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Intelligent Prediction Model for Non-Revenue and Demand of Urban Water: Case Study Beitunia City

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Declaration

This is to declare herewith that, the thesis entitled "Intelligent Prediction Model for Non-Revenue and Demand of Urban Water: Case Study Beitunia City" under the Supervision Prof. Dr. Mohammed Awad, and Co-Supervisor Dr. Amjad Rattrout, was solely undertaken by me and does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

Signed: ……………

Burhan Ismaeel Taha Farah

Date: 19/8/2019

Dedication

This research project is dedicated to my parents for guiding and educating me. I also dedicate it to my family for they have been my source of strength and inspiration, and I have forfeited quality family time to focus on my research and studies.

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I would like to thank my supervisors Prof. Dr. Mohammed Awad, who has always provided me with support, encouragement, and guidance during this thesis, and I would like to thank Dr. Amjad Rattrout for his support and assistance too.

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Abstract

Water is an incomparable rare and strategic natural resource. It is one of the key elements for life and social development as well. Some people lack access to drinking water as a result of considerable leakages in water networks. Water losses and water supply demands are viewed as one of the most important problems facing the water sector in Palestine. More specifically, the municipalities and water utilities suffer from this problem in a manner that causes disruptions and low-quality water service, in addition to significant financial losses. Therefore, accurate prediction of water losses and supply demands is considered as one of the essential remedies that offer efficient support for water resources. Applying a reliable prediction in urban areas could provide the basis for operational, tactical and strategic decisions for water utilities, which is crucial. The public utilities need to forecast water supply demands for the basic needs of people in addition to the requirements for manufacturing and agriculture, as well as for the development of new water sources. Prior knowledge real causes of water losses and proactive response to damages in water networks treatment could reduce losses, and, more importantly, it may save the financial resources in a manner that will strengthen the water sector.

The large difference between the amount of water supplied and water consumed is one of the most important issues affecting water facilities, also known as "non-revenue water" [NRW]. Large amounts of water lost through leaks, non-invoicing to customers, illegal connections, poor water meter performance and inaccurate reading seriously affects the financial viability of water utilities. Thus, prediction of water losses and water demands have become important tools for managing and operating water supply systems. So, it is necessary to provide an approach that will help anticipate water losses and demand using artificial intelligence techniques to ensure a reliable water distribution system and solve the cause of water losses.

Our research depends on historical data representing water supplies and consumptions in addition to the real water losses of Beitunia city. The main goal of this research is to explore, investigate and develop AI models that could be more efficiently used in predicting water losses as well as forecasting water demands in Palestine, and, more specifically, for Beitunia city. In this thesis, the work methodology consists of the evaluation of different aspects of the design of predictive neural networks, such as the inclusion of new learning algorithms in different neural networks

architectures. Each neural network configuration is simulated and its predictions are compared with real data of NRW and demand for water.

The obtained results show that the learning algorithm called Levenberg Marquardt which is used to optimize the MLPNNs-LM model has achieved the best scoring metrics when it is compared to another learning algorithm in different ANNs models like (RBFNN-Newrb and GAs-MLPNNs), while ARIMA model was less accurate than other NNs models. This is because the ARIMA model relies on linear data to be accurate. Hence, the municipality of Beitunia can employ an efficient system that will reduce cost as well as best utilize and manage water resources. More importantly, such success will help generalize our model for the municipalities and water utilities.

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Abbreviations

AI	Artificial Intelligent
ACF	Autocorrelation Function.
ANNs	Artificial Neural Networks
AR	Autoregressive.
ARIMA	Autoregressive Integrated Moving Average
ARMA	Auto-Regressive Moving Average
AWWA	American Water Works Association
CMWU	Coastal Municipalities Water Utility
DCL	Dynamic Clustering Learning
DMA	District Meter Area
DMA	District Metered Area
GAs	Genetic Algorithms
IWA	International Water Association
JSC	Joint Service Council
JWC	Joint Water Committee
JWU	Jerusalem Water Undertaking
LM	Levenberg Marquardt
MA	Moving Average.
MATLAB	Matrix Laboratory
MFFNNBP	Multi-layer Perceptron Feed Forward Backpropagation Neural Networks.
MLP	Multi-layer Perceptron
MLPNNs	Multi-Layer Perceptron Neural Networks

MRA	Multiple Regression Analysis
MSE	Mean Square Error
Newrb	Matlab function implements the RBFNNs
NNs	Neural Networks
NRW	Non-Revenue Water
PACF	Partial Autocorrelation Function.
RBF	Radial Basis Function
RBFNNs	Radial Basis Function Neural Networks
SLNNs	Single layer Neural Networks
WHO	World Health Organization
WHO	World Health Organization
WSRC	Water Sector Regulatory Council
WSRC	Water Sector Regulatory Council
WSSA	Water Supply and Sewerage Authority

CHAPTER ONE
INTRODUCTION

1.1 Introduction

Water shortage is a major global problem that is especially concerning in the Arab world, where is rapid population growth, as is the situation in Palestine. Palestine, like the countries of the region, suffers from a water crisis. The primary responsibility for this crisis besides the lack of rainfall is the Israeli occupation, its control over the water, the denial of millions of Palestinian residents despite international conventions, which is supposed to be guaranteed by laws, human rights organizations and peace treaties [1]. This problem is one of the most serious issues. The amount of water losses is one of the most important problems facing the water sector in Palestine. It reached a high rate of up to 50% as indicated in studies [2, 3]. Therefore, the Palestinian government is working hard to reduce losses through rehabilitating networks in public drinking water systems; which limit the amount of water loss and provides the energy used to pump these quantities of water.

Due to the increasing impact of water losses problem on the world, it has attracted the attention of many types of research in an attempt to finding (a) solution(s) on purpose of reducing losses of water amounts. In the past few years, considerable efforts have been made for the development of predictive models for better numerical and statistical systems for the better of forecasting losses of one of the main sources of people. Nonetheless, the development of these systems requires extra efforts of improvements to give more accurate results; as it will be shown and presented in this research. Interestingly, in the field of Artificial Intelligence (AI) especially Artificial Neural Networks (ANNs) has shown the great capability of producing predictive models with excellent prediction results in the area of water losses and water demand[4, 5], which will be applied on the data set collected from Beitunia city. Artificial Neural Networks has the ability to recognize patterns from historical data and used learning algorithms to produce an efficient result of time series prediction[6]. The main objective of this research is to use models of ANNs with efficient learning algorithms to predict water losses and water demand in Beitunia city. Producing efficient prediction result of the future will help the Beitunia city municipality to improve its services in this sector.

The data used in this thesis were gathered from Beitunia municipality and from JWU. The data are the quantities of water demands and water consumption related to the three regions of Beitunia city over the years 2005-2017. This data is composed of the input and the output attributes. The output variable is the target label, which represents real values of Water losses and consumption. The regions are, the Flash area, which is one of the largest areas of the city which supplies about 125 cubic meters per hour, the Sunuqrot region which supplies about 14 cubic meters per hour and the third connection region is the College which supplies about 11 cubic meters per hour. Then, we collected the water demands quantities, which JWU provided to the municipality and we calculated the water losses for the whole city and for the other three regions. After that, we arranged the data and divided it into three parts each part related to one region of Beituna city. The target data is normalized as a range of continuous data between [0 and 1] to fit neural network activation functions that will be used in the applied NNs algorithms in our work. ANNs used to predict water losses and demands. Our aim is to introduce a more efficient AI model that can be used to forecast the coming future water losses and demands.

In our research, by using ANNs models aiming at examining and selecting the best model with the accuracy that can deliver the best prediction depending on the threshold value resulted from the value of calculating the Mean Square Error (MSE), which is employed to reduce the error in prediction. Three different models of ANNs employed in the experiment phase of this research, which is Multilayer Perceptron Neural Networks Model (MLPNNs) with Levenberg–Marquardt

[7] learning algorithm, Radial Basis Function Neural Networks (RBFNNs) with pseudo-inverse learning algorithms [8] and Hybrid model using genetic algorithms (GAs) and MLPNNs [9], we have used the statistical model the Autoregressive Integrated Moving Average (ARIMA) [10] to compare with the accuracy of Neural Networks Models result. These learning algorithms will be used to predict the water losses and water demands with the goal of decreasing the MSE values as much as possible between the expected and actual results. Besides the statistical (ARIMA) model, three applied models will be employed for the goal of our study. We will build a predictive model based on short-term time series forecasting methods. Short-term prediction approach will be used to predicting the next future period. Time series methods will be used to reorganize data sequentially; sequential time slots, using the proceedings as a target to forecast next slots.

1.2 Thesis Objectives

Predicting water losses and water demand has special importance and presence to researchers and decision makers; because of the importance of its great impact on the large increase in financial revenues, in addition to playing a prominent role in the process of strategic planning. Because the methods used to predict water losses and water demand in Palestine are simple statistical methods, we aim to explore, investigate and introduce an AI model that could be more efficiently used in forecasting water losses and water demands in Palestine, and specifically for Beitunia city. Several Neural Networks models including their architectures and variations of associated learning rules have been studied in order to obtain a predicting model for water loss and water demands.

- We aim to compare the efficiency of the desired model against the current applied models using metrics such as error values and the number of neurons experienced in an attempt to find the best model with least error value.

- It is intended to determine a robust and reliable model that can be nationally generalized over the whole country; by providing solutions for water utilities and municipalities on the purpose of reducing water losses (NRW) and solve the problems of water demands.
- This work is primarily focused on the use of ANNs trained on historical water losses and water demands in order to perform the forecasting. This goal will be primarily achieved employing Learning algorithms on different Neural Networks models utilizing historical data of losses and demand.
- Most importantly, we aim to investigate and introduce such a model could help implement and deploy one of the important systems in the real local water utilities and municipalities. Moreover, such a system will be a more efficient replacement of the current classical statistical models.

1.3 Research Obstacles

Data collection is one of the key steps in building predictive models. As known this phase is vital and such studies extremely depend on data at the beginning of the study. One of the most important obstacles encountered during this research is the lack of data. In the first stage, when we collected the data, we found that there were many quantities of water demanded which the Beitunia Municipality bought it from Jerusalem Water Undertaking (JWU) was missing, therefore, we searched for that data in the archive of the water department in the municipality, so we found that some data are not available, especially data between 2005 and 2008 and that it is necessary to request it from JWU. At first, JWU refused to provide us with the missing data, and after requesting it once again they handed it to us in hard copy and in an unarranged form, which took a great amount of time and effort to arrange it.

The second phase, where we encountered a lack of data, was in the file of the water network infrastructure and pipelines. The file contains information about the water network in terms of pipeline life, length, and diameter, as well as the conditions of the pipelines. Table 1.1 shows this information collected and arranged for subsequent use. We worked with the department of engineering in the municipality of Beitunia on the ARCGIS in order to obtain the necessary data where it requires a great effort.

Table 1.1: Beitunia networks and Pips information

Area	Diameter	Material	Condition	Surface	Contractor	Year	Pipe Length
Flash	2	Steel	Bad	Concrete	Unknown	1985	85.7
Flash	2	Steel	Bad	Concrete	Unknown	1985	7.8
Flash	3	Coated Black Steel	Good	Asphalt	Al Amour	2004	249.8
Flash	2	Steel	Good	Asphalt	Mun.	2001	56.2
Flash	2	Steel	Good	Asphalt	Mun.	2001	36.8
Flash	3	Coated Black Steel	Good	Asphalt	Al Amour	2004	10.0
Flash	3	Coated Black Steel	Good	Asphalt	Al Amour	2004	184.6
Flash	3	Coated Black Steel	Good	Asphalt	Al Amour	2004	85.8
Flash	3	Coated Black Steel	Good	Asphalt	Al Amour	2004	13.3
Flash	3	Coated Black Steel	Good	Asphalt	Al Mahole/PICDAR	1998	62.3
Flash	2	Galvanized Polyethylene	Good	Asphalt	Al Amour	2004	40.8
Flash	3	Coated Black Steel	Good	Asphalt	Al Mahole/PICDAR	1998	292.8
Flash	3	Coated Black Steel	Good	Asphalt	Al Mahole/PICDAR	1998	120.7
Flash	3	Coated Black Steel	Good	Asphalt	Al Mahole/PICDAR	1998	148.1
Flash	3	Coated Black Steel	Good	Asphalt	Al Mahole/PICDAR	1998	220.6

The lack of data also was represented by the lack of information about water pressures and the lack of sufficient information about the pipeline’s leakages in terms of history and quantities of water that was lost due to these leakages. In addition to the inability to distribute the amounts of water losses and consumption data on the three areas of the city, which prevented us from implementing the most important multiple regression analysis (MRA) model, through which we can calculate the amount of water loss and find out what are the most important factors such as pipeline age, length, and condition ....) Which have the prominent role in water loss for each area of Beitunia city and that certainly has the greatest impact on the water demands process.

1.4 Contribution

This research performs applying different learning algorithms and a statistical model that offer predictive models that can be enabled to predict water losses and water demands depend on the historical data of Beitunia city. The prediction will be performed for water losses and water demand of the whole city and for the 3 independent regions in this city. The AI models will use the historical data to recognize patterns in the training phase and testing data to predict the future period of the water losses and water demand. In our experiment, the model will predict continuous data which requires to apply regression models through supervised learning. The first model is MLPNNs with Levenberg Marquardt as a learning algorithm, Radial Basis Function neural networks with pseudo-inverse to optimize weights, and its use constructs identical symmetric Gaussians around each data point for centers, the radius varies depends on centers. The third model is a hybrid model of MLPNNs with use Genetic Algorithms to optimize the weights. The result of applying these AI models in addition to the statistical model to predict water losses and water demands will allow selecting the best models for prediction.

1.5 Thesis Structure

This work is organized as follows, in chapter 2, we introduced the thesis background topics, we provided an introduction of the water in Palestine, and then we provide an introduction of Non-

Revenue Water, we provide the time series prediction concept. Then, we provide an introduction of ANNs and its types, then we presented the Radial basis function Neural Networks and newrb, and a hybrid model of MLPNNs and Genetic algorithm, also, we presented the Autoregressive Integrated Moving Average Model (ARIMA). And finally we show the related work of the several proposed approaches; we show numerous related works about water losses and water demand forecasting techniques using different learning methods. Chapter 3 explained the applied models starting with a description of Dataset contents, the preprocessing process, and data normalization. Chapter 4 described the experiment and result. Finally, conclusion and future works are presented in chapter 5.

CHAPTER TWO

BACKGROUND

2.1 Background

Water comprises nearly two-thirds of the Earth's surface, yet sadly, fresh water is limited in availability to humans. The focus is on freshwater resources as it is used for consumption, industrial and agricultural purposes. According to [11] Total fresh water available on earth constitutes only about 2.76 %, and less than 1% of this water can be accessed and used by humans. In the Arab world, water shortage is a major problem due to the rapid population growth, limited freshwater resources, and poor water management.

In 2011, approximately 75% of the Arab population suffered from water shortage, and nearly half of them were under extreme water scarcity level of 500 m^3 per capita per year, and this percentage is increasing significantly [12]. In order to predict water losses from water distribution networks, we must have a complete idea of the parts and structures of the networks. Water distribution networks are a wide range of water pipes with different sizes, which start from the main distributing meters which transport and distribute the water throughout the city and end with the points of consumption at houses, mosques, schools, industrial facilities, and others. Water loss or non-revenue water (NRW), has been a major challenge in managing water utility around the world and is even more challenging and dangerous in developing countries. In most developing countries, there are no resources to develop basic infrastructure to provide sufficient quality water to supply consumers continuously. This is aggravated by the lack of technical expertise and equipment to deal sufficiently with water loss in most water utilities, thereby reducing the availability of sufficient water for consumers [13].

water losses in most cities of developing countries are assuming alarming proportions of about 40% to 60% of the total water supply [14] and Beitunia city is no exception. The water supply system in Beitunia is beset with a number of problems. According to the water department of

Beitunia municipality, among these problems are; low coverage, high non-revenue water, high rate of cut-offs (some areas get supply twice a week) and intermittent water supply. There are also frequent pipelines bursts (as a result of the old pipelines, some laid as far back as1971s) and leakages which also affect the quality of the water supplied. It is therefore hoped that this research would contribute for an efficient, effective and practical way to deal with the problem and reduce the NRW

2.2 Water in Palestine

Palestine, similar to other countries of the region, suffers from a water crisis. The primary responsibility for this crisis is the Israeli occupation, its control over the water, denial of millions of Palestinian residents. Palestine is actually very rich in water resources; the West Bank has an exceptionally high rate of groundwater recharge and a low rate of runoff. This means that it has a good reservoir of groundwater, but Israeli violations of the human right to water prevent Palestinians from getting access to clean water, affecting the daily lives of Palestinians as well as the long-term prospects of their viability [15].

According to International and regional standards, Palestinians have less access to freshwater resources. The West Bank is the lowest in terms of access to water. For example, the average West Bank uses about 70 liters per day [1]. In some rural areas, the amounts are 20 liters per day, which is far below the 100 liters per day recommended by the World Health Organization (WHO) [1]. The United Nations has repeatedly found that Israel violates the human right to water, but Israeli violations are increasing. Israel controls access to Palestinian water, restricts the delivered amount which does not meet the needs of life; It controls 90% of the water resources and sets procedures and obstacles for Palestinians to take advantage of the remaining quantity, by controlling the resources of Water and land, restrictions on the movement of people and goods, besides the complex system of obtaining permits approval from Joint Water Committee (JWC),From the Israeli army and other authorities, before the implementation of water projects in the territory of the Palestinian State; Which leads to delays in the implementation of water, as well as policies of the demolition of Palestinian water installations, such as: artesian wells, and rainwater harvesting wells in areas B and C [15].

