Optimum Length of lining to Reduce Losses in Watercourses by Using Advanced Non Linear Modelling

By

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(MCE153020)

MASTER OF SCIENCE IN CIVIL ENGINEERING

(With specialization in

Water Resource Engineering and Management)

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A research thesis submitted to the Department of Civil Engineering, Capital University of Science & Technology, Islamabad, Pakistan in partial fulfillment of the requirements for the degree of

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CERTIFICATE OF APPROVAL

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DEDICATION

This endeavor is dedicated to my esteemed and loving whole family, who helped me through all hard times of my life and forfeited all the coziness of their lives for my optimistic future. This is also a tribute to my honorable teachers who guided me to face the challenges of life with patience and courage, and who made me what I am today.

Arsam Ahmad Awan
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LIST OF ABBREVIATIONS

ANN	Artificial neural network
TLBP	Two layer back propagation
BFGS	Broyden Fletcher Goldfarb Shanno
MAF	Million Acre Feet
IBIS	Indus Basin Irrigation System
Lps	Liter per second
m/sec	Meter per second
cusec	Cubic feet per second
cumec	Cubic meters per second
BWN	Bhawalnagar
DG Khan	Dera Ghazi Khan
PIPIP	Punjab Irrigated Productivity Improvement Project
r	Variance
ℾ	Statistics

ABSTRACT

Life on earth is dependent on water. It is very valuable natural resource. Distribution of water on earth is not uniform in its both forms i.e. surface water and ground water. The quality of groundwater is varying from fresh to brackish in many areas. So it may not be fit for drinking and irrigation purposes. Surface water has fresh quality water and mostly used for irrigation purposes by diverting water from rivers and stream into canals. As this precious and scare resource moves into the irrigation system, certain part of water is lost. There is shortage of canal water supply in the dry spell and mostly during the winter season due to less availability of water and comparatively significant losses in the system. The losses in the watercourses is much more than those in the main canal and distributaries. So farmer's face acute shortage of irrigation water issues. In addition to this ground water pumping is also increasing that is decreasing ground water table. The conveyance losses in the watercourses can be minimised by applying some lining techniques. To overcome this problem, there is a need to work out optimum length of lining that ensures maximum water saving.

The estimation of water conveyance losses in watercourses is very important. A detail study has been carried out in the work to calculate conveyance losses using operational inflow and outflow approach. The losses from both lined and unlined watercourses of a similar geographical area have been calculated and used to compute the percentage saving of water. In this research work too from the field measurements, huge losses in unlined watercourses and a less losses in the lined watercourses have been observed. In this research work, the lining percentage is also authenticated numerically evaluated and authenticated.

The determination of this struggle is to safeguard both water and economy at the same stint. A total of 32 ANN models of actual and predicted water saving against the percentage length of lining are developed and analysed against the 8 polynomial regression forecasting method. The performance of TLBP and BFGS models is studied in terms of variance, R Square, Root mean square error. As anticipated, TLBP performed better as compare to BFGS for respective length of data. TLBP models have better values of random and systematic error than BFGS. It also shows better R square values in most of the cases. The percentage of water saving against increase in percentage lining were modelled using polynomial regression and optimum lining length for unlined water courses. The optimum percentage length of lining has been evaluated as 50% that ensures maximum economic benefits and 80% saving of water.

LIST OF INTENDED PUBLICATIONS

Journal article

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Intended refereed conference article

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CHAPTER 1

INTRODUCTION

1.1 Prologue

Water is very precious commodity now-a-days. Water resources are divided into natural and artificial. Natural resources comprise of precipitation, glaciers, lakes, streams and rivers. However, artificial or manmade resources of surface water from rivers in result of rainfall or melting of glaciers, over land and ground water flow. The quantum of water is stored in dams, reservoirs and is used for different purposes like hydropower generation and irrigation. Water is one of the main factors for agricultural productivity in developing countries especially in Pakistan where almost 70% population has agriculture as an occupation. The main source of Surface water supply in Pakistan is the Indus Basin Irrigation system (IBIS) as shown in fig. 1.1. It consists of a network of reservoirs, barrages, head works, link canals, main canals, distributaries, minors and watercourses. Annually 138 MAF surface water is drawn by the river Indus and its tributaries. Western and Eastern rivers contributes 137.71 MAF and 0.29 MAF, respectively. About 31.31 MAF is drained out into the sea. Approximately 80% of total available water is utilized for irrigation purposes through IBIS network (Sufi et al., 2011). As the climate is changing, so that fluctuation in available flow is also changing and is expected to experience more change in future. It is the fact that no new additional water is entering the system. On the other hand, demand of irrigation water is increasing day by day as the cropping intensity reached more than 150 percent for irrigated areas (Agri. Census, 2010). The IBIS is an aged system running without sufficient and necessary maintenance resulting in high water losses during its conveyance from reservoirs to agricultural farms. The conveyance losses in watercourses are due to seepage, evaporation, vegetation, rodent holes, spillage and operational inefficiencies, out of these seepage, operational and spillage are the major losses. These water losses must be minimized in order to increase the efficiency of the system and also to meet the future demands of irrigation water. This efficiency can only be increased by the efficient irrigation water supply and practices. Conveyance losses of watercourses controlled through lining may diminish the drainage requirement and lead towards better irrigation efficiency. So, estimations of conveyance losses in watercourses before and after lining are very beneficial for evaluating the performance of the system. Although, the percentage of water saving increases with the increase of lining but provision of lining for the whole length of watercourse is highly uneconomical. Only those reaches, points or portion should be lined from where maximum losses can be controlled but, relation between these two parameters is highly nonlinear and depends upon many geological as well as geographical parameters. The length of lining is more critical near outlets rather at tail or far end of water courses.

This study has been carried out to provide an economical solution by evaluating optimum length of lining that ultimately results in reduction of water loss and ensure increased water saving. The study is unique in a sense that its first of its kind that covers a large area (contains 8 districts) and provides a general idea of selecting lining length in the watercourses of Punjab province through the advance nonlinear techniques. This measure will help in more availability of irrigation water for agricultural productivity.

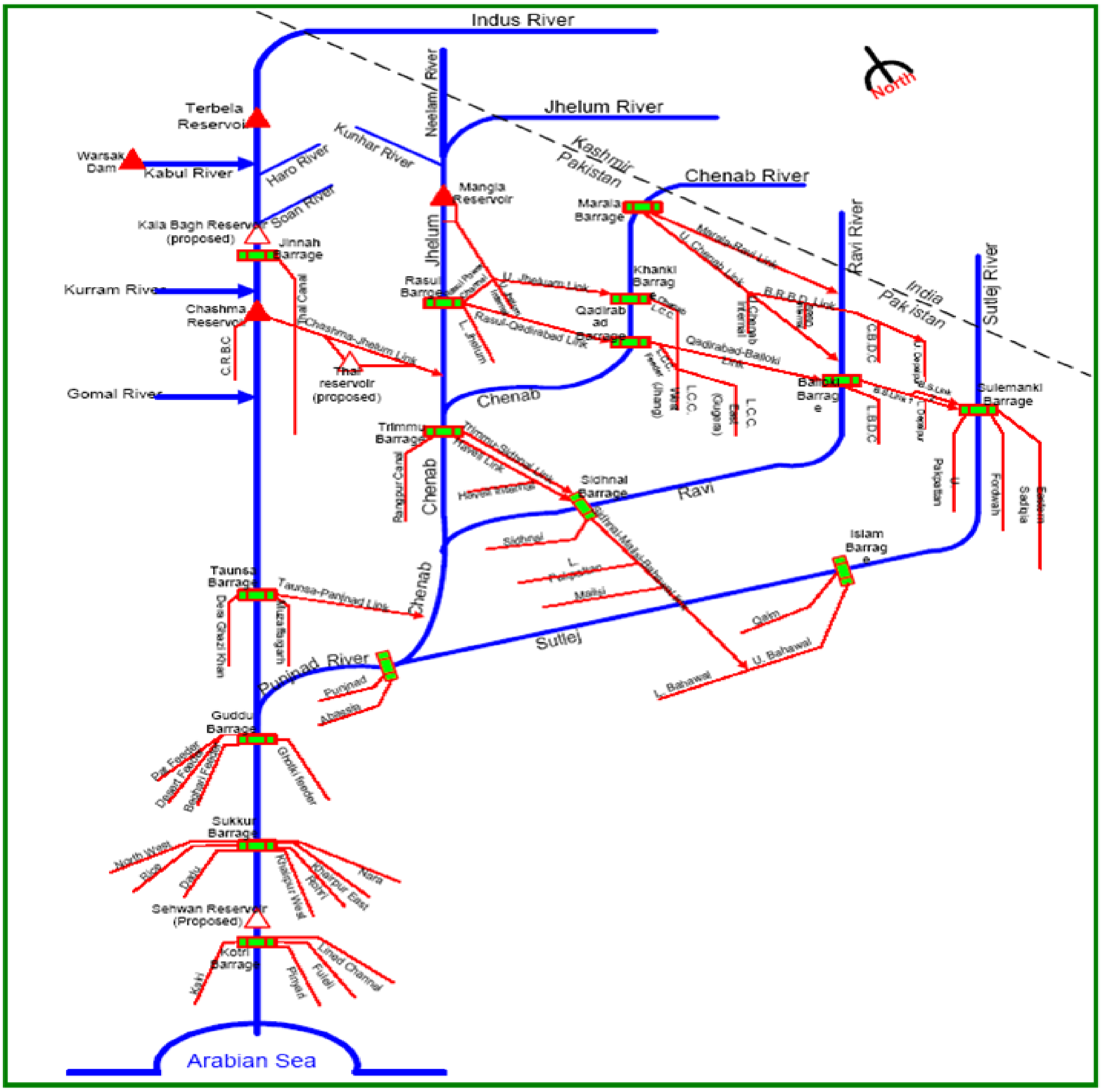

Figure 1.1: Schematic diagram of the Indus Basin irrigation system (after http://tiempo.sei-international.org/newswatch/xp_feature090518.htm)

1.2 Research motivation

The drought conditions in Tharparkar district of Sindh province (Pakistan) has been prevailing since 2013. It resulted in death toll of 190 children and thousands have so far been shifted to hospital for treatment in 2016 (Assessment capacities project 2016). Crop production failure happens as a result of less rainfall than average, which is causing 34-53% reduction in harvesting and 48% reduction in livestock. People of such areas do not have sufficient water for agriculture productivity and sometime even drinking purposes (FAO, 2016). Less water leads towards the less agriculture production. Due to this, food security issue is rising with the incremental growth of population. The motive of this research is to protect the people from drought, ensure the availability of food and better livelihood for public.

1.3 Overall and specific research objectives

The general objective of the research work is to provide irrigation water more efficiently in fields, so that sufficient water is available for existing cultivated lands and new lands could be brought under cultivation. It is done by applying the lining in watercourse up to certain length that harness considerable amount of conveyance losses.

In this research work, the proportional estimation of percentage water saving with respect to percentage length of watercourse is studied. The study also include the prediction of percentage water saving by artificial neural network modelling, checking of the model performance and validation through the regression analysis. Therefore, the specific goal of this thesis research is as under:

"Optimum percentage length of lining to reduce maximum amount of water losses in watercourses by using advanced nonlinear modelling".

1.4 Brief of Research methodology

The selection of eight (8) unlined and four (4) lined watercourses have been selected in eight district of Punjab (Pakistan). Water courses is divided into three parts and Cut throat flumes are installed for data collection of discharge at points. Collected data is analyzed through polynomial regression analysis. An ANN technique is applied through Two Layer Back Propagation (TLBP) and Broyden Fletcher Goldfarb Shanno (BFGS) for models development. Mainly two models of each technique is generated for each site. These two are named as training and testing model. The actual water saving is plotted against the predicted water saving. Variance, Bias, Mean and Root square are calculated to check model efficiency. The values of percentage water saving are taken from model against queried percentage of length. These results are plotted and compared for obtaining the optimum percentage lining length of watercourses. Details are given in chapter 4.

1.5 Thesis layout

The thesis layout comprises of main six chapters. These are:

Chapter 1: It is titled as introduction. It explains the background of IBIS losses and watercourse losses, research motivation, research objective and methodology, and thesis layout.

Chapter 2: It explains the literature review related to previous researches on losses. It consists of background, history of losses studies, Application of artificial Neural Network studies in Water resources, Water losses measuring techniques and summary of chapter 2.

Chapter 3: It is named as study area, data and methodology. It consists of background, it also tells about the study area and data set. It also covers methodology, introduction to win gamma, and advance non-linear modelling and summary of chapter 3.

Chapter 4: It covers background, loss rate in the eight districts. It also contains results of gamma test and application of ANN based models and polynomial regression of eight districts. It consist of TLBP and BFGS models and polynomial regression graphs, consists of results and analysis regarding the percentage length of watercourses and percentage saving of water. It provide details about the error, bias, variance and Root square between predicted and actual water saving, percentage lining length against percentage saving and summary of chapter 4.

Chapter 5: It consists of conclusion, benefits of study and future recommendations.

References

CHAPTER 2

LITERATURE REVIEW

2.1 Background

Significant conveyance losses are observed in IBIS. The losses vary in canals, distributaries, minor and watercourses. The water losses in watercourses are much more than those in other components of irrigation network. The main reasons of these are poor maintenance and less control of flows, evaporation and seepage through unlined or in appropriately lined sections (Thomas 1981). Other causes are leakages, spillages, vegetation, dead storage, zigzag shape, holes made by rodent, and stealing losses (Zeb et al., 2000; Arshad et al., 2009). The intensity of losses varies with the length of the watercourse, variation in discharge, time of retention, soil type and compactness of soil. Lining of an irrigation channel is most commonly used practice for saving water, which also helps salinity control and to improve system efficiency. There is need to find the economical length of lining to reduce major losses considerably. Seepage and conveyance losses have been discussed in detail in this chapter.

2.2 History of Losses studies

Lining of canal is the most widely used method to reduce seepage losses. An increase of 25% in conveyance efficiency was observed due to lining on entire canal length (Arshad and Ahmad, 2011). The delivery losses ranged from 38 to 62 % in the watercourses of Khushab district were observed (Copland, 1987). Akkuzu (2012) also carried a similar research for calculation of seepage loss in Turkey using Mortiz and Davis empirical equations and found the average seepage losses were 107.61 cubic meter/second/kilometer, 32.1 liter/second/ 100 m and 11.7 liter/second/100 m for main canals, branches and distributaries, respectively. He further suggested lining of canals as an economical solution for this purpose. Numerical modeling has also been applied for estimation of conveyance losses in canals by Wachyan and Rushton (1987). According to Martin and Gates (2014) water losses from minor and distributaries were varies from 1.8 to 2.0 m^3/day/meter, respectively. Uncertainty and non-linearity in seepage losses was observed by using flowing water balance with acoustic Doppler devices. Uncertainty tells about the insufficient information regarding the seepage losses information may be inadequate and nonlinearity shows that there is no linear relationship between discharge and seepage losses. The study also investigated the severity of seepage and potential benefits of seepage reduction and the main conclusion was that the losses were increased as the wetted perimeter increased. Chatha et al. (2014) investigated the seepage losses by inflow – outflow method. They noted that average value of seepage losses varied from 1.91 Lps/100m to 3.08 Lps/100m. These losses should be controlled to save the irrigation water and to ensure system efficiency by doing lining to save the water during conveyance process.

Shaikh and Lee (2015) estimated the earthen water channel seepage losses. The study was intended to improve the water use efficiency. Losses were measured by using the inflow and outflow method. Selected water courses were located at different places. The discharge and physical conditions were changed. The studied results showed that average velocity and average wetted perimeter varied from 0.17 to 0.42 m/sec and 0.99 to 2 m, respectively. The channel flow rates were varied from 0.027 to 0.125 cubic meter per second and seepage losses rates were observed 0.001998 cubic meter per second at 0.99 m wetted perimeter and 0.004728 cubic meter per second for 2 meter wetted perimeter. The study showed that the losses increased as the wetted perimeter increased. Further the inflow and outflow method was considered as the most reliable method which is able to measure the most of the losses except evaporation (Planning and Development, 1988).

Skogerboe et al. (1979), Moghazi and Ismail (1997), and Arshad et al. (2009) also supported the inflow-outflow method and concluded that this is the only method that can be applied under all operational condition (free and submerged) of watercourses.

Sarki et al. (2008) investigated the seepage losses in watercourses of Tando Jam, Sindh. Two methods were adopted by them, one was inflow-outflow method and other was ponding method. Loss rate was 0.0016 Lps/100 meter in inflow-outflow method.

Alam and Bhutta (2004) investigated the seepage losses in canal with the help of physical measuring technique. The emphases of the study was to reduce the irrigation system losses. The seepage losses varied from 9.76 to 17.54 cm/day. Their research work also showed the discharge and seepage rate in different canals. Their results for the seepage losses are lower than those by the other researcher's studies. So their results cannot be applied as such. It needs some calibration and factor. Table 2.1 shows seepage rate (cm/day) for discharge in various channels as studied by Alam and Bhutta (2004). In this table, noted that seepage rates increased with the decrease in discharge, but there is no perfect relationship seen between the discharge and seepage rate. It happened due to low slope, low velocity, time of retention increases and big wetted perimeter.

Table 2.1: Loss rate and discharge by Alam and Bhutta (2004)

Channel name	Discharge (cumec)	Seepage rate (cm per day)
3-L	0.57	7.20
Daulat	4.36	8.83
Mohar	0.95	7.34
Phogan	0.81	23.16
Soda	2.2	19.01
Fordwah	4.74	5.53

Greater the length of lining, greater will be the saving of water and ultimately it will produce an incremental effect on agriculture crop productivity. On the other hand, lack of lining also increases the rate of ground water abstraction, reduction in salinity and water logging. It leads towards degradation of soil and effects the crop yields by decreasing the channel's design capacity. (Reuss et al., 1979; Trout, 1983). Kahlown and Kemper (2004) evaluated different types of lining for the reduction of water losses from watercourses. The results were compared between the rectangular brick masonry sections and concrete trapezoidal sections with varying wall thickness and lining of bed. Water losses were measured on earthen, newly lined and aged watercourses with different lining options. Their results showed that there was minor difference of losses between earthen and aged lined watercourse.

Arshad et al. (2009) studied the comparison of water losses in unlined watercourses in Jhang District of Pakistan. The study was carried out to emphasize the importance of water saving for Pakistan. The unlined watercourses were chosen having the considerable fair reaches and cross sections. Cut throat flume was used for measuring the flows and losses. It was noted that average loss from unlined watercourse varied from 64 to 68% and could significantly be reduced through lining. This study also showed the excessive loss in unlined channel. The losses occurred in water channel where no turnout existed and at weak reaches due to humans and animals usage.

Javaid et al. (2012) studied the performance assessment of watercourses in Jhang district, Pakistan. The study was intended to identify effects of unlined channels and suggested future directions. Conveyance efficiency was measured by one point method. Current meters were used for this purpose. The average loss rate per 100 meter in lined watercourses varied from 0.3 to 0.6 litre per second (Lps) and in unlined it ranged from 1 to 2 Lps. The losses in unlined watercourses varied from 36 to 69%. There was large variation shown in the results of unlined watercourses. This was mainly due to the physical condition of watercourse, leakage, discharge and time in use.

T. Sultan et al. (2014) reported improvement in conveyance efficiency by 12% and 25% for watercourses in India and Pakistan, respectively. Very similar trend of lining impact was seen in Turkey and Egypt, where the reduction in conveyance losses reduced to 17% and 7%, respectively.

Tareen et al. (2016) studied six watercourses of Mubarak distributary in District Tando Muhammad Khan, Sindh, Pakistan. Inflow-outflow method was used for conveyance efficiency measurements. Conveyance efficiency (CE) of unlined water courses is shown in the table 2.2. Watercourse lined length, inflow, outflow and conveyance efficiency are given in this table. No significant difference was seen in the conveyance efficiencies after lining.

Table 2.2: Lined watercourses conveyance efficiency (CE) by Tareen et al. (2016)

Watercourse No.	**Length (m)**	**Inflow (Lps)**	**Outflow (Lps)**	**CE (%)**
3-R	600	148	143	96.62
4-AR	284	86	84	97.67
18-CL	738	184	180	97.83
19-L	339	57	56	98.25
45-R	960	197	191	96.95
46-R	960	145	140	96.55

Conveyance efficiency of unlined water courses is shown in table 2.3. Watercourse unlined length, inflow, outflow and conveyance efficiency is given in this table. This shows that as the length is increasing, conveyance efficiency is decreasing, conveyance efficiency of 4-AR is 77.38% with 661 meter of length but the conveyance efficiency of watercourse no. 45-R and 46-R are 71.20% and 71.43% with the length of 2240 meter. A reasonable difference seen among the conveyance efficiencies after lining. So, lining proved better option for improving the system efficiency and to control the conveyance losses.

Table 2.3: Unlined watercourses conveyance efficiency (CE) by Tareen et al. (2016)

Watercourse No.	**Length m**	**Inflow Lps**	**Outflow Lps**	**CE %**
3-R	1400	143	106	74.13
4-AR	661	84	65	77.38
18-CL	1722	180	134	74.44
19-L	931	56	43	76.99
45-R	2240	191	136	71.20
46-R	2240	140	100	71.43

Saha (2015) studied the water losses in canal and measured reduction in flows. Comparative study of different researches was done for the reduction of conveyance losses and reason of the losses was also identified. Lining is option for improving the conveyance efficiency. Reason of losses were also mentioned as seepage, evaporation, operational and leakage. Fig 2.1 shows an unlined watercourse showing the different feature of water losses in a watercourse. Watercourse have the spillage and seepage problem. Evaporation from water surface also occurs. There is no proper alignment of watercourse. It causes the water losses during its conveyance. These losses also varies with the length and physical condition of watercourse.

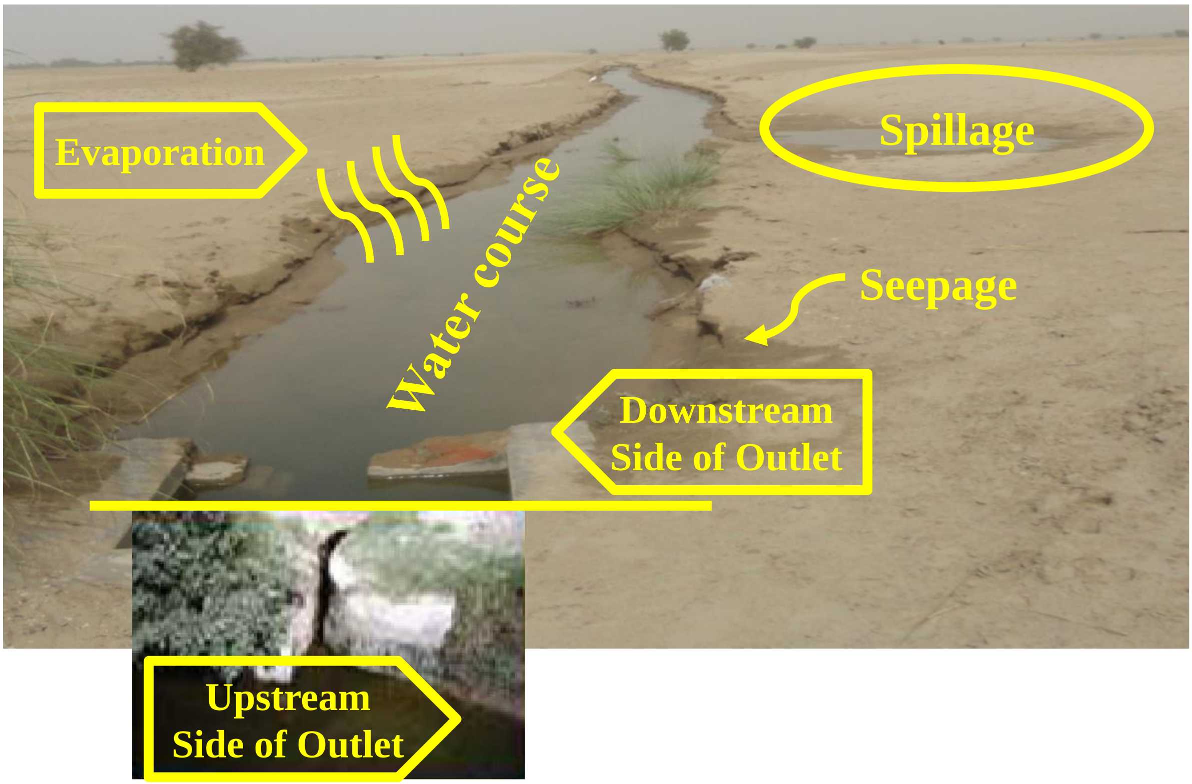

Figure 2.1: Earthen watercourse showing the water losses

2.3 Application of Artificial Neural Network (ANN) in water resources studies

Artificial neural network methods in water resources have fetched a new aspect to hydro meteorological forecasting. ANN is emerging as the commanding predicting tool as a result of vigorous efforts and developments (Remesan et al. 2010). A foremost development was accomplished regarding the application of ANN to non-linear systems and current forms of ANN that are used in various fields particularly in water resource, hydrology etc. The adaptation and use of ANN based models are very pivotal for understanding and decision making particularly in developing countries like Pakistan, reason for this is the resources constraint due to poor economic position (Habib, 2001). American Society of Civil Engineering (ASCE) recognised the beneficial prominence of ANNs, which is explained in ASCE (2000). The capability of ANNs to model multifaceted hydrological systems, has been extensively recognised in literature. It has been verified through demonstration of capturing few properties like surface flow, base flow and infiltration etc. (Jain et al., 2004). The main advantage of ANN is its execution time which is quite less in comparison to that of other model and also it can work on slow computer machines (Shamseldin, 2010). The use of ANN is widespread for flow measurements, sediment transport in several part of world. For instance Tayfur (2002) used ANN to simulate experimentally, observed flow and sediment instabilities from altered gradients under a number of rainfall intensities. ANN is used to simulate daily flow along with suspended sediment load at two places on the Tongue River in Montana USA (Kisi, 2004). A three-layer feed-forward ANN model by introducing back-propagation algorithm to forecast daily river flow and suspended load in it, has been used by Tayfur and Guldal (2006). Different reaches of Tennessee River basin were tested to obtain better results. Thus, the time of need is to exploit this constructive nonlinear technique to the complex processes of water losses in watercourses where the purpose of physical parameters with accuracy is very riotous.

Hassan et al. (2014) studied the stream flow prediction to a multiuse reservoir by using ANN modelling and regression analysis. The study was carried out in the upper Indus basin of Pakistan. The study explores the use of upland watershed information, containing of hydro-metrological records for inflow estimate to Tarbela reservoir. The study establishes that the standard regression, step wise regression and ANN based model can be castoff for river flow estimation for effectual management of water with in the watershed of upper Indus basin to realistically great notch of accuracy. The study reveals that through the bony period with dwindled flows standard multiple regression and stepwise regression may possibly be useful. On the other hand the ANN constructed models could show to be efficient for the duration of medium and peak flow period, as their assessments was comparatively better. This study has provided an important impact for forthcoming water management with in Indus catchment.

Tanty and Deshmukh (2015) conducted a review on application of artificial neural network in the field of water resources and hydrology. Artificial intelligence works can be well represented through application in rainfall-runoff modelling, river flow modelling, water quality modelling and application in ground water. Feed forward back propagation is broadly practiced in several hydrological problems but few other methodologies were also in use like in case of rainfall-runoff, the stream flow modelling recurrent neural network is employed, in water quality modelling cascade correlation artificial neural network model is used. ANN is pretty help full for understanding hydrological forecasting. ANN is gaining acceptance among researchers day by day.

Solaimani (2009) rainfall-runoff prediction based on artificial neural networks (a case study). The paper enlightens the applications of the feed forward back propagation for the rainfall forecasting with several algorithm with enactment of multi-layer perceptions. The inquiry discovered the competencies of ANN and performance would be equated to the conventional methodologies used for river flow forecast. The outcomes visibly showed that ANN are proficient to model rainfall-runoff correlation in arid and semi-arid areas in which rainfall and runoff are very asymmetrical. The comparative research shows that the ANN technique is more suitable and capable to foresee the river runoff than classical regression method.

Shafie et al. (2011) studied performance of artificial neural network and regression techniques for rainfall-runoff prediction. The study tells that ANN is a different procedure with flexible mathematical arrangement. It is accomplished of detecting multifarious nonlinear relationship between input and output data. From the comparison to the classical modelling techniques, for performance evaluation of anticipated model, three statistical parameter were castoff namely, correlation co-efficient (R), Root mean square error (RMSE) and Correlation of determination (R^2). The results analysis showed that ANN method is more suitable to predict rainfall-runoff than classical method of linear regression. This modelling technique is quite efficient and valuable alternate for reckoning of rainfall runoff correlation.

Mutlu et al. (2008) did the assessment of ANN models for hydrologic forecasting at multiple gauging places in an agricultural watershed. The research work primarily assess the ANN models to forecast daily discharge at multiple gauging places in Eucha basin. Results indicate that ANN models are advantageous tools for projecting the hydrologic response at multiple points in basin.

Rani and Parekh (2012) studied the application of ANN for reservoir water level forecasting. This study tells about the possible future water level forecast, which is quite helpful in irrigation sector, hydropower generation, water supply distribution etc. The principle input are incorporated to work out water level at t+1 time are: inflow water level at time (t) and release water. The statistical parameters RMSE, R and R^2 were compared to catch best model out of three options. The study exposes that amongst the three algorithms, ANN using feed forward distributed time delay is an applicable forecaster for real time water level prediction.

Abdulkadir et al. (2012) investigated the application of artificial neural network model to the management of hydropower reservoirs along river Niger, Nigeria. The study was carried out by forecasting its future storage for the purpose of hydropower generation, domestic, industrial and irrigation. Neural network summary yielded 95% and 69% of good forecasts for Jebba and kainji hydropower dams, respectively. The correlation coefficients are 0.64 and 0.79. These values indicate the reliability of neural networks for forecasting. It can be extracted that forecasting using ANN is a handful tool in dam operation and management.

Yuhong and Wenxin (2009) studied the application of artificial neural network to predict the friction factor of open channel flow. The results of ANN derived models were compared to the results taken from the empirical formula. It demonstrated that ANN model has been able to forecast the nonlinear relationship between the friction factor and its swaying factors but enough samples are required for the better prediction. This study provides the stage to solve the other archetypal hydraulic problems.

