42.12
Shannon Entropy	RF	WC	8.31	1.26	2.99	0.98	9.81	5.65
	T.Max	WC	13.23	1.35	1.9	1.62	1.51	5.38
	T.Min	WC	12.25	10.43	8.56	7.74	8.76	9.77
	RH	WC	11.14	0.26	3.08	0.12	9.27	6.11

Table 5.8.1 represents the result of different Entropy used in modeling the water consumption for compressed approach. From the table it is found that, RMSE value is high for log energy entropy in the case RF as input. Similarly for T-Max, T-Min and RH input performance for Shannon entropy is found better compared to log energy.

Table 5.8.2: Results of RMSE (MLD) for different entropy used (denoised)

Wavelet (db2)	Input	Output	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Log Energy Entropy	RF	WC	60.51	61.67	64.91	60.93	60.30	58.94
	T.Max	WC	48.64	45.05	35.79	42.31	50.99	52.55
	T.Min	WC	35.13	39.85	39.81	43.04	57.66	54.19
	RH	WC	35.31	38.48	38.16	36.01	38.94	38.86
Shannon Entropy	RF	WC	29.47	28.64	33.62	7.28	8.21	9.13
	T.Max	WC	13.34	11.34	10.02	8.83	9.85	10.22
	T.Min	WC	12.25	10.43	8.56	7.74	8.76	9.77
	RH	WC	11.06	4.82	7.92	6.55	7.57	9.04

Table 5.8.2 represents the result of different Entropy used for modeling the water consumption, for denoised approach. From the table it is found that, RMSE value is high for log energy entropy for RF input. Similarly for T-Max, T-Min and RH input performance for Shannon entropy is found better compared to log energy Entropy. Since during denoise operation, more coefficient will be removed, So Shannon entropy will not distribute properly as in the case of compressed signal.