Municipalities and other water utilities continue to provide water services in the West Bank, the largest and oldest multi-municipal utility in the West Bank is the Jerusalem Water Undertaking (JWU) in the Ramallah and Al Bireh area. JWU was established in 1966 when the West Bank was still part of Jordan, serving the two cities, as well as 10 smaller cities, more than 43 villages, and 5 refugee camps [16]. The second small multi-municipality is the Water Supply and Sewage Authority (WSSA) Serving Bethlehem and neighboring towns of Beit Jala and Beit Sahour.[17] In other cities such as Tulkarm, Qalqiliya, Nablus, Jenin, Jericho, and Hebron, as well as in small towns, municipalities provide water and sewage services. Both utilities and municipalities rely to varying degrees on bulk water supplies by the Israeli water company Mekorot, which provides about 80 percent of the water used by the JWU [17]. In rural areas, water is provided by the water utilities of the village council. In the northeastern Jenin area, water is provided to the Joint Service Council (JSC), which is formed by six villages [18].

Gaza Strip In all 25 municipalities in the Gaza Strip, water supply responsibilities are assigned to Coastal Municipalities Water Utility (CMWU. However, the utility is still in the process of being established and exercising its legal functions. The intention is for municipalities to receive technical assistance from the CMWU and to gradually transfer its staff and assets to it. According to the World Bank, this model has led to improvements such as faster leakage repair and economies of scale. However, the plan is far from fully implemented. This model has faced serious problems, mainly due to unstable political conditions in the Gaza Strip since 2008, including differences between municipalities controlled by Hamas and Fatah, with some municipalities refusing to transfer assets and employees to CMWU [18].

2.3 Water Losses Problem

Increased population growth and urbanization with inadequate water resources availability and frequent droughts have made drinking water as a scarce resource that managers of water networks have to provide water qualitatively and quantitative. The problem of water loss from water distribution networks is one of the most serious problems leading to water shortage in Palestine. Some studies showed that the rates of water loss resulting from it are higher than 30% [19], while other studies argued that in some Palestinian areas this percentage reaches up to 50% [2, 3]. According to Water Sector Regulatory Council (WSRC) in the West Bank as shown in the Table 2.1, over the past three years, Tulkarm and Jenin still hold the highest rates of NRW (50% and 49% consecutively), which reflects the weak efforts exerted towards improving the service, compounded by the mismanagement of available resources and its impact on the sector especially in light of limited available resources. In Qabatiya and Al ‘Auja the rate of NRW in 2016 increased to reach 49% and 45% consecutively, while the areas of South East Nablus, North West Jenin, Dura, and Salfit recorded the lowest rates of NRW: 11%, 11%, 15%, and 15% consecutively Service providers who registered a marked improvement in the rate of NRW is Deir al Ghusun municipality which was reduced to 27% after it was 44% in 2015, after the municipality replaced a large number of old meters with new ones, and rehabilitated some of the main lines.

Table 2.1: Percentage of Non-Revenue Water – West Bank

#	**NRW (0%-21%)**	**NRW (21%-30%)**	**NRW (30%-37%)**	**NRW (37%-50%)**
1	Halhul	**Beitunia**	Nablus	Jenin
2	Ya’bad	AlFar’a	Tubas	Qabatiya
3	Illar	Attil	Hebron	Tulkarem
4	Azzun	Yatta	Tuq’u	Anaba
5	Salfeet	Arraba	Al Sawahreh sl sharqia	Al’Auja
6	Kafr Ra’i	Qalqelya		Al Ezareya
7	Dura	Bedia		Beit Ummar
8	Jerico	Maythalon		
9	Sa’er	Abu Dies		
10	Tarqumia	Za’tara		
11	Northwest Jenin	Deir Al Ghuson		
12	Southwest Nablus			
13	Southwest Jerusalem			
14	Bani Na’em			

Tubas and Mythaloun still need to follow up despite the fact that the rates of NRW still remain within the average, however reading the indicator for the last 3 years shows an increase which should urge the service provider to find out the causes of NRW and control it [20]. The high rates of water loss are due to illegal pipes connections, pipelines bursts, the depletion of network piping systems and poor functioning utilities. In particular, in the Gaza Strip, illegal pipe connections cause heavy losses. Water shortages and insufficient supplies are the main reason for the illegal use of water. In addition, the conditions of the water supply utilities suffer from serious shortcomings that cause high dropout rates and weak water pulse in the system, due to the institutional weakness and In addition to many restrictions by the occupation on the development of the water sector in the west bank and Gaza blockade [21].

2.4 Target Area: Beitunia City

Beitunia, is a Palestinian City located in the center of the West Bank - Palestine, together with the neighboring city of Ramallah which is form one of the largest residential, commercial and industrial centers in Palestine, Beitunia city is located 3km South West the Ramallah city, and about 15 km North of Jerusalem. It is situated in the central high lands in the West Bank, on the western slaps of the middle mountains and overlooks the meditation coast. It represents an attractive residential center from all the West Bank as a result of the encouraging policy of the Municipality of Beitunia to attract the investments, in addition, the availability of the Palestinian Authority main Headquarters, and the ministries within the two neighboring Ramallah and Al-Beireh According to the Palestinian Central Bureau of Statistics, the City had a population of 36,000 in 2017, making it the third largest locality in its governorate after al-Bireh and Ramallah [22].

The daily water supply per person according to Beitunia municipality is 62 L, and the water supply area is divided into three districts. The city has 1 reservoir. The total length of the network is 57 km. DMAs were built in Beitunia that divide all water supply districts into separate ones. The DMA system of Beitunia consists of three DMAs or three main connection points which are Flash, Sunugrot, and college. JWU provides Beitunia municipality with water through these connection points. As the Israeli side has reduced the proportion of water supplied to the Palestinian side, Beitunia suffers from water scarcity, where the municipality has a great responsibility in securing sufficient quantities for its citizens; Figure 2.1 shows the study area.

2.5 Water Resources

According to Municipally records, four springs are located in Beitunia, but only one of these is being used for the purpose of vegetable cultivation with a daily average-0pumping rate of 20 cubic meters, while the three other springs are not being used due to their location within area C.

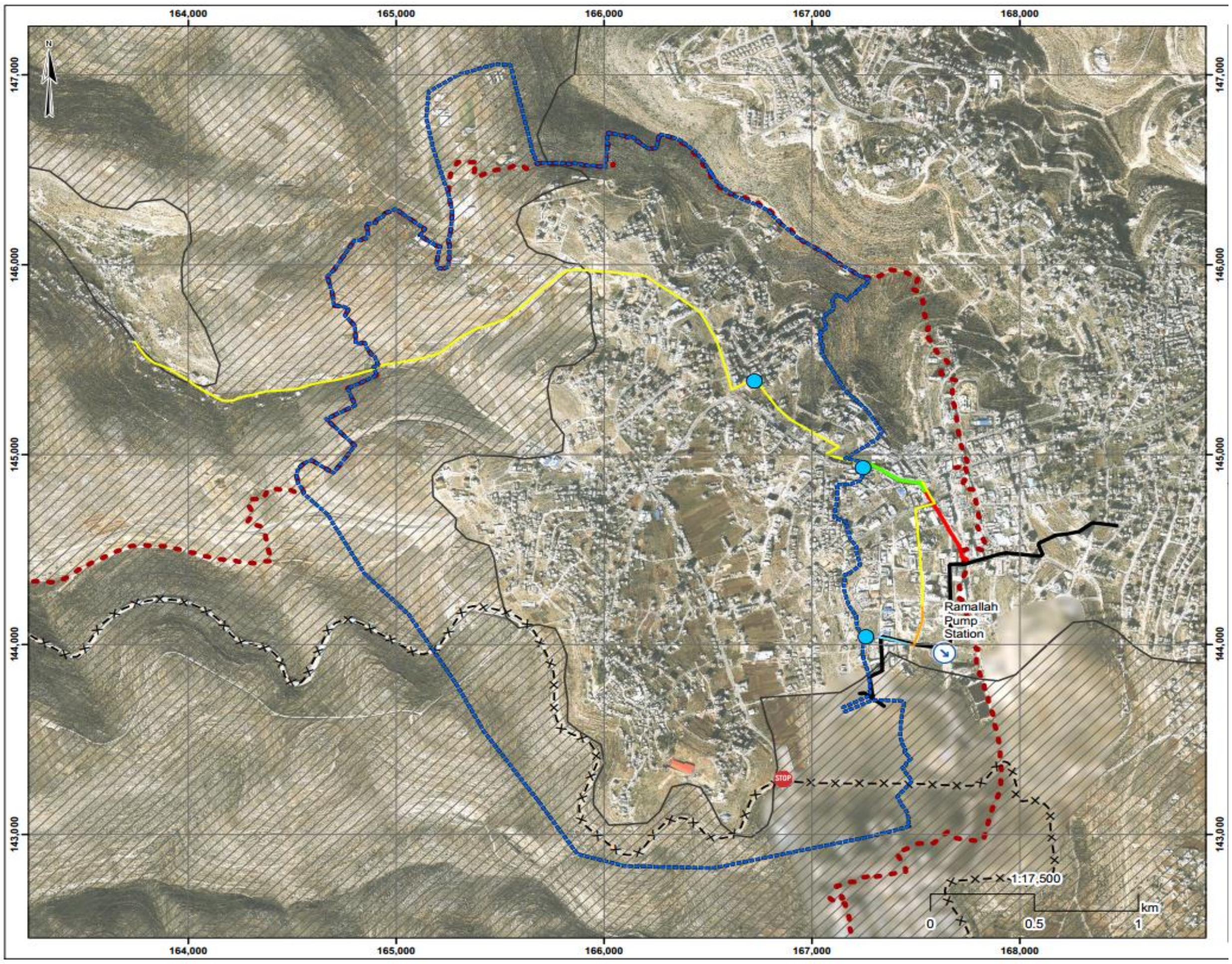


Figure 2.1: The study area.

2.6 Non-Revenue Water

According to [23] Non-Revenue Water (NRW) can be described as “the difference between the volume of water put into a water distribution system and the volume that is billed to customers”. Loss of water is inevitable in any water distribution system; however, water losses should be reduced to the lowest economic levels especially if water utilities are to operate sustainably. NRW can be divided into several categories, leakage or technical losses, illegal communications, unbilled water, weak performance meters, inaccurate waters reading. Non-payment of bills cannot be considered NRW, but they are included in the strategies of reducing the losses because increase billing process reduces NRW [23]. The World Bank recommends that NRW have to be less than 25% [23]. Palestine's target is 20%. A high percentage of NRW has a negative impact on the financial capabilities of water utilities, in addition to the significant impact on water quality service. American Water Works Association (AWWA) recommends that physical and apparent losses and the annual cost impacts of these losses must be tracked by water utilities.

Increasing the financial revenues of the water sector, which is suffering from financial difficulties and increasing the access to scarce resources, are the objectives and advantages of the process of reducing NRW, which increase and improve the efficiency of services provided to customers. The existence of many illegal connections prohibits people who are committed to paying for from getting enough quantities of water, in addition, to pay for the water that is stolen, which is unfair.

2.6.1 Components of Non-Revenue Water

Water losses should be reduced to the lowest economic levels if water utilities are to operate sustainably. In the early '90s in the distribution system, there was no normative term for the expression and evaluation of water losses. "International Water Association" (IWA) identified this problem and created its WLTF Working Groups. The Commission examined best international practices and developed standardized terminology for NRW. IWA identified this problem and created the water loss task force (WLTF) which explored the best practices and formulated standardized terminology for NRW[24].

2.6.1.1 Physical Losses

Physical losses, which is called real losses, are water extracted from natural resources then it is processed to be used in the distribution system, but customers never consumed this amount of water. Water losses occur in all distribution networks old and new ones, the distribution systems of the water in the developed countries are very old and they are built decennia ago. The systems are presently degraded because of their age. Mostly the system is indeed leaking water before water utilities start with the rehabilitation or replace the current system [25] .The following are the components of Physical losses**:**

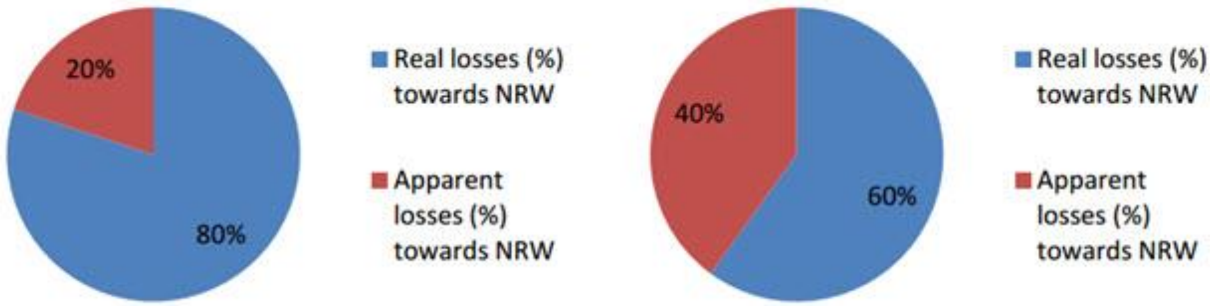
- Leakage of transmission and distribution pipes
- Leakage and flooding from utility tanks and storage tanks
- Leak on the service connections up to the customer's meter

2.6.1.2 Apparent Losses

Apparent losses or commercial losses are those found in metering data, whether through under-reading meters, billing inaccuracies (mishandling or processing billing data) or illicit bypasses of meters, as water is delivered and consumed by customers, but is not paid for. Apparent losses are the most expensive losses within the water system, as they directly tie to sales revenue. The apparent losses can be greater compared to real losses, and often have greater value, because reducing commercial losses increases revenue, while real losses reduce the costs of production[26]. The component of the apparent loss in developing countries is nearly as high as the physical losses component, it is about 40% of the total water losses (NRW) [23]. This can be clarified by the corporation and management causes, such as fraudulent activities and rottenness [25]. The ratios of physical losses and apparent losses in developing and developed countries are illustrated in Figure 2.2

2.6.1.3 Unbilled Authorized Consumption

Unbilled authorized consumption includes water used by a utility for operational purposes, that used in firefighting, and that provided free to certain consumer groups such that mosques, public garden, and schools. The unbilled authorized consumption should be a small part of the water equilibrium, it's valued less than 1% of the system input volume.



NRW in developed countries NRW in developing countries

Figure 2.2: Physical losses and Apparent losses ratios in developing and developed countries [27].

The first time the unbilled authorized consumption is measured, the value can be unduly high. As long as a utility does not compute the unbilled authorized consumption, the consumption cannot be administered to result in surpassing the normal part of less than 1% of the system input volume. Water utilities must be able to manage he unbilled authorized consumption and decrease it to the normal ratio by using appropriate measurements [28].

2.6.1.4 Non-Revenue Water in the World

The global volume of non-revenue water (NRW) is staggering. Each year more than 32 billion m^3 of treated water are lost through leakage from distribution networks. The global NRW percentage is around 35%, there is a volume of 32 billion m^3 of real loss water and an additional volume of 16 billion m^3 of apparent loss water every year. The costs for these losses are estimated at the US $14 billion per year [29], while [23] has estimated the costs of water loss at approximately US $141 billion per year. Even though these values do not correspond with each other, it can be concluded that action is needed to diminish the water and money loss. Figure 2.3 shows the NRW (%) values for several countries and cities [30].

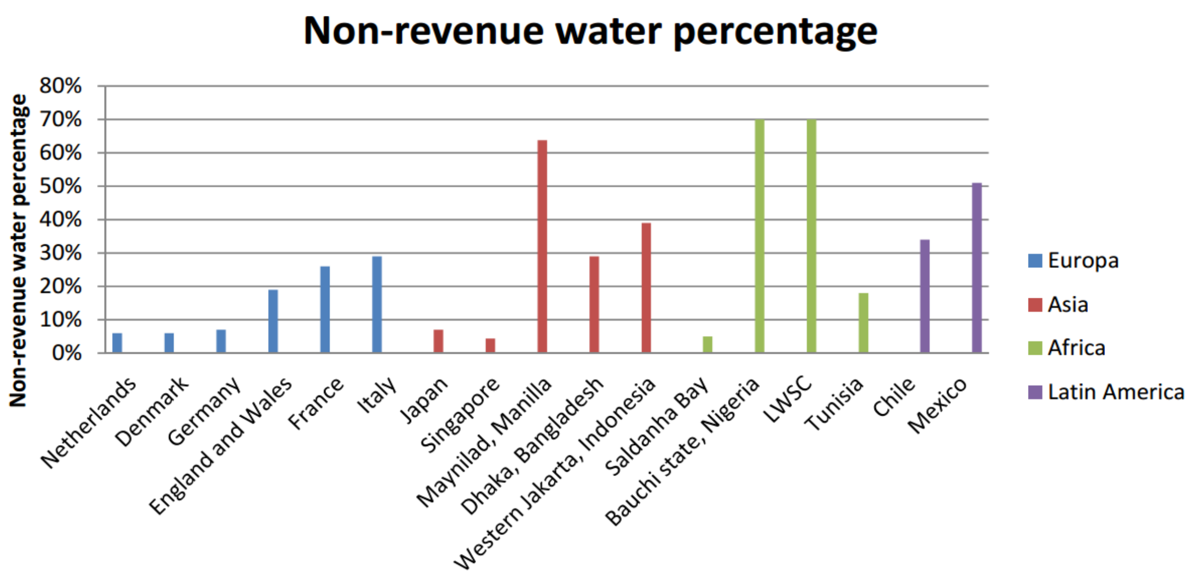


Figure 2.3: Non-revenue water percentages over the world [30].

2.7 Datasets Description

The existence of water-related data is very important for use in the consumption and water loss forecasting process, as these data are arranged in usable time. Water service utilities seek to predict water demands and water losses through clear policies to promote and develop sustainable services for customers. The data used in this thesis were collected from Beitunia municipal records and databases and from JWU. The data are the quantities of water supplied by JWU and the consumption data that the municipality sold to the customers.

As we mentioned before, Beitunia city was divided into three regions, the data of each region was processed separately. Initially, we collected the quantities of consumption in Excel tables containing columns; each column represents the consumption in cubic meters for a water cycle of two months (60 days). Quantities of consumption were distributed over the years from 2005 to 2017, and the process of compilation and arrangement of this data was a difficult process that took a lot of effort and time. Table 2.2 contains the consumption amounts of water for the whole city.

We have collected the quantities of consumption in the same way for the Flash area and the Sunuqrot area as well as the College area.