Campolo et al. (2003) investigated predicted flood in river through feed forward neural network technique with standard back propagation training algorithm. The data of rainfall, hydrometric and reservoir operation at Arno River, Italy was used to predict the water level on hourly basis. The study reveals that model was capable to predict the six hours ahead water level. It also tells that predicted error increases with the increase in time ahead. More error was seen at lower level than higher ones.

Unal et al. (2010) estimated the flow capacity of compound channels using ANN with Levenberg training algorithms. The comparison was also made with some traditional modeling techniques. Forecasted results shows that ANN perform was good among all other methods. ANN is promising for predicting the discharge and sediments. Ghumman et al. (2011) looked into the runoff forecasting by artificial neural network and conventional model. The performance is evaluated in training, validation and test phase. It has been found that ANN performance in training stage is more proficient but in validation and test phase performance of ANN is quite alike to the schematic model. ANN models are relatively easy to develop. The big advantage of the ANN modelling is that it doesn't depend upon the hydrological and geological parameters, these two parameters are the main difficulty in the development of conventional models.

2.4 Water losses measurement techniques

Water losses from watercourse can be measured by physical methods or with empirical formulae. In physical methods, water losses are measured directly from the field either by directly measuring by measuring discharge (Q = A/V). Empirical formulae designate the relationship of loss rates with channel parameters; these parameters are also obtained physically.

Planning and Development (1988) and Kraatz (1977) described the methods to measure water losses from the watercourses. These methods are as follows:

2.4.1 Inflow-Outflow method

This method entails measurement of discharges at the head and tail of the selected length of watercourse. The difference of inflow and outflow is calculated as the water loss from the watercourse in that particular section. The evaporation is measured with evaporation pan and is subtracted from the difference after multiplying with appropriate pan coefficient but in case of watercourse, evaporation is usually ignored as the surface area is quite small. The flow rate is physically measured by the help of current meter or flume. Throughout the experimentation, flow rate of the water is kept constant. This inflow-outflow technique is based upon the water balance method. It involves the direct measurement of the water flowing into and out of watercourse. Eq. 2.1 gives the water budget equation for a section shown in fig 2.2. It tells about the loss rate of water from watercourses.

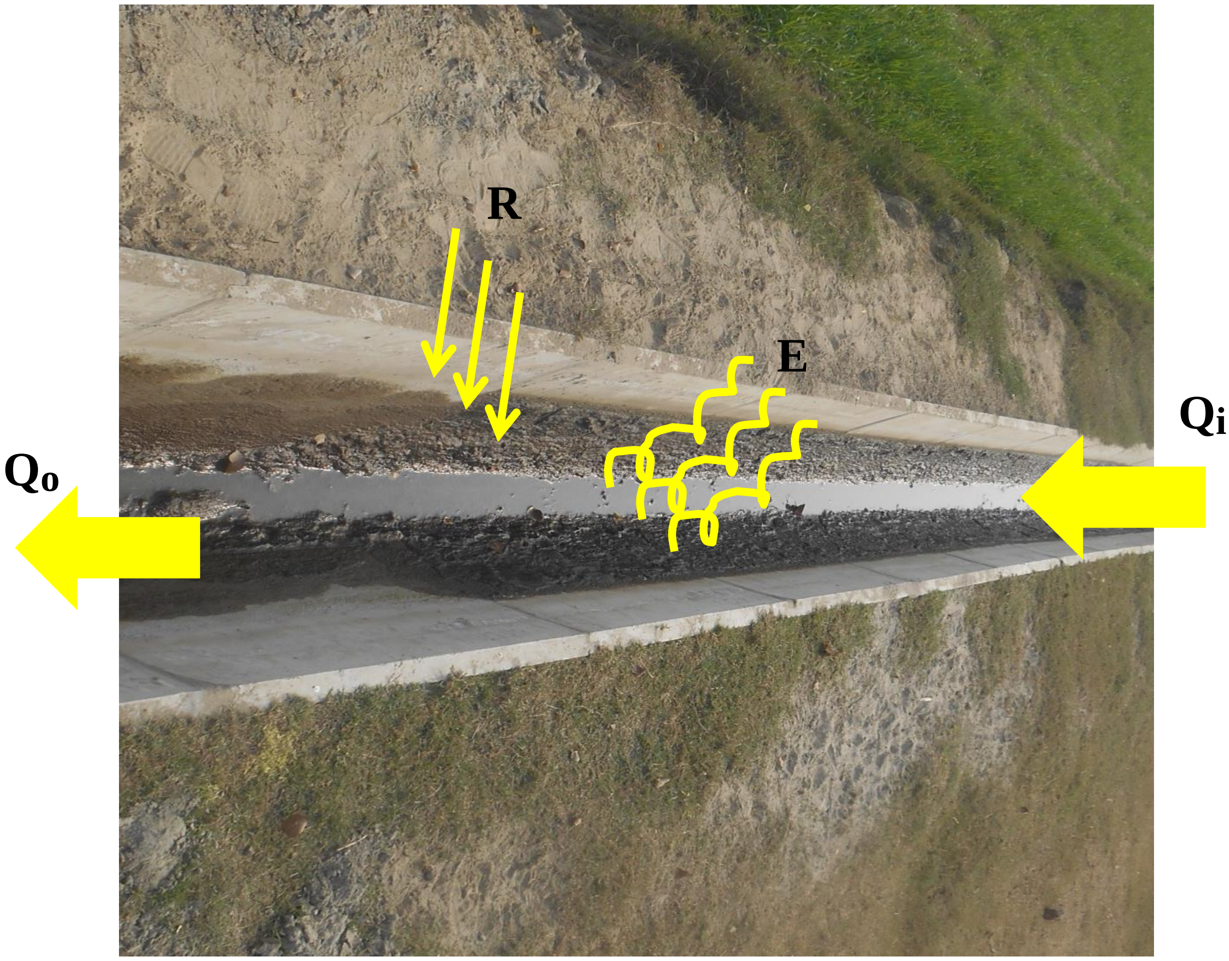

Figure 2.2: Mass balance for the inflow-outflow method

$$S = Qi + R - Q_o + D + I - E \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.1)$$

Where S is the seepage rate; Qi is the upstream inflow; R is the direct rainfall; Qo is the downstream outflow; D is the flow diverted along the reach; I is the inflow along the reach; and, E is evaporation.

2.4.2 Ponding Method

In this method, a selected reach of the watercourse is actually isolated by making temporary water sealed dikes at the head and tail end of the selected length. The selection criteria of experimental section must follow the minimum variation in the cross section of watercourse. The pond is filled with water and average loss rate is measured by using eq. 2.2.

$$q = \frac{\Delta A . \Delta H . L}{\Delta t} - \frac{E_p L T}{\Delta t} \qquad \text{.............................. (2.2)}$$

Where q = average loss rate (cusecs);

ΔA = change in cross sectional area w.r.t time Δt (Sq.ft);

ΔH = change in water depth of water (ft.);

E_P = Pan evaporation with incorporation of pan factor (ft./day);

L = selected length (ft.); and

T = top water width (average over length L) (ft.);

Δt = time change (sec)

A little modification is made later on for a precise measurement for a known volume of water that should be added in the pond to keep the stage constant. A modification to the above procedure is to add water to the pond to maintain a constant surface stage. The added water is defined as the total water loss rate during the noted time.

This method takes a long time for measurements, so that evaporation and rainfall must be considered during the test. This method gives satisfactory results for low loss rate only. As the tested section length is long, the results of loss rate may be lower than the actual due to the current present at the bottom due to silt deposition. This method is not used without the interruption of watercourse operation.

According to Planning and Development (1988) WAPDA did their experimental work by using the ponding method to measure losses from 13 irrigation channels, but this method was not suitable for large canals due to dikes construction, water filling in whole test length and uneconomical. The use of this method is limited to only low discharge watercourses and minor canals.

Blackwell 1951 and United States Geological Survey (1977) determined the ponding method as the correct method to quantify the seepage rate, but it did not present the actual operating circumstances of the irrigation system (e.g. this test is usually performed during the dry or closed irrigation season under non-flow conditions, the sediment load and other suspended materials in the water are able to deposit on the walls and the bed of the channel, thus reduction of the seepage rate occur.

2.4.3 Seepage Meter Method

The main theme of this method is to isolate the small area at the bed or side of the watercourse or canal. A metallic bell column is put under the bed material and the water drop over the bell column is noted. This rate of drop is correlated to the loss rate. Seepage meters are of two types: (a) first is constant head seepage meter and (b) second is falling head seepage meter (Awan, 1978) and (Kraatz, 1977).

The fundamentals of seepage meter method are quite similar to ponding method but the only difference between the two is that seepage meter method is applied without closing flows in watercourses or canal. Its equipment is adequate for measuring local seepage loss rates in the watercourses or canal. The devices can be easily and quickly mounted and they provide reasonable results. This method is mostly used for identification of localized heavy loss length of watercourses, but the limitation of using this method is that velocities should not be usually more than 2 feet per second and fixed bed should not be used for measurement. The device is delicate and susceptible to stretch very erroneous results. Awan (1978) investigated the loss rate with seepage meter. The reported loss rates were found 23 to 58 % more in comparison to ponding method, it was due to the excessive disturbance of the subsoil, pushing the bell into the bottom of the watercourse or canal.

According to Planning and Development (1988) WAPDA made several initial tests on minor canals and watercourses in the IBIS. The results acquired were not satisfactory due to errors coming from various inherent sources during the measurements.

2.4.4 Tracer Technique

Tracer technique is used for seepage measurement from both lined and earthen canals and watercourses by the (Irrigation Research Institute, 1984). This method works on the principle of measuring the velocities of seepage flow direction originating from the channels. Dilution rate of injected tracer gives the velocity of flow lines. These reading are taken on the either side of the bank of channel at an equal distance interval.

Ordinary salts like sodium chloride and potassium bromide etc. are used. The bore hole is used for the tracer injection. Injection is done on different horizons in hole and the rate of injection is converted into velocity along bore hole depth for the determination of actual seepage rate per unit of length. The velocity of the seepage flow is determined by the equation 2.3.

$$C - C_i = (C_o - C_i) \exp \frac{8V.\ r_1^2\ .\ r_2\ .\ t/Vo}{\frac{k}{k^*}(r_1^2\ -\ r_2^2\ ) + r_1^2 + r_2^2} \quad \text{……..} (2.3)$$

Where, C = tracer conductivity which is equal to electrical resistance of the saline column, at a given horizon in the screened well at time t;

C_o = conductivity of tracer in the screened well within same horizon at time t = 0;

C_i = Initial conductivity of the groundwater flowing in and out of the screened well before the addition of the tracer;

V_o = constant volume of water in the screened well per unit of its length;

V = un-perturbed horizontal velocity in the aquifer;

r_1 = outer radius of the shrouding;

r_2 = inner radius of the strainer pipe;

k = permeability of the aquifer; and

k^* = permeability of the compound unit consisting or strainer and shrouding

BRDB link canal is tested by applying this technique by Irrigation Research Institute Lahore. It has been observed that it is a sensitive technique and small seepage measurement is possible from this technique. It is also observed that it has satisfactory results only for small velocities like .001 ft/sec.

The core problem in this method is the determination of flow direction and bifurcation of seepage and groundwater flow, due to this reason, the results may not represent the true picture of loss rate.

2.4.5 Empirical Methods

Few researcher examined the outcomes of water losses experiments on the canals of Chaj and Rechna Doabs. The results showed a range of water losses in Punjab.

These varied from 0.014 to 0.025 cusecs per sq.ft. Before this, the measurement were done by physical methods. He derived the following empirical formula (eq. 2.4) for estimating losses in terms of discharge:

$$q = C\ Q^n \quad \text{…………………………………….. (2.4)}$$

Where q = water losses (cusec per sq.ft);

Q = discharge (cusecs)

'C' and 'n' are constants. They depend upon characteristics of neighboring media. The value of C and n are 3.75 and 0.05, respectively.

WASID (1963) evaluated the loss measurements results from the canals of Rechna, Chaj and Thal Doabs. About 70 out of 300 measurements were sorted out for further analysis. The main theme was to find out the relationship between losses and discharge. Remaining readings were rejected due to inaccuracies in flow measurements. The decision was that an approximate relationship is given in eq. 2.5.

$$s = C\ Q^n \quad \text{……………………………………. (2.5)}$$

In this eq. s is Cusecs per canal mile. Results of each doab were independently analyzed. The values of 'C' and 'n' were define as 0.06 and 0.68, respectively for Thal Doabs; 0.03 and 0.71 respectively, for Chaj and Rechna Doabs with mean values of 0.04 and 0.68.

Molesworth and Yennidunia's empirical formula is used in Egypt by Egypt's Irrigation Department, and is given in equation 2.6.

$$q = C\ .\ L\ .P\ \sqrt{R} \quad \text{……………………………. (2.6)}$$

Where

q = conveyance losses (m^3/sec) per length of canal;

L = length of the canal (km);

P = wetted perimeter (m);

R = hydraulic mean depth (m)

C = a constant that depend upon the nature and temperature of soil (C = 0.015 for clay and C = 0.003 for sand)

Mortiz Formula as developed by U.S.S.R:

$$q = 0.2\, C\sqrt{\frac{Q}{V}} \qquad \text{………………………………} \quad (2.7)$$

Where

q = seepage losses (cusecs per mile length of canal);

Q = discharge (cusecs);

V = flow velocity (ft. /sec);

C = a constant, value varies with the soil types;

Hungarian formula for calculating the seepage losses, this equation (2.8) is used for trapezoidal sections only, (ICID, 1967):

$$q = 1700 d_a\, H(B + H S_o) \qquad \text{…………….} \quad (2.8)$$

Where

q = seepage losses in cubic meter (m^3) per day per meter length

d_a= active diameter of the soil grains

H = depth of water;

B = bottom width, and

S_o = bed slope

International Commission on Irrigation and Drainage, ICID, (1967) described the practice of the following formula for seepage losses measurement from canals in India:

$$q = C\,.\,P\,.\,H \qquad \text{……………………} \quad (2.9)$$

Where

q = total loss (cusecs);

P = area of wetted perimeter (million sq. ft);

H = water depth in the canal (ft);

C = a constant, depending upon channel material. The value of C varies from 1.1 to 1.8.

2.5 Summary

All the factors which contribute towards the losses are important. The consideration of these factors is quite essential for the correct estimation of losses with respect to increasing length and planning for reduction of losses. From the literature review, it is revealing that lining the length of watercourses is not specifically optimized for the reduction of maximum losses. This research study ponders all factors of losses. Different methods of measuring the losses are also discussed in this chapter. The results are confirmed by nonlinear modeling. The use of ANN models is reported for many engineering studies, like sediment transportation, reservoir storage prediction, compound channel analysis, flood prediction, structure analysis etc. These models work on nonlinear principle. Therefore, it provides more precise prediction and given accurate results in comparison to other linear techniques. Those linear models are unable to produce better results in presence of noisy data.

This study covers all factors responsible for water losses for a watercourse. Inflow outflow method has been used because of its more acceptance by researchers etc. ANN modeling has also been done due to its more reliable results.

CHAPTER 3

STUDY AREA, DATA AND METHODOLOGY

3.1 Background

The losses in the watercourses, an important component of irrigation system are much higher as compared to the other component of irrigation system. It is the demand of time and necessity to overcome these losses to maximum extent. The only way to reduce the losses is lining. Lining length must be selected according to the maximum losses reduction to ensure economy. There are different methods for modelling but ANN is relatively better because it can work easily in noisy data. Different physical and empirical method are available for the calculation of different types of losses in the watercourses. The study area, data set and methodoly is discussed in this chapter.

3.2 Study area

The study areas are Bhakkar, Bhawalnagar, Chiniot, D.G. Khan, Hafizabad, Kasur, Sahiwal and Vehari districts. These are shown in solid blue colour in figure 3.1 below. The land of Punjab province mostly contains of productive alluvial plains. It is the part of Indus valley, fed by Indus River and its four major tributaries i.e. the Jhelum, the Chenab, the Ravi, and the Sutlej rivers. Most areas of Punjab observe harsh extremities in weather with cold and fog in winters, high heat in summer and heavy rain during the monsoon. From the mid of February, the temperature begins to rise, spring season weather continues until mid-April. Punjab's region temperature averagely ranges from −2° to 45 °C, but can reach 50 °C (122 °F) in summer and −10 °C in winter. Cotton, wheat, rice, gram, sugarcane and citrus are the major crop grown in the area. Water losses are more and tremendous effort are required to develop the route of watercourse, such that the losses could be reduced to minimum.

3.3 Data set

Twelve (12) sample watercourses including Eight (8) unlined and Four (4) lined were located in eight districts of Punjab province. Table 3.1 gives details of selected watercourses as obtained from the Punjab Irrigation Department, Pakistan. The warabandi list (rotation manual) of the command area was also obtained and verified against the actual rotation practice.

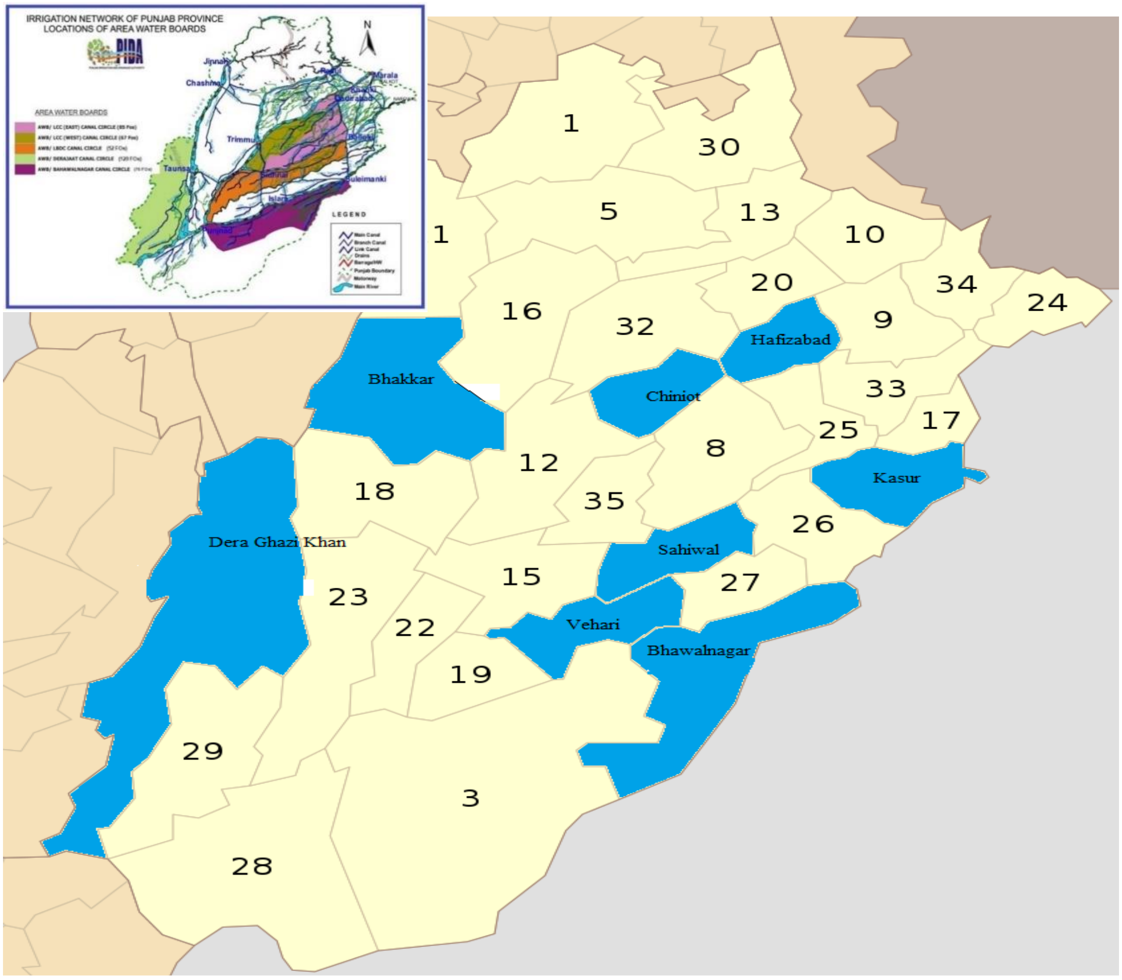

Figure 3.1: Map of Punjab province showing the selected study areas (Source: PC-I PIPIP, 2012)

3.4 Methodology

The inflow-outflow method provides direct measurement of water losses. This method is based on measuring the rates of water flowing in and out of a selected section of watercourse. The difference between inflow - outflow is attributed to losses. The inflow-outflow method is a practical approach and it responds well under dynamic conditions of flow. Furthermore, continuous measurements can be performed without any interference in the system operation. (Arshad et al., 2009). Moghazi and Ismail (1995) conducted the study for the losses calculation from field channel under arid conditions. It was revealed in the study, empirical equations usually under estimated the losses from channel. Direct measurement method of inflow and outflow was used for losses calculation. Accuracy in the results depends on accuracy of in-flow and outflow measurements. The flow chart of methodology is shown in Figure 3.2.

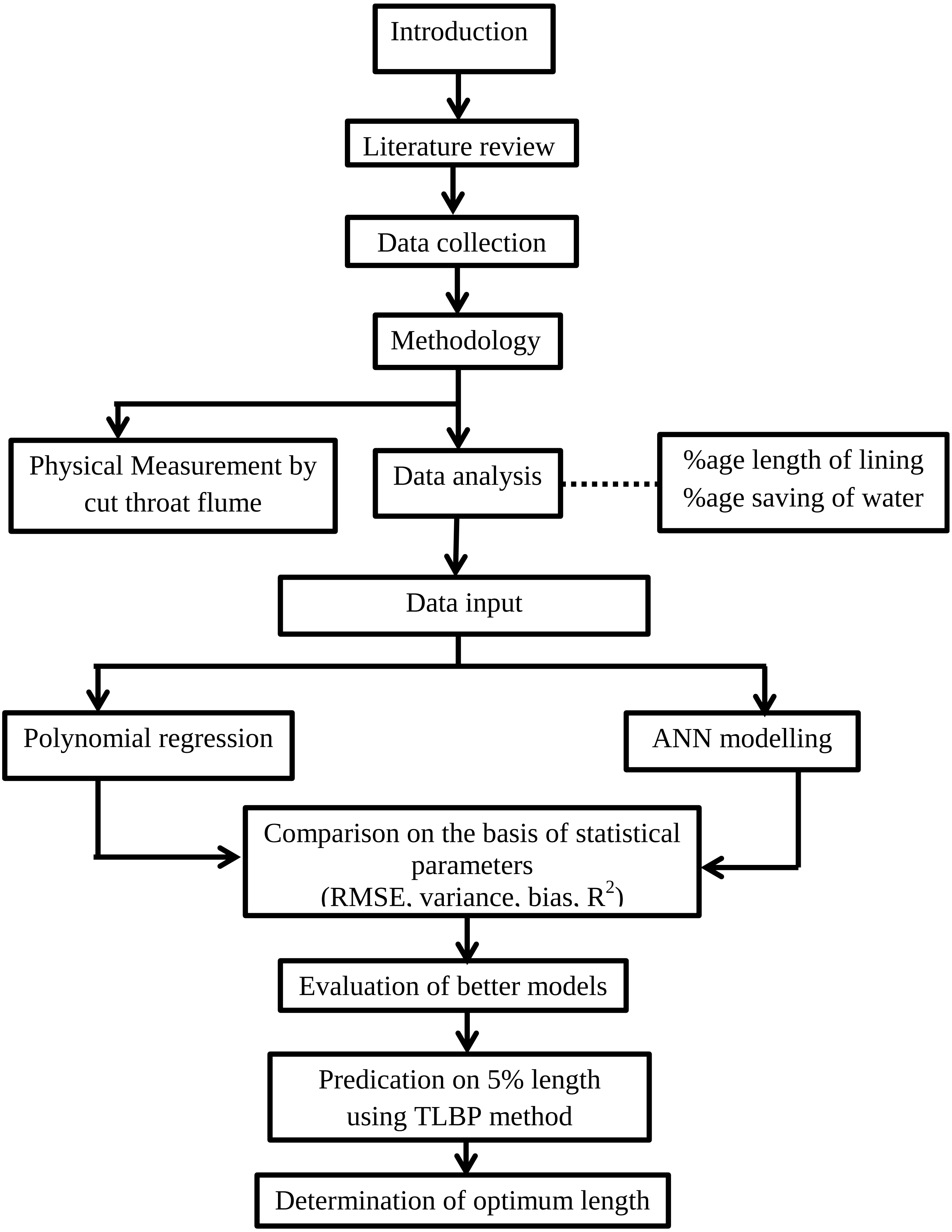

Figure 3.2: Flow chart of methodology

Table 3.1: Water Courses location Information and respective Command Areas

Stations	Status	Outlet Location	Distributary	Main Canal	Length (m)	Command Area (Acres)
Sahiwal	Unlined	21780-R	9L	LBDC	5310	400
Kasur	Unlined	72432-R	Kasur	BRBC	3420	275
Vehari	Unlined	49173-L	2BR	Pakpattan	6717	453
Chiniot	Unlined	35409-L	Gilotran	Jhang Branch	6716	430
Hafizabad	Unlined	15461-L	Fethki	LCC	9889	707
Bhawalnagar	Unlined	6-R	Fateh	Sadqia	4645	369
Bhakkar	Unlined	31250-R	Mahota	Thal	4908	708
Dera Ghazi khan	Unlined	16594-R	Oorwaahi	DG Khan	6777	550
Bhawalnagar	Lined	3-AL	Madrassha	Sadqia	3800	291
Dera Ghazi khan	Lined	32000-R	Qasim Wala	DG Khan	3500	224
Bhakkar	Lined	56610-R	Khansar	Thal	3100	546
Kasur	Lined	14260-L	Handal	BRBC	3350	275

The two types of watercourses unlined and lined are selected. Unlined watercourses are the earthen watercourses having no material on its cross section. While on the other hand lined watercourses means earthen watercourses and its cross section is usually covered with bricks as per design. The tracer methods reckonings for seepage losses only while ponding method covers seepage and evaporation losses in watercourses. The Inflow-Out flow method covers an extensive range of losses and considered the most preferable method for measuring the losses in the watercourses. Table 3.2 shows the comparison of different factor affecting losses in various methods

(Planning and Development, Punjab, 1988). It shows that inflow-outflow is the only method that count for all the loss factors affecting water loss. The other methods majorly address seepage only except ponding method that also address evaporation.

Table 3.2: Comparison of Losses in various methods (Planning and Development, Punjab, 1988)

Factor Affecting Losses	**Tracer Method**	**Ponding Method**	**Inflow-Out Flow Method**	**Empirical Method**
Seepage	Yes	Yes	Yes	Yes
Evaporation		Yes	Yes	
Spillage			Yes	
Rodent Holes			Yes	
Breaches/Cuts			Yes	
Dead storage			Yes	
Infiltration			Yes	
Operational			Yes	

3.4.1 Cut throat flume

The flume is commonly suited in both flow conditions i.e. free and submerged, for flow measurement (Skogerboe et al., 1973). Also, it can be used for varied range of flow discharges. The collected data for conveyance loss is applied to the entire watercourse system using water rotation time (called warabandi) of each watercourse under study to estimate the total loss. Distances between flumes are measured as a segment length and loss/100 meters for each segment is also calculated. The loss rates so obtained are further used to calculate the volumes of water loss for each segment. A detailed drawing sketch of cut throat flume is shown in Fig. 3.2. It shows the dimensions along with the converging and diverging sections of flume.

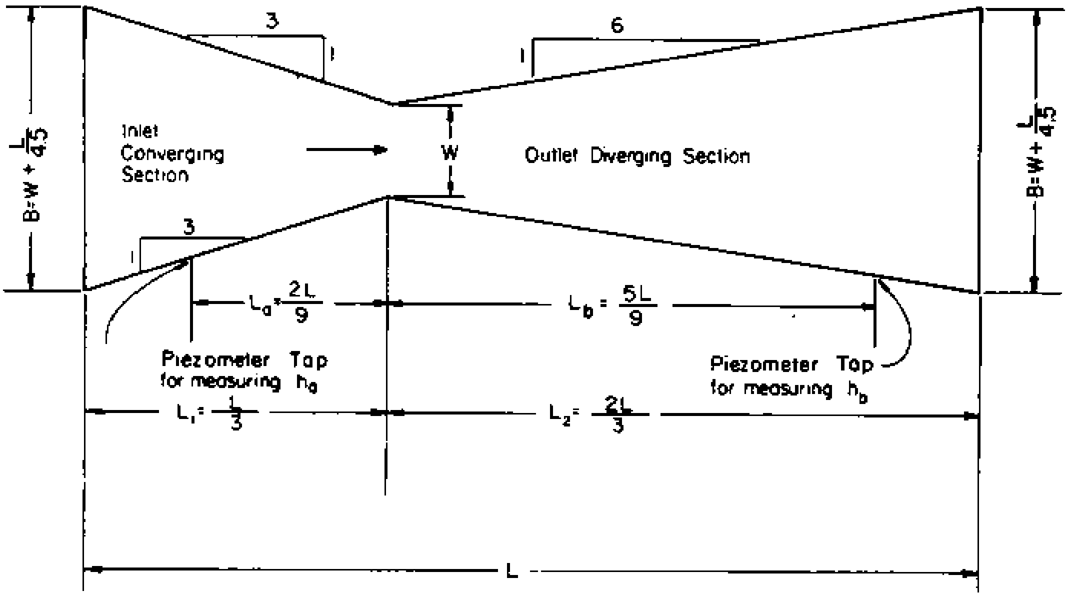

Figure 3.3: Sketch of Cut Throat Flume

A physical picture of cut-throat flume is shown in Fig. 3.2. Scale on the upstream and downstream side sides of the flumes is shown here for the measurement of heads on both sides. It has converging section on upstream side and diverging section on downstream side. The ratio of head upstream and downstream determines the condition of flow either submerged or free.