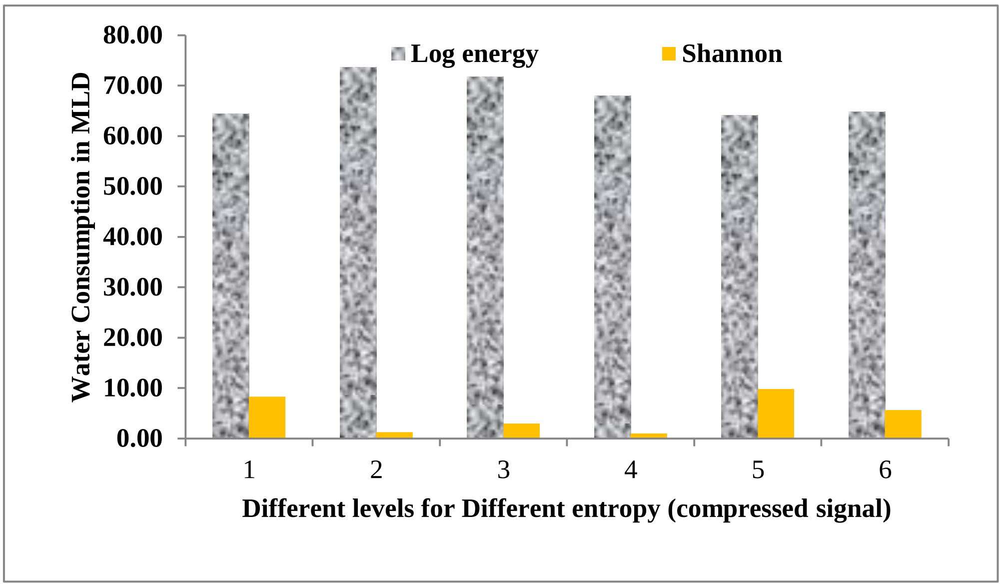


Figure 5.8.1 Comparison of different entropy for compressed approach

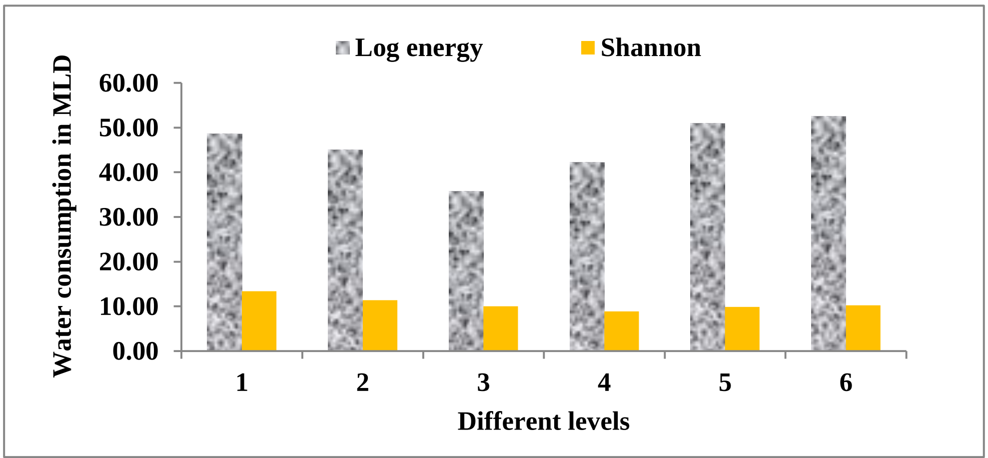


Fig 5.8.2 Comparison of different entropy for denoised approach

Figure 5.8.1 shows the comparative result of different wavelet used for RF Input combination using compress approach. From the result it is observed that value of RMSE is very low in the case of Shannon entropy, since it captures suitable information by spreading over a wavelet.

Figure 5.8.2 shows the comparative result of different wavelet used for T-max Input combination. From the result it is observed that value of RMSE is very low in the case of Shannon entropy, since it captures suitable information by spreading over a wavelet. But compared to compress signal, Shannon entropy having higher value of RMSE, since removal of noise during the denoise process.

5.9 Results of different performance evaluation indices

Different performance evaluation indices were studied to identify the best estimation model. Due to reduction in the degree of nonlinearity, model performance varies. Hence performance evaluation indices values were found to be different for different levels. Results of different performance evaluation indices commonly employed in modeling work for compressed and denoised approach were represented in the table 5.9.1 and table 5.9.2.

Figure 5.9.1 Results of different performance evaluation indices for compressed signal

Level \ Type	RMSE (MLD)	MAE (MLD)	PE in %	BIAS
Level 1	0.95	0.28	1.98	1.21
Level 2	1.22	0.35	2.48	0.97
Level 3	3.54	1.02	7.37	0.92
Level 4	0.27	0.22	0.51	1.13
Level 5	0.29	0.19	0.66	1.25
Level 6	0.14	0.11	0.24	0.94

.

Table 5.9.1 shows the comparative result of different performance evaluation indices used in selecting the best model. From the table it is found that, for the first level value of RMSE is low , MAE is low and BIAS is more than 1, indicating the over estimating model. Since the estimated value is higher the observed one in the level 1, value of RMSE is low. RMSE is square of mean error, single large value result in the increase of error. But the MAE is the difference of mean value of observed and estimated, hence single larger value will not increase. Higher the value of RMSE model indicate the bias value less than 1 showing under estimated model in majority cases. Hence RMSE and MAE were selected as best performance evaluation indices for modeling work.

Figure 5.9.2 Results of different performance evaluation indices for denoised signal

Level \ Type	**RMSE (MLD)**	**MAE (MLD)**	**PE in %**	**BIAS**
Level 1	30.11	27.49	17.89	0.821
Level 2	29.46	26.90	17.48	0.825
Level 3	28.64	26.14	17.00	0.829
Level 4	33.61	30.69	19.99	0.800
Level 5	7.27	6.64	4.28	1.042
Level 6	8.28	7.49	4.83	1.048

Table 5.9.2 shows the comparative result of different performance evaluation indices used in selecting the best model for denoised approach. From the table it is observed that, for the first level value of RMSE, MAE is high and bias is less than 1, indicating the under estimating Since the estimated value is lower than observed one in the first level, value of RMSE is high.

Chapter 6

SUMMARY AND CONCLUSIONS

6.1 Summary of the Work

This research work highlights the advantage of fuzzy-wavelet technique to estimate the municipal residential water consumption. From the result it is proved that wavelet transforms is able to distinguish frequency behavior as well as intermittent, which is not visual in time series. An attempt was made to investigate the use of wavelet based denoise and compress technique as a preprocessing method for estimating water consumption using fuzzy logic method. Suitable mother wavelet and proper decomposition level for different type of input variables are determined.