Table 2.2: Water consumptions quantities for the whole city in m^3

Year	(Period 1) Months 1+2	(Period 2) Months 3+4	(Period 3) Months 5+6	(Period 4) Months 7+8	(Period 5) Months 9+10	(Period 6) Months 11+12
2005	59016	68649	80430	87237	83043	69072
2006	62745	72336	82057	99141	90592	67089
2007	71635	79149	93550	99470	98510	84833
2008	74553	91374	100262	99120	100719	93288
2009	83866	85515	107531	106853	96738	100256
2010	88429	103411	111473	118665	112152	108182
2011	95662	102436	116940	123073	129248	104028
2012	100933	105153	124432	137532	135362	99975
2013	101712	115391	119785	136460	128274	121072
2014	109571	118272	110611	138020	130963	111666
2015	125082	114718	130116	136009	134556	128647
2016	129618	143524	147458	132133	142218	130177
2017	134506	138960	142031	131873	140381	130031

The second phase consisted of collecting the water demands that the municipality purchased from JWU, in Beitunia city there are three main meters. Each meter feeds (serving) a certain area of the city. The Flash meter supplies Flash area with an estimated capacity of 125 cubic meters per hour, and Sunuqrot meter supplies the area of Sunuqrot with an estimated capacity of 14 cubic meters per hour, and the last meter is the College meter, which meter supplies College area with an estimated capacity of 11 cubic meters per hour.

Table 2.3, shows water quantities purchased from JWU for the whole city, the data was collected and distributed over the years 2005-2017 and divided into 6 water cycles in order to facilitate the calculation of losses. We have taken this step to find the water losses for all three areas of Beitunia.

Table 2.3: Water quantities purchased from Jerusalem Water Undertaking for the whole city in m^3

Year	(Period 1) Months 1+2	(Period 2) Months 3+4	(Period 3) Months 5+6	(Period 4) Months 7+8	(Period 5) Months 9+10	(Period 6) Months 11+12
2005	77440	116930	114120	135960	103180	114350
2006	115280	129600	120000	177050	154560	109830
2007	117590	127040	135151	160090	121241	111993
2008	96907	135987	155287	130992	141562	155998
2009	127360	131570	173874	124133	159484	133538
2010	169428	117108	134450	131124	125843	139085
2011	129591	121986	135107	136409	205401	148233
2012	183390	118953	183003	163883	168066	148140
2013	166747	145797	155718	173559	186824	141923
2014	140305	166634	167383	165935	185028	157353
2015	174980	148500	161255	180949	162299	165175
2016	167237	173527	180029	178588	197524	186358
2017	181611	180617	180749	164459	188976	174449

In the third phase, we calculated the water losses of the city for the three areas, since the difference between the quantities of water purchased and the quantities of water pumped into the network is considered as water loss (NRW). Table 2.4 represents the amounts of losses in Beitunia city for the years 2005-2017.

Figure 2.4 shows the ratio of water losses to the three areas of the city in cubic meters until 2017, calculated by using the data from Excel tables that were arranged in such a way that it is easy to carry out these calculations. It is important to mention that these steps are an important introduction to data processing for use in the models of this research (Neural Network models and ARIMA statistical model).

As it is illustrated in figure 2.4, the Flash area is the most area of water loss since it is the largest areas in the city, followed by the College area where the loss of water is much less than the Flash

2. 4: Water losses quantities (NRW) for the whole city in m^3

Year	**(Period 1) Months 1+2**	**(Period 2) Months 3+4**	**(Period 3) Months 5+6**	**(Period 4) Months 7+8**	**(Period 5) Months 9+10**	**(Period 6) Months 11+12**
2005	18424	48281	33690	48723	20137	45278
2006	52535	57264	37943	77909	63968	42741
2007	45955	47891	41601	60620	22731	27160
2008	22354	44613	55025	31872	40843	62710
2009	43494	46055	66343	17280	62746	33282
2010	80999	13697	22977	12459	13691	30903
2011	33929	19550	18167	13336	76153	44205
2012	82457	13800	58571	26351	32704	48165
2013	65035	30406	35933	37099	58550	20851
2014	30734	48362	56772	27915	54065	45687
2015	49898	33782	31139	44940	27743	36528
2016	37619	30003	32571	46455	55306	56181
2017	47105	41657	38718	32586	48595	44418

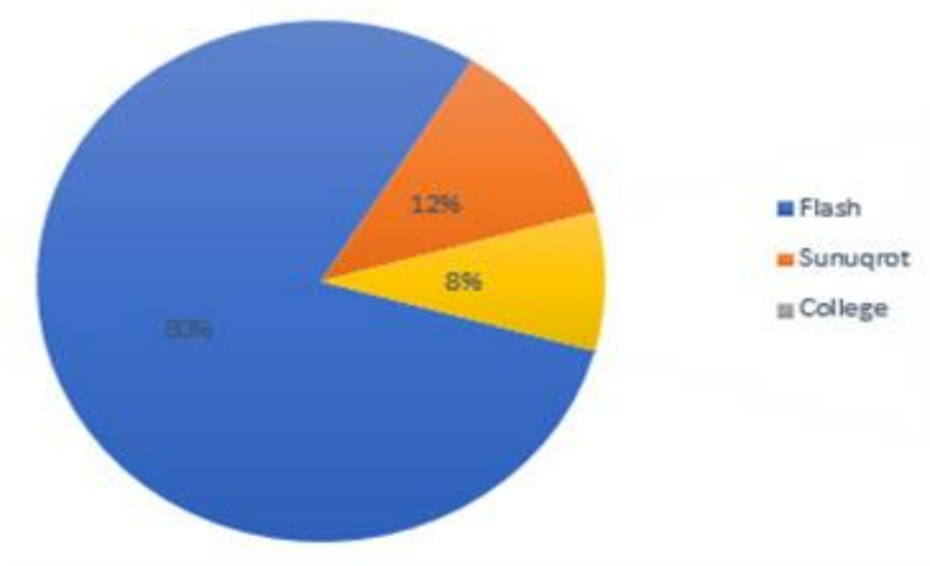


Figure 2.4: : Ratios of water losses (NRW) for Beitunia regions

area. In terms of water losses, College is close to the Sunuqrot area, which lost 8% of water since 2017.

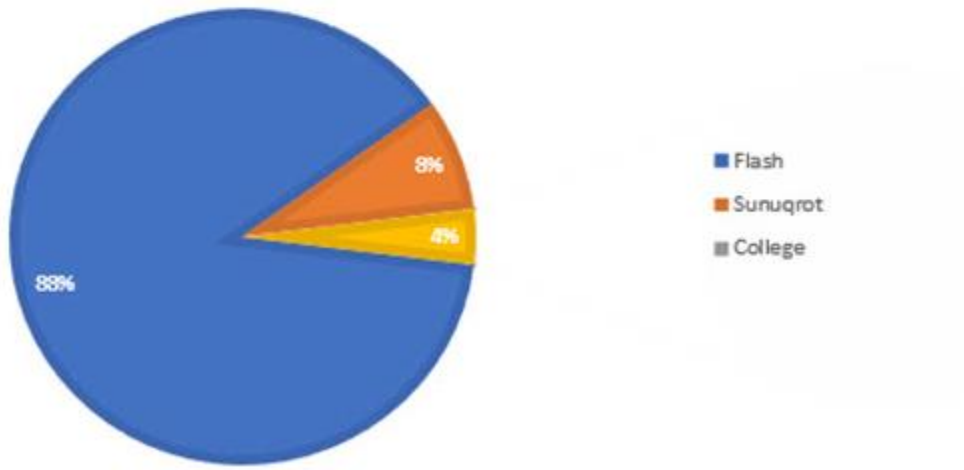


Figure 2.5: Ratios of water consumption for Beitunia regions

The consumption ratio for the three regions of the city until 2017 was shown in Figure 2.5, which also shows that the largest consumption was for the main meter (Flash region), which supplies the largest area in the city, in Flash area, water consumption was 80% of the total consumption of all other regions. Note that the percentage of consumption in the College area is small compared to other regions.

2.8 Time Series Prediction

Time series modeling and prediction is of fundamental importance to various practical fields such as water prediction, physical science, daily temperature, control systems, engineering processes, bioengineering, and environmental systems. Therefore, many active research works have been going on in this subject for several years. Usually, researchers collect data in the time series form where issues such as description, data elements like periodicity and trend are very considerable. To improve the efficiency and accuracy of time series forecasting important models have been proposed in the literature. ANNs and other learning methods are able to predict future values by understanding and learning from how the data are originated and how it is changing over time [31].

Time series is considered as one of the most valuable applications to learn prediction models. The main role of prediction is to extract the associated information related to time series data and utilize that to estimate future values, where the associated information contained in a time series data are typically based on trends and periodicity [32]. Simply, the predicted value x(t+1) (next value) is assumed to be related to the current value x(t). The conclusion in such a situation is that the estimated $x(t+1)$ matches $x(t)$ as in the following equation 2.1:

$$x(t+1) = x(t) \qquad 2.1$$

For time series forecasting, this equation is useful because for majority actual environmental situations it can provide very good predictions. Therefore, this method is considered to be as a benchmarking method for which results achieved by other methods should be compared with the results of this method. This next time step for which the value x(t+1) needed to be predicted may be very far from the current time step *x(t).* Moreover, the more multiple time steps predictions the more complicated than single time step prediction [33].

Estimating x(t+2) can be achieved in two scenarios: one is predicting x (t + 2) directly from x (tm) ... x (t) where the predicted value is comparable to predicted x (t + 1). Nevertheless, in this situation, estimation of *x*(t + 2) takes in consideration estimation-error occurred in predicting x (t + 1). The little slips in this step-by-step based forecasting method are weak, therefore it is considered to be a vulnerable prediction scenario. The other more advisable scenario is the direct approximation of x (t + 2) [33] based on x(t), however, it is also sensible to consider more previous time steps such as x(t-1) and x(t-2) beside considering x (t) in the approximation of x(t+2) point, figure 2.6 depicts this situation.

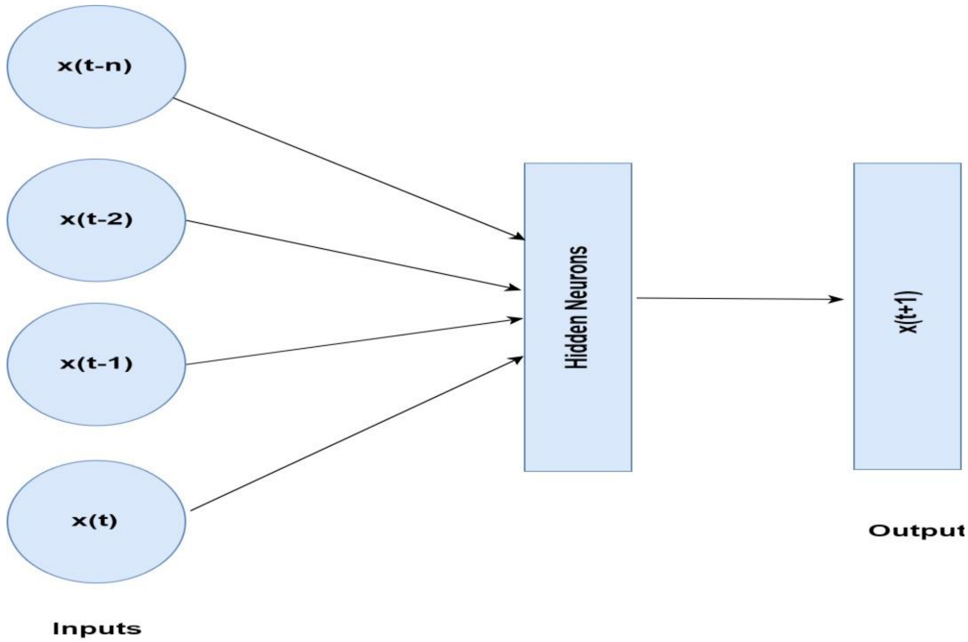


Figure 2.6: General time series prediction using ANNs

The tendency in the dataset applied in this thesis is an upward and downward tendency, therefore, the process of discovering the non-linear dependencies in order is basically automated by using the NN model. The overall goal is setting up the prediction models in order to make predictions and estimate ahead elements based on the past time series.

An advantage of such time series data is that it is known experimentally and in some other circumstances that the data is coming from a time series. Wherever the measured values are based and depend on another variable is considered similar to a time series situation. In such cases, the allocation of the data will bring nothing even it been taken into consideration, although plotting data against the index will not clarify the dependency of the data. Discovering the variable (or variables) that basis the dependency can be found through sometimes only by trial and error, wherein artificial neural networks this is evolved and guided during the learning phase by guesswork and experience through learning rate, weights, and weights re-adjustment [33].

2.9 Autoregressive Integrated Moving Average Model (ARIMA)

ARIMA is a model for statistical analysis of time series to predict future data. This model does not take the form of one equation or parallel equation models, but the emphasis on the analysis of the probability or random properties of the time series itself. The parameters of the ARIMA models are typically approximated by the method of least squares or the maximum likelihood approximation method. However, the ordinary least squares method requires imposing, strict assumptions on the model specifications during the approximation of the parameters to realize meaningful results and therefore it is ineffective to use with complex or nonlinear models.

ARIMA model is based on the famous Box-Jenkins principle [34, 35], generally, ARIMA called Box and Jenkins models or shortly Box-Jenkins model. There are two linear models that are largely used in time series, autoregressive (AR) and moving average (MA) [34, 35] models. By bringing these two models together, another model was proposed, called the ARMA. In ARIMA models, a non-stationary time series is performed by applying a restricted difference of data points. The mathematical formulation of ARIMA(p,d,q) model using lag polynomials [35] is given below in equation 2.2:

$$\emptyset(\mathrm{L})(1-\mathrm{L})^{\mathrm{d}}\,\mathrm{y}_{\mathrm{t}}=\theta(\mathrm{L})\varepsilon_{\mathrm{t}}$$

$$\left(1-\sum_{i=1}^{p}\emptyset_{i}L^{i}\right)(1-L)^{d}\;y_{t=}\left(1+\sum_{j=1}^{q}\theta_{j}L^{j}\right)\varepsilon_{t} \qquad 2.2$$

The value of the integers q, d and p are greater than or equal to 0. In 2.2 equation to refer to the order of the I, AR, and MA of the average model respectively. In the differencing process, we use “d” to control the level. So its value 1 or 0, when d=1 this is mostly enough the model is ARMA(p,d,q). When the value of d =0, then the model is ARMA(p,q).

Specifying (p,d,q) is the first step in estimating the ARIMA model, where p or AR refers to a number of automatic conditions, q or MA indicates a number of moving and intermediate terms and d indicates the number of times that the string must be different to motivate the stationery.

a useful generalization of the ARIMA models is an autoregressive model of the Fractionally Integrated Moving Average (ARFIMA), which allows the noninteger of the different parameter *d*. ARFIMA has a useful application in a modeling time series with long memory [36]. In this model, the expansion of the term $(1- L)^d$ is to be done using the theory of “general binomial”. The researchers have contributed towards estimating general ARFIMA parameters. The final model is used to produce forecasts about future values and hence calculate the forecasting errors and developments of the new values of the time series and to control these errors.

2.10 Artificial Neural Networks

Artificial neural network (ANNs) is a network of units that are interconnected to each other. The study of neurobiological systems inspired the development and of this type of artificial networks. The concept on which artificial neural networks based is the simulation of the model to access data of these units in order for classification, prediction, analyzing or any other treatment of input data, Therefore, scientists and researchers have been attracted and interest in the study and application of ANNs in different disciplines.

The first appearance of Neural Networks (NNs) was in the sixties of the last century as a model of human brain functionality. This model is depending on learning of a series of mathematical structures (known as neurons) that are arranged and interconnected in a particular way in order to solve sophisticated problems. The way in which these neurons are organized varies from simple to a more complex structure to finally form what is known as a neural network. Neural networks have shown the capability of solving problems in a wide range of research and applications fields such as engineering, math, function approximation, communications, and water predictions. In the field of water prediction, it has tried for many years, to learn how future events could be predicted so that preventive actions could be taken to avoid losses of water resources [37]. ANNs can be introduced in two learning methods: supervised and unsupervised. The supervised ANNs, on one hand, depending on the availability and comparability of ANNs output to the desired output. In this type of ANNs, the final output is found by processing input data through the series of neurons using special activation functions and weights, the outputs of these activation functions are finally summed linearly to achieve the final output. By comparing ANNs output to the desired output (which is known as a label) and finding the error, the weights used by neurons are updated iteratively to decrease the error rate of approximation. A training network as shown in Figure 2.7, consists mainly of three parts which are the input, hidden neurons, and output layers. A neuron is found in the hidden layer, where these neurons can be defined as elements with a state which is changed internally depending on the received signals based on a transition function (activation function) included in neurons. The activation function allows neurons to control the received signals from neurons, whether to be connected or disconnected from the outside [38].

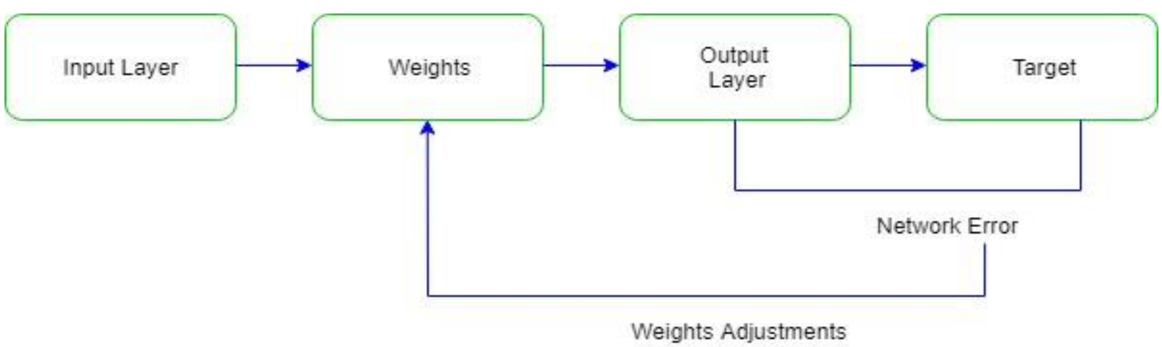


Figure 2.7: Feedforward backpropagation technique

Contrary, unsupervised learning lack of such guidance while the learning process. Where in this type of learning the comparability of generated output from the neural network to the target or desired output is missing. The learning process in such guidance fewer environments usually depends on the input data items and the commonly shared feature [37]. Figure 2.8 demonstrates the general structure of neural networks.