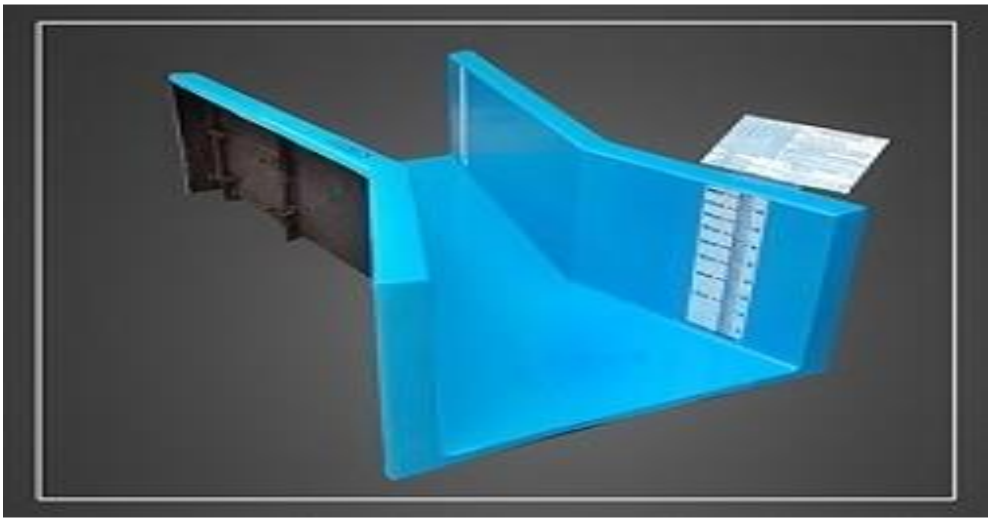

Figure 3.4: Cut Throat Flume

The formula used for measuring the losses in the watercourses is as under.

$$Q = C_s \, {(H_u - H_d)^{nf}}\big/{(-\log S)^{ns}} \quad \text{.......................} \; (3.1)$$

$$\text{Loss}/_{100\text{m}} = {(\text{Q}_\text{i} - \text{Q}_\text{o})100}\big/{\text{Measured Length}} \quad \text{............} \; (3.2)$$

Where Q is the discharge in cubic meter per second; Q_i and Q_o represents inflow and outflow, respectively. H_u is upstream head and H_d is head at downstream. E is the evaporation loss and S is the submergence, Cs is experimentally determined separately for free and submerged flow, n^f and n^s are dimensionless exponents. Cut throat flume having dimensions (8″x36″) has been used to measure inflow and outflow discharge at the designated points. The main watercourse has been divided into three sections i.e. head, middle & tail sections by installing three cut throat flumes.

3.4.2 Polynomial Regression Analysis

Royston and Altman (1994) introduced the regression procedures based upon fractional polynomial (FP) transformation of continuous predictors. It is beneficial method of examination which keeps predictors as unbroken in the model. The application of nonlinear regression has been gauged in the numerous fields of water resources for instance to calculate demands of irrigation canals (Ticlavilca et al. 2013), low flow guides (Joshi et al. 2013), watershed modeling (Marshall et al. 2007), loading of nutrients (Wellen et al. 2012; Vigiak and Bende-Mich 2013), and stream flow modeling (Block and Rajagopalan 2009; Liang et al. 2013). Polynomial regression models are usually fit using the method of least squares. The least-squares method minimizes the variance of the unbiased estimators of the coefficients, under the conditions of the Gauss–Markov theorem. Although it fits a nonlinear relationship between the value of independent variable (x) and the corresponding conditional mean of dependent variable (y), despite of the fact that it has a linear regression function applied on unknown parameters. Mathematically, it can be expressed as eq. 3.3.

$$y_i = a_o + a_1 x_i + a_2 x_i^2 + \cdots + a_m x_i^m + \epsilon_i \qquad \text{………………………. (3.3)}$$

Where a_o, a_1, a_2 …..a_n are constant coefficients, m is the non-negative integer and x is an argument.

3.5 Introduction to Win Gamma Software

For Data or measured numbers or observations processing, it can be reflected as a spreadsheet of data, Columns are distributed into two categories: input columns and output columns. In any row we may demand to find out the values of the outputs, when these are not known but the corresponding inputs are known.

A data model is an algorithm constructed from a set of observations (for which all input sand outputs are known) which enables us to predict the outputs from a given set of inputs. This software is concerned with constructing data models of a particular type.

3.5.1 Introduction to Gamma test

Stefanson et al. (1997) and Kon čar (1997) firstly developed the Gamma test, it is principally a modeling technique based upon data driven, intended for building the data derivative models. These models can be efficaciously applied in numerous fields including control theory (Kon čar 1997), feature selection (Chuzhanova et al. 1998; Durrant 2001), control of chaotic systems (Tsui 1999; Tsui et al. 2002; Jones et al. 2002), and secure communications (de Oliveira 1999) over and above hydrological modeling (Remesan et al. 2008; Remesan et al. 2009; Moghaddamnia et al. 2009, Piri et al. 2009)

3.5.2 Data driven modeling

These models are generated directly from the measured data of any system. It is also not necessary to assume any prior acquaintance of the fundamental principles that gives the way to measurements (Evans 2002). Without additional suppositions, the prospective models class is colossal oscillating from smooth and rational to parameterized tasks.

The set of input-output observations of the form (eq. 3.4)

$$\{ (xi\, , yi) | 1 \leq \; i \; \leq \; M \} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (3.4)$$

Where the inputs $x \in R^m$ are vector quantity limited to certain barred bounded set $C \subset R^m$ and without the loss of generality, conforming outputs $y \in R$ is scalars. In a universal case, as the vector quantities are the outputs, the application of algorithm can be applied independently on each factor at very minute additional computational price. Equation (3.1) can be used for model building to foresee the output y corresponding to a formerly unknown demand vector ***x.***

3.5.3 Noise in measurement data

In the light of previous works done in past few years, researchers pointed out the main issue with the data models is the presence of noise in the data that leads towards the corrupted measurement. Noise is fundamentally significant component of an output; it cannot be accounted for by an even transformation of the corresponding output. Evans (2002) stated that noise may happen in a set of taken data due to following reasons

- Inaccuracy of measurements,
- Not all causative variables influencing the output could be included in inputs,
- Underlying relationship between inputs and outputs is not smooth.

3.5.4 Applications of data derived to estimate noise

Vital applications of having an efficient technique like Gamma test for estimating variance ***(r)*** are detailed below. Variance is known as the random variation and it is denoted by ***r.***

i). Assessment of data quality:

Evans (2002) stated that lesser gamma value can be compared to the variance of the output y, the more the possibility that the output can be obtained from the inputs through selected smooth model. Gamma test provides the suggestion whether the presented dataset could be adequate enough to build a smooth non-linear model or not it also tells efficiency and performance of the model. One might increase the accuracy of the measurement, as the forecast error is too great regardless of the extent of data used. On the other way, it can also be patterned, that all input variables, that may impose the effect on the output have been included or not.

ii). Determination of ideal input combination:

Gamma test can be a very useful tool for the assortment of input arrangement that could best model the output. This argument can be derived from the fact that low noise levels will only be encountered when all the input variables that affect the output have been considered in the model development. This comes from the fact that some input variables could be irrelevant and incorporating them in the model may prove to be counterproductive, as this could lead to higher level of noise.

iii). Minimum number of data points for building a model:

If a sequence of Gamma statistics Γ_M is computed for an increasing number of points M, then the value of Γ at which the whole sequence stabilizes, is normally considered as our estimate for *Var(r)* (Evans, 2002). In other words, if M_0 is the number of points required for Γ_M to stabilize, to within some prescribed error of Γ, then at least this number of points would be enough to build a model, whose prediction will have a mean squared error of Γ.

3.6 Advanced Non-Linear Modeling

Decision making for an input data is beneficial and Gamma test is very helpful in this regard. Prediction has been carried out through the development of nonlinear models of the data. The availability and complexity of current data in the different field of science and technology, many of the researchers have adopted the nonlinear artificial intelligence modeling techniques. These techniques includes Artificial Neural Networks, Support Vector Machines, Fuzzy Logical systems, Polynomial function, Bayesian Belie networks and decision trees etc. This thesis work is mainly emphases on Artificial Neural Networks and Polynomial regression analysis.

3.6.1 Artificial Neural Networks (ANNs)

Artificial neural networks (ANN) are black box model techniques that are used for predicting and assessing purposes in various diverse extents of science and engineering. An ANN in the framework of statistical analysis is a substitute to or in addition to multiple regression. ANN's mimic the behavior of biological (brain) neuron, each of which receives, process and send s information so as to construct fuctional relationship between the past and future events or values (Shamim et al. 2010). ANN is composed of highly interconnected set of simple information processing Artificial Neural Networks are dominant technique now days in the field of artificial intelligence, It has been applying is the numerous field for prediction and estimation. It is therefore vital to discuss about the Artificial Intelligence. Few descriptions are set below. It constructs an intelligent artifact through an Artificial intelligence module, a branch of computer science (Ginsberg, 1993 and Nilsson, 1998). In this module, reasoning and action are perceived by performing a series of computations (Ginsberg, 1993).

3.6.2 Background

The idea of creating the ANNs was firstly introduce by McCulloh and Pitts (1943) and Rosenblatt (1962) did more work in this concept and float the idea of perceptron's, It include only single layer feed of McCulloh and Pitts neurons but the main obstruction on the development of ANNs arose by Minsky and Papert (1988), They pointed out the basic deficiencies in single layer perceptron (a specific type of ANN), computation was carried out by using mathematical analysis. Dearth of computers availability also backed to the fact that only few researchers continued their efforts on ANNs building. The revival of interest in ANNs was happen in 1980s, many researchers done their work in the fields of like medicine, publicizing, industrial, weather forecasting, precipitation, chemical progression mechanism and real estate analysis (Bernard et al. 1994).

3.6.3 Working of ANN

ANN is an artificial intelligence technique that is capable to capture and characterize multifaceted input/output relationships. ANN is also be reflected as an input/output processing unit. Input data *(Xn)* can be in the form of digital data, image pixels, and any voice or sound signals etc. for different types of processing. ANN processing unit structure is capable of powerful series operations resulting to produce an output Y*(m)* regarding the input data (see Fig. 3.2).

It is to clarify that, Output *Y(m)* is a correlated to *X(n)* via transformation progression through ANN. Both input *X(n)* and output *Y(m)* data is fed with examples, for getting any beneficial output. Training process is carried out with the same set of data, It will learn to produce the output values based on both known and unknown values of input *X(n).*

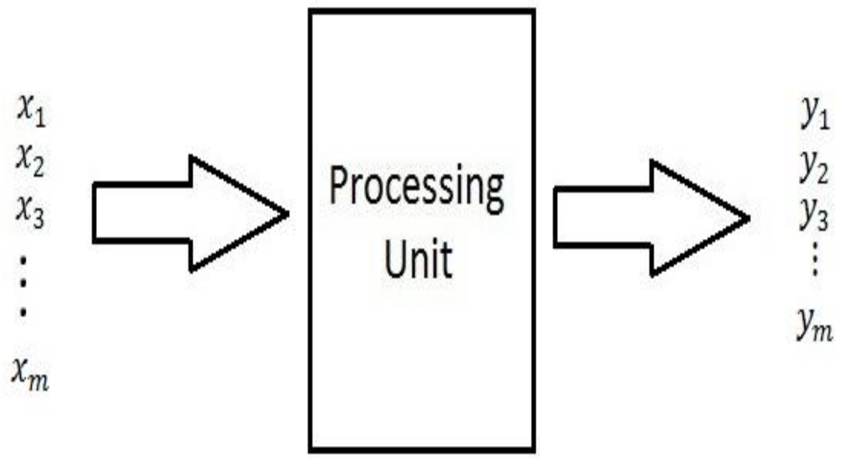

Figure 3.5: Input/output processing unit.
(After http://qingkaikong.blogspot.com/2016/11/machine-learning-3-artificial-neural.html

As much as artificial neuron model is concerned, it comprise set of joining relations that obtains the n input signals X, reproduces these with corresponding synoptic weights, W= 1,2,3,…………….., n. Later, hints are added up in the summing junction through a linear combiner. The activation function f (.) confines the largeness of the output and provides its nonlinearity. Mathematically it was given by (Agalbjorn et al. 1997).

$$\sigma = \sum_{i=1}^{n} XiWi \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.5)}$$

And

$$Y = f(\sigma + b) \ \} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.6)}$$

Where, b shows bias. A neuron only cannot prepare anything and is of no usage, until and unless the combination with other neurons were added up to form a network. During the past few years limitless number of methods were suggested by which a number of neurons could be connected together to form a network with algorithms arrayed to train them.

An ANN has the capacity of store the information regarding the problem. These storages are in terms of weights of inter-connections. The procedure of determining ANN weights is known as learning or training. The model is trained with drill set of the input data and known output data. The initial weights or value of weights has been assigned randomly or depend upon experience basis. The weights are adjusted systematically changed by the training algorithm as to achieve the minimum the minimum difference between actual and ANN output. Performance evaluation of the model have been established on the statistical basis. Number of statistical criteria are available to compare the goodness of any model. The most commonly practiced statistical criteria are the Root mean square error (RMSE), Variance, bias, R^2.

3.6.4 Back propagation neural networks

Back propagation is a communal technique of coaching artificial neural networks for the accomplishment of given task. Arthur E. Bryson and Yu-Chi Ho describe this impression in 1969. Later on in 1974 by the efforts of Paul Werbos, David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams, that it gained recognition, and it headed to a “reawakening” in the area of ANN research. ANN is a supervised learning method and it is a simplification of the delta rule. In this method teacher is required, know or able to calculate the anticipated output for whichever input in training set. This is very helpful in feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). The stint is an abbreviation for "backward propagation of errors". Back propagation involves that the activation task used by the artificial neurons (or "nodes") be differentiable. Back propagation training algorithm are quite popular and adaptive, but their performance is quite slow as it needs small training rates for stability in learning.

i). Two or Multi-layer:

Layered structure is used in the feed-forward network. It consist of two or more than two layers. Every layer contains the elements which collect their input from entities from a layer directly below and drive their output to elements in a layer directly beyond the entity. On that point are no connections within a stratum. The Ni contributions are fed into the foremost layer of NH; 1 hidden entities. The input entities are only 'fan-out' entities; no processing takes place in these elements. The energizing of a hidden unit -is a function Fi of the weighted inputs and a bias, as given in eq.3.7.

$$yk(t+1) = Fk(Sk(t)) = Fk(\sum jWjk(t) + \theta k(t)) \ldots\ldots\ldots (3.7)$$

The process is repeating itself until it reached at last layer. Even though back propagation can be pragmatic to networks with any number of stratums, Keeler, & Kowalski, (1990) that distinct one stratum of concealed unit's success to estimate any task with finitely numerous cutoffs to arbitrary precision as long as the activation functions of the hidden units are non-linear (the universal approximation theorem). In most applications a feed- forward network with a single layer of hidden units is used with a sigmoid activation function.

3.6.5 BFGS (Broyden Fletcher Goldfarb Shanno)

BFGS is an iterative method for resolving unconfined nonlinear optimization problems. The BFGS technique estimates Newton's method. Newton's method and the BFGS techniques do not need to congregate except the function has a quadratic Taylor expansion near an optimum. The first and second derivatives were used in these methods. However, the performance of BFGS has also recognized for non-smooth optimizations.

In quasi-Newton methods, the Hessian matrix are used, there is no requirement of second derivatives to be weighed directly. In multidimensional problems, to calculate the root of first derivative quasi-Newton method in combination with secant method is used. The secant equation does not stipulate an inimitable solution for multi-dimensions and quasi-Newton methods be at variance in how they limit the answer. The BFGS technique is among of the most prevalent members of this kind of techniques. In this research work, an artificial neural network models were trained by Two layer back propagation and BFGS for the forecasting of percentage saving.

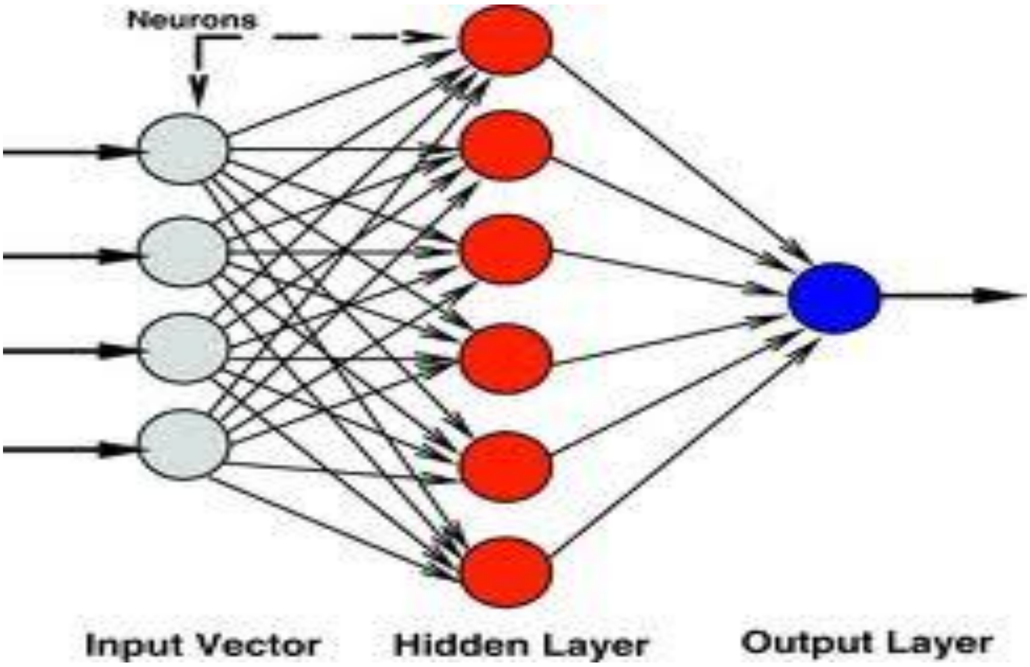

Figure 3.6: Schematic diagram of Ann's (After http://www.iitbhu.ac.in/faculty/min/rajesh-rai/NMEICT-Slope/lecture/c14/l1.html

3.7 Summary

The eight districts were selected for the study purposes in different parts of the Punjab Province. The Inflow and Outflow method is used for the measurement of losses in discharge. The cut throat flume is used for these measurements. Gamma test is applied on the data for noise reduction and best neighbor combination. ANN technique is quite good for prediction of losses, which used in this study. There are many ANN combination developed over the period of time. This study include TLBP and BFGS neural networks models for modelling and prediction the losses. Training has been performed for predicting the better results from TLBP and BFGS models.

CHAPTER 4

RESULTS AND ANALYSIS

4.1 Background

The selected study area is discussed in previous chapter. Where different methods for measurement of losses have also been discussed. Inflow-outflow has been selected due to its wide range. Polynomial regression for prediction and analysis in addition to Artificial Neural Networks (ANN) for prediction, modelling and analysis. The models are developed in ANN according to the guidelines mentioned in section 2.3. This chapter discuss the results obtained by using methodology described in chapter 3.

4.2 Loss rate of watercourses

The loss rates were determined through inflow outflow method for every watercourse by dividing each watercourse in three sections, head, middle and tail. Table No. 4.1. Discharge was computed at each point and difference between the discharges is taken as the loss.

Table 4.1: Water losses lps per 100 meter

Stations	Status	Outlet Location	Water loss lps per 100 meter at			
			Head	Middle	Tail	Average
Sahiwal	Unlined	21780-R	1.34	2.26	1.59	1.73
Kasur	Unlined	72432-R	1.85	1.20	1.10	1.38
Vehari	Unlined	49173-L	1.3	1.2	0.90	1.13
Chiniot	Unlined	35409-L	1.25	1.34	0.48	1.02
Hafizabad	Unlined	15461-L	2.57	1.85	1.09	1.84
BWN	Unlined	6-R	1.20	0.94	0.94	1.03
Bhakkar	Unlined	31250-R	1.37	1.72	0.90	1.33
DG khan	Unlined	16594-R	1.45	1.37	1.17	1.33
BWN	Lined	3-AL	0.3	0.15	0.15	0.20
DGKhan	Lined	32000-R	0.3	0.28	0.22	0.27
Bhakkar	Lined	56610-R	0.45	0.4	0.3	0.38
Kasur	Lined	14260-L	0.3	0.25	0.2	0.25

In case of unlined water courses, highest average loss rate/ 100m = 1.84, was observed in watercourse No.15461-L of district Hafizabad and Lowest loss rate/100m = 1.02 in watercourse No.35409-L of district Chiniot. Few district have higher loss rate in unlined watercourses at the middle, it is due to the physically bad condition of watercourse at the middle. Very less loss rate was seen in lined watercourses, it varies from 0.15 to 0.45 per 100 meter. After determining losses from every water course difference of losses from lined and unlined water courses was considered as a saving of water achieved through lining.

4.3 Performing Gamma Test

Gamma Test is used to diminish the noise in data. Gamma values have been calculated for different combinations to smoothen the model.

A total 37 different grouping are prepared, among these eight (8) groupings have been carefully chosen on the basis of minimum gamma value for building of smooth and reliable model. The minimum Gamma value for different districts are listed in table 4.2.

Table 4.2: Selected Minimum Gamma Value for each district

Sr. #	District	No. of trials	Gamma values
1	Bhakkar	01	0.5347
2	Bhawalnagar	06	14.89
3	Chiniot	08	1.9007
4	Dera Ghazi Khan	05	1.0132
5	Hafizabad	01	0.534
6	Kasur	13	1.3431
7	Sahiwal	02	5.6553
8	Vehari	01	0.2435

4.4 Application of ANN Based Models and Polynomial Regression

Two Layer Back Propagation (TLBP) neural network and Broyden Fletcher Goldfarb Shanno (BFGS) neural network have been developed for eight districts. These models were trained with 70% selected input and remaining 30% was tested. The results of one district is discuss below. Other results are included as annexures.

4.4.1 Results of District Bhakkar

ANN based model results for district Bhakkar including training, testing and polynomial regression results are shown in figures from 4.1 to 4.6. The results are listed in table 4.2.