Various fuzzy-wavelets denoise and compress models were developed using discrete wavelet transform. Mother wavelets, Haar, Daubechies (2 to 6) and Discrete Meyer Wavelet are employed. After the wavelet transform operation, denoise and compress technique are done to reduce the degree of non-linearity. Different types of entropy such as shannon and Log energy are utilized to develop the Fuzzy wavelet model. Comparing the results of fuzzy wavelet hybrid approach with single fuzzy approach using performance evaluation indices such RMSE, MAE, PE, BIAS etc.

Single fuzzy models were developed for triangular and trapezoidal membership function, for different rules criteria and for different fuzzy set using Mamdani fuzzy inference system. Performance of the model for individual variables and combined variables studied separately to identify the significant Influence of the climatic variables. The key issue like limitation of the data set and quality of the data set are addressed in the research work.

Multiple linear regression and ANFIS models were developed for different input combination for comparison purpose. Rainfall, maximum temperature, minimum temperature and relative humidity data were used on monthly basis for modeling the water consumption using regression, single fuzzy, hybrid ANFIS and hybrid Fuzzy-wavelet approach.

Comparative results reveal that fuzzy-wavelet denoised and compressed technique performances are found to be better than single fuzzy model. Compared to denoise fuzzy wavelet model, developed fuzzy wavelet compressed model found effective for Daubechies wavelet of order 2, level 4 with Shannon entropy. Hence hybrid fuzzy-wavelet technique is highly capable to handle the nonlinear data efficiently.

6.2 Contributions

Following are the contribution from this study

- Advantages of soft computing technique in modeling the nonlinear data compared to conventional method are highlighted.

- Various fuzzy models were developed using different membership function, rules criteria and fuzzy set. Also their performances were analyzed.

- Applicability of wavelet denoise and compress technique in data normalizing are examined.

- Coupling and combining wavelet technique with fuzzy technique to enhance the model accuracy is carried out effectively.

- Performance of different mother wavelets for various resolution levels were evaluated.

- Accuracy of the developed model for different performance evaluation indices is checked and found satisfactory.

- Socio-economic factors play a dominant role in controlling the water consumption. However, climatic factors should also be included to capture the effect of future climatic change.

6.3 Conclusions

a) In the present research work, temperature and rainfall were found to be most important parameters which affect the model performance in estimating the municipal residential water consumption. Whereas minimum temperature and relative humidity were treated as significant variables, which improves the model accuracy.

b) Triangular membership with three fuzzy set and twelve rules criteria performed better compared to trapezoidal membership function as found in fuzzy logic modeling of municipal residential water consumption.

c) Hybrid model, adaptive neuro fuzzy inference system performed better compared to single fuzzy and regression techniques in modeling water consumption.

d) Fuzzy-wavelet denoise and compression approach found to be better compared to single fuzzy model in modeling water consumption.

e) Fuzzy wavelet compress approach found effective compared to fuzzy wavelet denoises approach.

f) Among different wavelet groups, Daubechies wavelet of second group (db2) of level 4 with Shannon entropy for compressed approach found to be better compared to Haar wavelet and other Daubechies wavelet group.

6.4 Limitations of the Work

- Fuzzy logic technique is limited for more number of input and output combinations due to slow convergence.
- Accuracy of the developed model is limited for optimum number of rules, fuzzy set and membership functions.
- Although wavelet technique has wide application, but the issues were related to selection of mother wavelet and optimum decomposition level.
- Availability of quality and lengthy data of water consumption is found to be major limitations of the study.
- Real field data collected in the field survey through questionnaire seems to be improper representative of water consumption pattern in the study area.