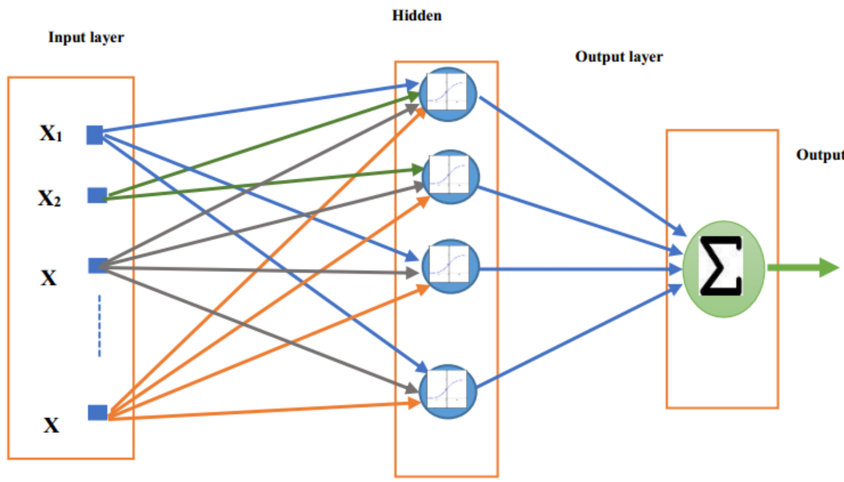


Figure 2.8: General Structure of an Artificial Neural Network

The neurons contained by the hidden layer determine the action to be made to the input data received from the input layer, the weights of these neurons which are developed by the learning process play the major role of the decision [39]. later, the data might be transferred to the output layer by applying the activation functions included in the neurons [40].

Many proprieties of the neural networks can be summarized from the literature; Among of these properties is their capability of carrying out adaptive learning and the capability of performing tasks via training [41]. They are self-organizing which implies that the system is composed and altered so as to complete a particular goal. Moreover, neural networks can carry out its processes in tangible time, because of the parallel implementation, the concurrent execution of tasks is achievable, therefore saving the time of training and testing [42]. The data vector *X* is the data that every neuron gets to process. Every input data has a related estimation of weight *W*. This esteem is a factor of significance since it updates itself within the training of the neural network with the goal that it shows signs of improvement conduct. The output of the NN $f(x)$ as shown in equation 2.3 is determined by utilizing the accompanying general equation, which is utilized in most of the supervised kinds of NNs [43].

$$y_{output} = f(\sum_{j=1}^{m}(Xj.Wj + bj)) \qquad 2.3$$

Where *m* is the number of inputs, *Wj* is the related weights vector, and *Xj* is the input vector and b_j is the bias. The stimulation function *f* known also by activation function- is performed at each neuron in order to generate a non-linear output [43]. There are many types of activation function that are widely utilized by perceptron NNs including the step, identity, and logistic functions. The most common mathematical formula represents this function is shown in equation 2.4 [44]:

$$f(x) = \frac{1}{1+e^{-x}} \qquad 2.4$$

Generally, the network consists of an input layer, hidden layers, and an output layer, as previously shown in Figure 2.8. In the input layer, the network receives the data vectors for processing, usually, the neurons in the input layer do not do any processing to the input data except forwarding of the data through the connections to the next layer which is first hidden layer. The number of hidden layers varies among NNs, the more hidden layers the more complicated NNs, a hidden layer is defined as the group of neurons, and these neurons are not directly connected to a previous layer and a next layer. In normal cases, a neuron in a layer has incoming connections from all neurons in the previous layer and outgoing connections to all neurons in the next layer without forming any type of loop [45]. Each neuron has one of the activations as described in equation 2.4. To make the representation of NNs in figure 2.8 simple, the neuron and its transfer function are usually drawn together. Usually, the activations function is used as the multilayer perceptron transfer function for hidden layers while the output layer uses the linear transfer function.

The general objective of using ANNs in this thesis is to utilize various types of artificial neural network (ANNs) and different forms of learning algorithms to produce a computational Intelligence model capable to predict the non-revenue water [NRW] and the actual water demands. Which aims to help water utilities to increase income and reduce losses in order to reach sustainable services. In literature, different types of ANNs were invented to be utilized by many applications and for the aim of optimizing the solutions (training algorithms), the following sections explains more about the most common types of NNs including the single layer perceptron NNs, the multi-layer perceptron NNs, and the radial basis functions NNs, where usually the problem under consideration plays a major role in the determination of the suitable type to be utilized.

2.10.1 Single Layer Neural Networks (SLNNs)

This type of NN consists of one hidden layer of neurons. Although the hidden layer may contain one or more neurons (multi-neurons). As described earlier, the received input vector X is represented at the input layer by ($x_1, x_2,.. x_m$) input nodes, each of these nodes is connected to neurons ($n_1, n_2, \dots, n_m$) in the hidden layer. The vector of weights ($w_{11}, w_{12}, \dots, w_{1m}$) represents the weights that x_1 will be multiplied by before transferred to the corresponding neuron in the hidden layer, and so on. At the neuron in the hidden layer, the activation function is applied to determine the output of that neuron [32], figure 2.9 shows the architecture of SLNNs.

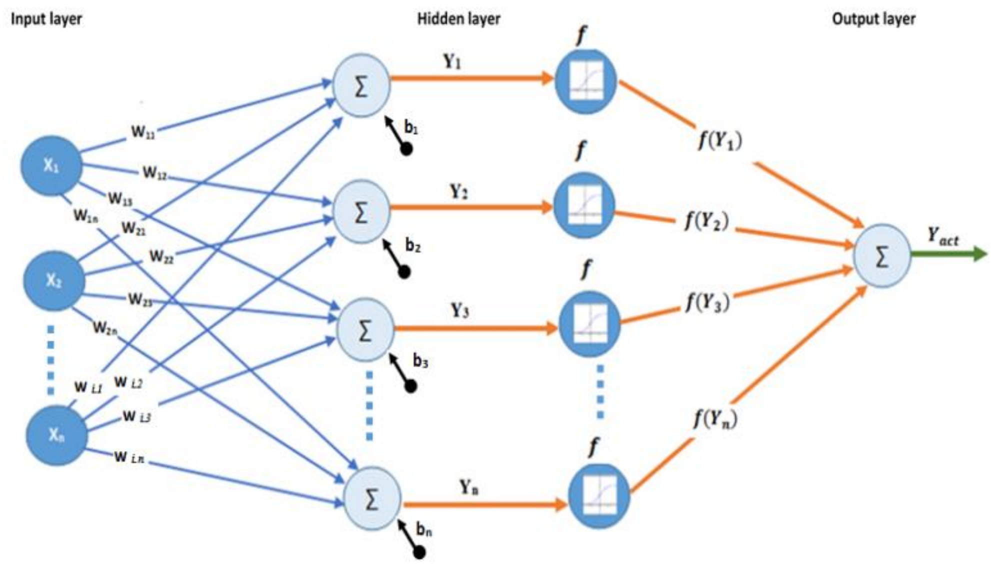


Figure 2.9: Single layer neural network (SLNNs).

2.10.2 Multi-layer Perceptron Neural Networks (MLPNNs)

To take care of complex issues that SLNNs were not able to handle such a complex problem, in this manner, we need progressively intricate and powerful NNs structure which composed of many hidden layers to change non-linear distinguishable problems into different areas where they became linear separable, the multilayer perceptron NNs, as shown in figure 2.10, includes an output and an input layer, in addition to more than one hidden layer. Usually, this ANNs structure is utilized for solving nonlinear systems.

As in the SLNNs, the input nodes of the input layer are fully or partially connected to the neurons in the first hidden layer with their associated weights. The outputs of neurons in one hidden layer ($a_1, a_2, \ldots a_m$) are considered as the inputs of the next hidden layer and it has its particular weights. The outputs of the last hidden layer are connected to a single neuron in the output layer.

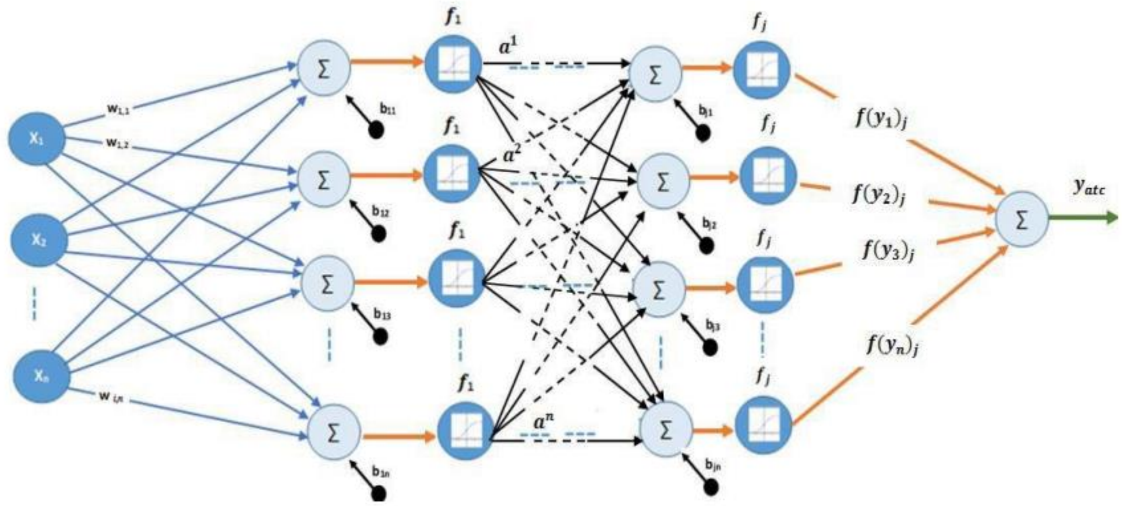


Figure 2.10: Multi-layer Perceptron NNs

In MLPNNs the sigmoid activation function is mostly used [46]. As the sigmoid function is applied, the following equations 2.5, 2.6 and 2.7 are used to find the vector of outputs of one hidden layer to be fed to the next layer, the equations show the calculation on the output of layer one to be used as inputs to layer two.

$$a^1 = f^1\left(\sum_{j=1}^{m} x_j . w^{j,1} + b^1\right) \tag{2.5}$$

$$a^2 = f^2\left(\sum_{j=1}^{m} x_j . w^{j,2} + b^2\right) \tag{2.6}$$

$$a^n = f^n\left(\sum_{j=1}^{m} x_j . w^{j,n} + b^n\right) \tag{2.7}$$

Where W is the matrix of weight, X represents the inputs, b is the bias vector, and the output vector of a layer is a. The error will be calculated between the output and target value and the weight will be updated during the learning phase to minimize the output cost function, which may be calculated using different methods. In this thesis, the Sum of Square Error (SSE) method is used[47], as illustrated in equation 2.8:

$$E_{sse} = \frac{1}{2}\sum_{i=1}^{m}\sum(Y_i - Y_i')^2 \qquad 2.8$$

Where Y is the real value, Y' is the output or the predicted value, and "m" is the number of inputs.

To complete the weights updating process, the gradient descent algorithm is usually employed where it is computed based on the following equation 2.9:

$$\Delta w_{jk}^{m} = -\mu \frac{dE(w_{ik}^{m})}{dw_{ik}} \qquad 2.9$$

Where μ which is usually a value ranges from [0 to 1] represents the learning rate, and the output of the final layer depends on different elements such as the outcome of all proceeding layers, weights vectors, and the training algorithm [48].

Usually, to stop the training process of forecasting we have used the Mean Square Error (MSE) as shown in the following equation:

$$MSE = \sum(Y - Y')^2 \,/\, m \qquad 2.10$$

Where Y is the real value, Y' is the output or the predicted value, and "m" is the number of inputs

2.10.3 Radial Basis Function Neural Networks (RBFNNs)

Radial Basis Function Neural Networks (RBFNNs) is another type of NNs, that can be utilized for time series forecasting and function approximation. RBFNNs that uses a policy called "the problem of curve fitting in a space of high dimension", which comprises of creating a domain with a multidimensional space that creates the better adaptation of the network[49]. RBFNNs are a special form of ANNs, unlike to the MLPNNs; they take in their consideration the aggregate input vector points, which are located in the proximity of the centers of the radially symmetric activation functions. In the hidden layers of RBFNNs systems, the activation function is a radially symmetric function where the reaction of the function increases or decreases according to the distance from a central point [8].

As illustrated in Figure 2.11, in RBFNNs architecture there are three layers: the input layer, the hidden, and the output layers; every layer is connected with the next layer, for example, the node in the input layer is connected to all the nodes in the hidden layer. The complexity and the type of application (problem) determine the number of nodes in the input and the hidden layer. In RBFNNs the input layer, as usual, passes the feature values to the hidden layer, which is, in this case, is an RBF layer.

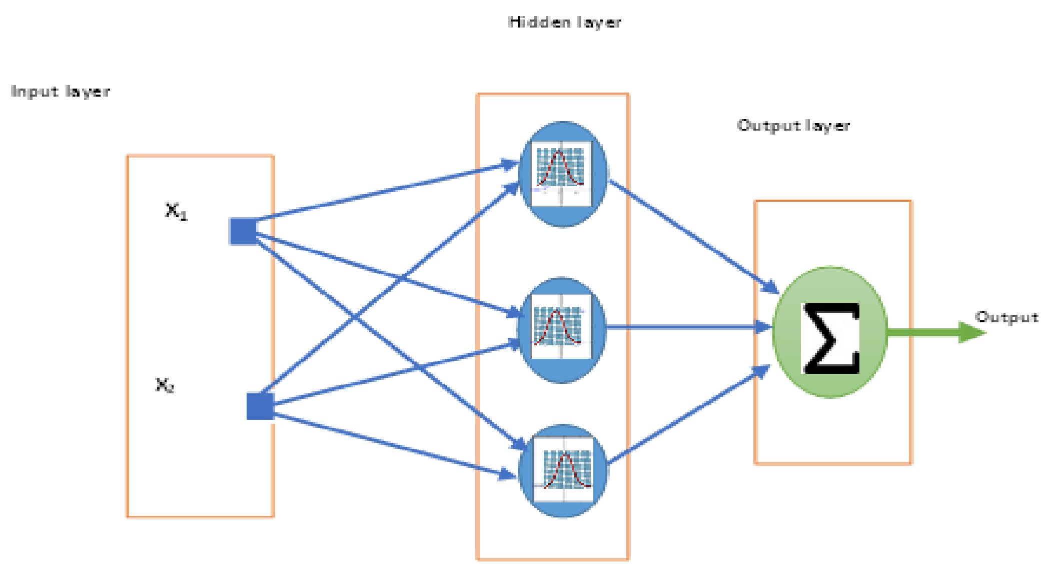


Figure 2.11: RBFNNs Architecture of three layers.

The hidden layer applies a non-linear multi-dimensional matrix transformation to the data coming from the input layer to take them to another vector space that usually has a larger dimension. The activation functions of RBF neurons are Gaussian functions, which rely on two parameters that are center and radii, where the RBFNNs structural behavior is controlled by these two parameters. In the output layer, the values of the hidden neurons from the RBFs layer are linearly summed and multiplied by the weight, which is the third parameter of the RBFNNs [8]. The typical Gaussian function $h(x)$ used in radial basis neurons is given in the following equation:

$$h(x) = \exp\left(\frac{-(s-c)^2}{r^2}\right) \qquad 2.11$$

Where "*r*" is the radius of the Gaussian function, "*c*" is the center, and "*s"* is any specific point of input data [50].

RBFNNs is utilized for curve fitting, regression, classification, and exact interpolation, where all data points must lay on the output function. The exact interpolation is performed by providing one function non-linear ϕ for each data sample given by the equation $\phi\|x\text{-}x^p\|$, where the pa*th* function is a Euclidean distance based function between x and x^p given by $\|x\text{-}x^p\|$. The following equation 2.12 represents the output of the RBFNNs system [44]:

$$f(x) = \sum_{p=1}^{N} \|x - x^p\| \qquad 2.12$$

Output using the Gaussian activation function is illustrated in equation 2.13.

$$f(x) = \sum_{p=1}^{N} W_p \phi_p(x) = \sum_{p=1}^{N} W_p exp_p\left(-\frac{\|x - x^p\|^2}{\sigma^2}\right) \qquad 2.13$$

Generally, the training process aims to generate the best weights associated with each input following the next steps [51].

Selecting the number of RBF ϕ as a matrix based on either the random or learning methods where bad fitting outcomes may be resulted because of the random selection method; however, the aim of matrix selection is to find the least count of radial basis functions from the data points. Moreover, randomness method may be used to determine the center of the basis function which also may cause the risk distribution of the centers; however, the K-mean clustering method is one of the learning algorithms which can be utilized for center determination. Gaussian activation function requires the use of a proper value of σ, the use of low σ value causes narrow peaks, while high σ values cause wide peaks, and therefore, the following expression is utilized for the best value of σ:

$$\sigma = 2d_{avg} \qquad 2.14$$

“d” is referring to the average distance. By the employment of Micchelli’s Theorem, the weights are updated. The aim of this process is to find the weight matrix *w* which based on *xi,* where *i* = *1... N* is the set of distinct points in R^d, and the interpolation matrix (N-by-N), where j_{ith} element of this matrix $\varphi_{ji} = \varphi(\|xi - xj\|)$, is a non-singular as depicted in equation 2.15:

$$W \; D^{-1} = F \qquad 2.15$$

The used function to calculate the error in Micchelli’s theorem illustrated in equation 5.16:

$$E = \sum_{p}\sum_{k}^{N}\left(t_k^p - y_k(x^p)\right)^2 = \sum_{p}\sum_{k}^{N}\left(t_k^p - \sum_{j=0}^{M} W_{kj}\,\Phi_j\;(x^p),\mu,\sigma_j\right)^2 \qquad 2.16$$

W represents the weight W and it is updated using the equation 2.17 and c represent the center and it is updated using equation 2.18, whereas r is the radii and it is updated using equation 2.19.

$$\Delta w_{jk} = -\acute{\eta}_w \frac{dE}{dw_{jk}} \qquad 2.17$$

$$\Delta\mu_{ij} = -\acute{\eta}_{\mu} \frac{dE}{d\mu_{ij}} \qquad 2.18$$

$$\Delta\sigma_{j} = -\acute{\eta}_{\sigma} \frac{dE}{d\sigma_{j}} \qquad 2.19$$

RBFNNs in this thesis is used for time series prediction of water losses and water demands to get the future values of losses water and demands using the actual data of water losses and water demands collected from all regions of Beitunia city to guide the training of the RBFNNs.