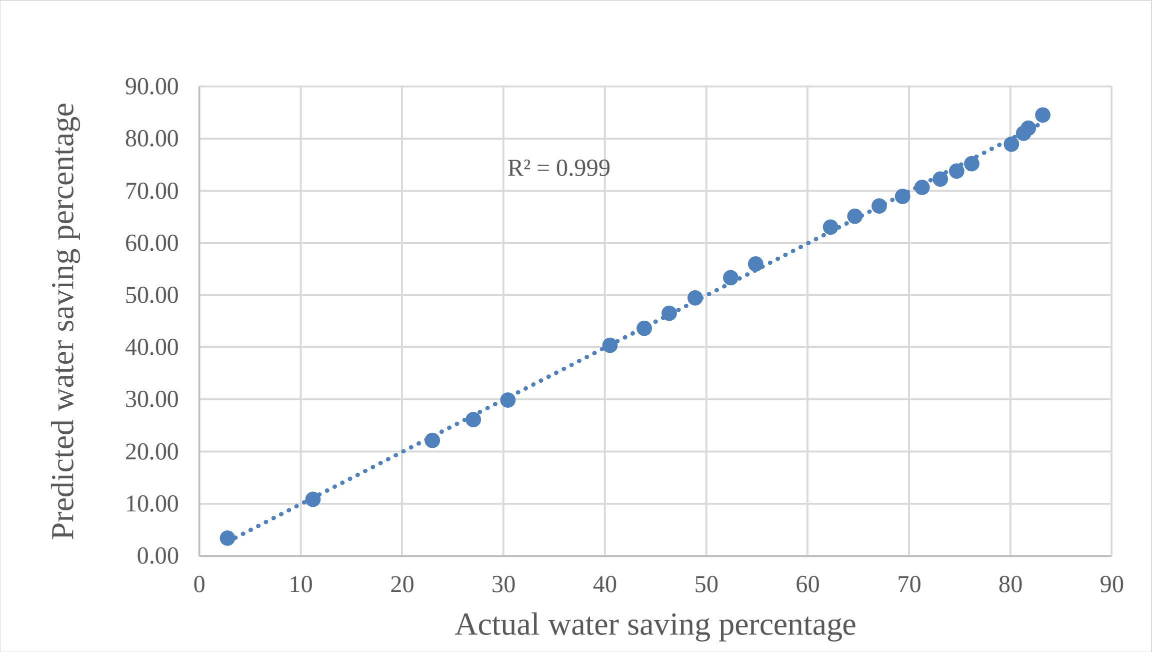

Figure 4.1: Training Model BFGS Bhakkar District

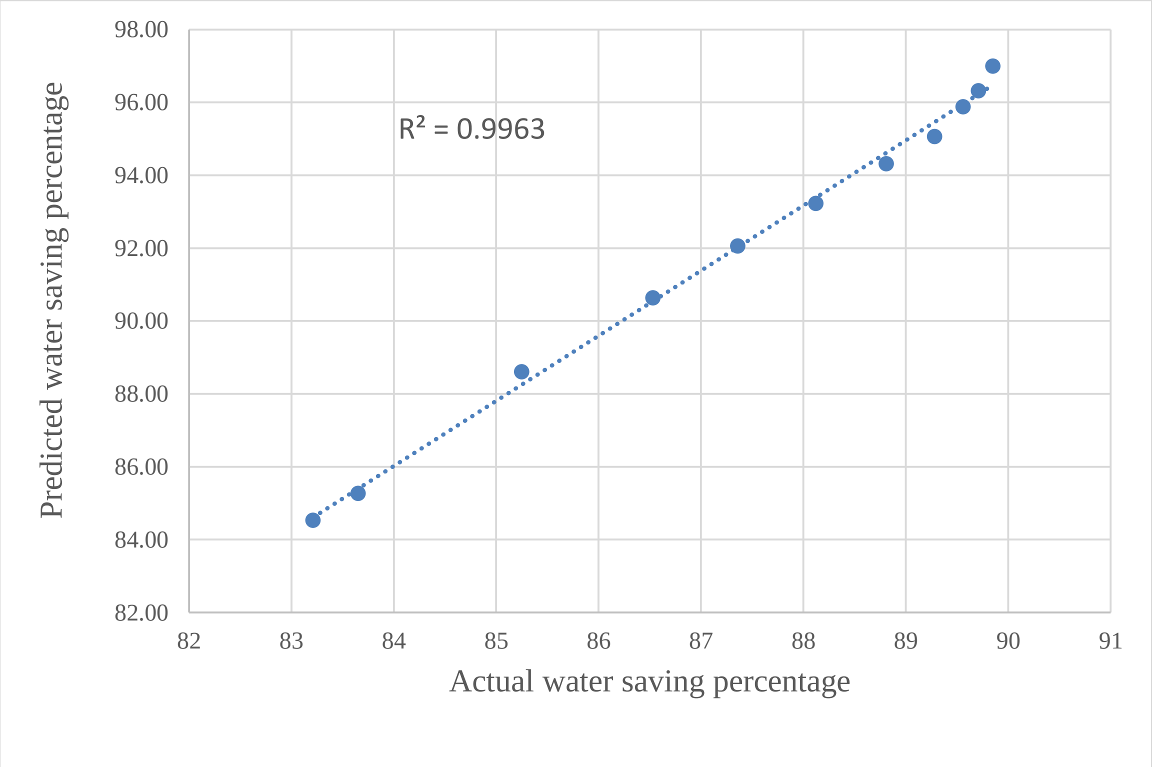

Figure 4.2: Testing Model BFGS Bhakkar District

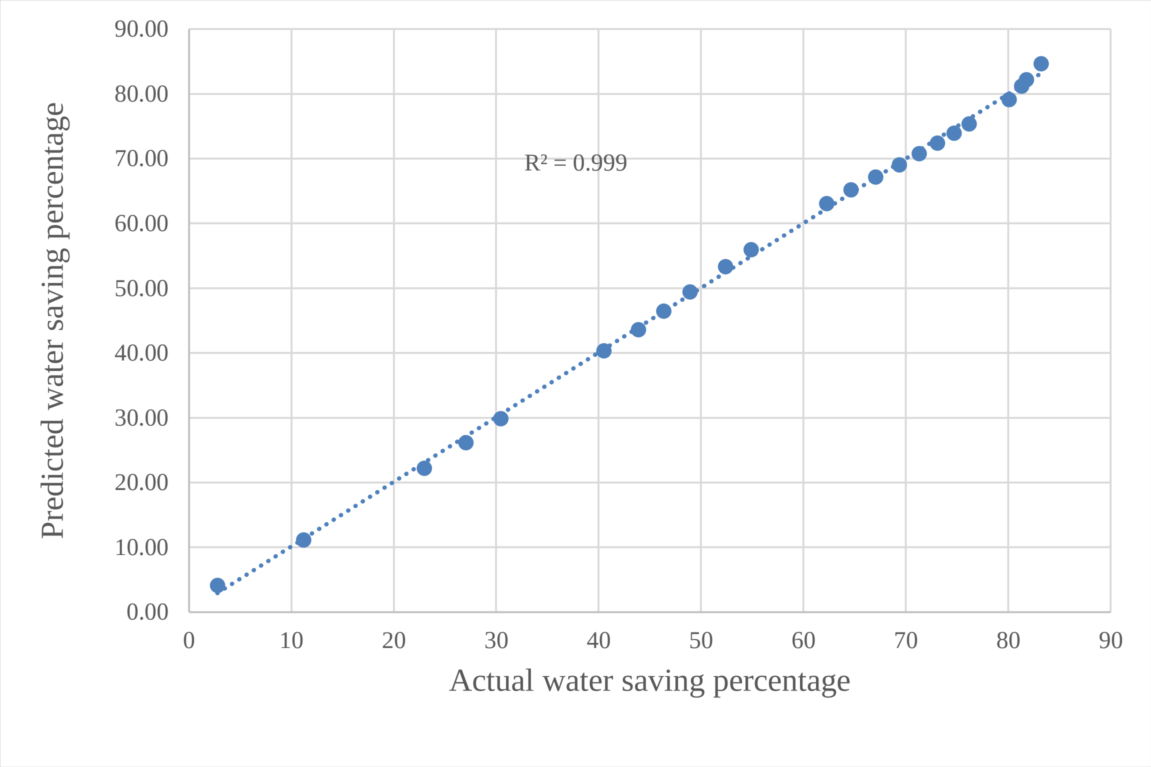

Figure 4.3: Training Model TLBP Bhakkar District

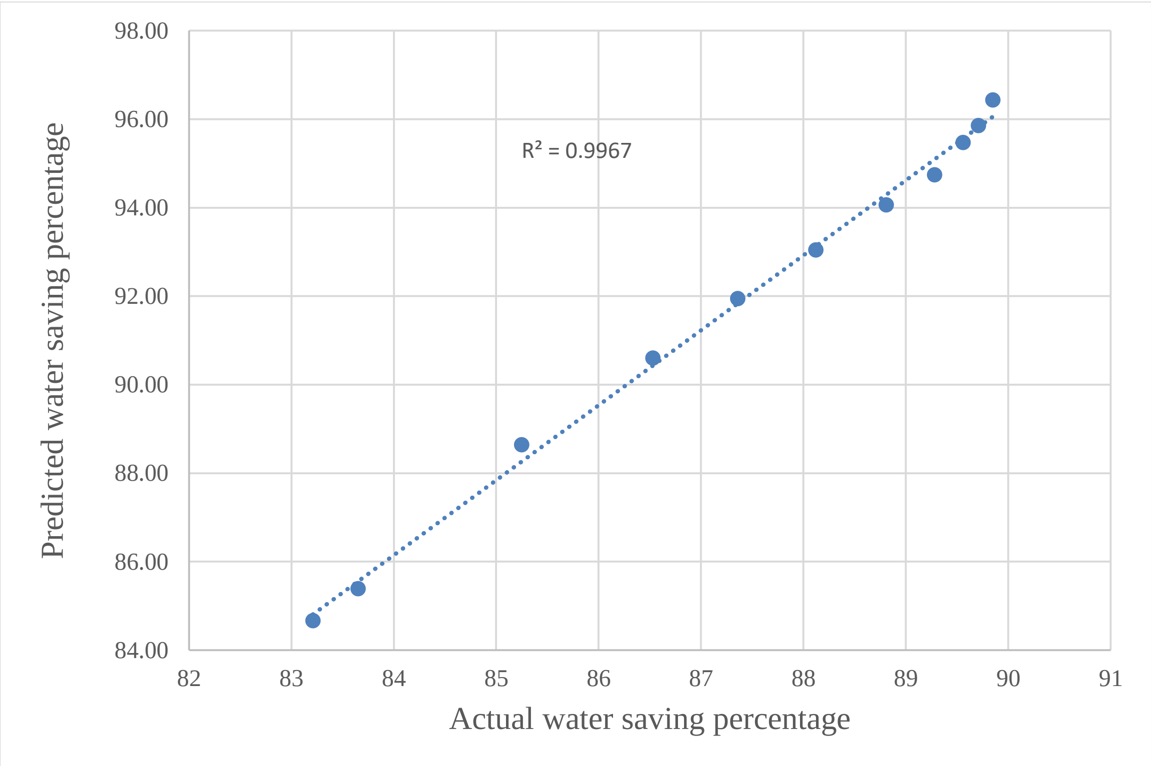

Figure 4.4: Testing Model TLBP Bhakkar District

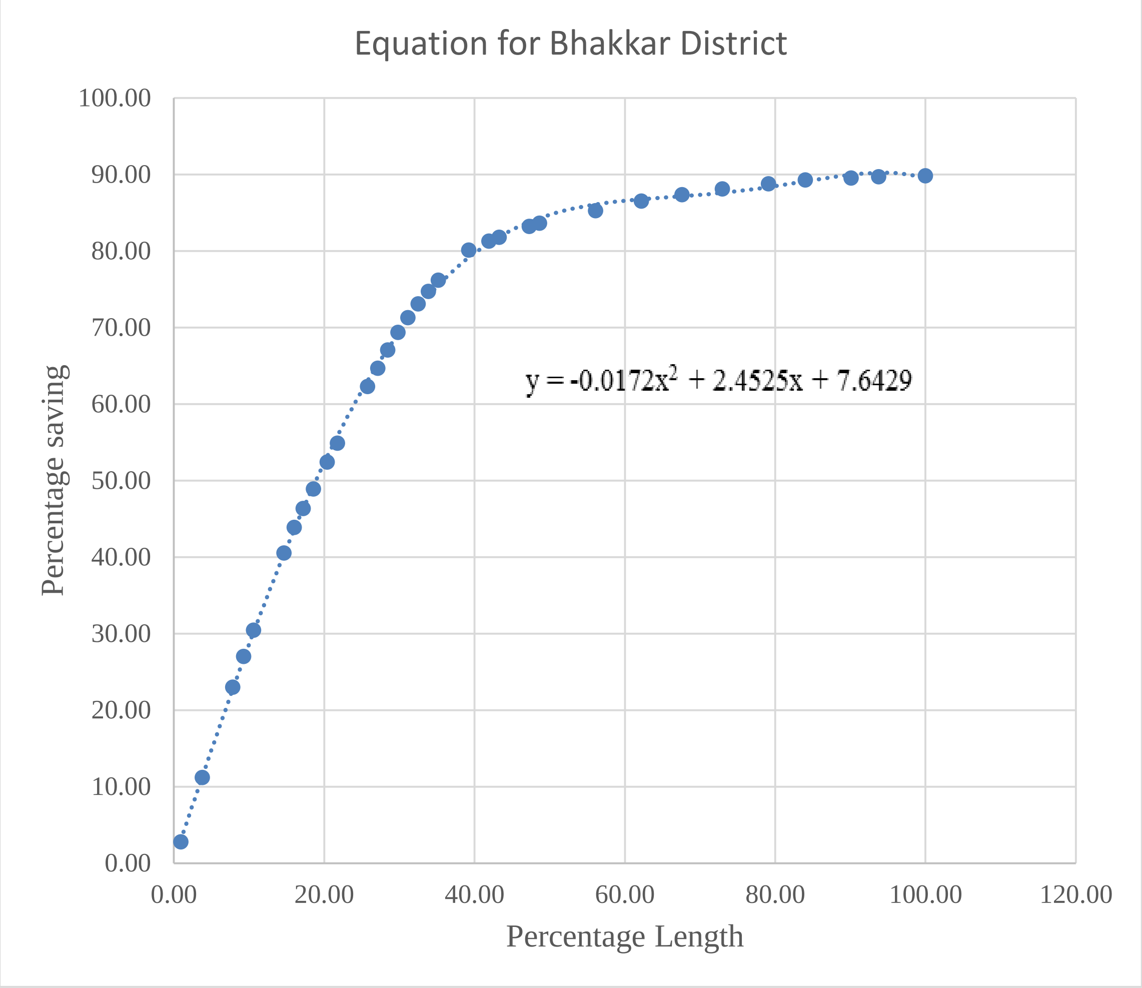

Figure 4.5: Polynomial Regression of Bhakkar District

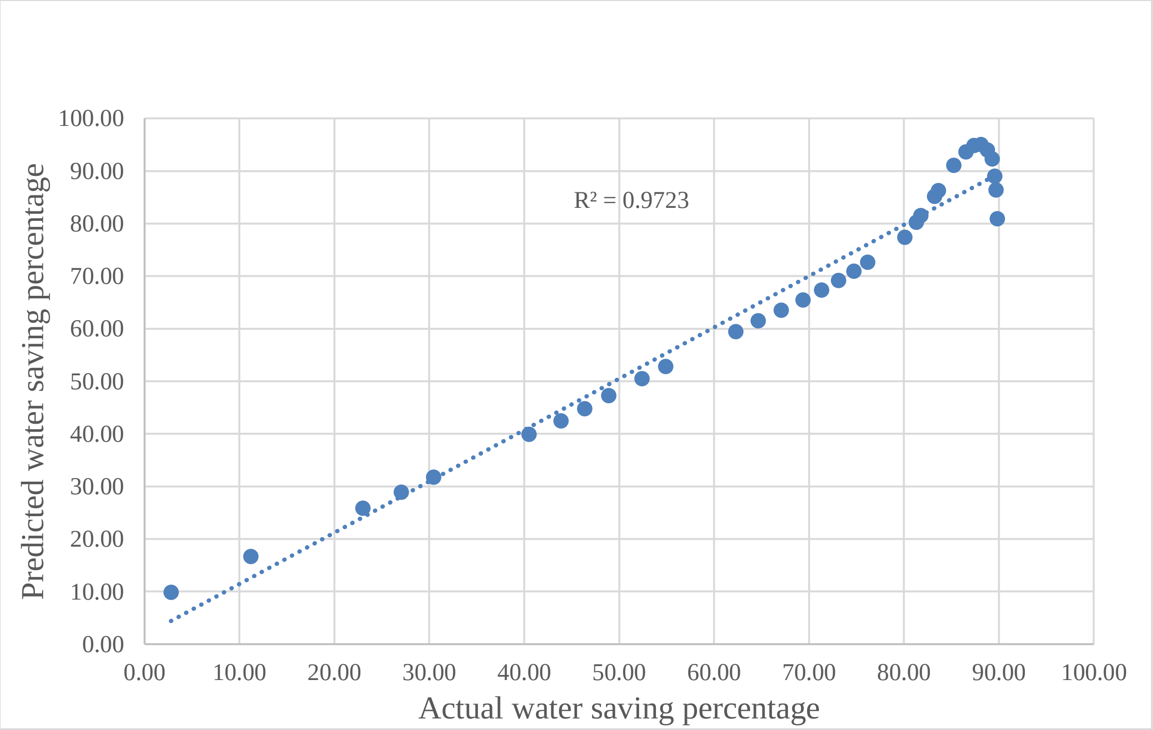

Figure 4.6: Polynomial Regression Bhakkar District

Table 4.3: ANN and Polynomial Regression results of Bhakkar

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	0.52	0.72	55.07	54.99	-0.08	0.01	0.60	99.90
Testing	25.36	5.04	87.39	92.08	4.69	21.98	20.68	99.63
				TLBP				
Training	0.53	0.73	55.07	55.09	0.02	0.00	0.51	99.90
Testing	22.90	4.79	87.39	91.89	4.50	20.26	18.40	99.67
				Polynomial Regression				
-	16.60	4.07	64.99	66.83	1.84	3.38	14.77	97.23

Table 4.3 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure 4.1 to 4.6 and tables it is clear that TLBP (type of ANN) outperformed BFGS and polynomial regression technique with high values of model efficiency, in both training and testing phase.

4.4.2 Other Districts

The results of other seven districts have been figured out and tabulated in annexures A to G. Their discussion is as under.

a) District Bhawalnagar

Table A1 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. When A 2 is compared with similar other figures of districts. There is different trend seen, the probable reason for this different trend (almost reverse) may be with data distribution irregularity of 30% data. To overcome this issue instead of using 30% data, testing has been carried out on 100% data. The trend is normal and shown in Figure A 2(1). Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure A1 to A6 and tables it is clear that TLBP (type of ANN) outperformed BFGS and polynomial regression technique with high values of model efficiency, less random and systematic error in both training and testing phase.

b) District Chiniot

Table B1 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Testing model of BFGS shows different trend because of the distribution of data. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure B1 to B6 and tables it is clear that TLBP (type of ANN) outperformed BFGS and polynomial regression technique with high values of model efficiency, less random and systematic error in both training and testing phase.

c) District DG Khan

Table C1 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure C1 to C6 and tables it is clear that polynomial regression outperformed BFGS and TLBP technique with high values of model efficiency, less random and systematic error in both training and testing phase.

d) District Hafizabad

Table D1 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure D1 to D6 and tables it is clear that TLBP (type of ANN) outperformed BFGS and polynomial regression technique with high values of model efficiency, less random and systematic error in both training and testing phase.

e) District Kasur

Table E1 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure E1 to E6 and tables it is clear that BFGS (type of ANN) outperformed TLBP and polynomial regression technique with high values of model efficiency, less random and systematic error in both training and testing phase.

f) District Sahiwal

Table F1 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure F1 to F6 and tables it is clear that TLBP (type of ANN) outperformed BFGS and polynomial regression technique with high values of model efficiency, less random and systematic error in both training and testing phase.

g) District Vehari

Table G1 shows the detailed comparison of ANN models (training and testing) build from two different methods and it have been compared with the results of polynomial regression method. Not all models and techniques are capable to estimate percentage of saving with high accuracy but few of them can be practiced to foresee reasonable values. Out of these three unique methods, the utmost vigorous technique has been gauged on the basis of maximum model efficacy and minimum systematic and random errors. From the figure G1 to G6 and tables it is clear that TLBP (type of ANN) outperformed BFGS and polynomial regression technique with high values of model efficiency, less random and systematic error in both training and testing phase.

4.4.3 Summary

As per results of section 4.4.1 and from Annexure A to G, TLBP performed well as compared to BFGS and Polynomial Regression for all districts except Dera Ghazi Khan for which Polynomial regression performed well and Kasur for which BFGS perform well. The variation between actual and predicted values are less. Maximum systematic and random error have been observed with the maximum watercourse length (9889 m) in case of BFGS and polynomial regression but low values are observed in TLBP. As values of bias is -0.02 and 5.50 for BFGS, -0.08 and 0.54 for TLBP and 1.01 for polynomial regression, the variance values are 0.55 and 28.56 for BFGS, 0.23 and 1.36 for TLBP, 20.355 for polynomial regression. Negative value of bias shows that systematic error is slightly over estimated by the model. TLBP model provides a good idea about the water losses in watercourses.

4.5 Percentage Lining Length with Percentage saving

Three different techniques are tested, TLBP perform well in comparison to BFGS and Polynomial regression. Table 4.11 indicates the percentage lining length and percentage of water savings. It shows that about 50% lining of entire length, minimum 77.6% water losses are saved in Bhawalnagar district, while maximum water saving is seen in Bhakkar district with 86.07%.

Table 4.4: Percentage Lining length and Water saving

Lining Length	Water Saving %age								
	Watercourse No.								
%age	21780-R Sahiwal	72432-R Kasur	49173-L Vehari	35480-L Chiniot	15461-L Hafizabad	6-R Bhawalnagar	21780-R Bakhar	16594-R DG Khan	Average
5.0	17.5	14.5	29.1	17.4	14.7	12.5	14.39	17.5	17.2
10.0	25.2	25.4	36.7	32.9	29.2	24.5	28.16	27.6	28.7
15.0	34.3	37.2	44.9	47.9	40.9	37.2	41.21	36.9	40.1
20.0	44.4	48.6	53.1	59.6	51.2	47.9	52.51	45.5	50.3
25.0	54.5	58.3	60.6	67.6	61.2	55.9	61.83	53.4	59.2
30.0	63.8	65.9	66.8	72.8	69.8	62.1	69.31	60.5	66.4
35.0	71.4	71.4	71.6	76.3	76.1	67.1	75.19	66.9	72.0
40.0	77.3	75.3	75.1	78.8	80.0	71.3	79.76	72.6	76.3
45.0	81.6	78.1	77.4	80.8	82.5	74.7	83.31	77.6	79.5
50.0	84.5	80.3	79.0	82.4	84.0	77.6	86.07	81.8	82.0
55.0	86.3	82.1	80.5	83.9	85.0	80.1	88.23	85.4	83.9
60.0	87.6	83.7	82.2	85.1	85.8	82.1	89.95	88.2	85.6
65.0	88.4	85.1	84.2	86.3	86.5	83.8	91.33	90.2	87.0
70.0	89.2	86.3	85.9	87.4	87.2	85.2	92.46	91.6	88.2
75.0	90.0	87.4	86.9	88.5	88.0	86.4	93.40	92.2	89.1
80.0	91.0	88.3	87.4	89.5	88.8	87.4	94.19	92.1	89.8
85.0	92.1	89.1	87.8	90.5	89.8	88.3	94.87	91.3	90.5
90.0	93.3	89.9	88.5	91.4	90.9	89.1	95.45	89.7	91.0
95.0	94.6	90.5	89.6	92.4	92.2	89.8	95.97	87.4	91.6
100.0	95.9	91.1	91.0	93.4	93.5	90.4	96.43	84.4	92.0

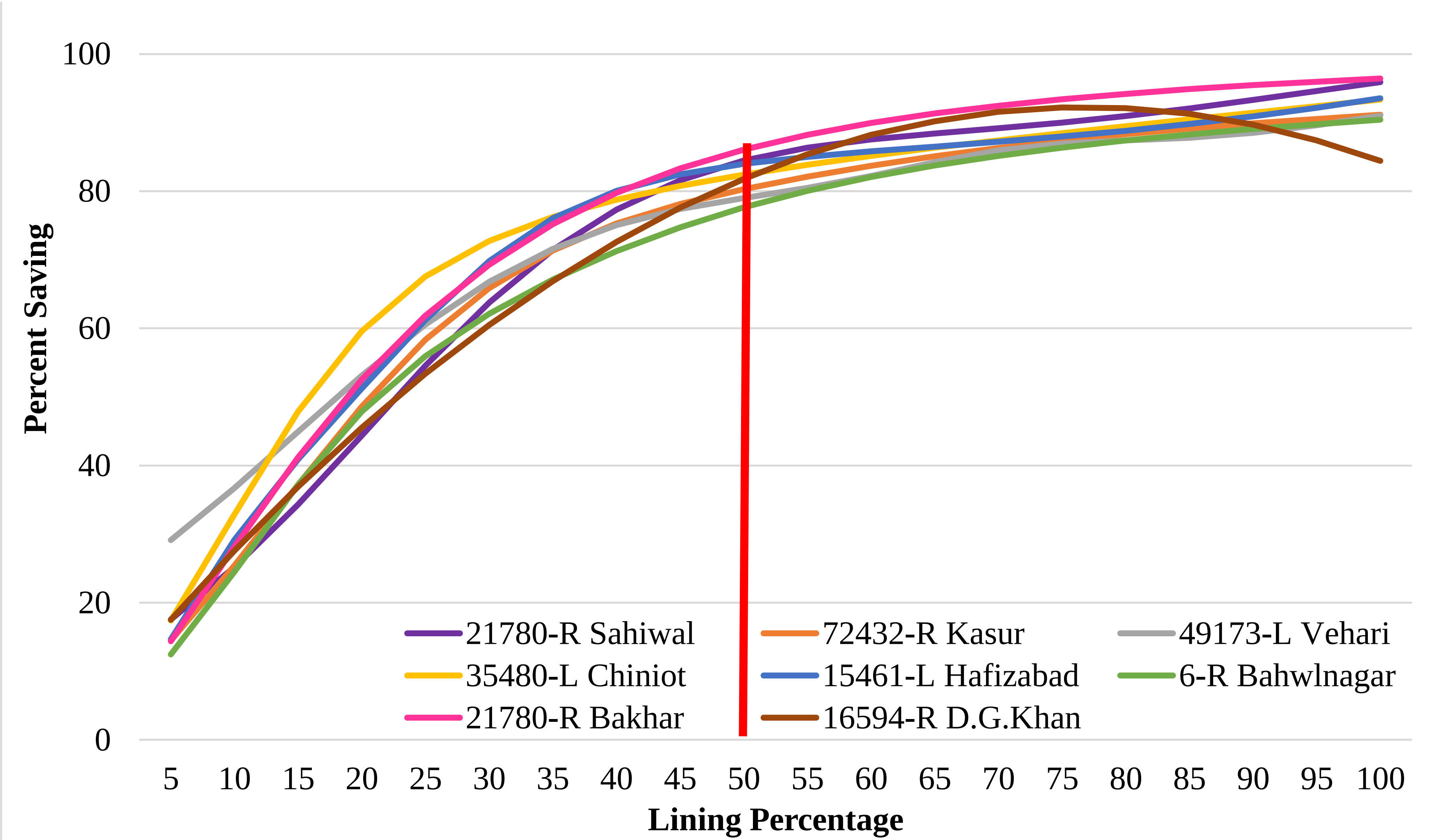

Figure 4.7: Relationship between percent Lining Length & Corresponding Loss Reduction (%)

Fig. 4.7 shows the relationship between percentage of lining length and corresponding loss reduction. Horizontal trend are seen after touching the 50% of lining which save almost 80% of losses. Due to this horizontal trend there is no significant to line the watercourse beyond this percentage because it covers only 20% saving against 50% remain length.

4.6 Summary

Data are taken from the on conveyance losses at head, middle and tail section. The Artificial neural network models are made by using the two technique of BFGS and TLBP. Training and testing models are developed. These models are compared in the Model efficiency and errors with polynomial regression. The analysis for 8 Districts are performed and is discussed in next chapter. The analysis shows that TLBP perform well among all. The results are plotted between percentage lining length and percentage of saving. Maximum economical water saving are up to 50% of lining length.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The study aims at the finding of optimum length of lining of water courses and ultimately to increase the conveyance efficiency by saving water and thus making the operation more viable and economical. For this purpose, a total of 8 stations of similar geographical conditions were chosen, including 8 for unlined watercourses and 4 for lined watercourses. The implementation of inflow outflow method has been made using cut throat flume and losses for both types of watercourses has been calculated. The difference in losses provides the percentage of saving water that was modeled with the percentage increase in length of watercourses using ANN models (BFGS and TLBP) and polynomial regression method for the prediction of percentage saving against actual. Systematic error, random errors and model efficiency are also compared with the polynomial regression for validation.

For this, two different neural network techniques (TLBP and BFGS) along with Polynomial regression technique have been executed order to develop number of models. Basically, the estimations are based on the data collected from the field measurements related to conveyance losses of watercourses along the entire length of each watercourse. It is obviously shown that the techniques implemented provide agreeable assessments mirrored in evaluations criteria (Graphs and Tables).Gamma test was performed on (37) combinations and out of these tests 8 best values were selected on the basis of minimum value criterion. After performing Gamma test, Input combinations and dataset length selected, were used for development of Polynomial regression models, two layer BP neural network models and BFGS based ANNs models for the prediction of percentage saving of water at different percentage of lengths of watercourses. Estimation of these models was performed using different error assessment parameters which are R-square, Variance, Bias and RMSE.

After interpreting the results, it is recommended that the lining of any watercourse is viable up to 50%, which may save the maximum water losses of about 80%, beyond that limit (50%) the marginal saving is very negligible and only about 20% in total against the remaining 50% of lining. Thus, it is concluded that the lining of watercourse be done to the maximum level of about 50%.

5.2 Benefits of study

The study validates that ANN based models are best for estimation of conveyance losses in watercourses to a realistically high degree of accurateness .The study could also demonstrate to be the pioneer in introducing new research ventures that comprises the use of data driven modeling within irrigation system of IBIS. It also reveals that Gamma test has the capacity to ascertain the best input combination for the building of smooth ANN models.

These results show that the lining of the 50% length of watercourse is good and economical for controlling the maximum percentage of losses. Thus, the engineers can securely use the results for future water budgeting and planning. The same idea can also be applied to in other parts of the country.

5.3 Future recommendations

It is suggested that number of measured points along with multiple input parameters must be increased for more precise and accurate results. The results of the study can be cross checked and validated for the other regions of the country as well. There is also need to include critical factors like temperature, humidity etc.