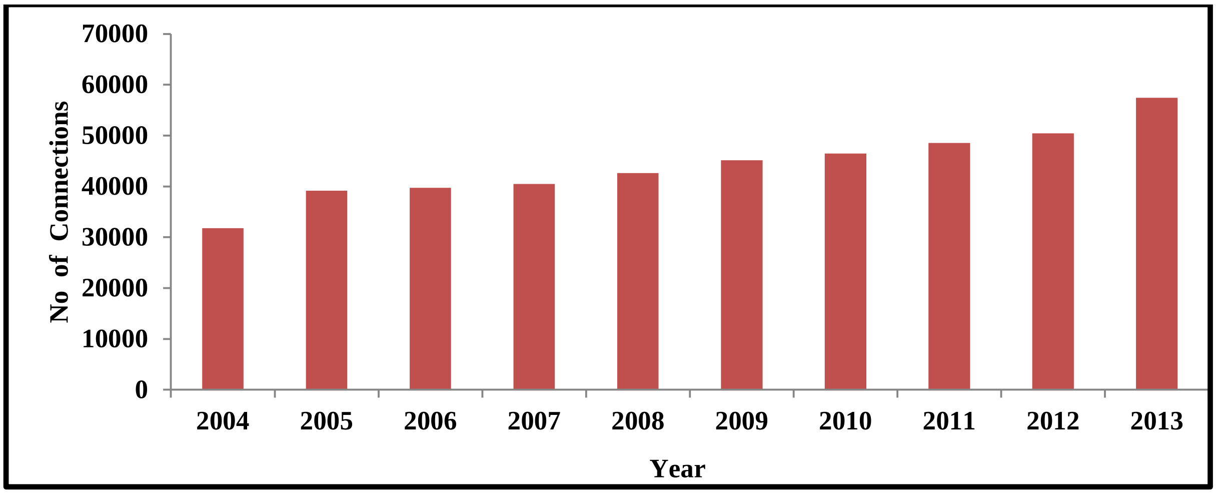
6.5 Future Scope of the Work

- The work can be extended separately for hourly, weekly, yearly, seasons wise and during special days.
- Real challenge involved in estimating the hourly water Consumption.
- Modeling of water consumption by combining both climatic as well as socio-economic factors with different index values.
- Exploring the various options of threshold based wavelet and wavelet packet transform in modeling water consumption.

APPENDIXES

1. Field Survey

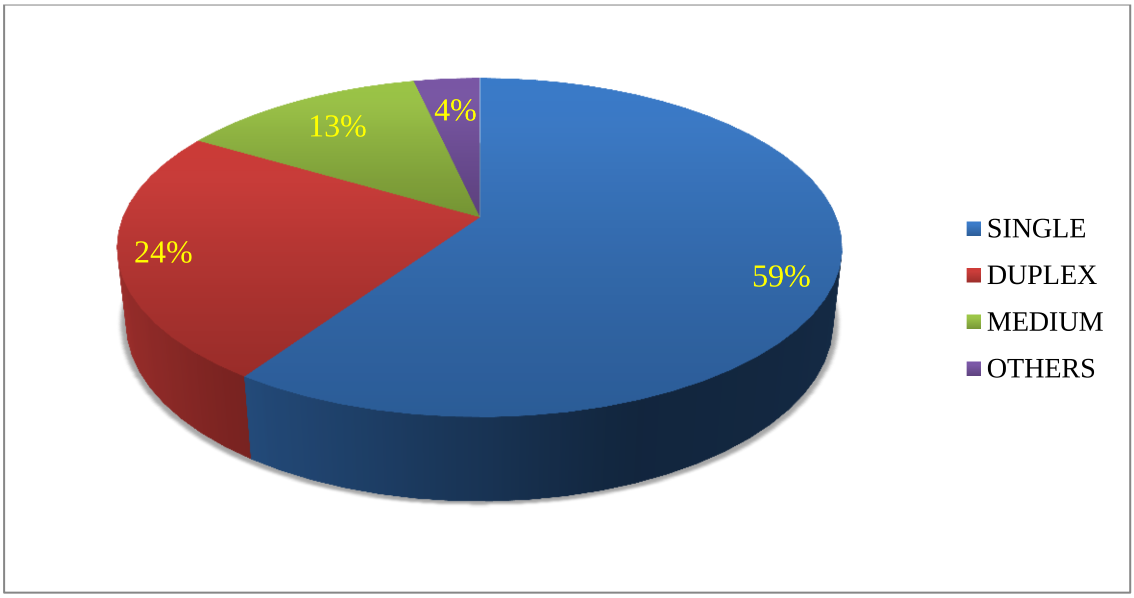
Field survey was conducted to understand the demographic pattern, consumer behavior towards water consumption and the information about socio economic factors. Since, apart from the climatic variables, socio economic factors play an important role in modeling the water consumption due to anthropogenic activities. Household survey was carried out with a team of five people. Survey was done in the month of April during the week end particularly in Sunday. Normally 20 minute is required to fill the details asked by the surveyor from each consumer. Instead of population details, the information regarding water consumption pattern and increase in water supply connection through field survey was extracted. Questionnaire information were collected from more than 50% of population, however qualities of data collected were found insignificant. Hence only 260 data were used. In this study, developed model is based on quality of the data set. Majority houses were surveyed but approximately 260 houses data were collected, which includes both single and attached house type. Survey data were divided on the basis of type of houses, number of members in family, age group, water bill, maximum usage of water per day. Field survey were also carried in educational institutions and commercial place like Hotels in order to know the consumer attitude for water consumption and their perception towards water conservation. Increased water connection in the study area is shown in the figure 1.1. Different types of houses surveyed are shown in the figure 1.2. Different types of water connections in the ward are shown in the figure 1.3. Statistics report of the field survey is presented in the table 1.1.