2.11 Genetic Algorithms (GAs)

Genetic Algorithms (GAs) is an evolutionary computation search algorithms founded by John Henry in 1975 [52]. GAs state that individuals who are best adapted to their environment are more likely to survive and to reproduce. The next generation represented by their offspring will inherit a combination of parental characteristics, and generate improved and bad individuals. The improved ones are more likely to continue and to reproduce, whereas the bad ones will disappear. After several generations in this process, the population is expected to develop and find an individual whose characteristics permit the best individual to be adopted.

The main characteristics of GAs include robustness to discontinuities of the fitness function; GAs does not require the fitness function to have a derivative and durability to a local minimum due to its global search characteristic. In addition, the GAs directed search does not require exploring the whole solutions space. The General steps of the genetic algorithm are depicted in figure 2.12:

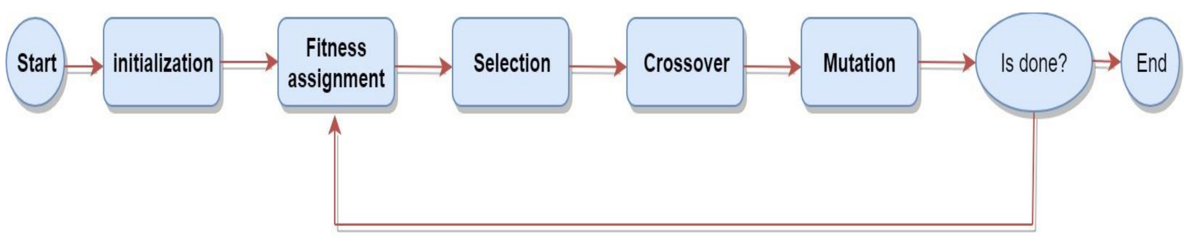


Figure 2.12: General steps of genetic algorithms

The following are the details on using GAs for the optimization.

- The **initial population** contains all the individuals that will be assessed by the fitness function and submitted to the genetic operators. Usually, it is generated by random sampling, in this work, the weights from MLP will be used in the population.

  Usually, when we try to solve a problem, we have a solution every time, but unfortunately, this solution is often not the best one, but we can clearly see that if we could combine this solution with a previous one, we could find the best solution. Therefore, the existence of a mechanism to integrate these scattered solutions can give us the best solution. If we imagine each solution as a sequence of genes within a chromosome and this solution exists within a group of different chromosomes (solutions) to the problem in a group of the population, then we can use crossover and mutation to produce new solutions.
- In **Chromosomic representation,** the binary chromosomic representation [52] is the most widely used representation and is applied to encoding genes' information that can assume zero and one values.
- **Fitness function** calculates a measure that is used to assess how adapted an individual is to the environment. This metric is used to direct the search for the characteristics that will result in a better-adapted individual, i.e., with better performance in a task.
- **Genetic Operators:** these operators consist of Selection, crossover, and mutation, the selection operator chooses 2 individuals from the population based on the result of the fitness function value in order to be used by crossover operator.

The process is repeated on another two individuals and the winner is selected. These two selected winner individuals are then submitted to the cross-over operator. Cross-over interchanges the chromosomic information between two individuals to create offspring with mixed characteristics. In figure 2.13 the general pseudo-code for a GAs is depicted.

Algorithm 1: Genetic Algorithms

BEGIN GAs
    Initialize the population
    Evaluate the fitness of the individuals
    REPEAT
        1: Select the parents (individuals);
        2: Generate new individuals using the two Operators (Crossover and Mutation)
        3: Evaluate the new population
        4: Select individuals for the next generation
    UNTIL THE TERMINATION CONDITION IS SATISFIED
END

Figure 2.13: General GAs pseudocode.

Through this hybrid model using genetic algorithms with MLPNNs algorithm, we aim to exploit the strength of genetic algorithms in the selection of best and appropriate weight and to use them in the MLPNNs algorithm to perform the forecasting of water losses and demands.

The general steps of the genetic algorithm are illustrated in the following figure 2.14.

Algorithm 2: Genetic Algorithm

Start GAs

Step 1: Initialize the population

Step 2: Evaluate the fitness *f(x)* of each chromosome *x*

Step 3: Carry out the following steps in order to get the new population:

a) **Selection**: Select two parent chromosomes for mating depending on the fitness of the chromosomes.
b) **Crossover**: Merge the genotypes of two selected parents to produce two new children. The produced children chromosome that has genetic material from both parents
c) **Mutation**: Spontaneously changes one or more alleles of the genotype. Genetic material is randomly altered to insert new genetic material into the population.
d) **Accepting**: put the new children in the new population

Step 4: Replace: Use the newly created population for the next run

Step 5: Testing: If the end criterion is satisfied, stop, and return the best solution

Step 6: Go to the evaluate function in step 2.

Figure 2.14: General steps of the genetic algorithm

2.12 Literature Review

In order to start with, it is considered as necessary as to surveying and reviewing the existing literature to establish a better view of the main issues involving water losses and water demands and what resolutions provided in regards. As presented in this study; that there is no official documentation on water losses and water demands for the water utility of Beitunia on the purpose of being able to access the situation in Beitunia through a scientific approach to forecast the water losses and water demands.

In the literature, machine learning and machine learning techniques are employed to predict and estimate the volume of water losses and water demands.

For instance, the authors, in [53], use Principal Component Analysis (PCA) and artificial neural network (ANNs). The outcomes of this hybrid model of PCA-ANNs with multiple hidden layers produces the best results of prediction. Authors in [9] recommend the addition of hyper-parameters for weight initialization and systemization to be enhanced in synchronization with the standard MLP topology and learning hyper-parameters. In addition, it analyses which hyper-parameters are more associated with categorized performance, allowing a decrease in the search area, which reduces the time and computation power needed to reach a satisfactory set of hyper-parameters. Results obtained with public datasets uncover an enhanced performance in comparison with comparable works. Likewise, the hyperparameters relevant to weights initialization and systemization are in the top 5 most relevant hyper-parameters to clarify the accuracy of performance in all datasets, emphasizing the importance of involving them in the enhancement process.

In order to surmounted the limitation of ARIMA/SARIMA which produce incorrect water level, and rather than using Backpropagation Neural Networks (BPNNs) and Nonlinear Autoregressive Exogenous (NARX) which similarly have difficulties to set the optimal network and regression weights Because their initial weights are random, researcher in [54] to predict the water level at the “Dungun River” they suggested hybrid Multiple BPNN-GAs to cope with the limitation of ARIMA/SARIMA, BPNN and NARX. The result displayed that M-BPNN-GAs with mean substitution is better than ARIMA/SARIMA, BPNN and NARX, and noticeably M-BPNN-GAs enhanced the performance of those techniques. Also, it was obvious that the performance of NARX is better than BPNN.

Moreover, the authors in [55], implemented a model by which it estimates the ratio of NRW using ANNs based on specific parameters that effecting leakages in water distribution systems in Incheon. This model was evaluated using “Scatter plot analyses” (SPA) to determine the best ANNs model. The experiment in this study shows that using the ANNs model produces more accurate predictions of NRW percentage compared to other algorithms such as “Multiple Regression Analysis” (MRA). Furthermore, it has been shown that the accuracy in the ANN model varies depending on the number of neurons in the hidden layer. Therefore, the optimum number of neurons in the ANNs model must be set. In addition, the accuracy of the “outlier removal” state was higher than that of the original data used state.

For the sake of predicting water demand, authors in [56] generated RBFNN model for water demand forecasting, using Dynamic Clustering Learning (DCL) algorithm in order to select the center of the cluster. The output charts show that maximum errors at the end of learning give varying predictive accuracy. The maximum error should not be extremely small; else, the result of forecasting will be overfitting and poor. RBF Neural Networks model has good nonlinear processing and estimation ability. The model features high computing speed, high forecasting accuracy, and appropriate application value.

In [57] to forecast deficiency of intensity indicator for water, authors used two ANNs models: the multilayer perceptron and the RBF ANNs, the outcome was RBF ANNs show a lower convergence between the anticipated results and the experimental ones than MLP ANNs; also the result shows that the maximum relative error in MLP ANNs is much lower than RBF ANNs, the results showed the multilayer perceptron can be used to model the failure frequency of water conduits, unlike RBF ANNs which are mostly not recommended for forecasting the failure rate indicator,

According to [58], it is necessarily required to develop and implement a strategy to manage NRW activities. This can be achieved by, prior, understanding the reasons and factors that could affect NRW components. Methods and techniques can be developed and adjusted to particular characteristics of the network and local factors; to handle each of the components according to its priority. Interestingly, the analysis in addition to the practical implementation of such an approach could be applied to other water supply companies, anywhere in the world. The development of a strategy; firstly, it starts with asking questions about network properties and Operating Practices. Then, the available tools and mechanisms can be used to propose the best fitting solutions to be employed in developing the strategy. Another approach developed by authors in [59] who built an intelligent water technology model that can proactively discover losses in water in the University of Lille. Specifically, they developed a model of the minimum night flow method, based on the determination of flow thresholds. More importantly, the model of the enhanced method is enabled to detect 25 unreported losses, which helps decrease the NRW level by 36%.

While in[5], Artificial Neural Networks (ANNs) was employed. This algorithm was experienced and compared with “Multiple Regression Analysis” (MRA) to estimate the NRW ratio in water distribution networks. The results in their study show that ANNs outperforms other conventional statistical methods. Likewise, ANNs models were also employed, as proposed in [60], to develop a model based on the amount of weekly rainfall, the weekly maximum temperature, and the amount of water demand for the last week, in addition to the occurrence or nonoccurrence of rainfall. The researchers compared their model performance with time series algorithms and other regression models. It was concluded that rainfall variable was a more significant factor than the amount of rainfall itself in short-term water modeling. ANNs models can also play the role of both time series and regression models.

In order to compare the relative performing of short-term municipal water demands, three models were employed; Multiple Linear Regression (MLR), Simple Linear Regression (SLR), Univariate Time Series and three ANNs models. This helped determine form usable size and classification standards for development. It is concluded that ANNs models compared with regression and time-series models attain the best performing [61]. In [6], a model was built utilizing data gathered from readings of daily consumption of water in addition to weather. Specifically, the authors built an ensemble model combining two algorithms of ANNs and time series. Their research presents and discusses the following topics; forecasting daily water demand for Al-Khobar city, comparing the performance of the technique to time series models in predicting water consumption, and studying the ability of the combined technique to forecast water consumption compared to the time series technique alone. The results show an model produces more accurate predictions compared to the results from using ANNs or time series models each separately.

Moreover, household water consumption can be predicted by applying time series algorithms. These algorithms are used quarterly in order to compare the results of ARIMA with the predictions resulted from ANNs models. Neural network shows that it can generate predictions more accurate;

very close to the actual data of the testing dataset used in their experiment. It is also indicated that water demands for residential use will represent around 18% of the total water demand of the country by 2025 [62]. Similarly, in [63], the authors developed a neural network model of short term (monthly) and long term (yearly) water demand prediction for Mecca city in Saudi Arabia exercising historical data of both water production and estimated visitors' distribution. For monthly and yearly predictions, the result also shows that the neural network predictions perform better than that of a regular econometric model.

The water distribution network was also studied in the literature. For example, in [19], the distribution network was investigated in order to evaluate and audit the levels of NRW of Hebron city. The research results show that the NRW ratio is more than 30%; due to unlawful consumption, inexactness in billing volumes, and incorrect meter readings. To improve and enhance the NRW ratio by reducing the losses in the water network, the research refers to two important issues, the first is that there is no appropriate staff qualified to execute activities for detecting water losses. The second issue is regarding providing of appropriate technologies that can help reduce (or stop) water losses. While in [3], research efforts were made in order to detect and reduce water losses in the water supply networks. Precisely, the author conducted an approach based on tracking and repairing leaks of the supply areas in addition to highlighting the leaks using electro-acoustic techniques. Thus, the research result shows that the amount of water leaks in the study area was largely reduced; from 5.6 L/sec to 0.16 L/sec.

For the water utility suppliers in Palestine, the authors in [64] performed an empirical evaluation of the factors that affect NRW. Furthermore, this was to evaluate the independent parameters of NRW and financial viability, in addition to investigating how the water stakeholders could successfully perform in order to decrease the NRW. More specifically, they applied two multiple regressions; one of these is to find the factors that impact the NRW. The findings show that there are some parameters such as staff productivity, energy cost, average price, daily consumption, and the size of the service provider impact and cause NRW; where daily consumption and average price have a negative effect.

Another study conducted in n Gaza Strip employing the Box-Jenkins model, by which the researches of that study analyzed seasonal time series data to predict future monthly water production. The result shows that the seasonal model of lag 12 (SARIMA (1, 1, 1) × (1, 1, 1)12) is the best model for predicting. The developed model also shows more accurate predictions. This was shown by comparing the output results against the observed values during this time period [65].

The author in this work [66] suggests a method (G-Prop-11) that tries to solve that problem by using a hybrid model that combine genetic algorithms (GAs) and Back-propagation BP to train MLPs using single hidden layer. Genetic operators GAs is used perform three things, first set the initial weights and second determine the learning rate of the network, and third changing the number of neurons in the hidden layer through applying specific genetic operators. G-Prop-11 brings together the advantages of the global search achieved by the GAs over the MLP parameter space and the local search of the BP algorithm.

CHAPTER THREE

THE APPLIED MODELS

3.1 The Applied Models

This chapter focuses particularly on the process of preparing collected water datasets to fit with neural networks that are used to predict future water demand and water losses NRW on the previously collected data from Beitunia city, Palestine. For the collected data, different Neural Networks Models with different learning algorithms will be used to forecast the future values of water demand and water losses NRW. These models will be described in details.

NRW and water demand prediction are performed by applying different types of ANNs models, which are widely used in such cases in an attempt to select the best model with the most accurate predictions. In our experiment of this research, for NRW and water demand we produce three prediction models; the first is MLPNNs model, the second is performed by using newrb Model using RBFNNs, and finally, a hybrid model using a genetic algorithm with MLPNNs is employed. The data used for the training as well as the testing are viewed as the input data collected from database sources of Beitunia municipality of water consumptions and water losses. Time series prediction takes a set of current data that is used to predict future data. The main goal of the time series is to build a model to derive future unknown data from current data by minimizing the error between input and output. To create an ANNs model for NRW and water demand prediction, the input data should be chosen from the city regions and it will be used to train and test the model, which will help produce more accurate predictions. It has been also shown that increasing the input data can help decrease the difference between the real and the predicted values of water losses; that is, it will provide results to the most close between the predicted and actual output data. The key point used to define the improvement of prediction, is to calculate the error value, which compares the target output of the NNs with the desired predicted output during training process; the computed error is usually expressed using equation 3.1:

$$\text{Error} = y_{jd} - y_{jt} \qquad 3.1$$

Where y_{jd} is the desired value of network output for each j^{th} element of input pairs and y_{jt} is the actual target value of the j^{th} element of input pairs, usually, this standard is used as a break condition to stop the forecasting process. To measure the performance of the applied models of NN we used Mean Square Error (MSE) as performance function [67] evaluated in equation 3.2.

$$\text{MSE} = \frac{1}{m}\sum_{i=1}^{m}(T - Y)^2 \qquad 3.2$$

Where m is the number of input data, T is the target label output (of the utilized dataset) and Y is the desired output.

In this thesis besides applying the ARIMA model, we have also applied three NNs learning algorithms as shown in figure 3.1 to evaluate the results generated by the employed NNs models.

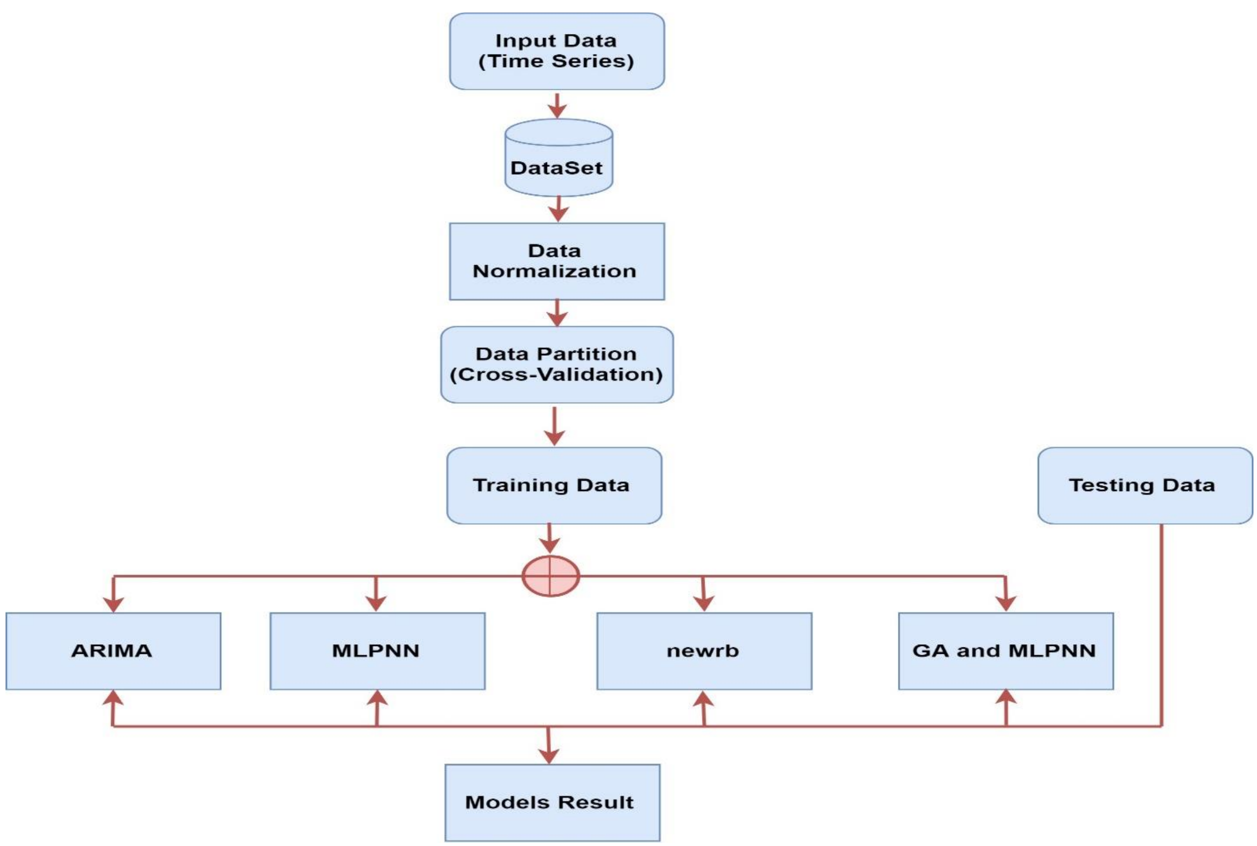


Figure 3.1: General method procedure flow chart.