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ANNEXURES

Annexure A

Results of District Bhawalnagar

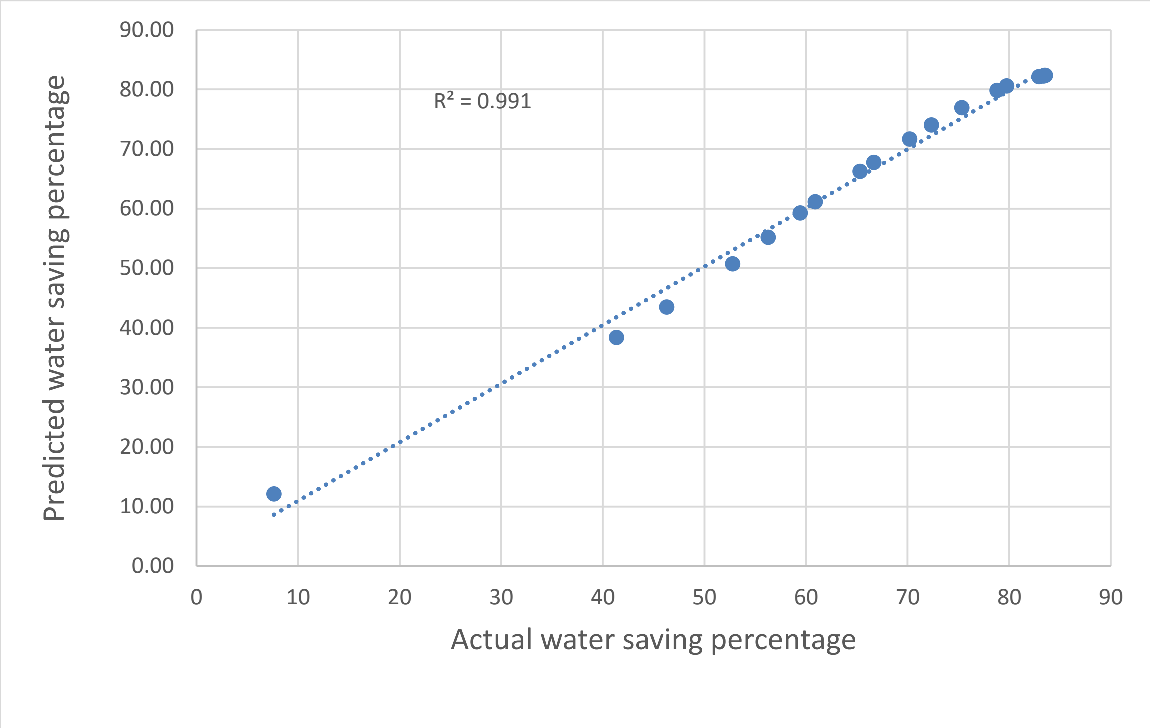

Figure A 1: Training Model BFGS Bhawalnagar District

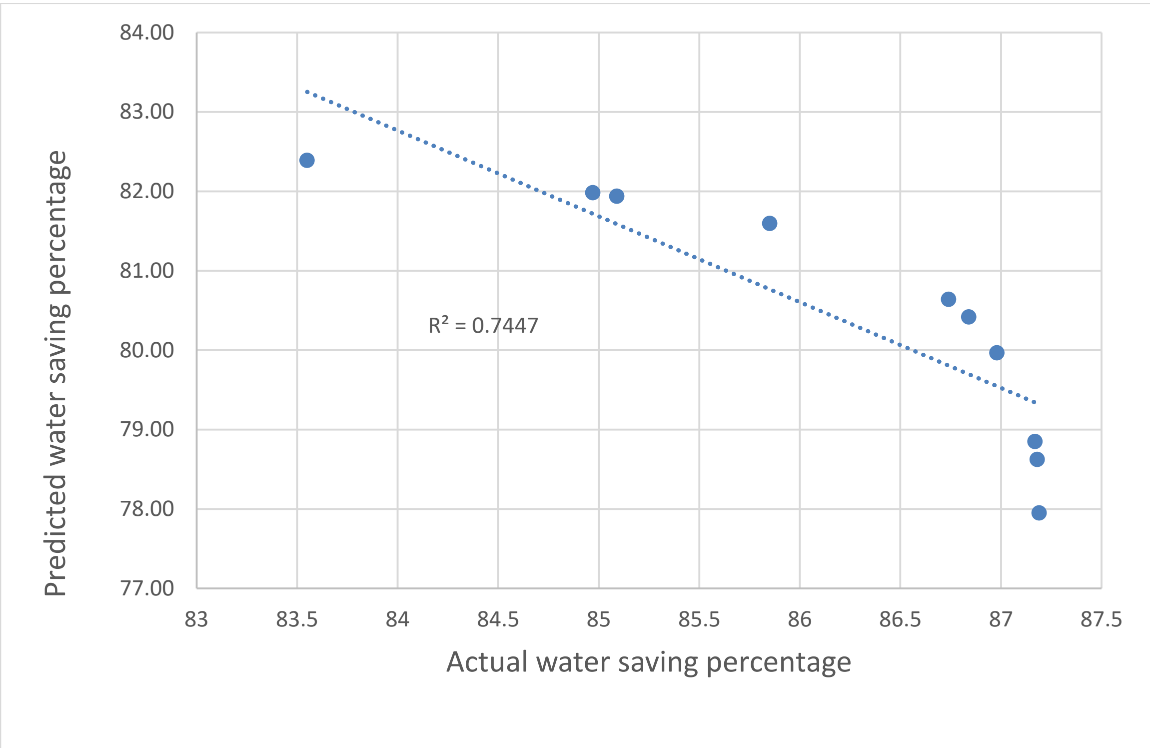

Figure A 2: Testing Model BFGS Bhawalnagar District

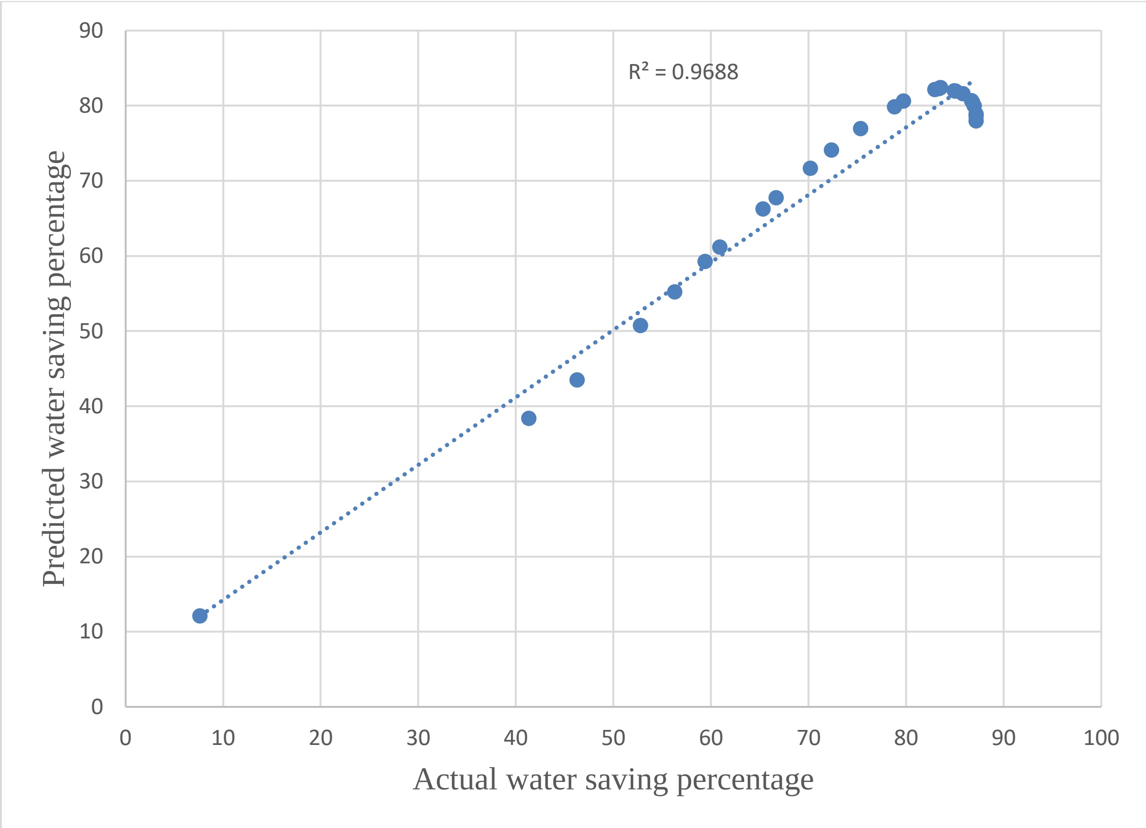

Figure A 2(1): Testing Model BFGS Bhawalnagar District

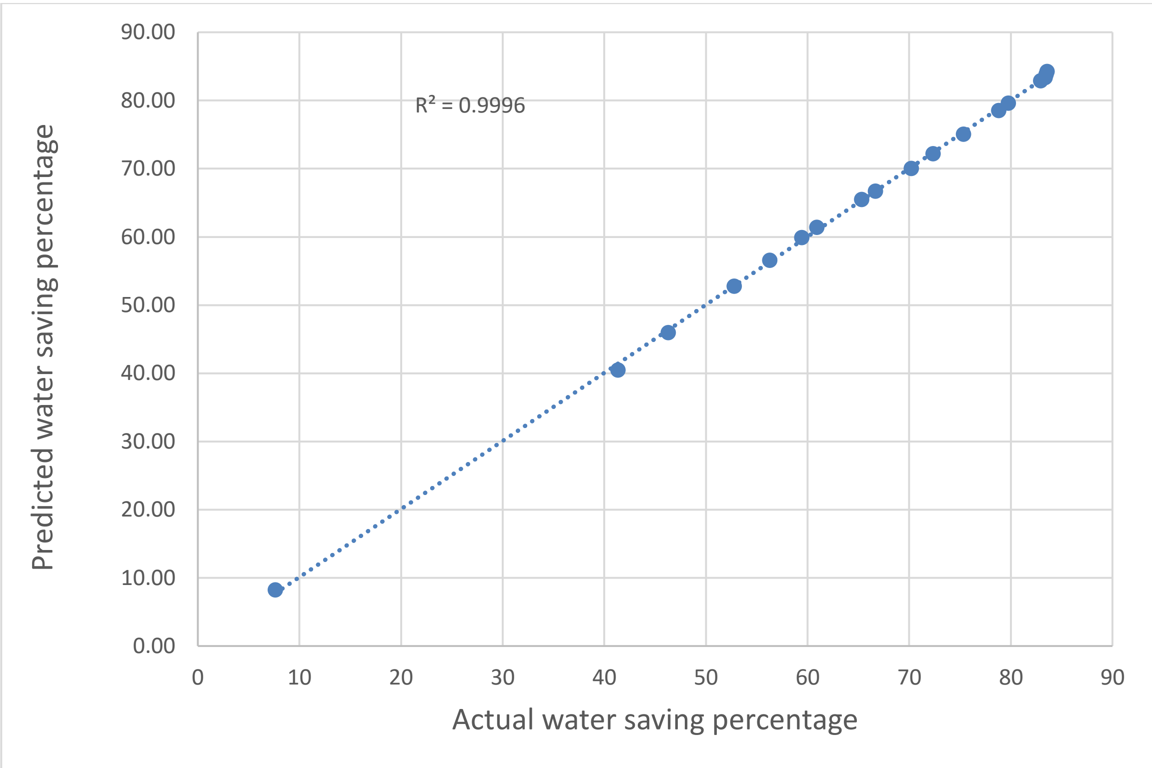

Figure A 3: Training Model TLBP Bhawalnagar District

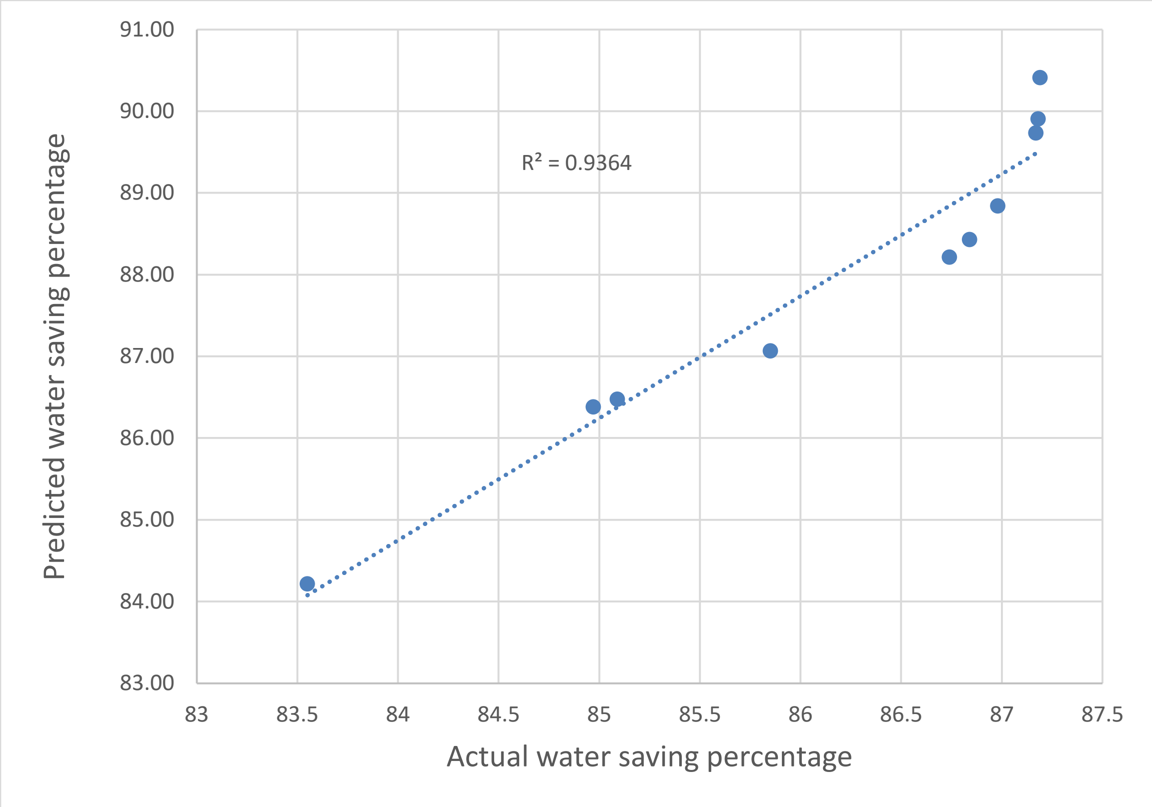

Figure A 4: Testing Model TLBP Bhawalnagar District

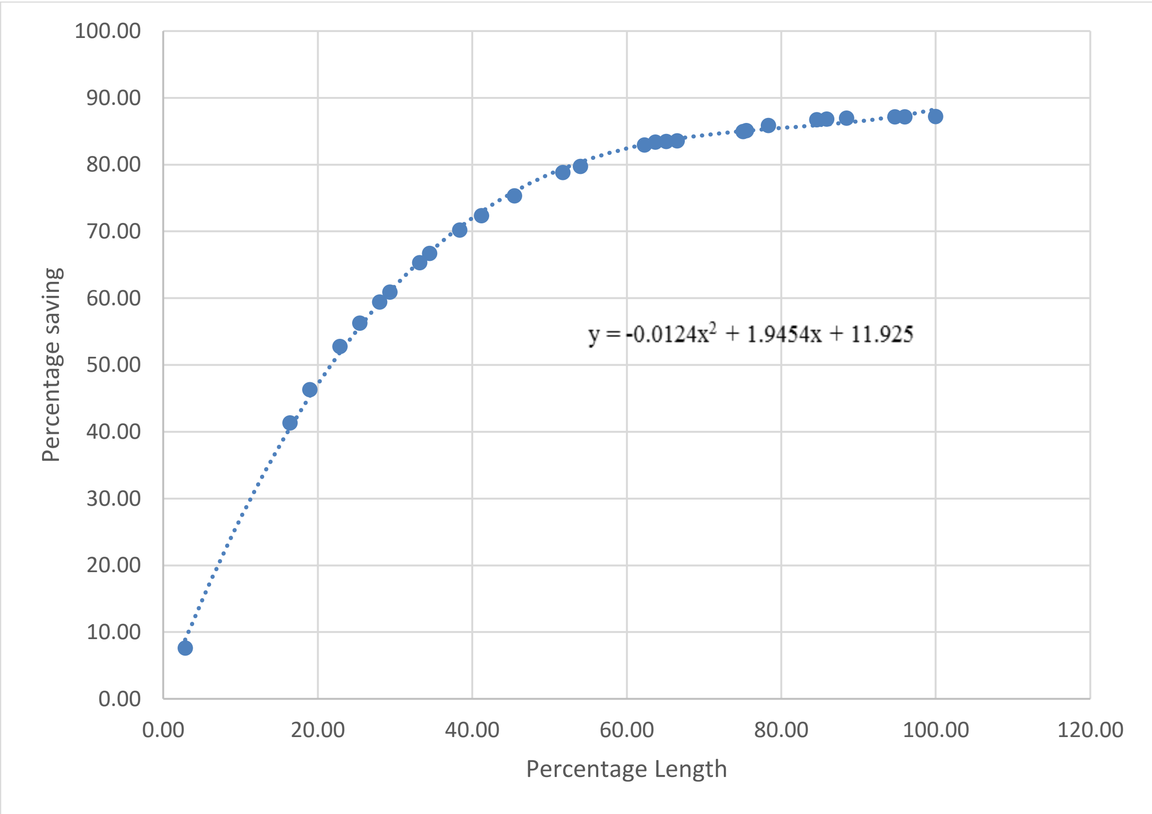

Figure A 5: Polynomial Regression of Bhawalnagar District

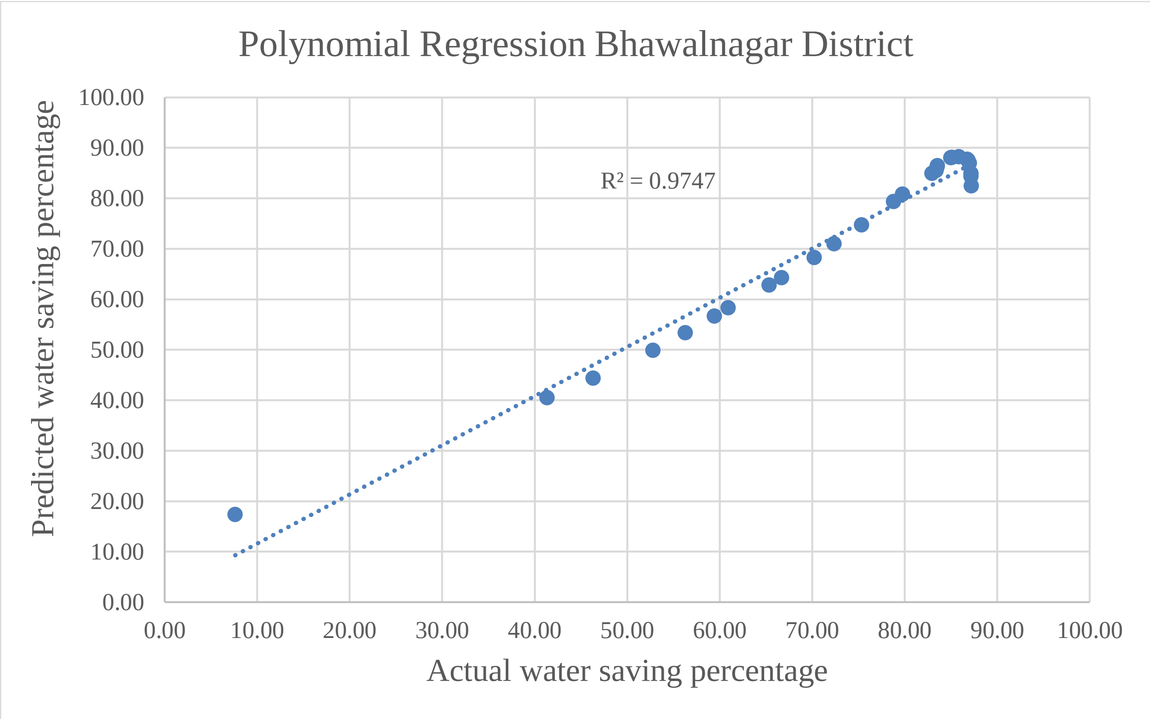

Figure A 6: Polynomial Regression Bhawalnagar District

Table A1: ANN and Polynomial Regression results of Bhawalnagar

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	3.22	1.79	64.81	64.82	0.02	0.00	3.20	99.10
Testing	39.38	6.28	86.16	80.44	-5.72	32.73	45.10	74.47
				TLBP				
Training	0.14	0.38	64.81	64.83	0.02	0.00	0.12	99.96
Testing	3.84	1.96	86.16	87.97	1.81	3.28	2.03	93.64
				Polynomial Regression				
-	8.67	2.94	72.02	74.08	2.06	4.26	6.60	97.47

Results of District Chiniot

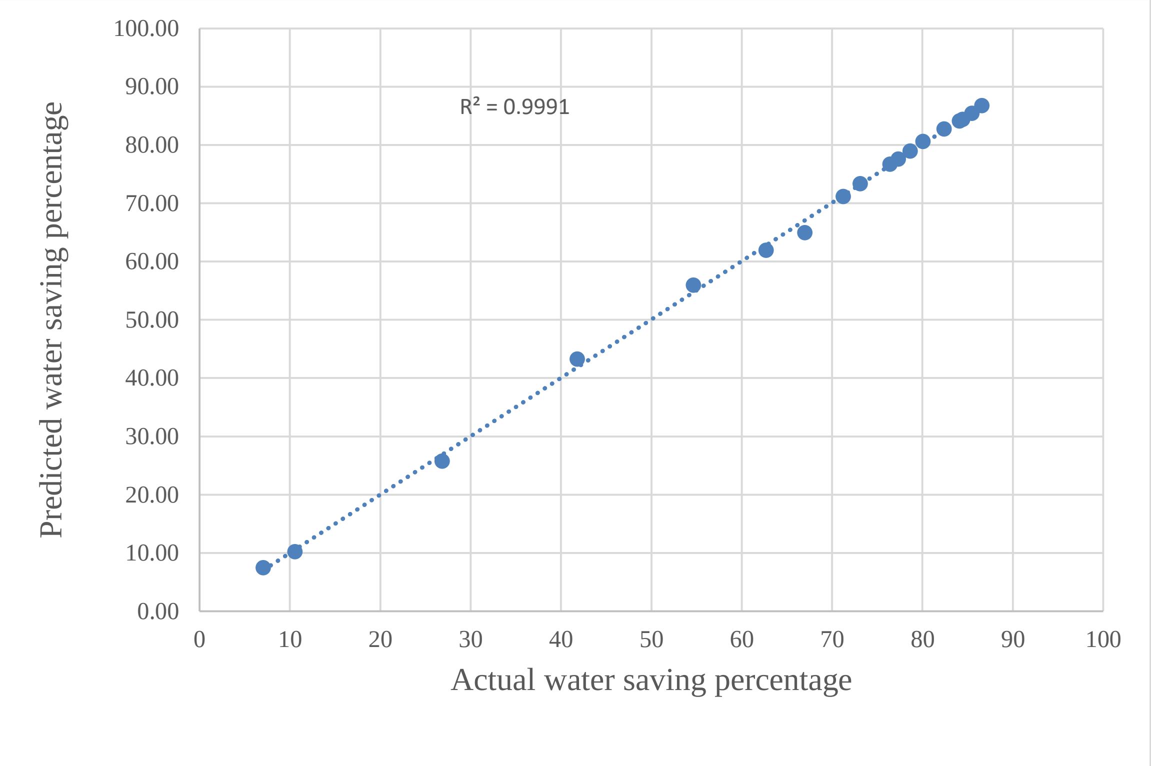

Figure B 1: Training Model BFGS Chiniot District

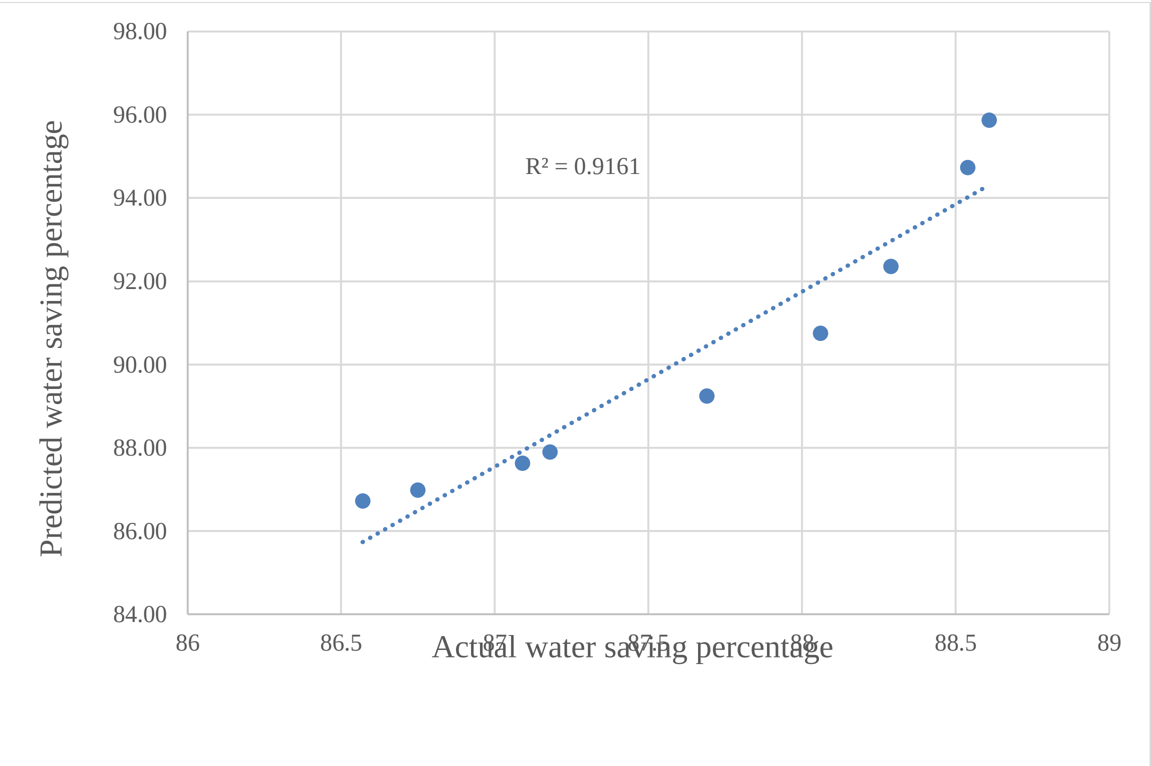

Figure B 2: Testing Model BFGS Chiniot District

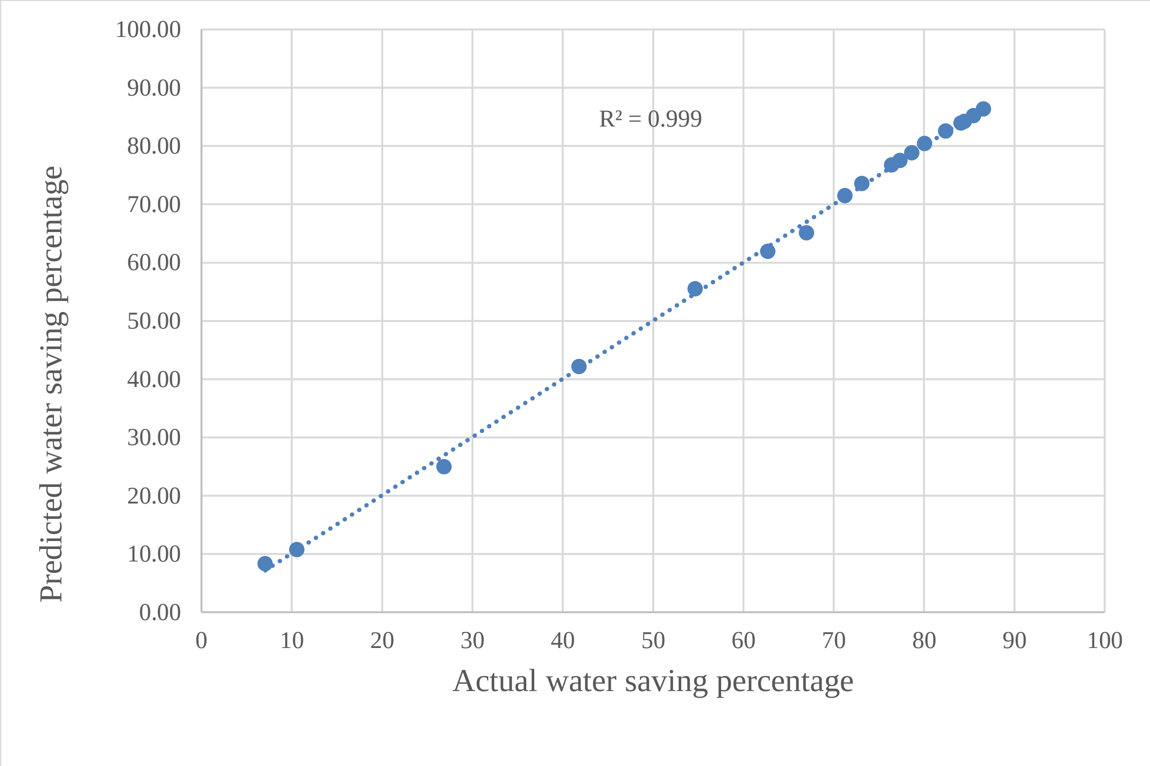

Figure B 3: Training Model TLBP Chiniot District

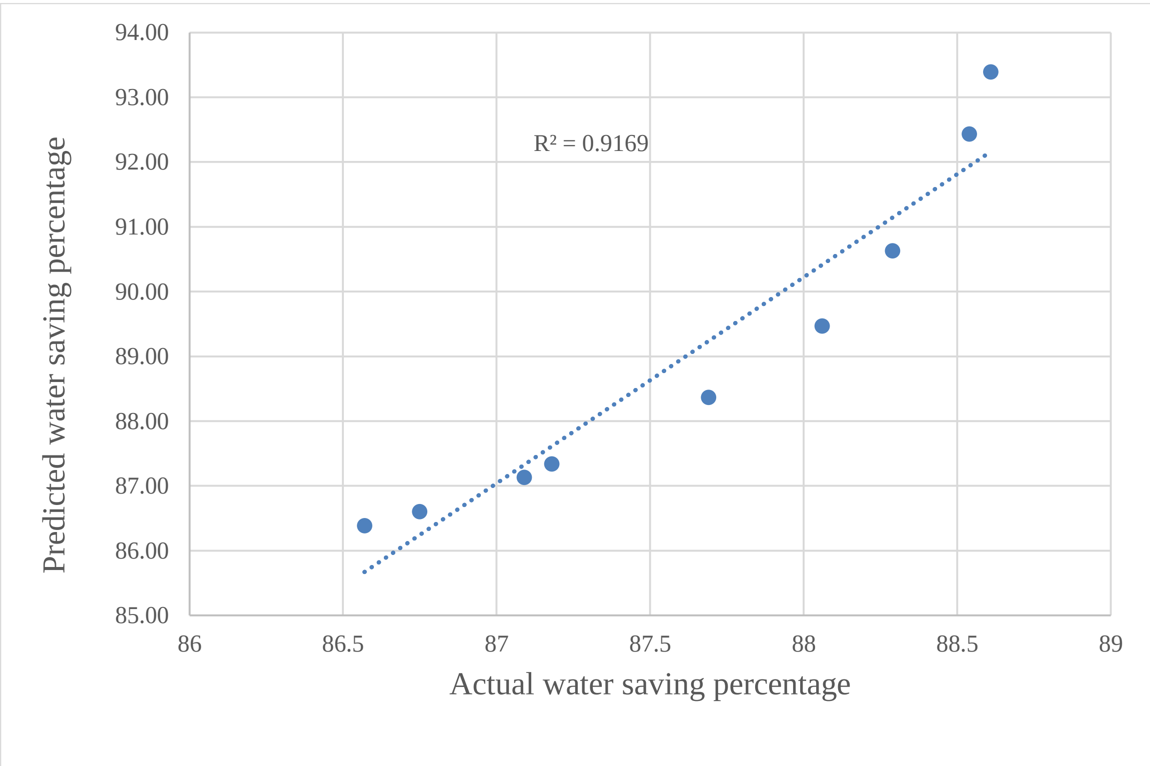

Figure B 4: Testing Model TLBP Chiniot District

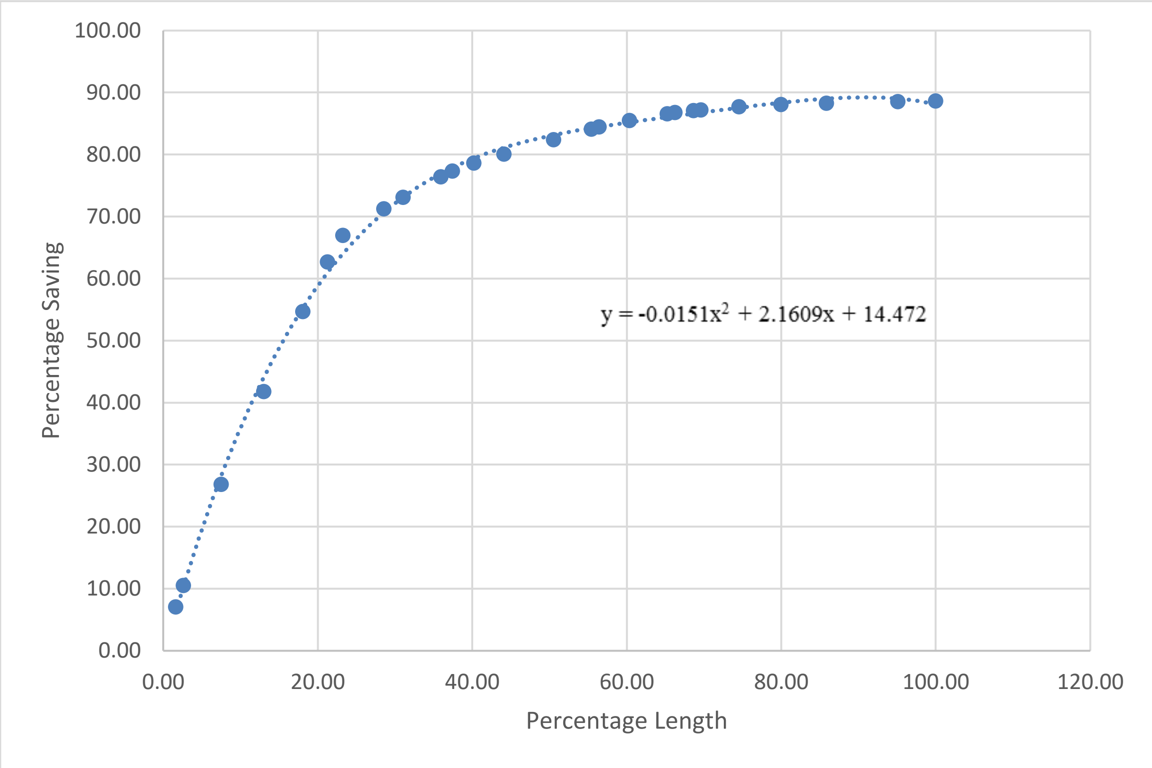

Figure B 5: Polynomial Regression of Chiniot District

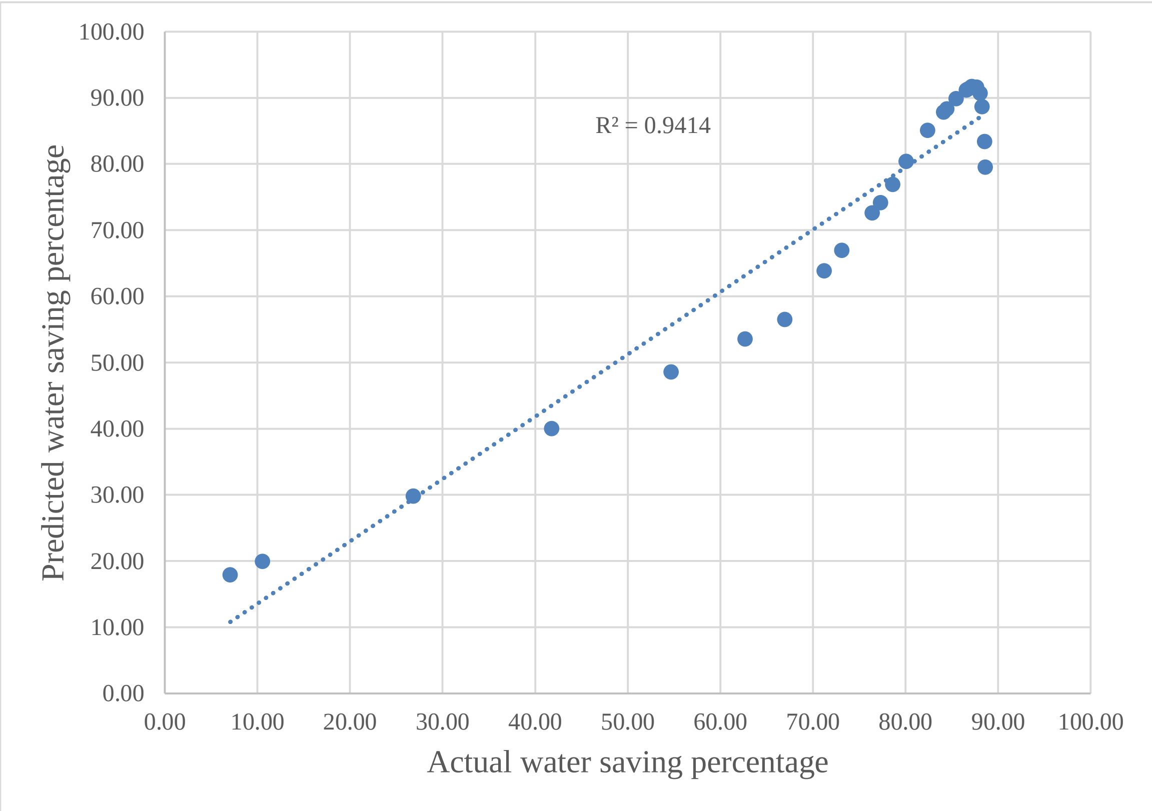

Figure B 6: Polynomial Regression Chiniot District

Table B1: ANN and Polynomial Regression results of Chiniot

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	0.59	0.76	63.91	63.96	0.06	0.00	0.53	99.91
Testing	13.12	3.62	87.64	90.24	2.60	6.77	10.52	91.61
				TLBP				
Training	0.61	0.78	63.91	63.89	-0.01	0.00	0.62	99.90
Testing	5.11	2.26	87.64	89.04	1.44	2.07	3.67	91.69
				Polynomial Regression				
-	32.21	5.68	71.25	73.39	2.14	4.57	30.07	94.14