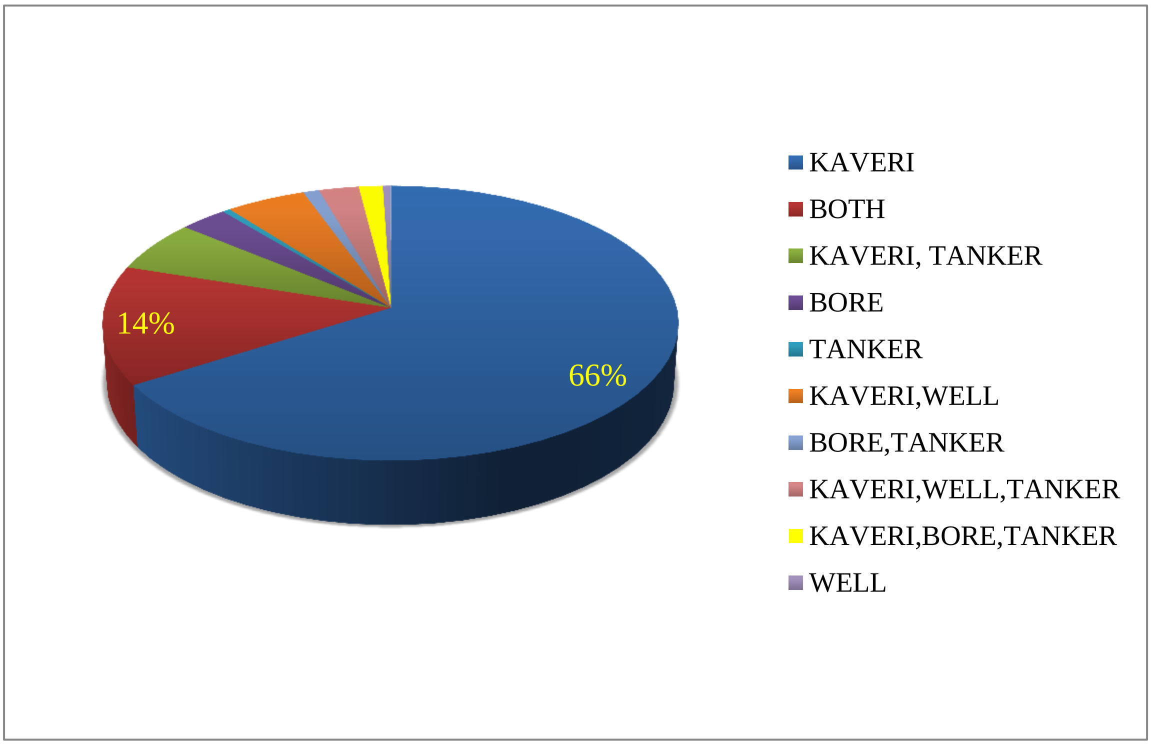
Appendix Figure 1.1 Water connections of last ten years

Appendix Table 1.1 Statistics of household survey

No of houses surveyed	260
Population in the houses	972
sources of water supplied (Kaveri, Bore-water, Well, Tanker)	4
Water requirement in MLD per month as per field survey	393.6
Approximate water supplied to the ward in MLD per month	258
Status	Deficient