3.2 ARIMA Models and Prediction using Box-Jenkins Approach

In chapter two, it has been presented and discussed how it could be the prediction of time series. It is a key point to select the most proper model that reflects the underlying structure of the series; in order to use the fitted model for future prediction. A time series can be an either linear or non-linear problem depending on the form of the past observations of a series whether it is represented as a linear or non-linear relation. Moreover, ARIMA is composed of autoregressive (AR) with a moving average (MA) methods. This hybrid method is integrated with data of different process, which is important to make sure that data being analyzed can be represented as data with stationary characteristics. As a result, the combination is called "Autoregressive Integrated Moving Average" (ARIMA). An autoregressive (AR) model is a representation of a kind of random process, which can represent some time-varying processes as time series data. The autoregressive model pointed out that the target variable depends linearly on its own previous values and on a randomness term, hence, the model is in the form of a stochastic difference equation[68].

Suppose that the series (*Rt*), t =... -1, 0, 1 ... is an evenly spaced feebly covariance stationary time series or stationary time series, Then the linear model for time series analysis can be expressed as follows:

$$R_t = \phi_1 R_{t-1} + ... + \phi_p R_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - ... - \theta_q \varepsilon_{t-q} \qquad 3.3$$

where the ϕ's are the autoregressive parameters to be estimated, the θ's are the moving average parameters to be estimated, the R's are the original series, and the ε's are a series of unknown random errors (white noise) which are assumed to follow the normal probability distribution. We say that (Rt) is a mixed "autoregressive moving average process of orders p and q and referred simply as ARMA (p, q). For the general ARMA(p, q) model, we say that εt, is independent of Rt−1, Rt−2, Rt−3,…, a stationary solution for the equation (3.4) the stationary solution exists if

and only if all the roots of the AR characteristic equation, (x) = 0 are outside the unit circle [34]. For determinism we have to assume that the roots of θ(x) = 0 are outside the unit circle. Where (εt) is a sequence of uncorrelated variables, it is also referred to as a white noise process, and $(\phi_1,\ldots\ldots,\ \phi_p\ ,\theta_1,\ldots\ldots,\theta_q)$ are unknown constants or parameters. The Box-Jenkins model can then be expressed as the following equation:

$$(1-\phi_1B-\phi_2B^2-\ldots-\phi_pB^p)R_t = (1+\theta_1B+\theta_2B^2+\ldots+\theta_qB^q)\varepsilon_t \qquad 3.4$$

where B is the backshift operator, that is BXt = Xt−1.

$$\phi(B) = 1 - \phi_1B - \phi_2B^2 - \ldots - \phi_pB^p \qquad 3.5$$

$$\theta(B) = 1 + \theta_1B + \theta_2B^2 + \ldots + \theta qB^q \qquad 3.6$$

In general, the ARMA (p,q) is a combination of an AR(p), and a MA(q) and it can be written as follow:

$$R_t = \sum_{i=1}^{p} \emptyset_i R_{t-i} + \sum_{i=1}^{q} \theta_i\, \varepsilon_{t-i} \qquad 3.7$$

In reality, it is often challenging to apply an ARMA model directly to a specified time series; this is because of its nonstationary, and, it also requires a transformation process. Usually, this is the case that time series of differences is stationary despite the nonstationary of the basic process. This leads to the application of the (ARIMA) model.

The series has a hybrid solution of Autoregressive and moving average, which results of a very general time series model [34]. More accommodated to our goal, the method of predicting water losses and demand using Box-Jenkins is shown in Figure 3.2.

The first step in the prediction cycle starts with the identification of the data model using ARIMA. This help determines the order of differencing required to produce a stationary time series. In this step, we identify the value of p (AR) and q (MA) components for both seasonal and non-seasonal series. In developing the ARIMA model, analysis of autocorrelation function (ACF) and partial autocorrelation function (PACF) required to be performed. These are obtained by plotting original series in addition to the ACF and PACF.

Algorithm 3: ARIMA Statistical prediction Model

Input: choose a dataset

Step 1: Plot the dataset against the time.

Step 2: is the plot stationary with time

Yes: Continue (go to step 3)

No: Difference the data until it appears stationary

Step 3: Plot autocorrelation (ACF) and partial autocorrelation (PACF)

Step 4: Get the value of ACF and PACF

Step 5: Check if the mean is stationary

Yes: Continue (go to step 6)

No: apply regular and seasonal differencing

Step 6: Selecting the Model

Step 7: Estimating the value of the parameters

Step 8: Perform diagnostics check

Step 9: Is the model adequate?

Yes: Continue (go to step 10)

No: go to step 6, change the selected model

Step10: Calculating the Prediction

Figure 3.2: Statistical prediction procedure using Box-Jenkins methodology

Then, it is required to estimate the parameter for chosen ARIMA model by using the data to train the parameters of the model. For validation, the model diagnostics checking is required to be developed. The diagnostic (residual) is performed to identify whether the residuals from the model are independent and whether they are normally distributed. The residual is the difference between the observed value and the predicted one of the quantities of interest. The residual should be uncorrelated; results of zero means and zero variance as well. Afterward, the prediction and error checking stage can be performed.

3.3 Multilayer Perceptron Neural Networks (MLPNNs) Model

In this model, we have used Multilayer Perceptron Neural Networks (MLPNNs), which can predict every time series function by tuning the network with the most appropriate hidden layers structure and a suitable number of neurons. It is known that the time series prediction is one of the most complex of the real-world applications. In addition, it is well known that the ANNs has a good characteristic of solving such complex problems. The training process is the mapping process between the input and output data of the NNs when the input patterns provided to the NNs with initial weights, the output of the NNs are given by the following equation: [40]

$$y_i = f(\sum_{j=1}^{m} w_{ij} x_j + b_i) \quad 3.8$$

Where W_{ij} is the connection of the weight, and X_j is the value of the ith inputs for a simple of the NNs, b_i is the bias, m is the number of neurons and f is the activation function. The MLPNNs is one of the most vastly used as time series prediction model, although it is impossible to find a single configuration for each application. The choice of training patterns is performed depending on the explicit needs of the prediction, which will show on the output in addition to the quality of information available. Any changes in the patterns of training will require different training parameters of the NNs, but the training process remains as the same [51, 69].

Developing a methodology to forecast future values of NRW and water demands necessarily requires knowledge about the previously measured values of water losses and consumption. Regression of the future values of NRW and water demand can be performed using different techniques as; prediction by numerical models, prediction by statistical methods, and time series prediction based on the application of statistical techniques linear (or nonlinear). Multilayer feedforward with backpropagation neural networks model is used to predict the future values of NRW and water demand. Prediction future values using only numerical models could introduce high Mean Square Error, thus, we have applied Multilayer feedforward with backpropagation neural networks (MFFNNBP) in addition to utilizing data of different years; with each year divided into six periods two months for each period. Multilayer feedforward with backpropagation neural networks (MFFNNBP) is an MLPNN that passes the inputs and the weights from one layer to the next one through the feed-forward process. Then it performs the weights update to be back-propagated to the previous layers in order to recalculate the weights [69]. Our proposed ANNs architecture for NRW and water demand regression for one year "2018" using historical data of losses and consumption of three regions in Beitunia city. The data processed and analyzing process flow is as displayed in figure 3.3. In MLPNNs, the output of a layer will be an input for the next layer passing from the input layer to the output layer; f^1 is the sigmoid activation function [69]. The equation used the output is shown as in the following equation 3.9:

$$\textbf{output} = f^2 \left(\sum_{j=1}^{n} output_1 . W_{jk}\right) \qquad 3.9$$

Where the output of the first hidden layer (*output₁)* is calculated using the following equation 3.10:

$$\textbf{output}_1 = f^1 \left(\sum_{j=1}^{n} in_i . W_{ij}\right) \qquad 3.10$$

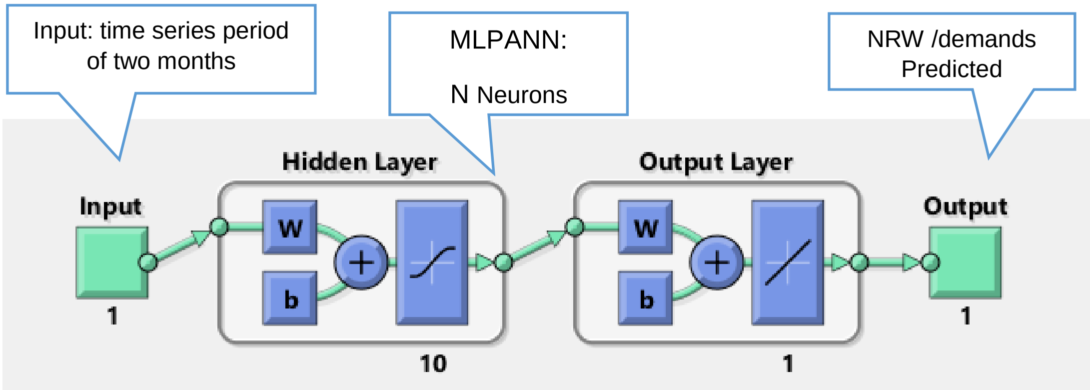


Figure 3.3: Proposed NRW and water demand Prediction using ANNs.

Where f^1 and f^2 are the activation functions for both output layer and hidden layer that calculated as in equations 3.11 and 3.12:

$$f^1 = \frac{1}{1 + e^{-X}} \qquad 3.11$$

$$f^2 = X \qquad 3.12$$

Where x is the input vector. Depending on equations 3.11 and 3.12, weights are updated use equation the following equation 3.13:

$$\Delta w_{jk}^{n} = -\mu \frac{dE(w_{jk}^{n})}{d\, w_{jk}} \qquad 3.13$$

μ is the learning rate with a value between 0 and 1. The final output depends on all earlier layer's output, weights, and the algorithm of learning used [70].

The backpropagation process calculates the gradient proper error between the desired and the predicted output by looking at the new weights each time. The gradient proper error is the most used in the simple random gradient descent algorithm to find the weights that minimize the error. The backpropagation process tries to help the algorithm to get out of local minimums, making a more global search than the standard algorithm. Adjusting weights makes it depends not only on the gradient value at the point where it is but also on the previous weight adjustment. The back-Propagation step used to update the weights depends on the calculation of the gradient decent error between the target output and the predicted output considering the new weights. In this thesis, we use one of the fast converging training algorithms, which is the Levenberg Marquardt Algorithm (LM) [7], which train the NNs and reduce the prediction error values by adjusting and updating the weights. LM converges according to steepest descent methods with better generalization. Figure 3.4 illustrates the proposed MLPNNs model that uses the Levenberg-Marquardt training algorithm (LM), adjusted for the water demand and water losses prediction process.

3.3.1 Levenberg Marquardt Algorithm (LMA)

Levenberg Marquardt Algorithm is implemented to solve problems of nonlinear least squares. **LMA** is based on curve-fitting method which is a combination of two methods: the gradient descent and the Gauss-Newton. [7], in other words, the iterative update depends on the value of an algorithmic parameter; (λ) is a non-negative damping factor which simplifies the graph. The update is Gauss-Newton if (λ) is small and close to the optimal value while a gradient descent is used when the value of (λ) is large. Equation 3.14 describe the matrix "Hessian" of quadratic error

$$H^{ij} = \frac{\partial^2 E}{\partial w^i \, \partial w^j} = \sum_{l=1}^{Z} \left[\frac{\partial y_l'}{\partial w^i} \frac{\partial y_l'}{\partial w^j} + (y_l' - y_l) \frac{\partial y_l'}{\partial w^i \, \partial w^j} \right] \qquad 3.14$$

Where "E" represents the error function, the "i^{th}" element of input layer weight is represented by "w^i", and the j^{th} element of output layer weight is represented by (w^j) ,(y_l') is the derivative output of "l^{th}" the neuron, (y_l) is output othe f "l^{th}" the neuron.

If we assume that errors are random and de-correlated with the second derivative, the second term of this expression can be neglected, as a result, it can be considered as white noise. Using the first edition of the Hessian, the matrix in equation 3.15 can be built [71].

$$J^{ij} = \sum_{l=1}^{Z}\left[\frac{\partial y_l'}{\partial w^i}\frac{\partial y_l'}{\partial w^j} + \lambda I_M\right] \quad 3.15$$

Where (I_M)is the identity matrix of order (*M)*, and (λ) is a parameter which is alike to learning in the algorithm of back-propagation. The adjustment of the weights with the (LMA) in the μ-*i*[th] learning cycle is calculated by one of the equations 3.16 and 3.17:

$$W(\mu) = W(\mu - 1) - J^{-1}(\mu - 1)\nabla E(\mu - 1) \quad 3.16$$

$$\Delta W = (JJT + \lambda l_M).j^T E \quad 3.17$$

Matrix J is calculated using Equations 3.18 and 3.19:

$$Ja_l^i = \frac{\partial y_l'}{\partial w^i} \quad 3.18$$

$$J = Ja^T Ja + \lambda l_M \quad 3.19$$

As shown, we didn't need more sophisticated calculations excluding for the back-propagation algorithm. Therefore, the auxiliary matrix (Ja) likewise produces the error gradient [74] as shown in equation 3.20:

$$\nabla E^i = \frac{\partial E}{\partial W^i} = \sum_{l=1}^{Z} Ja_l^i (y_l' - y_l) \quad 3.20$$

Levenberg-Marquardt Algorithm steps are summarized as follows:

- **Initialization process** can be done either by the use of fixed weights or random weights, in this study we used random initialization.
- **Forward phase:** in the hidden layer the Predicted output is calculated by using the sigmoid activation function. As a result; the hidden layer predicted output can be calculated. At the end of the forward phase, we will have the output value and the target value besides the error values which we need to reduce it as possible.

- **backward phase:** in this second phase, Mean Squared Error (MSE) is calculated, MSE is the difference between the network output values and target values, in this process we will use Levenberg Marquardt algorithms (LMA) in order to training the network and reduce the error by updating the weights, the phases of forward and backward is repeated several times until getting the minimum Mean Square Error (MSE) values, figure 3.4 shows Pseudocode of the proposed MLPNN model

---

Algorithm 4: MLPNN

Step 1: Load Data (time series data of water losses and demands)
Step 2: Initialize MLPNN

- Normalize the Input and the Target data
- Dividing the dataset into two parts training and testing using cross-validation
- Set initial Neuron number
- Initialize the Network Weights w randomly
- Initialize Network Bias b randomly

Step 3: Start Training Phase

- Predict
- Read the actual output
- Calculate MSE
- **While** MSE <= threshold Do:
    - Calculate ΔW for all weights from the output layer to hidden layer
    - Calculate ΔW for all weights from the hidden layer to the input layer
    - Update the Weights of the network
    - Predict
    - Calculate MSE Error between Predicted and Target outputs
- Record training MSE.

Step 4: Start Testing Phase

- Calculate Predicted output using testing data based on the generated model from Step 3.
- Calculate testing MSE.

Figure 3.4: The proposed MLPNN model pseudo code

3.3.2 Cross-Validation

Prior to moving a trained model to a production phase, it is necessary to verify and validate models to make sure that these models will forecast values with the lowest difference in case of regression models to the most needed values as possible. Cross-validation is one of the largely popular statistical methods used to. It is usually used in applied machine learning to compare and select a model for a given predictive modeling problem. Cross-validation is easy to understand and implement, in addition, the results could usually have a lower bias than other methods. According to [72], Cross-validation is considered as one of the better choices to avoid minimum over-fitting or underfitting. There are many different methods and techniques of cross-validation that can be used but, in the end, the core is similar. The holdout is a simple type of cross-validation based on dividing the dataset into two separate subsets, the first one is the training set and the second is the testing set which is used for testing. A prevalent approach is to divide the dataset into 70% of the training phase set and 30% to the testing phase. In order to train the model, first the model is trained on the training dataset partition, then the model is trained on the testing dataset partitions.

Another method of validation that can be used is K-fold validation, in this type of validation the dataset is split into (K) number of subsets(folds), then we carry out the training process on the all folds except one (k-1) subset, then we will use this subset for the testing in order to evaluate the model [73]. In the k-fold method in this method, we repeat (k) times with a different subset (fold) kept for testing phase every time. Hence every data point capture in a test set accurately. In order to verify and validate the used models, it is important to use the fastest and most accurate methods in order to obtain satisfactory results. Thus, in our thesis we split the water losses and water demands data into two randomly set(portions), for the training phase we used (70%) of the dataset and the remaining dataset (30%) is used for the testing phase [74].