Results of District DG Khan

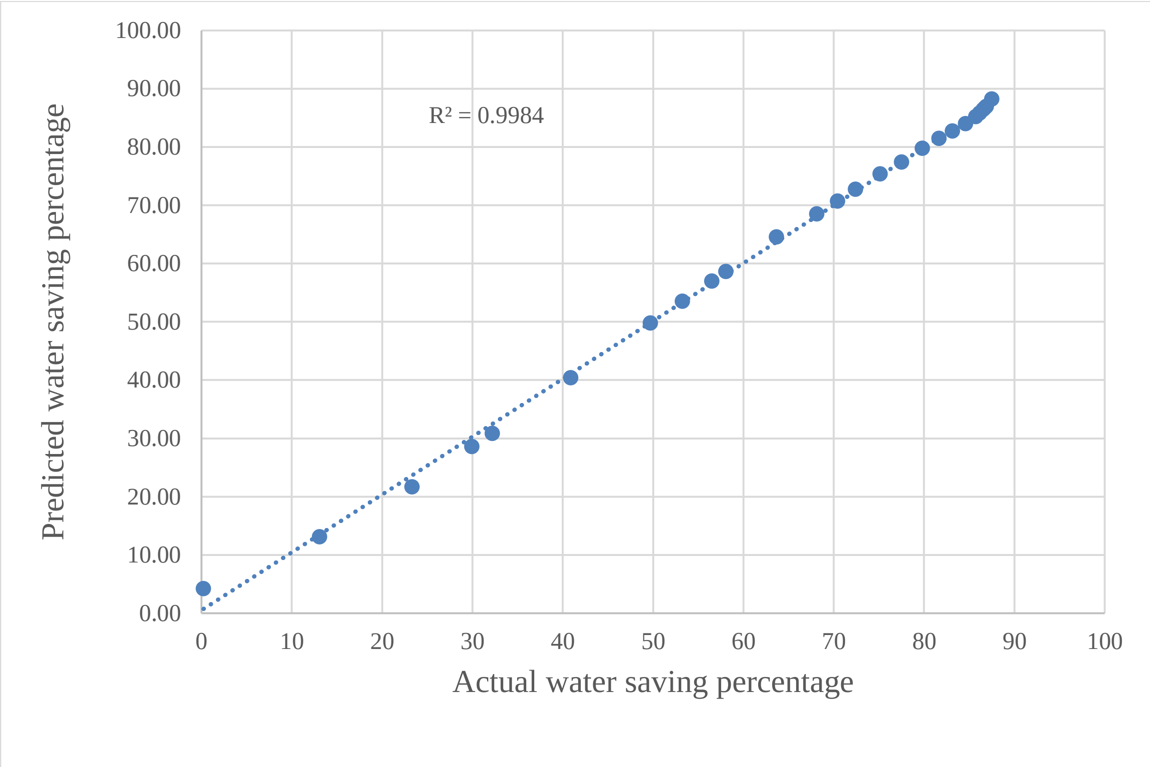

Figure C 1: Training Model BFGS DG Khan District

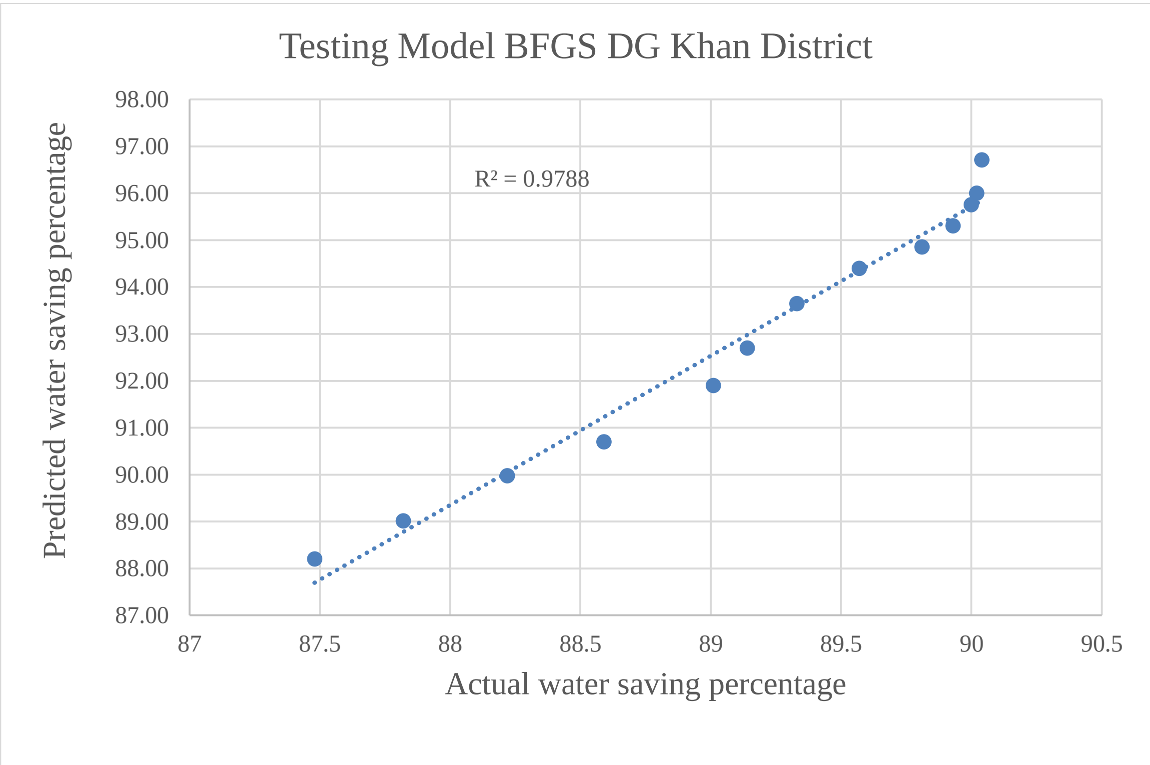

Figure C 2: Testing Model BFGS DG Khan District

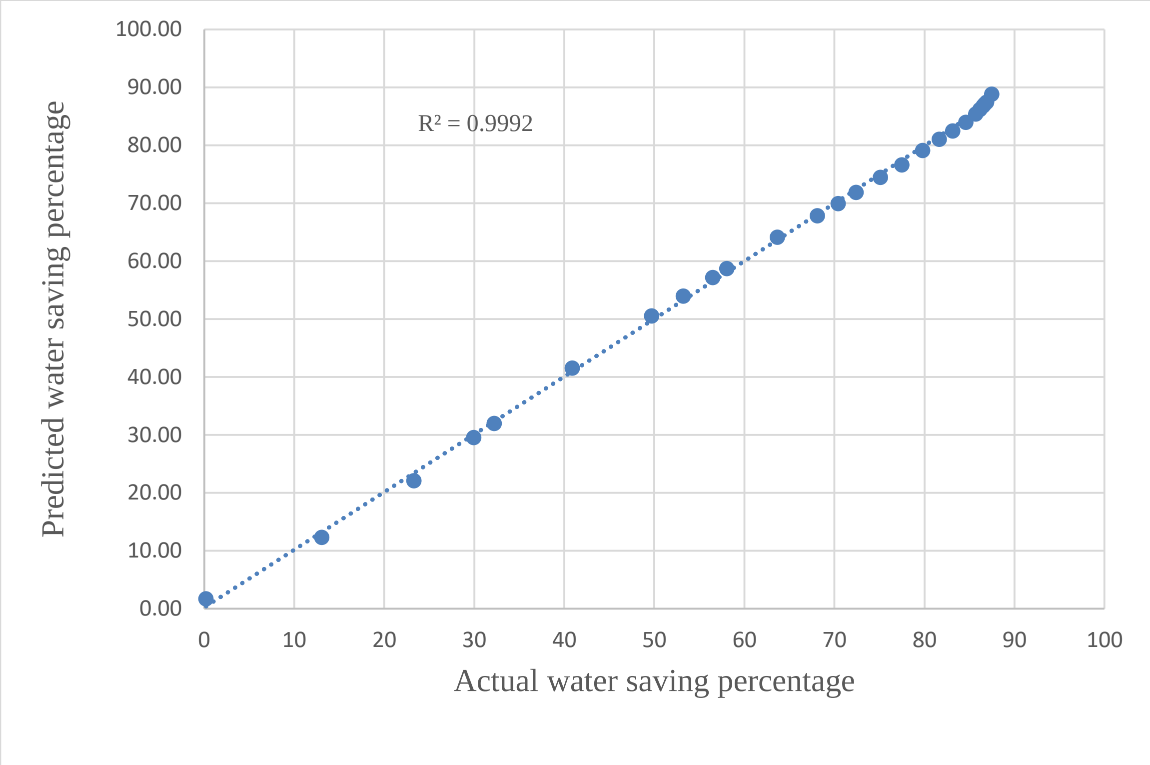

Figure C 3: Training Model TLBP DG Khan District

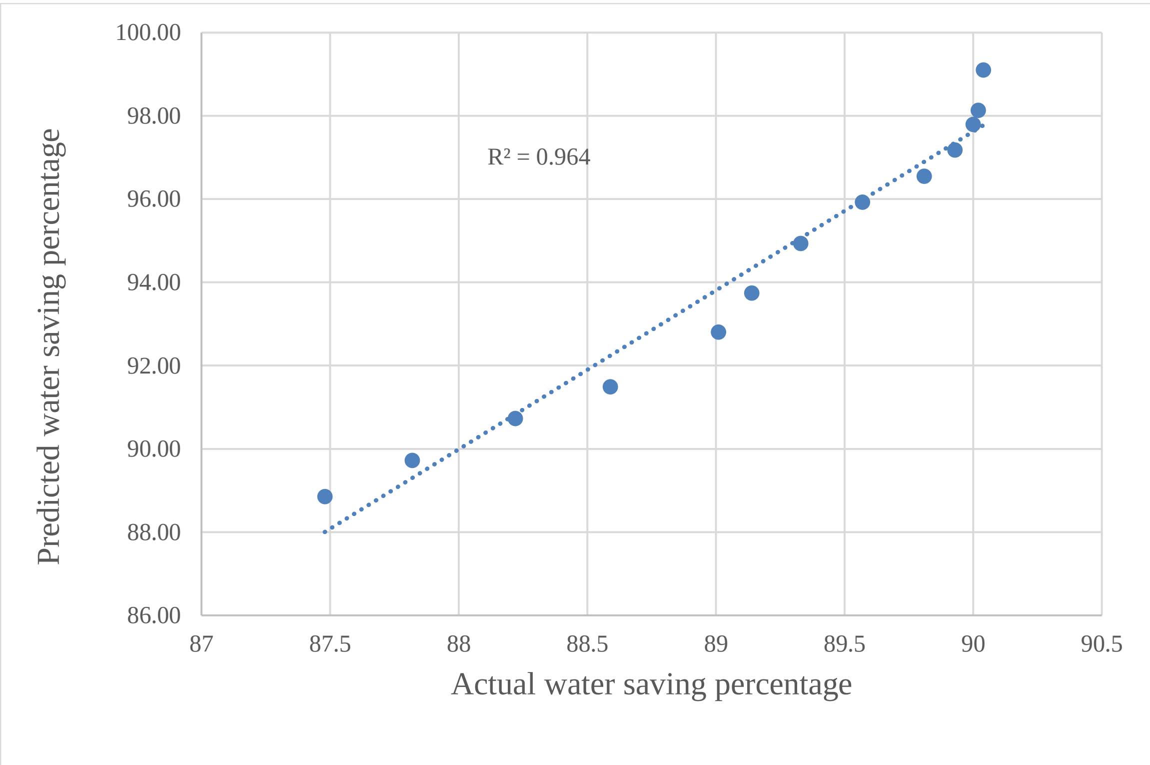

Figure C 4: Testing Model TLBP DG Khan District

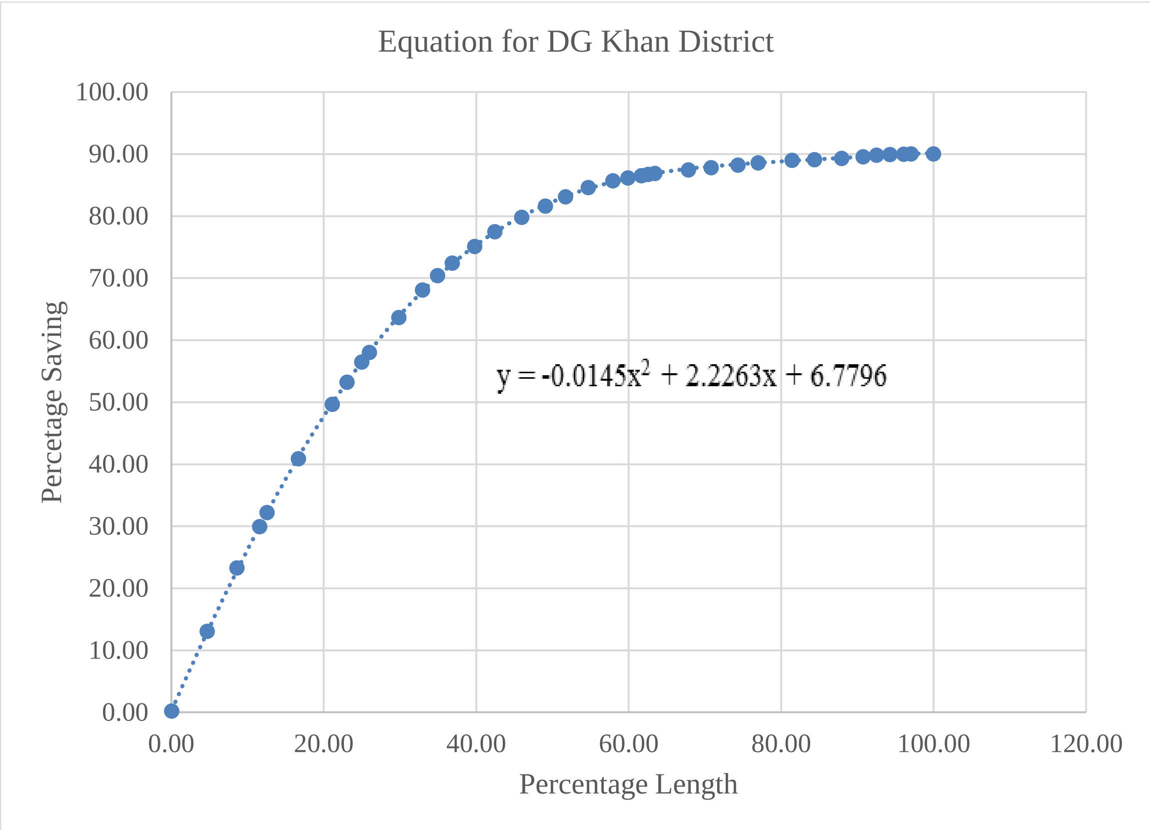

Figure C 5: Polynomial Regression of DG Khan District

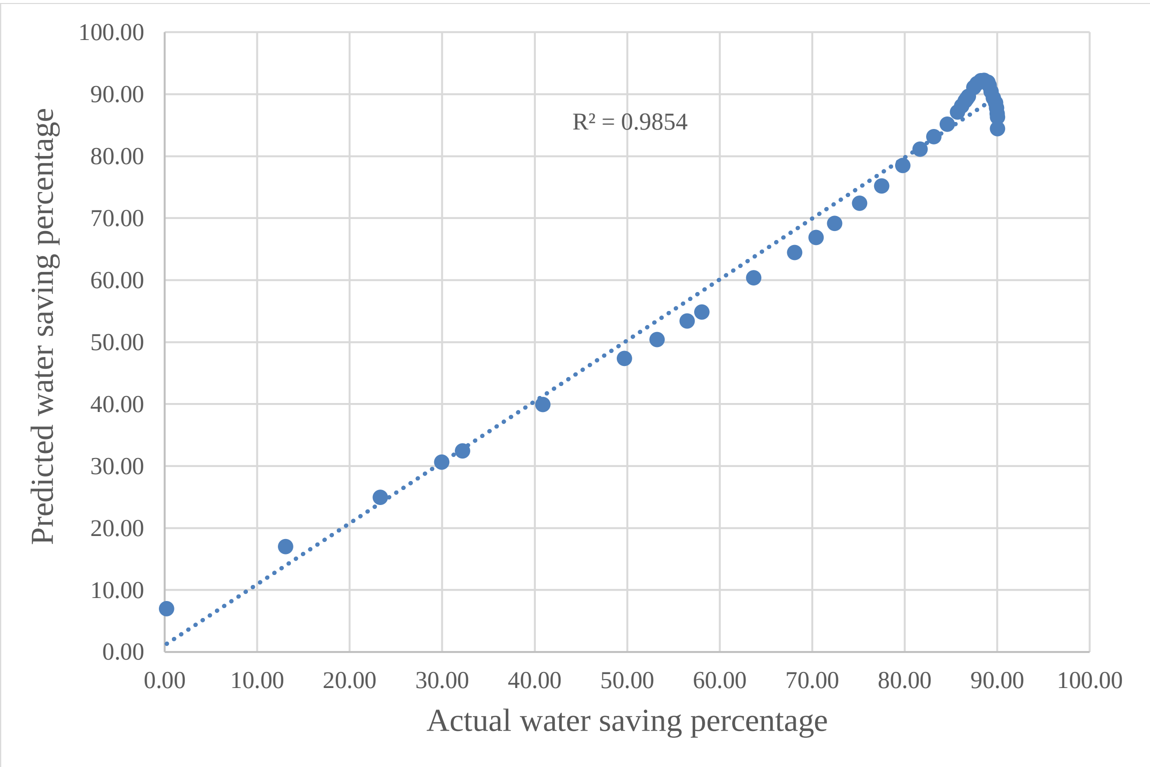

Figure C 6: Polynomial Regression DG Khan District

Table C1: ANN and Polynomial Regression results of DG Khan

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	1.0	1.0	62.81	62.86	0.05	0.00	0.95	99.84
Testing	18.48	4.30	89.15	93.01	3.86	14.92	14.62	97.88
				TLBP				
Training	0.51	0.72	62.81	62.80	-0.01	0.00	0.52	99.92
Testing	33.36	5.78	89.15	94.38	5.23	27.33	28.14	96.40
				Polynomial Regression				
-	8.44	2.91	71.17	71.09	-0.08	0.01	8.52	98.54