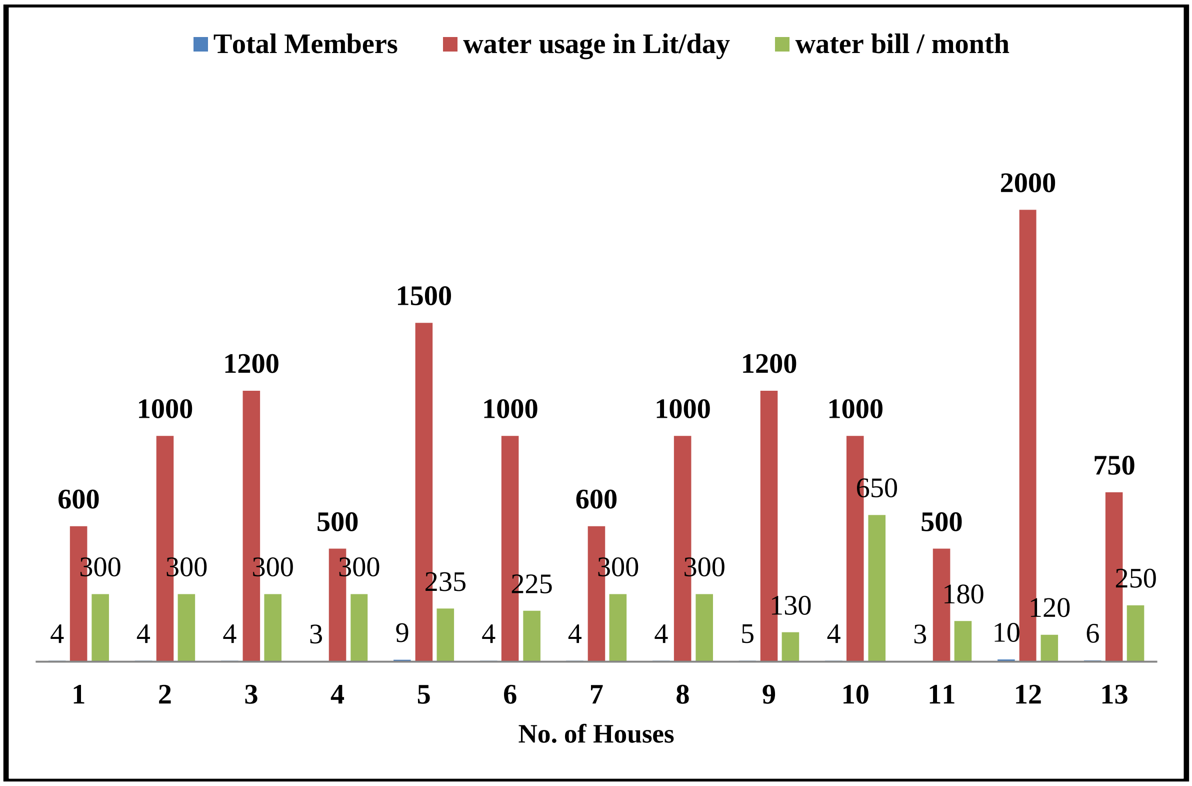


Appendix Figure 1.2 Different types of houses surveyed

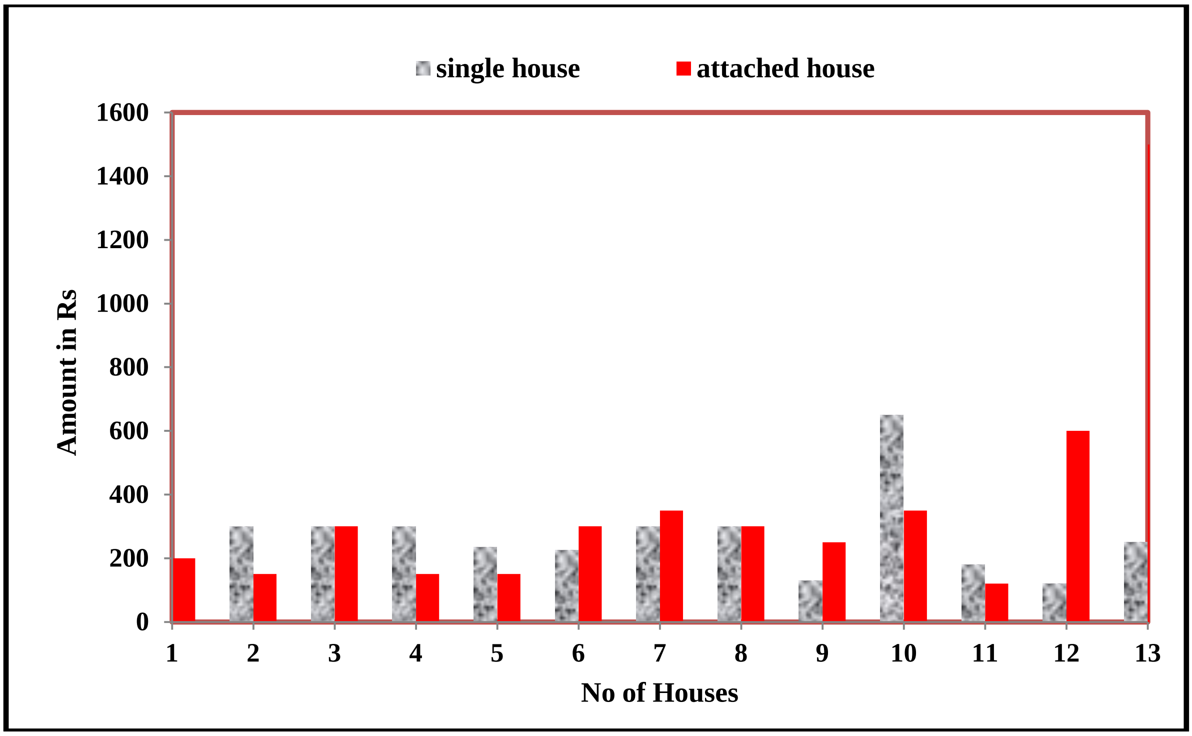


Appendix Figure 1.3 Source of water supplied

Field survey indicates that, number of family members remains same in most of the houses but the amount of water consumption will vary. Total water usage and water bill for same number of members in a family are shown in the figure 1.4. Water bill variation in single and attached houses were shown in the figure 1.5. Water usage and water bill in a single family is shown in the table 1.2.



Appendix 1.4 Water usage and water bill in a 4 members single family



Appendix 1.5 Water bill in Rs for single and attached family

Appendix Table 1.2 Water usage and water bill of single house family members.

Type of House	Members	Maximum usage of water in liter per day	Water bill in Rs
Single	4	600	300
Single	4	1000	300
Single	4	1200	300
Single	4	1000	225
Single	4	600	300
Single	4	1000	300
Single	4	1000	650

Water bill details were collected based on consumer interaction. Variation of water bill may be due to usage of tanker water when there is no water supply. Many houses gave exact bill of water usage and many houses gave details of total amount paid including previous month due. Hence water bill varies irrespective of the usage.

A.1.1 Discussions on the field survey:

a) Water consumption trend varies irrespective of the seasons in the study area.
b) Most of the responders do not have awareness about the water availability and scarcity.
c) Results indicate that, only few residents and education institution adopted the rainwater harvesting and recycling methodology.
d) Outcome of the survey results were incorporated in the knowledge part of fuzzy inference system for framing fuzzy set and different rules criteria.
e) Influence of demographic and socioeconomic factors play significant role compared to climatic variables.

A.1.2 Questionnaire prepared for household interview

1. Type of the house --

   (Ex: single house, attached, flat type, medium house)

   Note; If it is a block type, then number of flats in a block ------------

2. Number of family member in a house --------------------------------