3.4 Proposed RBFNNs Model Methodology

RBFNNs were used for function approximation and time series prediction, in this thesis it is used for time series prediction of water losses and water demands. This method can be applied to several applications areas such as image processing, voice recognition, and spam filtering [75]. The significance of the usage of such a method is to cluster dataset points around a set of popular highlighted points called centers. These points (center) are grouped to the centers based on another parameter for RBF network which is called radii (r); which agrees to the distances for each input data point to the center points of each cluster (or group) [76].

In this thesis, we have used newrb that was included in Matlab toolbox as standard training algorithm for RBFNNs neural network, in order to compare with ARIMA, MLPNNs, and GA-MLPNNs. newrb repetitively creates a radial basis network by using one neuron at a time. Neurons are added to the network until the sum squared error falls beneath an error goal or a maximum number of neurons has been reached. The used newrb function is expressed as follow:

$$net = newrb\ (Xt, Tt, Goal, Spread, M\_N)$$

where Xt is the input vectors, Tt is the target vectors and M_N is the maximum number of neurons.

In *newrb,* in each iteration of the input vector which leads to reduce the network error is most used to create *radbas* neurons. Then the new error is verified, and if it is small enough then the *newrb* is stopped. Else, the subsequent neurons are added. This process is repeated until two conditions are achieved, first if the target of the error is achieved, second if the number of neurons is reached to the maximum. In *newrb,* it is significant that the spread is sufficiently large that the *radbas* neurons react to overlapping regions of the input space, however, the value of spread shouldn’t be so large that all the neurons react in essentially the same way [77].

In order to predict the water losses and water demands, we have collected actual data of water demands and water losses from all regions of Beitunia city, for this goal *newrb* Matlab function was used to train the RBFNNs. Newrb function creates an RBFNNs used for function approximation, where the new neuron is being added to realize the determined error or to realize the best fit, in general, and depending to *newrb* used in Matlab, the function newrb repetitively creates a radial basis network one neuron at a time. Neurons are added to the network till the sum of squared error falls under an error goal or the maximum number of neurons was gotten, this model has the number of steps illustrated in figure 3.5.

Algorithm 5: RBFNNs-Newrb

Step1: *Initialize newrb model parameters:*
Net = newrb(I, T, goal, spread, M_N, N);

- *I: input vectors.*
- *T: target vectors.*
- *Goal: Mean squared error (MSE) goal (default value = 0.0)*
- *Spread: Spread of RBF (default value = 1.0)*
- *M_N: Represents the maximum number of neurons (Q is the default value)*
- *N: Represents the number of neurons to add (25 is the default value)*

Step2: *Train the system using the parameters (I, T, goal, spread, M_N, N)*

Step3: *If the training process finds the Goal:*
stop and return the RBFNN Architecture
Else go to ***Step2***

Figure 3.5: RBFNNs- newrb model

In RBFNNs, the newrb rely on spread value; when using too large value of spread that means requiring a lot of neurons in order to fit the fast-changing function, on the other hand using too small value of spread that means requiring a lot of neurons to fit a smooth function, and the RBFNNs perhaps not popularize well [78].

3.5 Proposed Hybrid Genetic Algorithms and MLPNNs (GAs-MLPNNs) Model

In the previous parts, we presented in details the MLPNN in addition to the training algorithm we used. Also, we presented GAs and how it works. Through the following subsection, we will explain the relationship between GAs and MLPNNs, and we will explain the importance of using GAs in order to improve the results of MLPNNs and by choosing the best weights then we will explain the hybrid model used in this thesis using GAs and MLPNNs.

3.5.1 Learning MLP with Genetic Algorithms

It is difficult to select the best parameters in NNs for the training process, so it is possible that the results of the training are unacceptable or sometimes bad and this is not because the data is complex or noisy or the algorithm used in the training is weak, but this is due to the failure selecting of the parameters. Therefore, the process of selecting the appropriate parameters increases the success of the training process, in addition, to enhance the accuracy of ANNs [79]. Once each problem has specificities about its data, to choose the optimal weights of an MLP usually involves a trial and error approach, which consumes time, computational resources and requires the researcher to have great experience to properly tune the MLP. It is thus highly desirable to have a method to automatically search for the optimal weights efficiently [9].

In general, the training process using MLP can be improved by selecting the Optimum parameters such as a number of neutrons in the hidden layers and initial weights. So, we need such a method to solve this problem, therefore, the optimization process can be implemented using the GAs. Genetic algorithms (GAs) and ANNs have been both employed together in two significant approaches.

First, GAs has been used in the training of ANNs. More specifically, GAs have been used to search for the most appropriate learning parameters and to find the most significant features. **Second**, the major type of collaboration was introduced to use GAs to design that emerges issues that cannot be resolved (easily). It is well known that solving non-linearly separable problems will require that the network has at least one layer between inputs and outputs; with the notice that tuning the number and size of the hidden layers can be achieved by experiment (trial and error). In other words, GAs is used to search for these parameters, as well as for the pattern of connections in addition to developmental guidelines for the network. Evaluating the fitting performance of each network involves measuring the quality of regression on the training set. Thus, for each fitness evaluation, the training set is passed through the network. However, this could be inefficient in case of large-volume training sets, but the fitness can be estimated using a sample of the training set according to [9]. In this thesis, we will focus on using GAs to optimize the network weights to use them in the MLPNN algorithm to perform the forecasting of water losses and water demands.

3.5.2 MLPNNs with Genetic Algorithm Process

The GAs is a stochastic optimization approach depending on the features of natural selection and biological evolution. It is better than other optimization algorithms and it has various advantages over them. GAs can be used to solve and optimize continuous and discrete issues. It is less probable to get trapped in local minima [13] if it is compared with other algorithms such as Backpropagation (BP). The idea behind GAs came from population genetics. It has been used mostly as function optimizers and it has been proved to be an efficient optimization algorithm, particularly for multi-model and non-continuous functions.

The GAs develops a population of individuals. GAs uses every individual Yj (j = 1,2,3, , n) (n , represents the population size) of population "Y" in order to solve the problem. Individuals are typically represented by strings and each element of which is called a gene. The value of a gene is typically rage from (0 to 1). The GAs is qualified for optimizing the fitness function F(.) for every individual of the population. The following operators are used in GAs:

- **Initialization**

Each gene is consists of a real vector of weights X_j,(j = 1,2,3, n) where n is the initial population size. The following expression defines the variable length of the chromosomes:

- $Chrom = [\{w_1\},\{w_2\} \dots \dots \{w_n\}]$

In our model, the chromosome is generated initially by MLP and it consists of weights, notes that this chromosome of weights generated once by the algorithm of MLP.

- **Evaluation Function**

In every chromosome, an evaluation function is used to calculate the value of the error (fitness) where the fitness function is the error between the target output and the current output. In this model, we will use the fitness function to calculate the error value as depicted in the following equation 3.21:

$$\text{MSE} = \sum(Y - Y')^2 / n \qquad 3.21$$

Where Y is the real value, $Y'$is the output or the predicted value, and "n" is the number of inputs.

- **Process termination**

In order to select and reproduce parents, GAs develops from generation to generation until reaching the end. In this model as shown in the expression below, we use the maximum number of generations as a criterion to stop the algorithm. This will finish the process when the maximum number of achieved generations surpasses a particular number of generations. In some cases, GAs stop the optimization process before the maximum number of achieved generations surpasses the particular number of generations, such as when GAs jumps generation to another without any fitness improvement[80].

If the current Generation $\geq$ *Maximum Generation* $\rightarrow$ *Stop the Optimization process*

- **Selection**: It is the process of selecting the parents, in this step a new generation Y_{new} is produced, which extracted from the replicating individuals of the old generation, Y_{old}. The selection process plays important role in the development the genetic algorithm to select the best individuals, in the selection process, the individual with the smallest value of fitness (error) has the highest chance to be chosen. Extraction of a new generation can be done in several ways such as Roulette Wheel Selection, Elitism Selection, Rank Selection and Stochastic Universal Sampling [81]. The choice of the standard roulette wheel is used for selecting individuals in the current population of weights depending on the probability of every chromosome (P_S). The probability of every chromosome (P_S) is calculated as the following equation:

$$P_s(x) = \frac{f(x)}{\sum_{i=1}^{m} f(x)} \qquad 3.22$$

Where $P_s(x)$ is the probability of Individual x, $f(x)$ is the fitness of individual x, and m is the size of the population [82]. Figure 3.6 illustrate Roulette wheel example; we can see different sections with different sizes every section represents a chromosome. If we rotate the wheel randomly, it will point to one of the sectors (chromosome). This process is repeated until the preferred number of individuals is gotten.

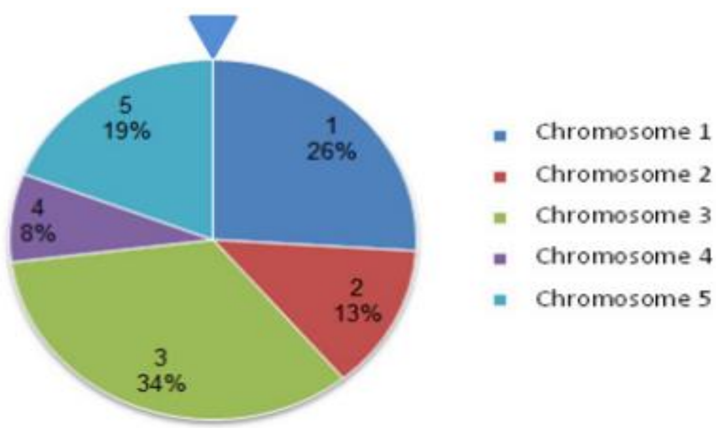


Figure 3.6: Roulette wheel selection example

It is visible that the individual that has a larger section size, will have the biggest chance to be selected for example chromosome 1 has the biggest chance to be selected. Therefore, the probability of choosing an individual depends directly on his fitness.

- **Crossover**: in this step, the operator is implemented in probability. (P_{cr}) is the probability of crossover. Through parents chosen from the selection process, each parent is mated to produce two new children. This process continues until a new group of chromosomes is found in addition to the parent group. There are many techniques used in Crossover, the most popular and widely used is Single Point Crossover. This technique eventually produces the next generation of chromosomes that are different from the first generation.

  Crossover selects two parents P1 and P2 and executes an interpolation of the two parents. Consider c1 and c2 as the new children are produced by equations 3.23 and 3.24:

$$C_1 = P1 * n + P_2 * (1 - n) \qquad 3.23$$

$$C_2 = P1 * (1 - n) + P_2 * n \qquad 3.24$$

  Where n is a random number, it is the probability of crossover between (0 and 1). Every couple is then recombined, and the new offsprings are founded by the interpolation of parents. The default crossover function used in this model is Crossover Scattered (CS), this function creates a random binary chromosomes, when the value of the chromosome equal to 1, CS function select the genes from the first parent P1, and when the value of chromosome equal to 0, CS function select the genes from the second parent P2 [83]. Figure 3.7 shows the scattered crossover.

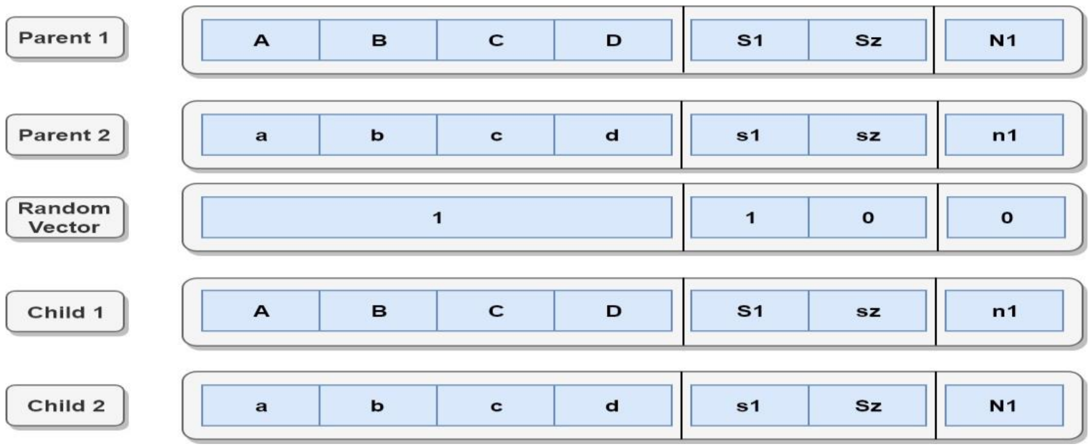


Figure 3.7: the scattered crossover.

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- **Mutation**: for every individual mutation operator adjusts one allele of the population in (P_{mu}) probability. In mutation, a new offspring is created using a single parent by reversing one or more randomly selected bits in the chromosomes of the parent as shown in figure 3.8 [84]. The probability (P_{mu}) of mutation is responsible for deciding how recurrent will be the section of chromosome Exposed to mutation.
- **Replace**: To put the new offspring (children) in the new population this operator is used and use the newly generated population for an additional algorithm.
- **Test**: to get the better and fitted solution of the current population the end condition must be satisfied

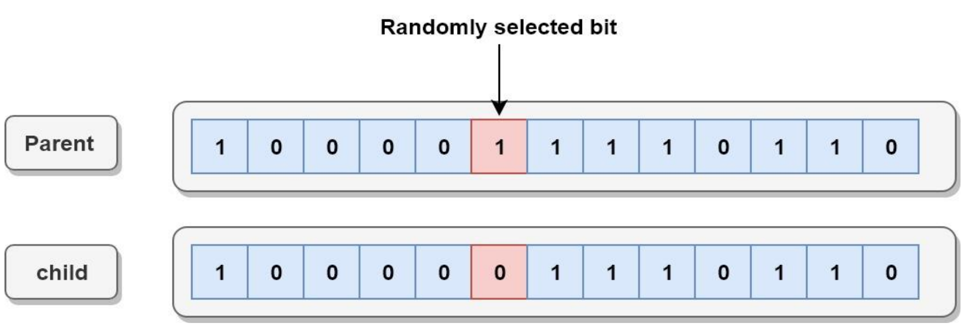

Figure 3.8: Single Point Mutation

The main steps of the proposed hybrid algorithm are depicted in Figure 3.9. This model describes a hybrid learning algorithm of MLPNNs by using the GAs to optimize the weights of the network. The procedure of the hybrid GAs- MLPNNs model is presented as follows.

1. Start MLPNN**:** In this step, the data of water losses and water demands are loaded and divided using cross-validation into two parts, training and testing, then the initial Neuron number is set and finally, the Weights and Bias are randomly Initialized.
2. Start Forward training phase: in this step the layers prediction output is calculated using the sigmoid activation function, then the if the error value is less or equal to threshold value this means the end of this phase, else the next step is to use GAs to optimize the weight in order to reduce the error.
3. Start GAs:
    - Chromosome (individual) Representation : in this step initialize the population using weights generated by MLP.
    - evaluate of the fitness f(x) of each chromosome x (weight)
    - in order to get the new population, all GAs steps will be carried out
        - Selection
        - Crossover and Mutation
        - Compare: All the previous and current best individuals (weights) are added in the population.

Algorithm 6: GAs-MLPNNs Model

Start MLPNNs

Step 1: Load Data

Step 2: Initialize MLPNNs

- Dividing the dataset into two parts training and testing part using cross-validation
- Set initial Neuron number
- Initialize the Network Weights W randomly
- Initialize Network Bias b randomly

Step 3: Start Forward Training Phase

Perform the following steps for every iteration

- Calculate the prediction output using sigmoid activation function
- Calculate MSE Error between Predicted and Target outputs
- Is the error value <= threshold value?
  - Yes: stop and get the MSE and output predicted the value
  - No : go to the next step (step 4) to optimize the weight in order to reduce the error value

Step 4: Start GAs

1) Initialize the population using weights generated in Step 3

2) evaluate the fitness *f(x)* of each chromosome *x (*weight*)*

3) Carry out the following steps in order to get the new population:

e) **Selection**: Select two parent chromosomes for mating depending on the fitness of the chromosomes.

f) **Crossover**: Merge the genotypes of two selected parents to produce two new children. The produced children chromosome that has genetic material from both parents

g) **Mutation**: Spontaneously changes one or more alleles of the genotype. Genetic material is randomly altered to insert new genetic material into the population

h) **Compare**: All the previous and current best individuals (weights) are added in the population.

i) Move the next population to the current population to ready the algorithm for the next run.

j) Evaluate the fitness *f(x)*

4) Get the Optimized weight

5) Calculate the MSE

6) Get the output predicted value

Step 5: Start Testing Phase

- Set Network Weights to computed in training phase
- Calculate Predicted output using testing data
- Calculate MSE

Figure 3.9: The proposed GA-MLPNN model

  - Move the next population to the current population to ready the algorithm for the next run.
  - Evaluate the fitness *f(x)*
- Get the Optimized weight then calculate the output

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 RESULTS AND DISCUSSION

As presented in the previous chapters, this academic work has made efforts in an attempt to build a predictive model that can forecast water demands and losses. This chapter shows and discusses a detailed description of the results produced. In addition, it presents the functional requirements by which our experiments have been conducted.

4.2 Introduction

In this research, experiments have been carried out to check and validate the developed predictive model. Different technologies and frameworks are applied to achieve the objectives of our study. For example, the models were designed and simulated using MATLAB 14a (8.3.0.532) under Windows 10 by computing machine with specifications; Intel Core (TM) i7-5600U, CPU @ 2.60GHz, 16GB RAM memory. According to [85], MATLAB is viewed as a high-level language for technical computing, which can be used by people who have no sufficient skills in programming. Furthermore, MATLAB is an interactive system which allows non-programmers to solve many technical computing challenges, specifically, problems with matrix and vector formulations, in highly productive manner; that is, it takes a shorter time than it would take using programming languages such as C or JAVA. Moreover, MATLAB is a programming environment that enables executing operations from the command line such as advanced calculator. It also helps build programs that could execute complex jobs, with the power of any other programming languages.

Most specifically, MATLAB provides libraries that support data visualization and processing. For instance, its environment is easy to use and tests algorithms immediately without recompilation and plotting of functions and data. It also provides Graphical User Interface (GUI) to help interpret data easier in models and curves. Nonetheless, MATLAB is considered as memory and CPU consumer; because of its complexity in running real-time applications [86].