Results of District Hafizabad

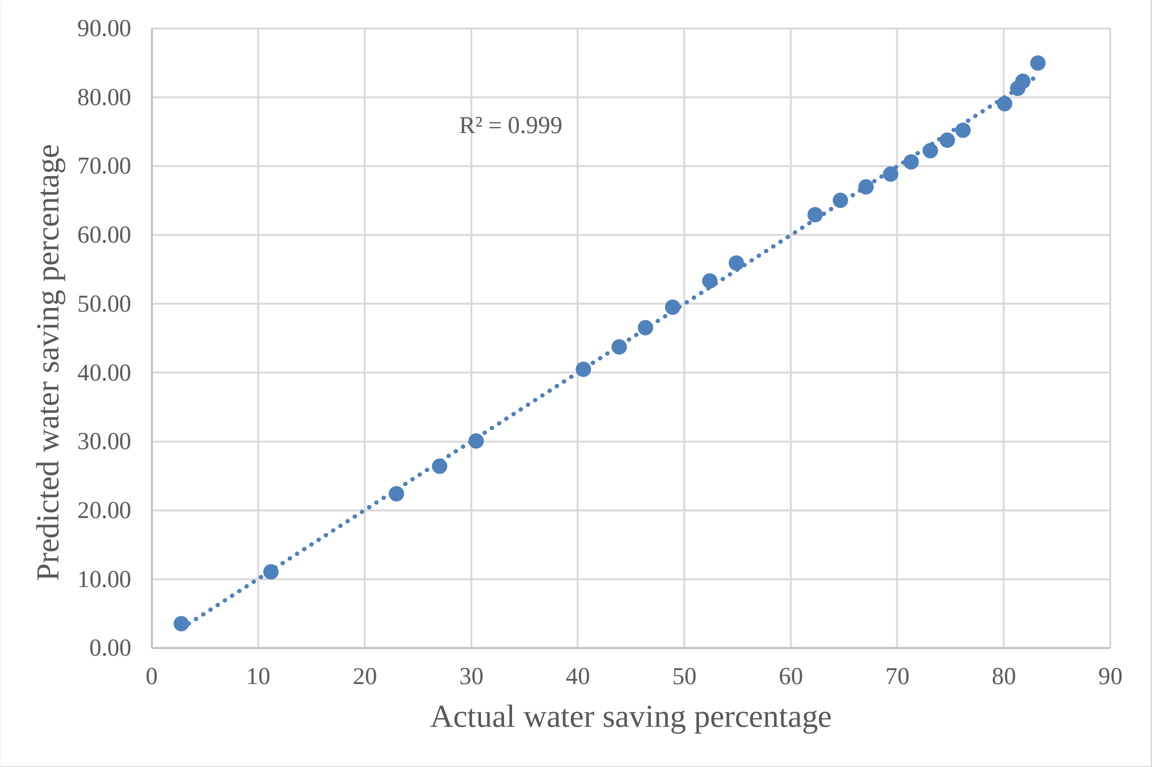

Figure D 1: Training Model BFGS Hafizabad District

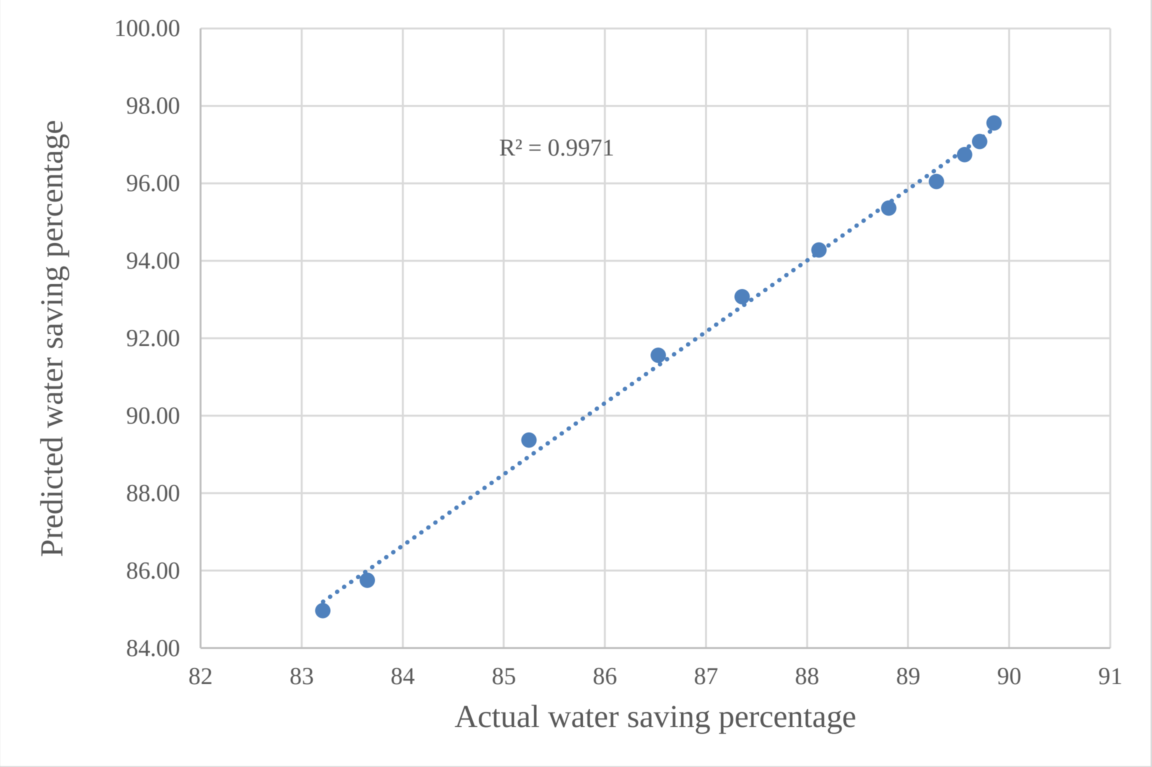

Figure D 2: Testing Model BFGS Hafizabad District

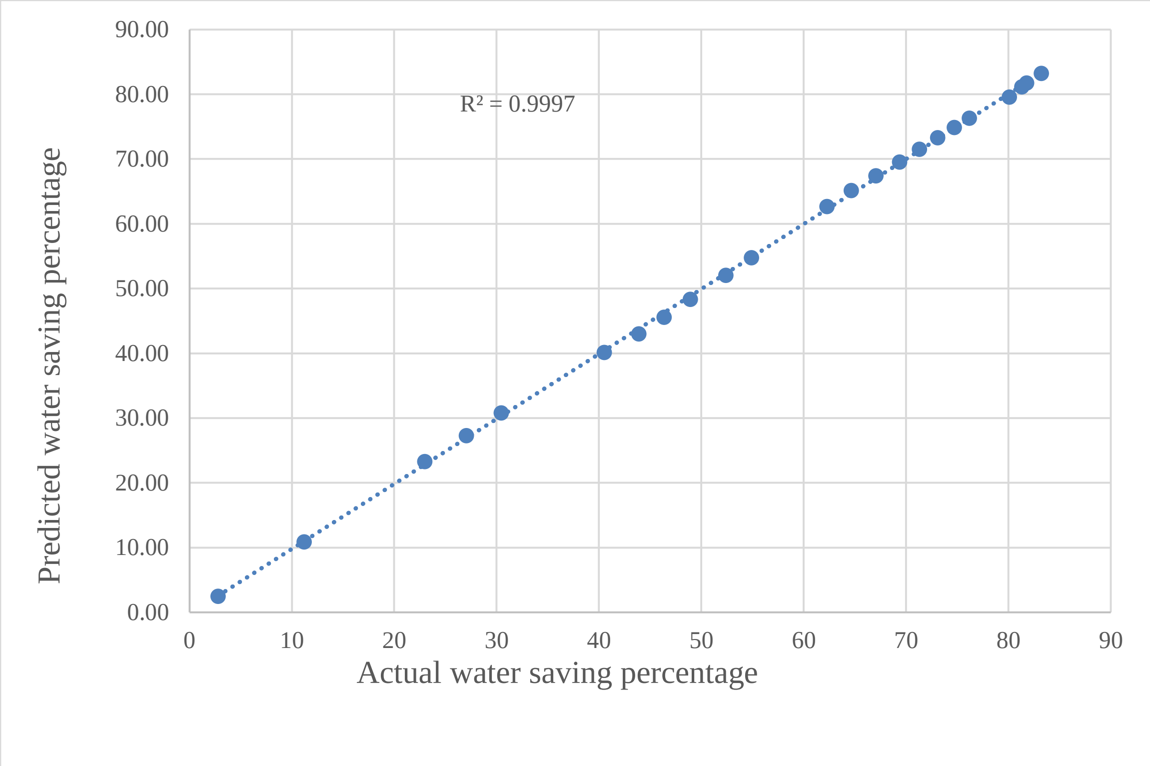

Figure D 3: Training Model TLBP Hafizabad District

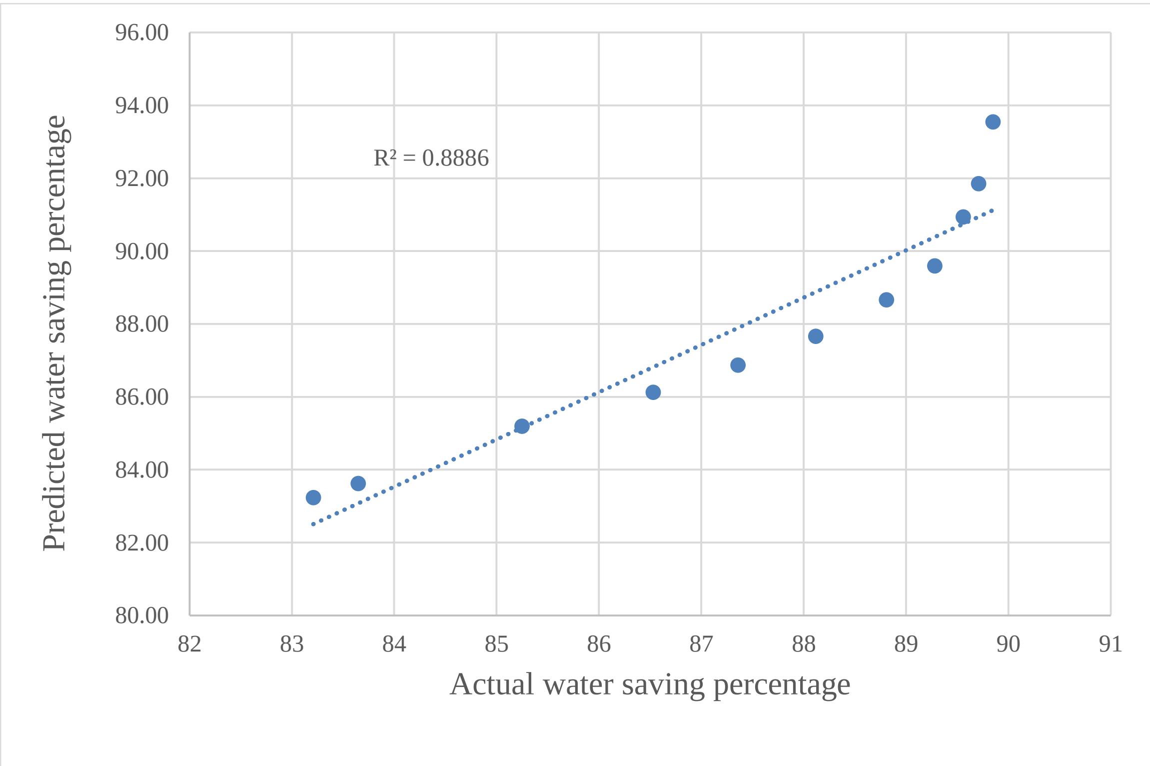

Figure D 4: Testing Model TLBP Hafizabad District

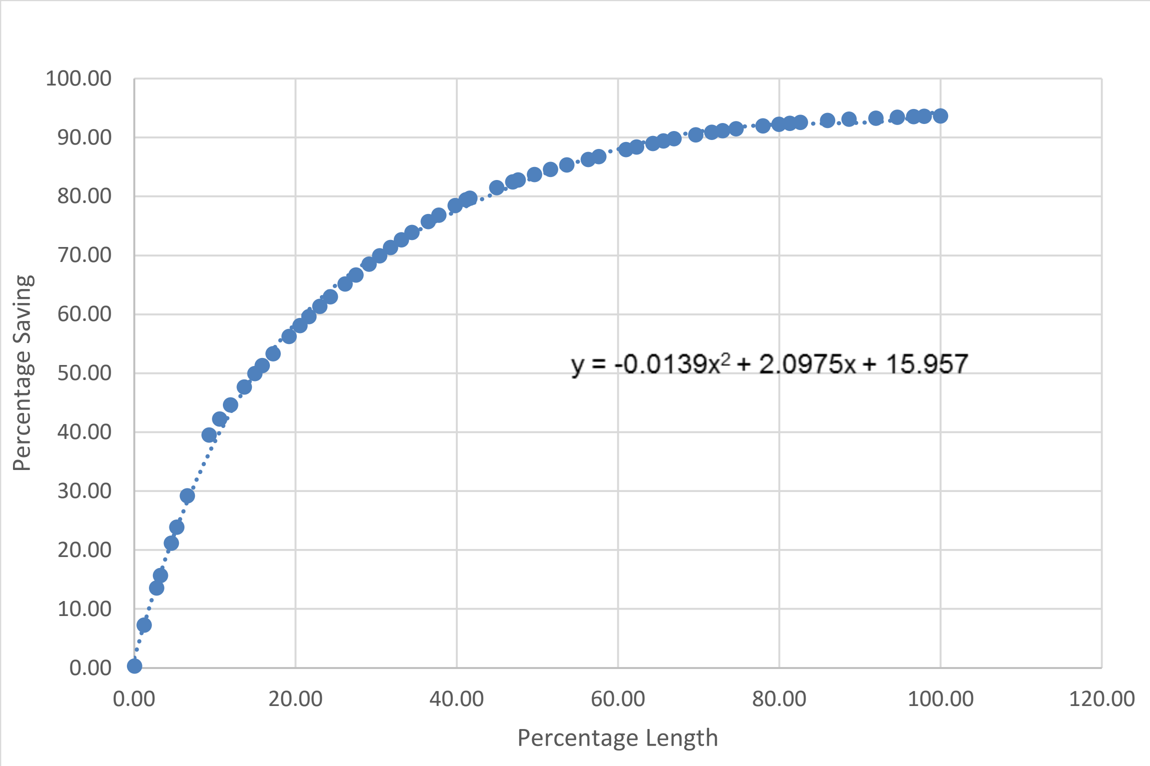

Figure D 5: Polynomial Regression of Hafizabad District

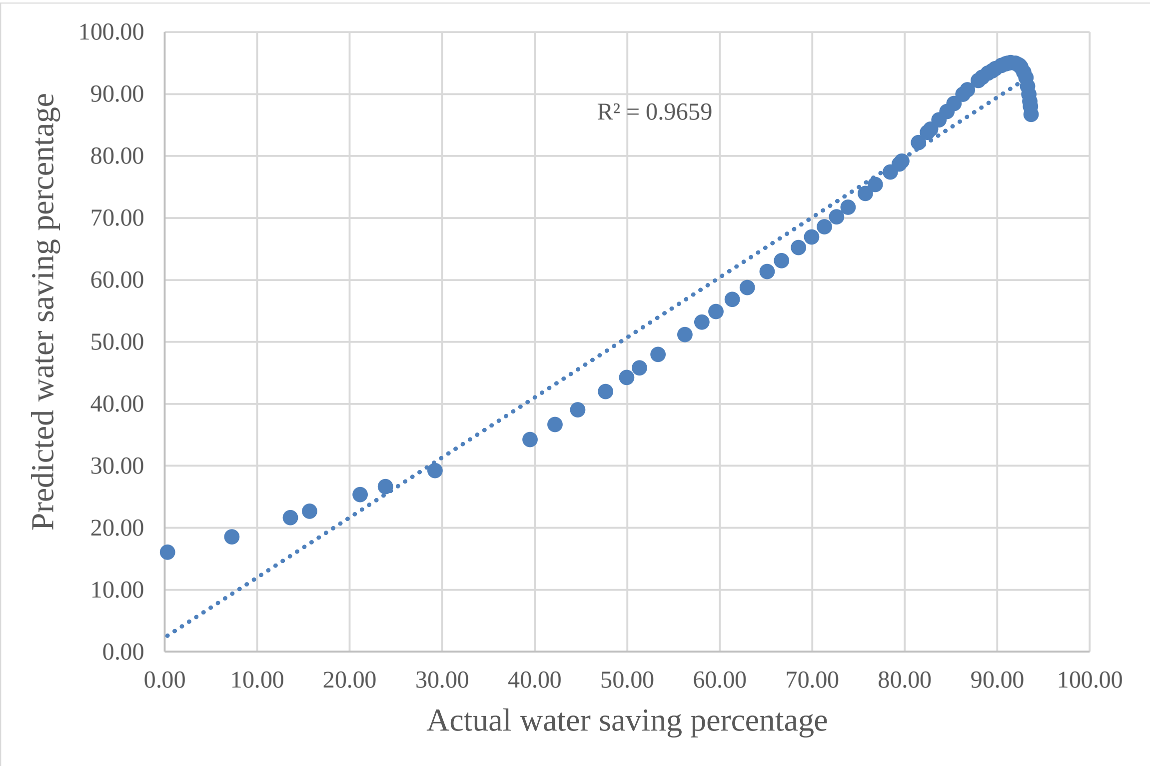

Figure D 6: Polynomial Regression Hafizabad District

Table D1: ANN and Polynomial Regression results of Hafizabad

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	0.53	0.73	55.07	55.05	0.02	0.00	0.55	99.90
Testing	34.06	5.84	87.39	92.89	5.50	30.23	28.56	94.60
				TLBP				
Training	0.15	0.39	55.07	54.99	0.08	0.01	0.23	99.97
Testing	1.90	1.38	87.39	87.93	0.54	0.29	1.36	88.86
				Polynomial Regression				
-	21.35	4.62	69.84	70.85	1.01	1.01	20.35	96.59

Results of District Kasur

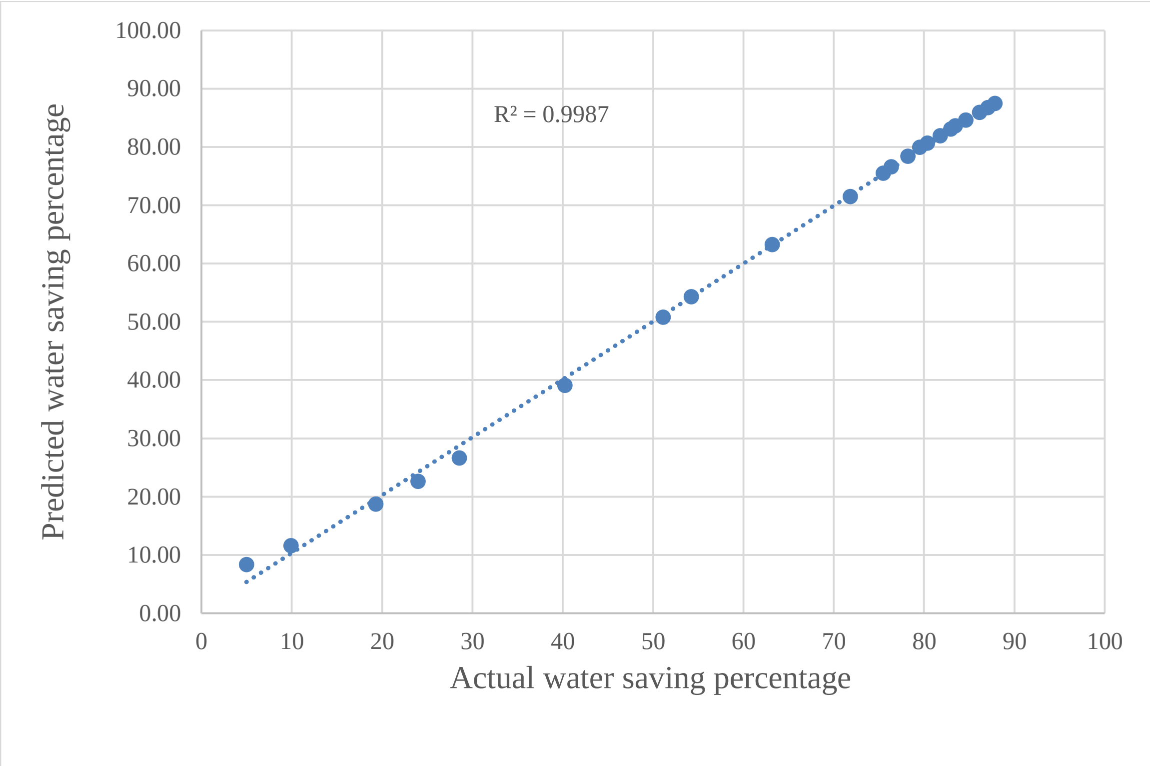

Figure E 1: Training Model BFGS Kasur District

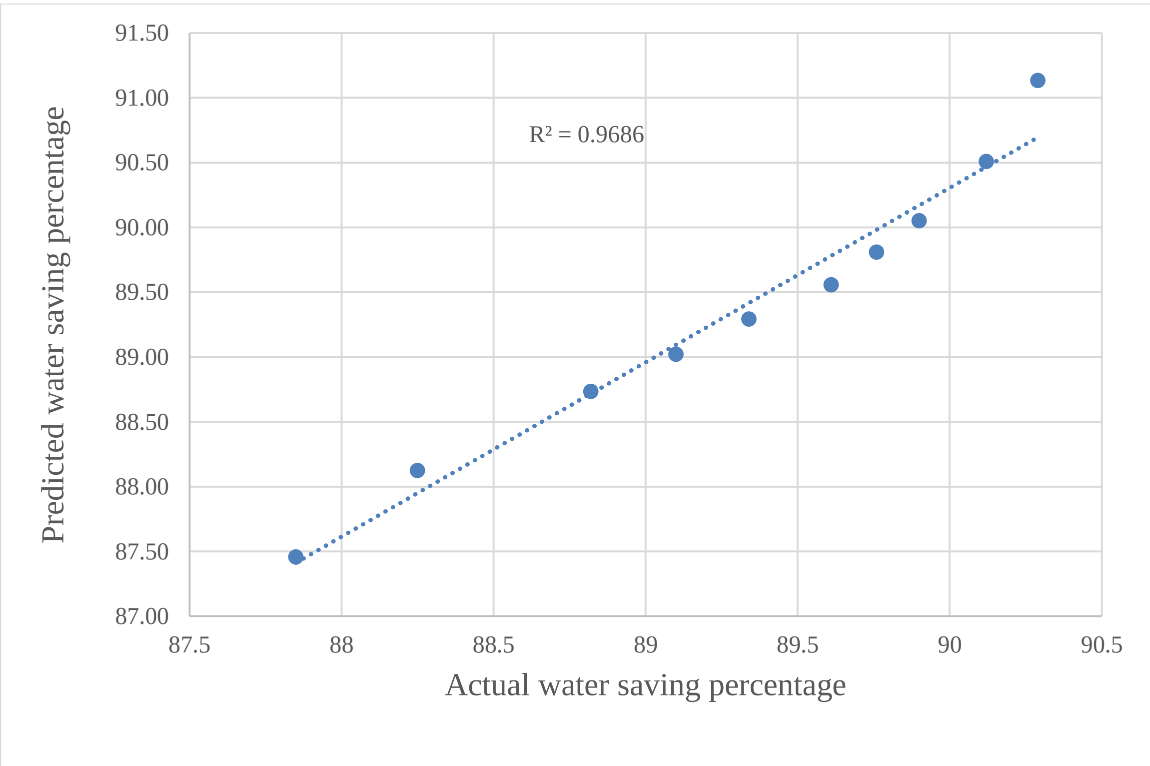

Figure E 2: Testing Model BFGS Kasur District

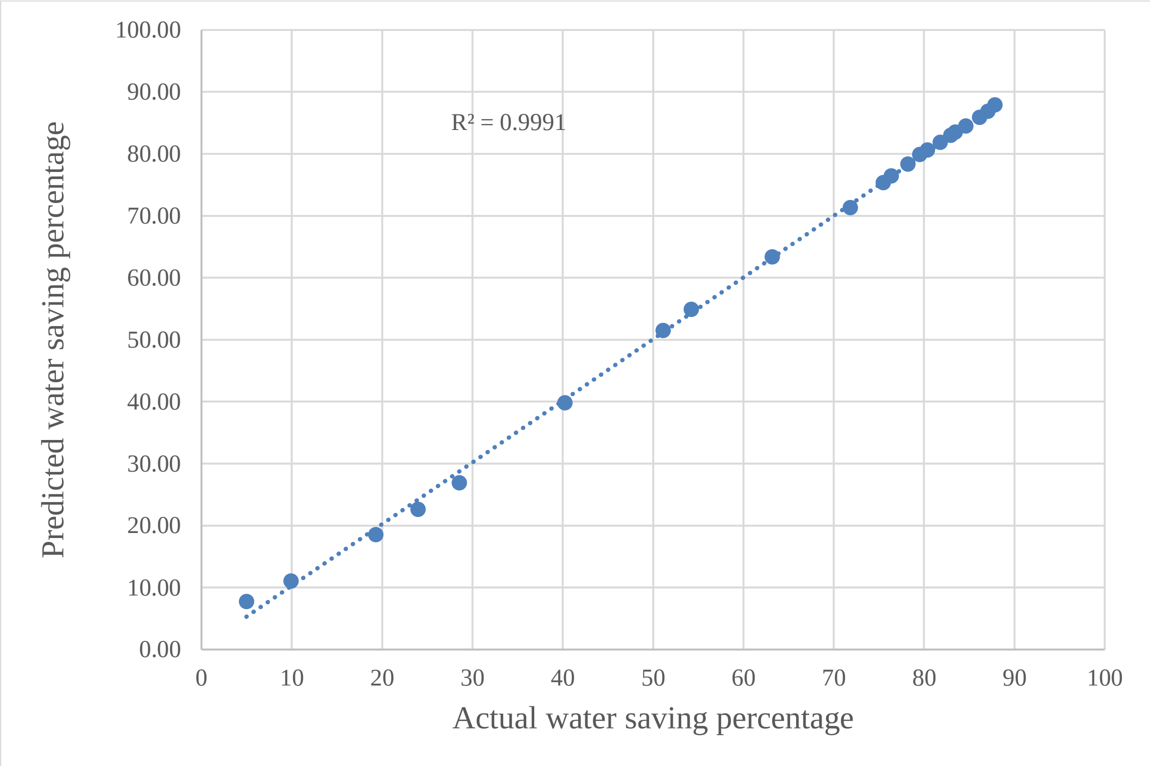

Figure E 3: Training Model TLBP Kasur District

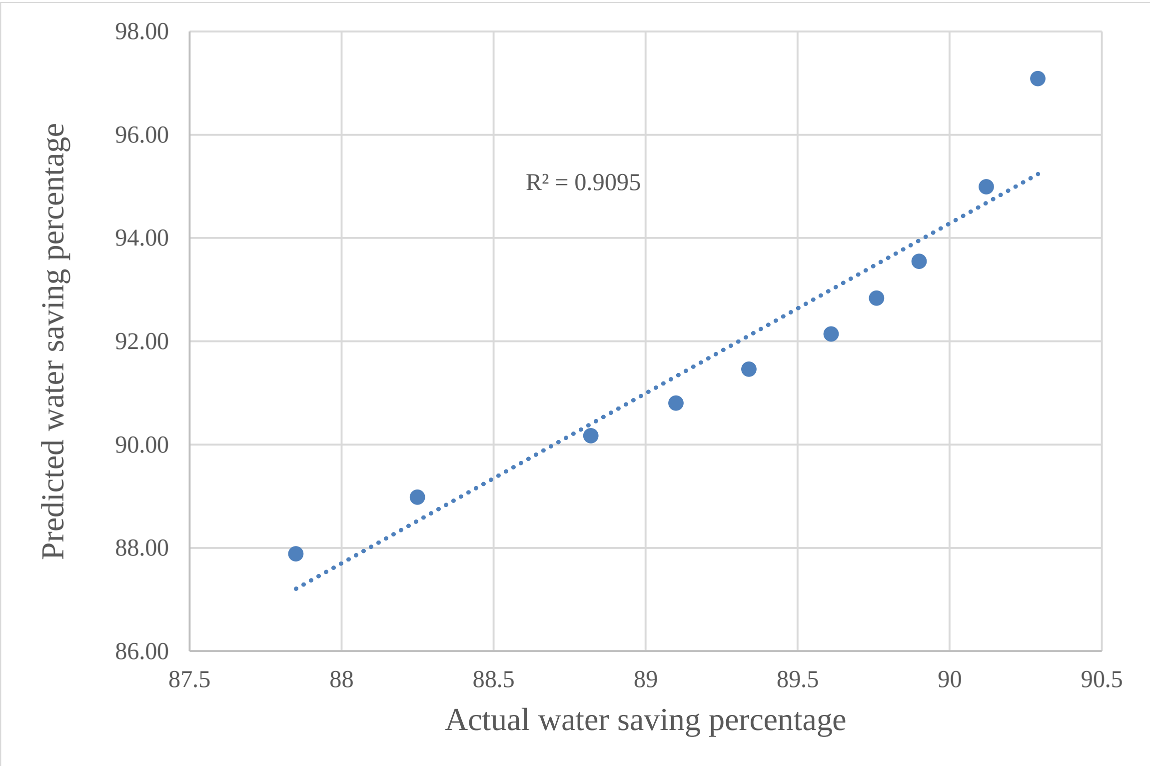

Figure E 4: Testing Model TLBP Kasur District

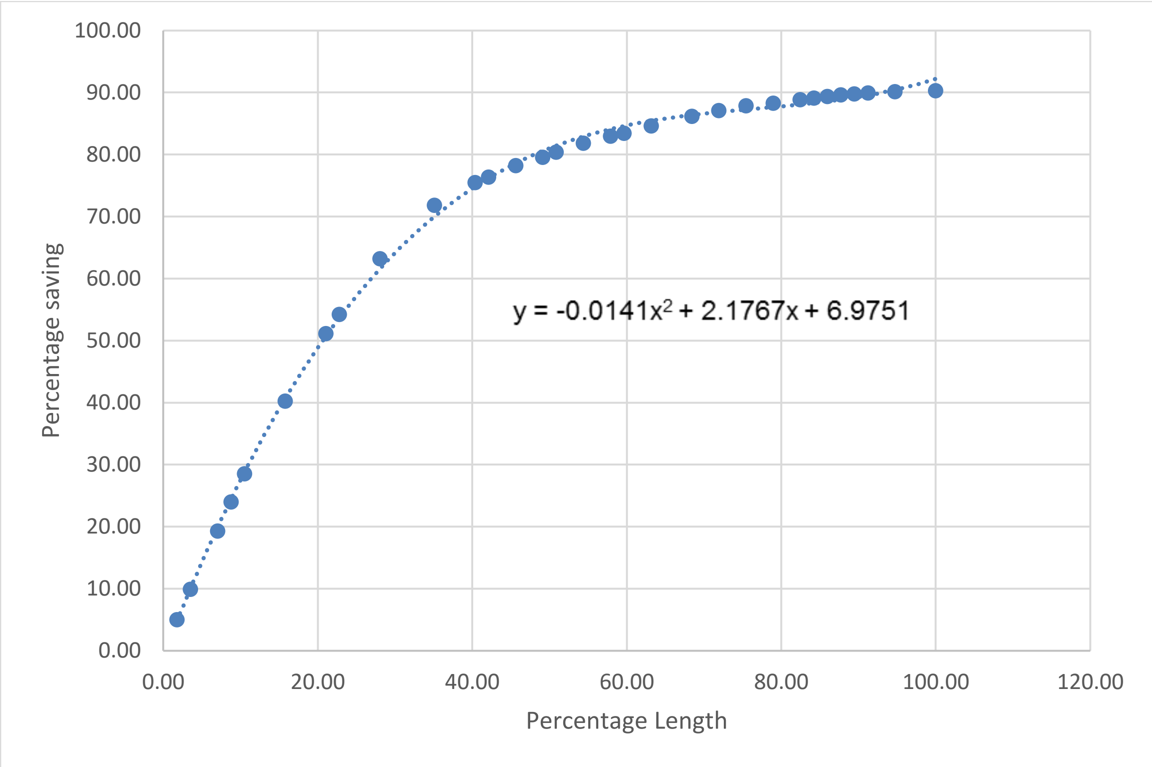

Figure E 5: Polynomial Regression of Kasur District

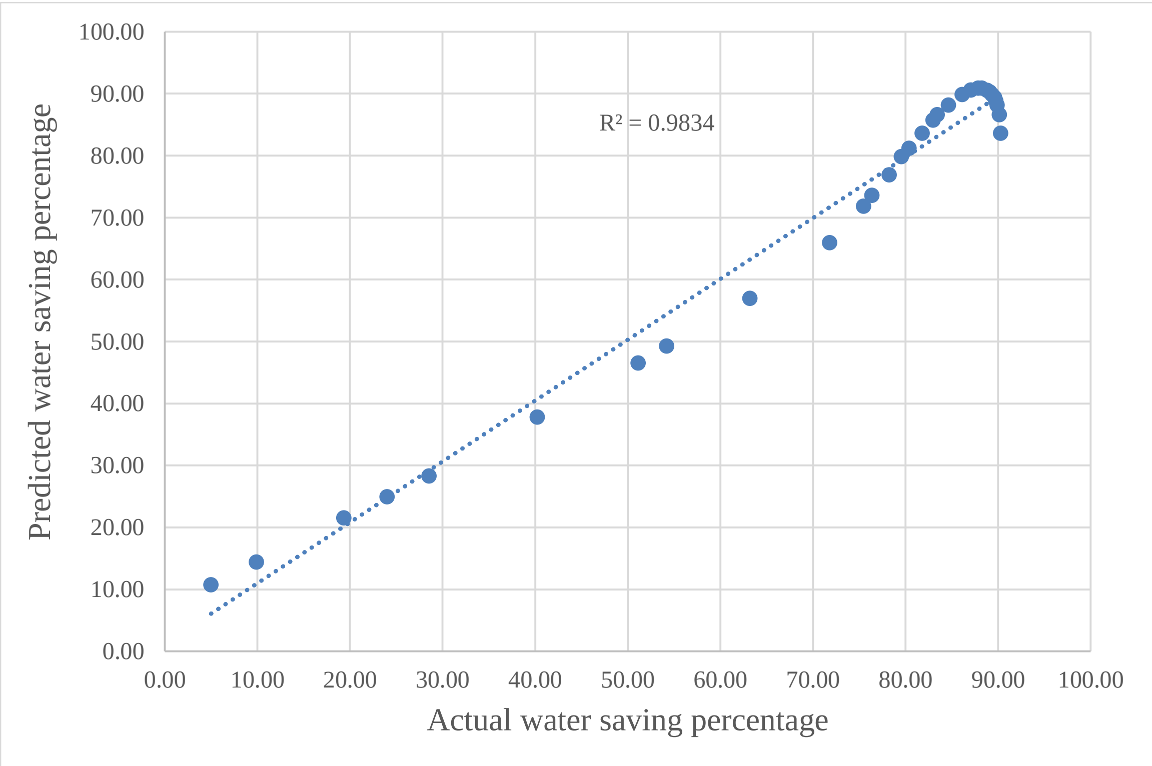

Figure E 6: Polynomial Regression Kasur District

Table E1: ANN and Polynomial Regression results of Kasur

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	1.0	1.0	61.42	61.42	0.00	0.00	1.0	99.87
Testing	0.11	0.33	89.30	89.37	0.07	0.00	0.04	96.86
				TLBP				
Training	0.70	0.83	61.42	61.45	0.03	0.00	0.66	99.97
Testing	10.7	3.30	89.30	91.99	2.69	7.23	8.21	90.95
				Polynomial Regression				
-	11.28	3.36	69.56	71.43	1.87	3.31	9.40	98.34