   (Mention age groups & employability)

3. From how many years the family members residing in that particular house--------
4. Whether number of residents in your family is increased / decreased --------------
5. In which day of the week normally more usage of water is their -------------

(Type of the day, month and year. If any special occasion, please mention that also)

.

6. What are the sources available for water use--

   (BWSSB, Bore water, rainwater, Tanker, if any other please specify)

7. (a) what is the maximum usage of water in a day (Liter)--------------------------

   (b) If you have any rainwater harvesting tank, what is the capacity of the tank-----

   (c) Type of the water meter ------------- (separate /attached with other house)

   (d) What is the approximate water bill that you are paying (Individual) ------------

8. Is the water usage is increased compare to previous years-----------------------------

(a) If yes write factors responsible for increase the water usage?

(b) If no also mention the reason for decrease in water consumption?

10. What is the range of the family income per day/ week/ month -----------------------

11. Education / knowledge level regarding water usage-------------------------------
(excellent or poor)

.

12. (a) Name of the interviewer--------------------------------------

(b) Time/ date of Interview---

(c) Type of the place ----------------------------------- (water deficient area, other)

(d) Response type -----------------------------------   (Good, medium, poor)

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PUBLICATION DETAILS

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<u>Book Chapter Publication</u> (related work)

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<u>Paper Citations</u> – 6 (related to work)

H J Surendra and Paresh Chandra Deka, Effects of Statistical Properties of Dataset In Predicting Performance of Various Artificial Intelligence Techniques For Urban Water Consumption Time Series International Journal of Civil Engineering & Technology, vol 3 (2), 2012, pp. 60 – 69**.**

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