Annexure F

Results of District Sahiwal

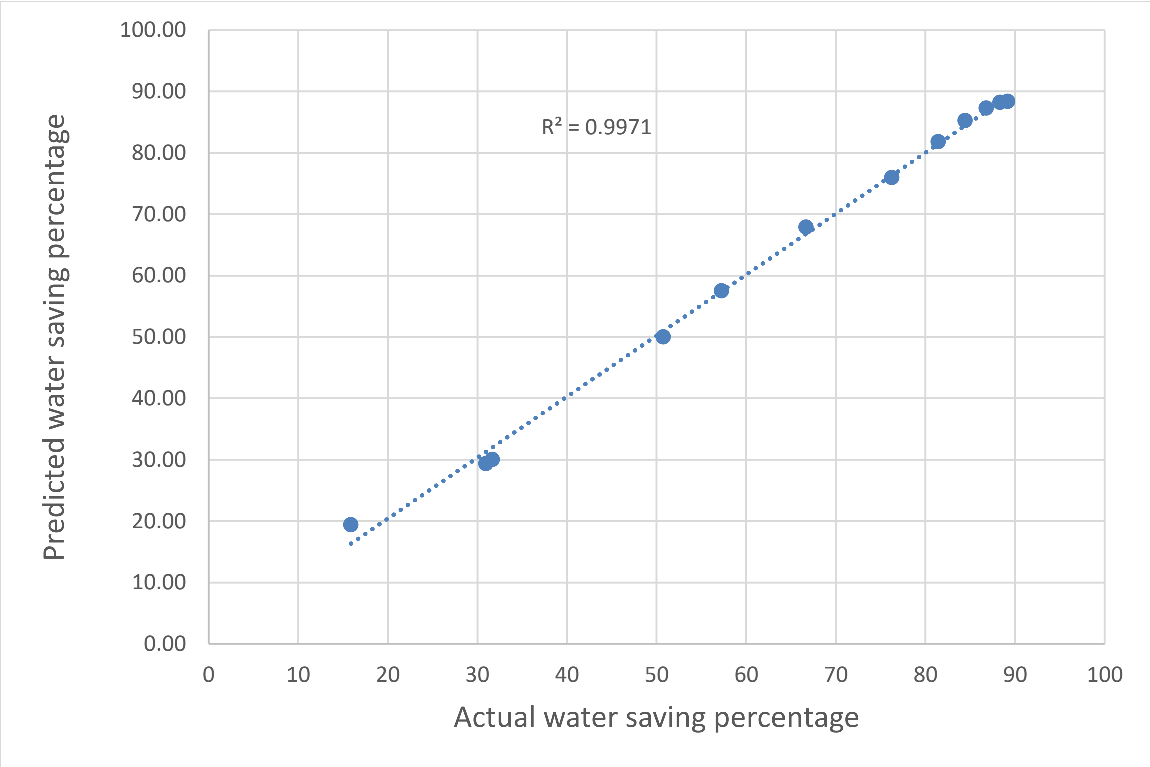

Figure F 1: Training Model BFGS Sahiwal District

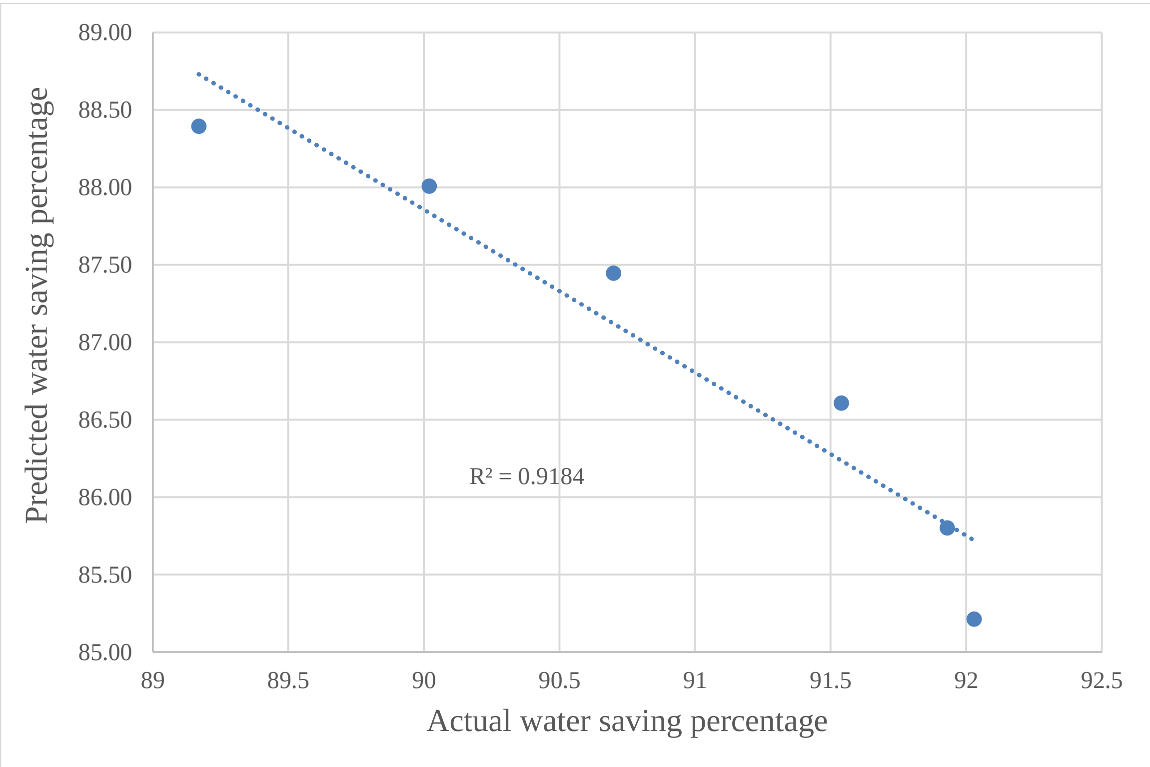

Figure F 2: Testing Model BFGS Sahiwal District

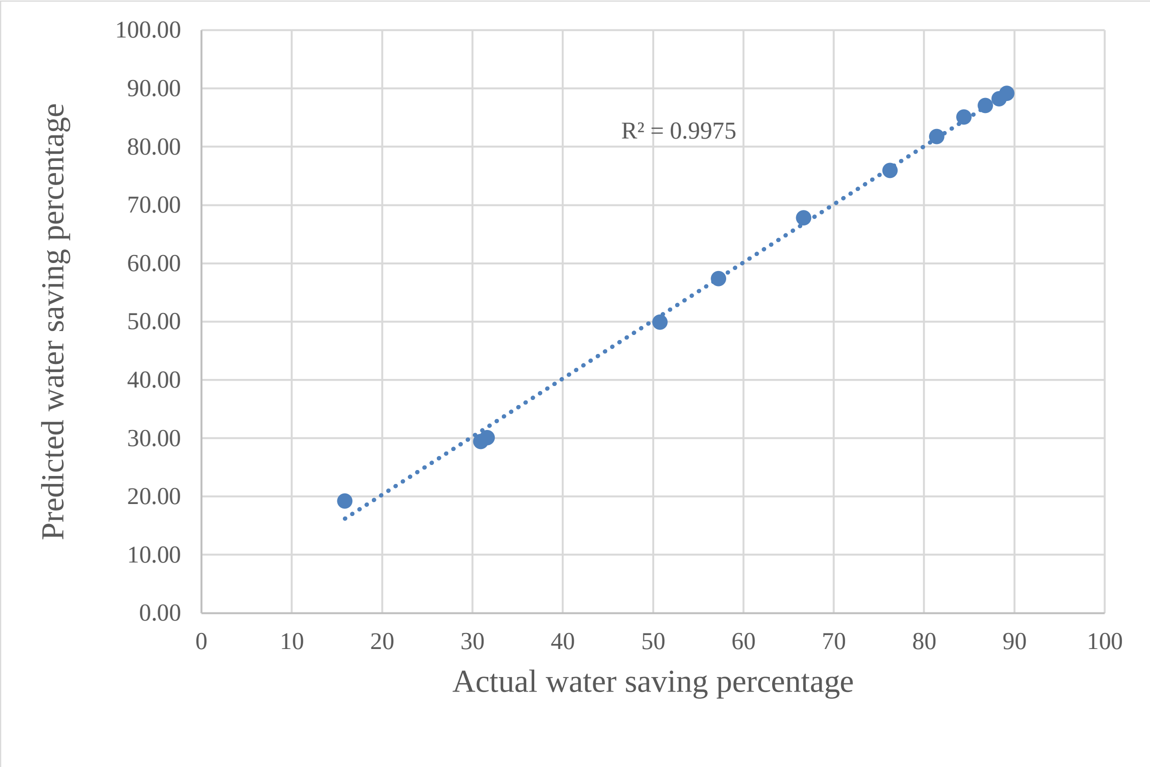

Figure F 3: Training Model TLBP Sahiwal District

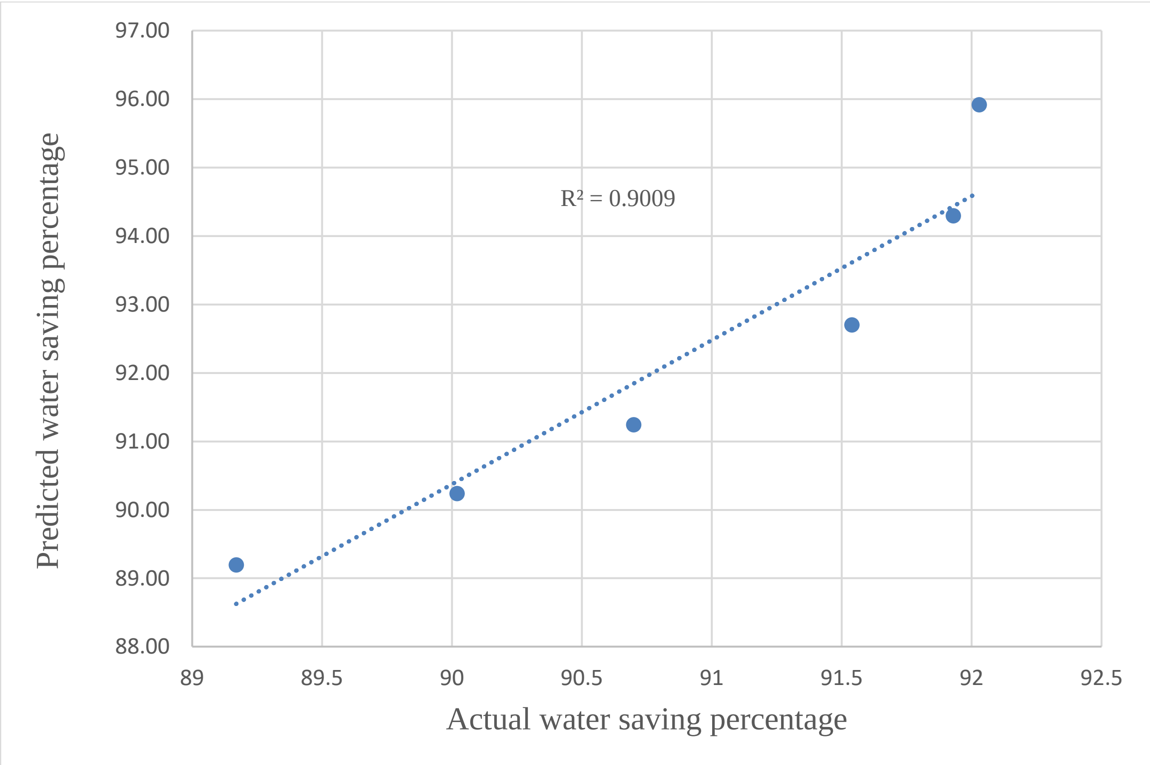

Figure F 4: Testing Model TLBP Sahiwal District

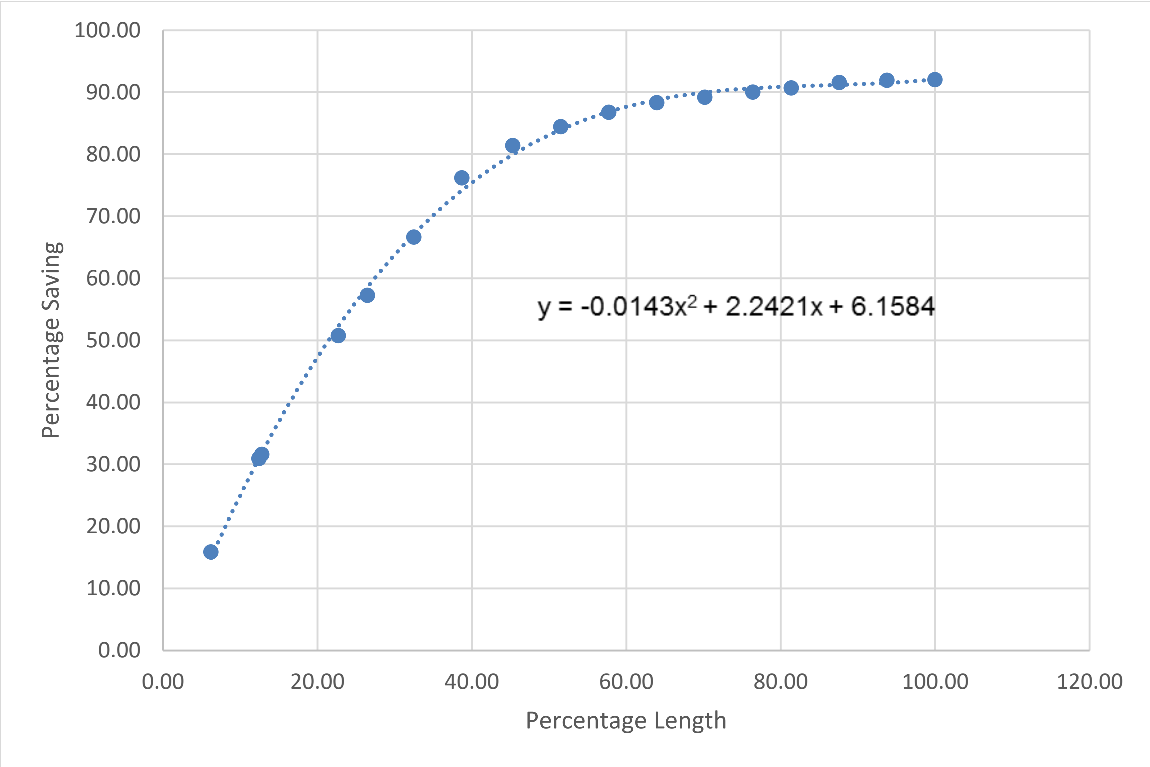

Figure F 5: Polynomial Regression of Sahiwal District

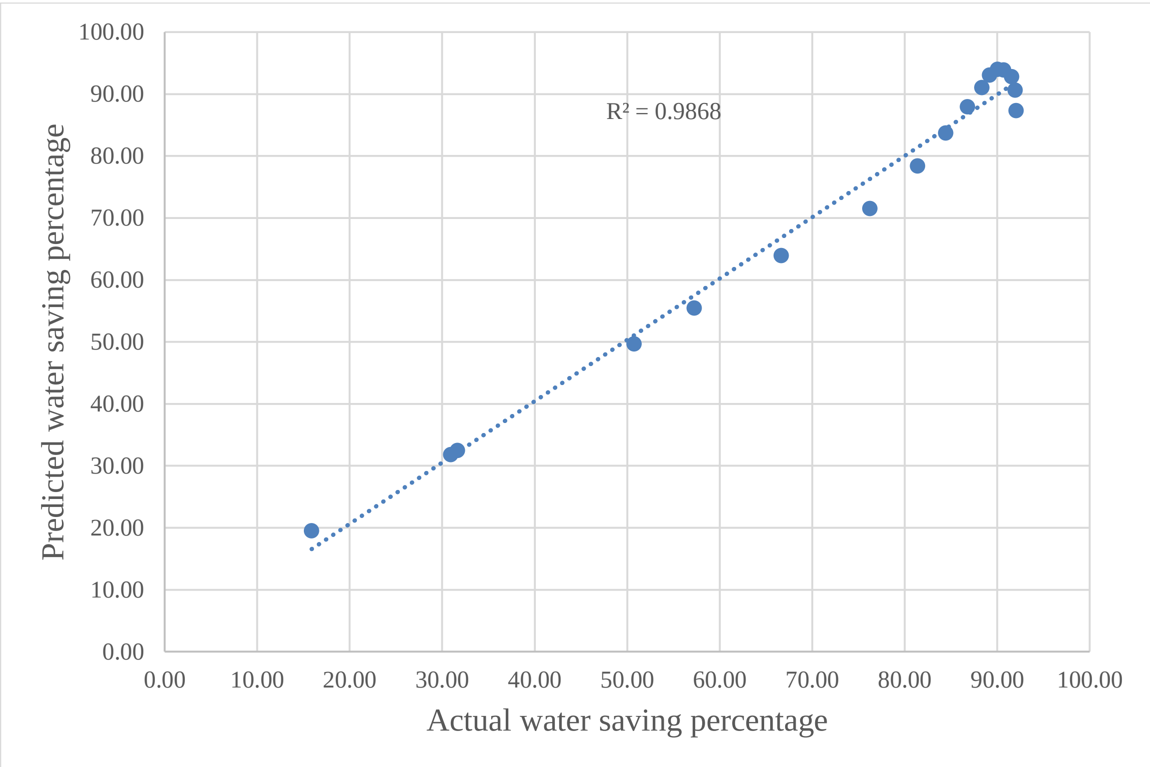

Figure F 6: Polynomial Regression Sahiwal District

Table F1: ANN and Polynomial Regression results of Sahiwal

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	1.79	1.34	63.29	63.45	0.16	0.03	1.63	99.71
Testing	20.60	4.54	90.90	86.91	-3.99	15.89	24.58	91.84
				TLBP				
Training	1.56	1.25	63.29	63.45	0.16	0.03	1.39	99.75
Testing	3.73	1.93	90.90	92.26	1.37	1.86	2.37	90.09
				Polynomial Regression				
	7.38	2.80	71.51	74.87	3.36	11.30	4.47	98.68

Results of District Vehari

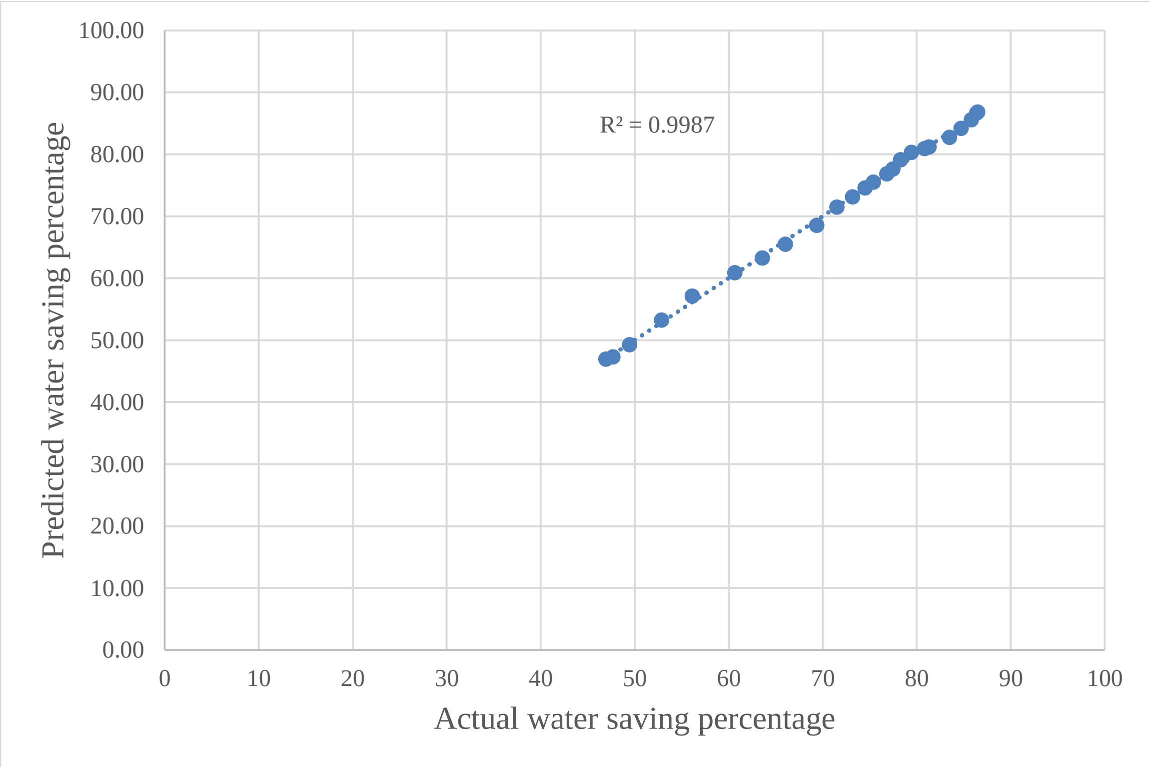

Figure G 1: Training Model BFGS Vehari District

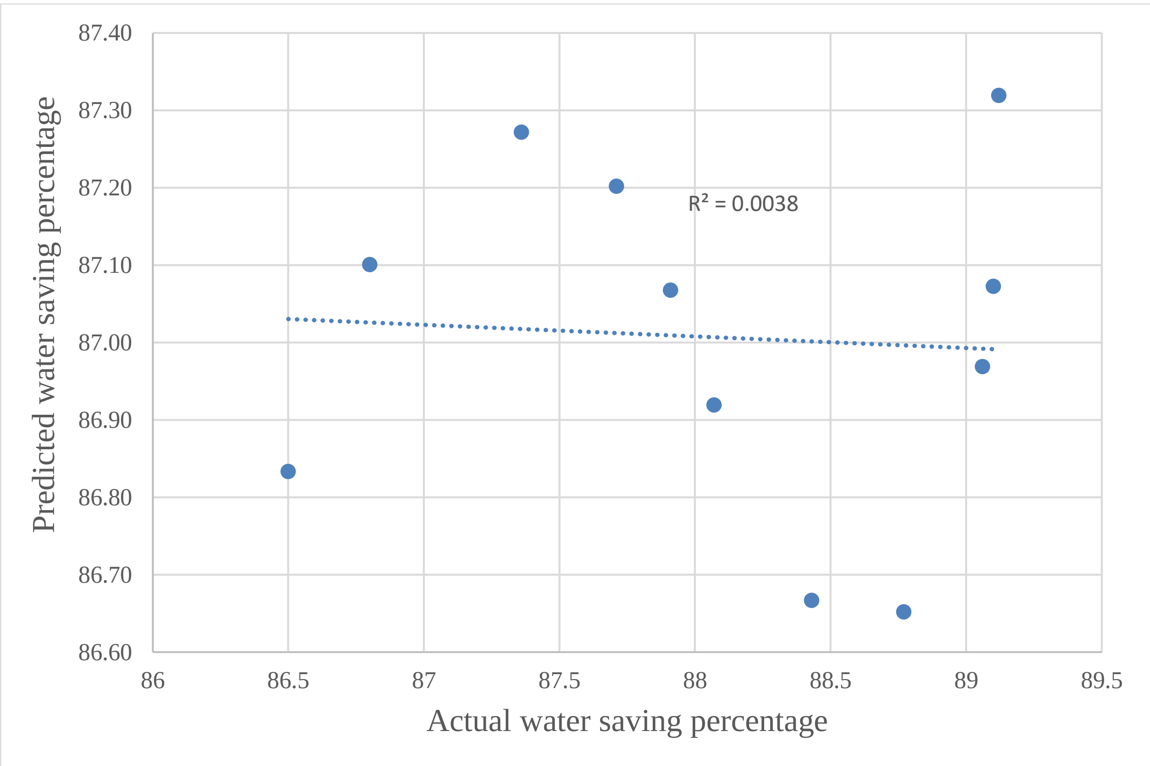

Figure G 2: Testing Model BFGS Vehari District

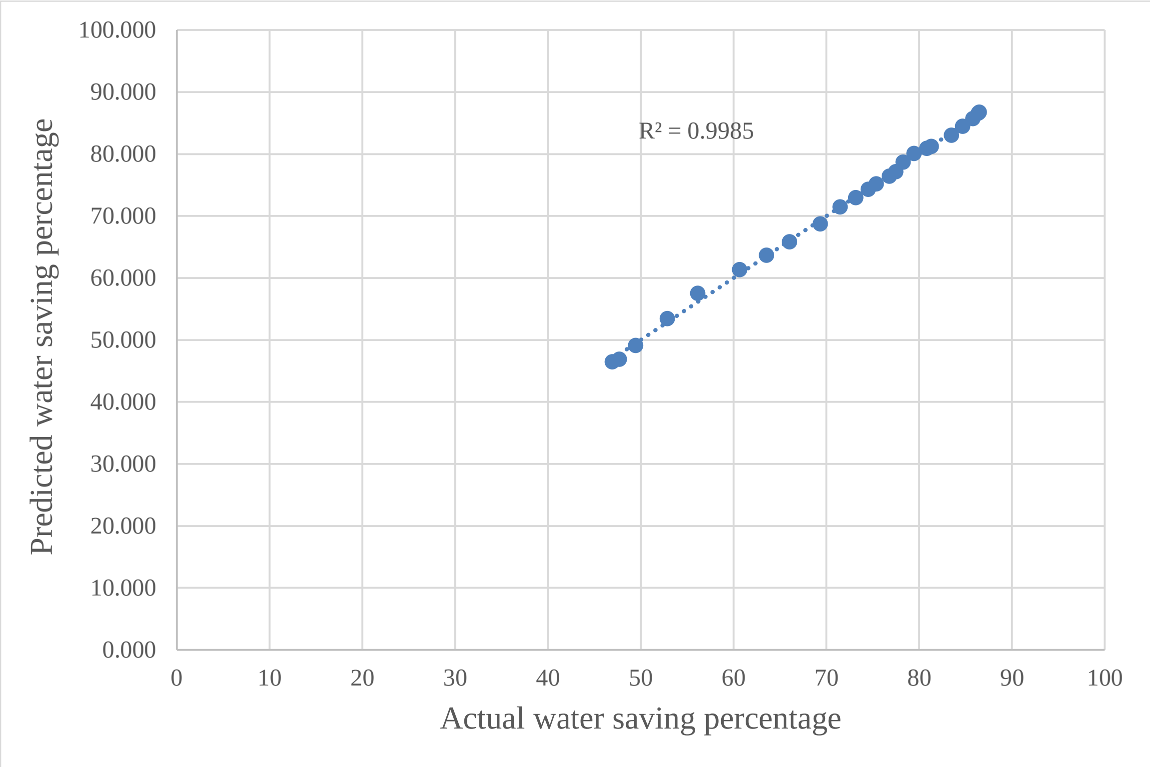

Figure G 3: Training Model TLBP Vehari District

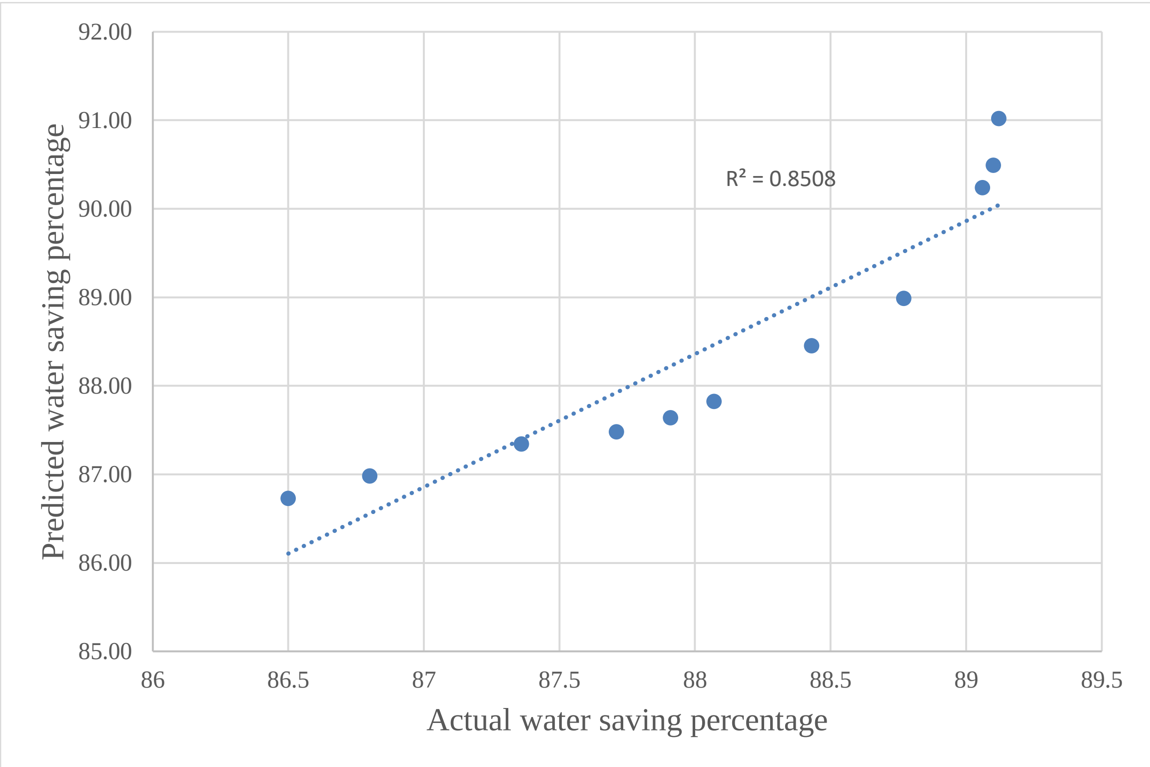

Figure G 4: Testing Model TLBP Vehari District

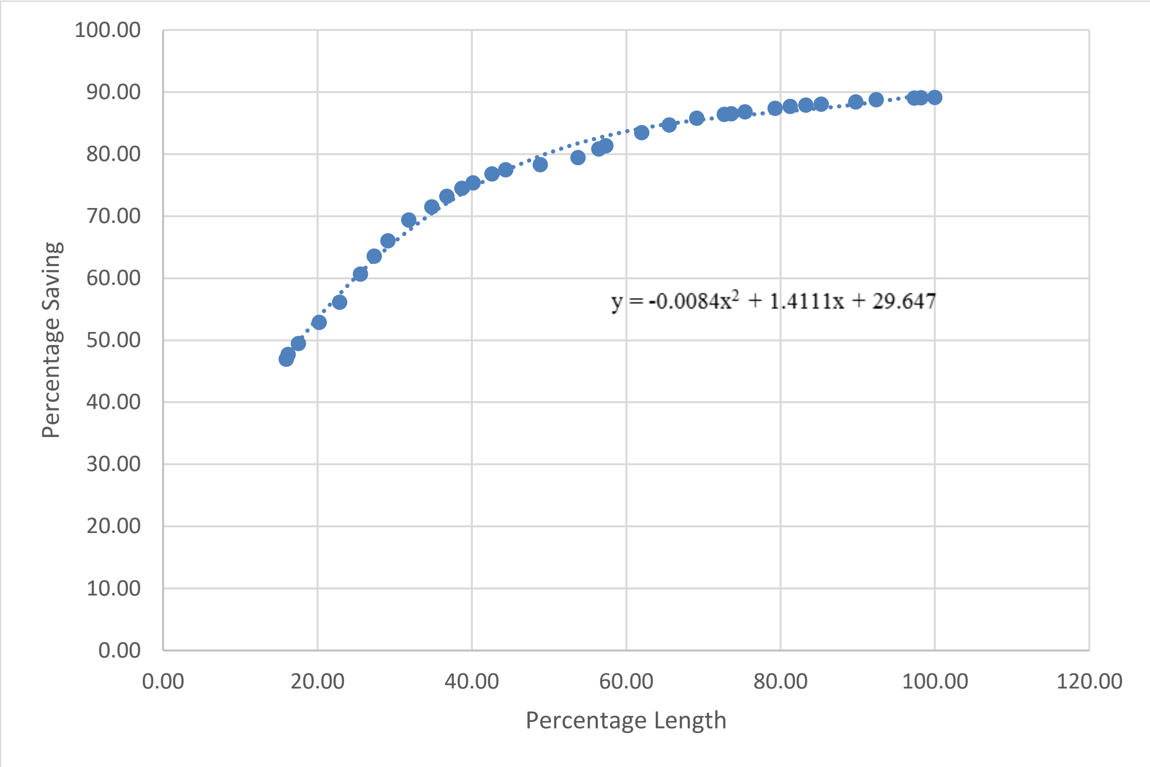

Figure G 5: Polynomial Regression of Vehari District

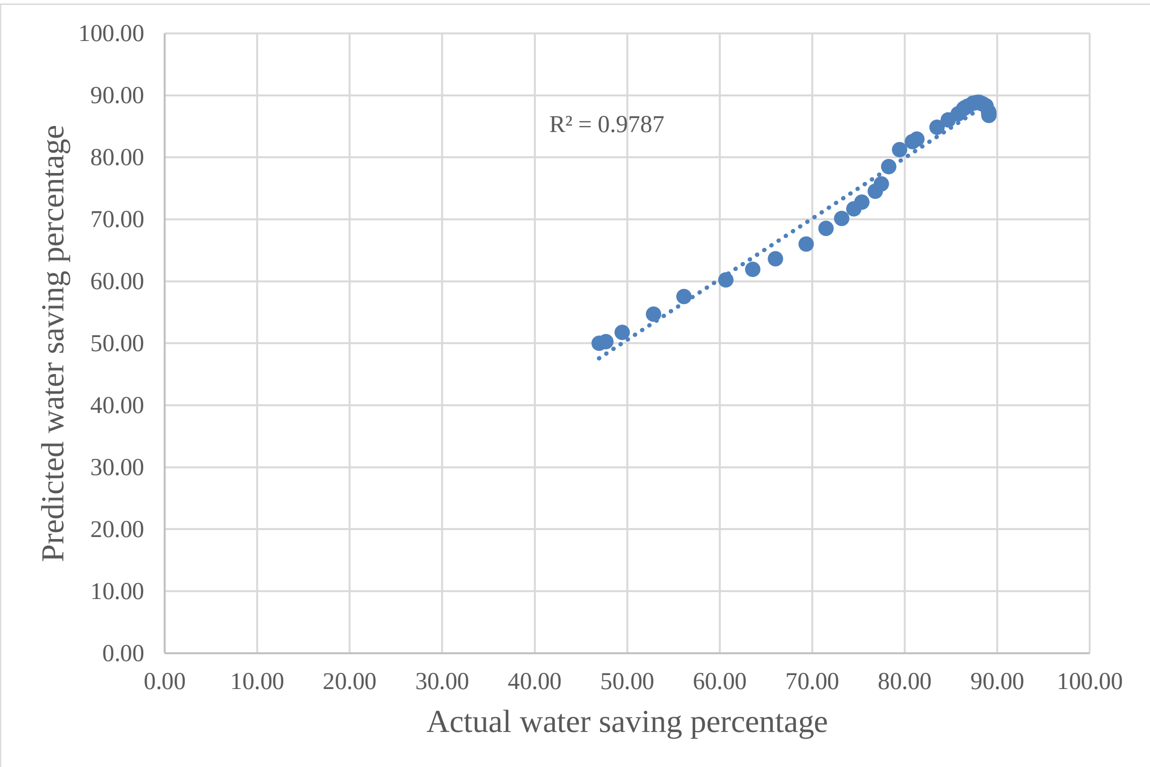

Figure G 6: Polynomial Regression Vehari District

Table G1: ANN and Polynomial Regression results of Vehari

Method	MSE	RMSE	Actual Mean	Predicted Mean	Bias	Bias Sq.	Variance	R. Sq.
				BFGS				
Training	0.21	0.46	71.18	71.19	0.01	0.00	0.20	99.87
Testing	1.98	1.41	88.08	87.01	-1.07	1.14	3.05	0.38
				TLBP				
Training	0.23	0.48	71.18	71.17	-0.01	0.00	0.25	99.85
Testing	0.66	0.81	88.08	88.47	0.40	0.16	0.26	85.70
				Polynomial Regression				
-	3.69	1.92	76.20	76.99	0.80	0.63	2.87	97.87