There are several programs and applications that can be used to build ARIMA models such as SPSS, MATLAB, MINITAB, and EViews. In this work we have used EViews, it is a modern economic statistical application used in forecasting processes. We have used EViews because it provides us with important, effective and easy to use tools, in addition, to generate high-quality graphics and charts besides to the Innovative Design such as multiwindow design, full-featured analytic engine and specialized forecasting [87].

In the beginning, prior to the experiment using the NNs models and ARIMA model, the historical data collected from Beitunia municipality databases, as well as from Jerusalem Water Undertaking. Data was prepared to suit NNs models and ARIMA models. As we have previously explained, Beitunia city has been divided into three main regions (Flash, Sunuqrot and College) and we have arranged the data for each region separately. Data in Flash area contains 66 readings representing 66 water cycles. This data represents the consumption of water in cubic meters from the years 2005-2017. In addition, and by using the quantities of demand for this region, we have calculated the water losses quantities, which are also 66 readings. Sunuqrot area also contains 66 readings representing water consumption and water losses in cubic meters for the years 2005 - 2017. Data in the College area contains 48 readings representing 48 of water cycles, which represent water consumption and water losses in cubic meters from the years 2010-2017.

Data of water demands and water losses was normalized as a range of continuous data between [0 and 1] to fit NNs activation functions that will be used in the applied NNs algorithms in this work as shown in equation 4.1, where (y_i) is the normalized value and (x_i) is the real consumption, *min* and *max* are the maximum and minimum values for real consumption[72].

$$y_i = \frac{(x_i - \min(x))}{(\max(x) - \min(x))} \qquad 4.1$$

Table 4.1 represents a part of the water consumption values of the Flash area. The table shows the period column which represents the water cycle, in addition to the actual consumption quantities in cubic meters and the actual normalized consumption quantities.

Table 4.1: Consumption quantities for the Flash region

No	Period	Normalized	Consumption	No	Period	Normalized	Consumption	No	Period	Normalized	Consumption
1	2007-03	0	66427	14	2009-05	0.2034	78836	27	2014-07	0.4777	95565
2	2007-05	0.1159	73498	15	2009-07	0.5402	99378	28	2014-09	0.856	118640
3	2007-07	0.3233	86149	16	2009-09	0.5395	99335	29	2014-11	0.7577	112643
4	2007-09	0.4197	92028	17	2009-11	0.3747	89283	30	2014-01	0.4662	94863
5	2007-11	0.4047	91109	18	2009-01	0.4289	92587	31	2015-03	0.7037	109349
6	2007-01	0.2002	78640			.		32	2015-05	0.5346	99033
7	2008-03	0.0519	69590			.		33	2015-07	0.699	109064
8	2008-05	0.2935	84326			.		34	2015-09	0.868	119371
9	2008-07	0.425	92351			.		35	2015-11	0.8038	115451
10	2008-09	0.4184	91944			.		36	2015-01	0.7685	113298
11	2008-11	0.4361	93026			.		37	2016-03	0.7442	111821
12	2008-01	0.3211	86012	25	2011-03	0.3036	84943	38	2016-05	0.9182	122428
13	2009-03	0.1787	77325	26	2011-05	0.4393	93221	29	2016-07	1	127420

In the next sections, c result in the form of tables and graphics based on each region data for both water demand and water losses. Then, the results of conducted experiments will be presented in addition to performing comparisons among different ANN and learning algorithms employed for the goal of our research; water demands and water losses predictions. In the first model, we applied MLPNN, then, we used newrb model, and, finally, we experienced GAs-MLPNNs as a hybrid model, besides using the statistical model ARIMA.

4.3 ARIMA (Box-Jenkins) Prediction Model

In the following sections, we will show and discuss the result of the ARIMA model of water losses and demands for the whole city and in all regions of Beitunia city using EViews.

4.3.1 ARIMA NRW Prediction Model Result

4.3.1.1 ARIMA NRW Result for the Whole City Region.

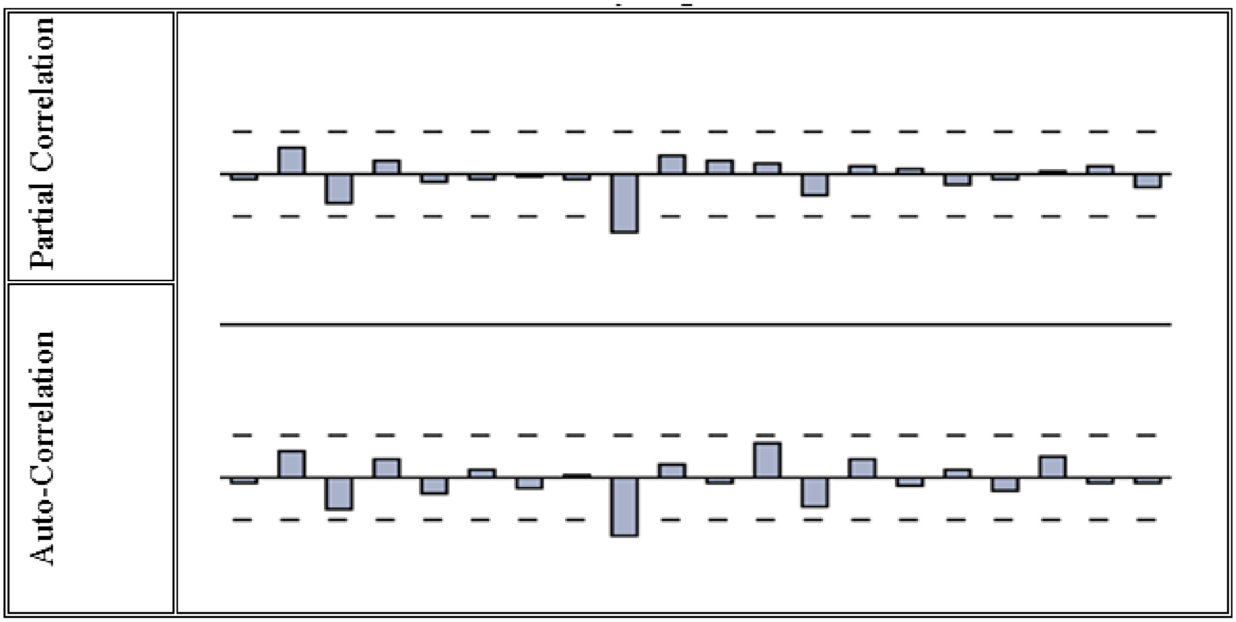

Figure 4.1: ACF and PACF Function for Water Losses (NRW) for the whole city region

As shown in figure 4.1, and according to the unit root test, that the whole city data series suffers from pattern interruption, which means that a unique ARIMA model can't be used for water losses data of the whole city region. In such a case, as we did, we usually fit what's known as "intervention model".

Table 4.2: MSE of NRW for the whole City region using ARIMA intervention model.

$MSE_{Training}$	$MSE_{Testing}$
1.45E-01	2.23E-01

Tables 4.2 shows the best Mean Square Error (MSE) of the intervention model, based on MSE

error values (training and testing) depicted on the table, we can say that the intervention model did not produce a good enough result for the future prediction of water losses. Furthermore, figure 4.2 illustrates in a graphic way the comparison between the actual and prediction value according to the ARIMA intervention model based on EViews. In addition, as shown in the figure 4.2, we forecast future quantities of water losses of the whole city region for 6 periods (12 months) of the year 2018 as illustrated in the highlighted area in the graph, later we will use this result to compare with ANN models.

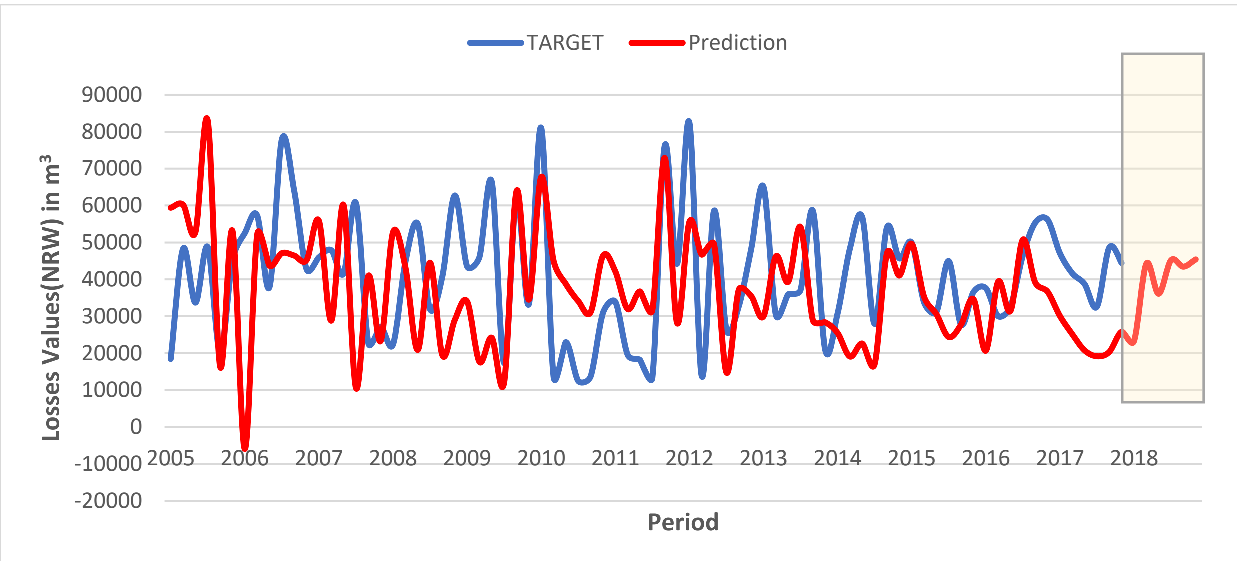

Figure 4.2: Actual and predicted losses values using ARIMA for Whole City region.

4.3.1.2 ARIMA NRW Result for the College Region.

The unit root test shows that the water real losses data of the College region is stationary at the first difference, so we apply the correlogram of the first difference to identify the elements of ARIMA model (MA and AR). Figure 4.3 shows the values of ACF and PACF, it is clear that ACF is negative at the first lag and PACF is negative at lag 1 but does not have positive value, this means the value of MA is 1 while the value of AR is 0, and by applying the second difference for stationarity; the best model in this area is ARIMA (0,2,1).

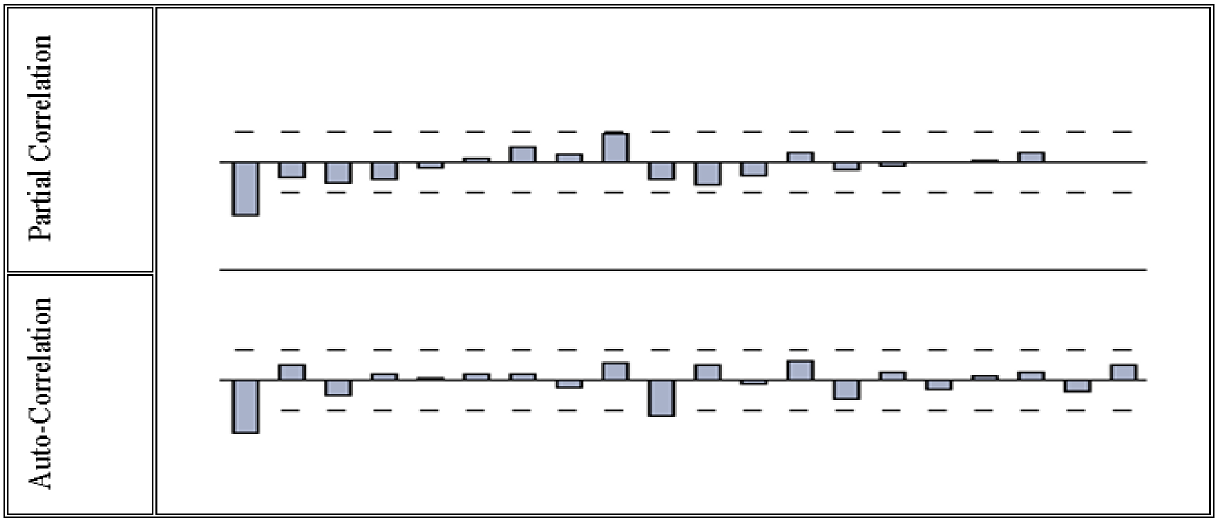

Figure 4.3: ACF and PACF Function of Water Losses (NRW) for the College region.

Tables 4.3 shows the Mean Square Error of the ARIMA model after selecting the fitted model. From this result, it’s apparent that the selected ARIMA model (0,2,1) produces good results based on the Mean Square Error of training and testing sets that obtained for the future forecasting of water losses in this Region.

Table 4.3: MSE of NRW for the College region using ARIMA.

$MSE_{Training}$	$MSE_{Testing}$
5.21E-02	1.64E-01

Likewise, figure 4.4 shows the comparison between the real and prediction losses values produced by the ARIMA model after applying the best model.

Also, in figure 4.4, we forecast future quantities of water losses of the College region for 6 periods (12 months) of the year 2018 using the best model ARIMA (0,2,1) as shown in the highlighted area in the figure.

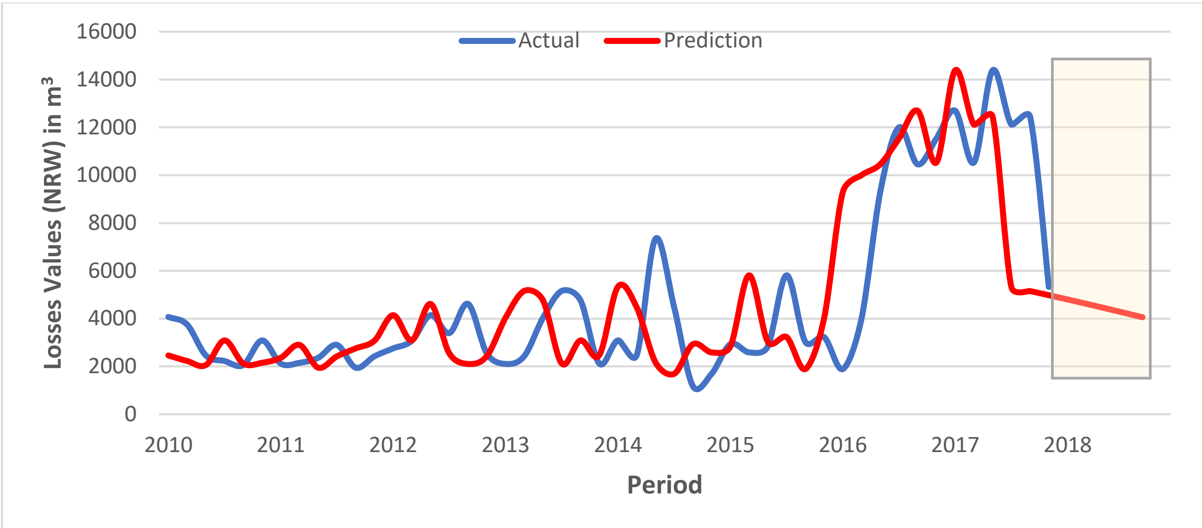

Figure 4.4 :Actual and predicted losses values using ARIMA for College region

4.3.1.3 ARIMA NRW Result for the Flash Region.

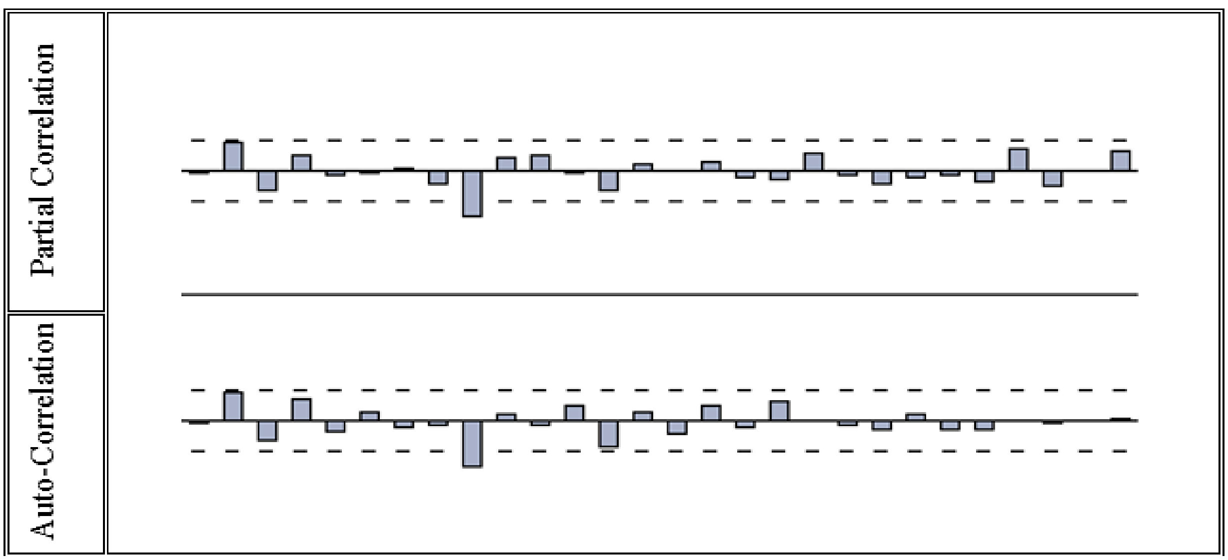

Figure 4.5: ACF and PACF Function of Water Losses (NRW) for the Flash region.

The water losses data in Flash region is stationary this means that there is no need for the differencing process, so we will apply the Correlogram to identify the MA and AR terms. As shown in figure 4.5 from the value of ACF and the PACF there is no ARIMA model, data series of Flash region suffers from pattern interruption, which means that a unique ARIMA model can't be used for the whole series. So we fit what's known as "intervention model", as we can see the series is significant at lag 9 or MA(9) of the ACF and for PACF values there is no suitable positive value above the dashed line.

Table 4.4: MSE of NRW for the Flash region using the intervention model.

MSE $_{Training}$	MSE $_{Testing}$
4.40E-02	1.41E-01

Tables 4.4 shows the Mean Square Error of the intervention model. Furthermore, figure 4.6 illustrates the comparison between the actual and prediction value produced.

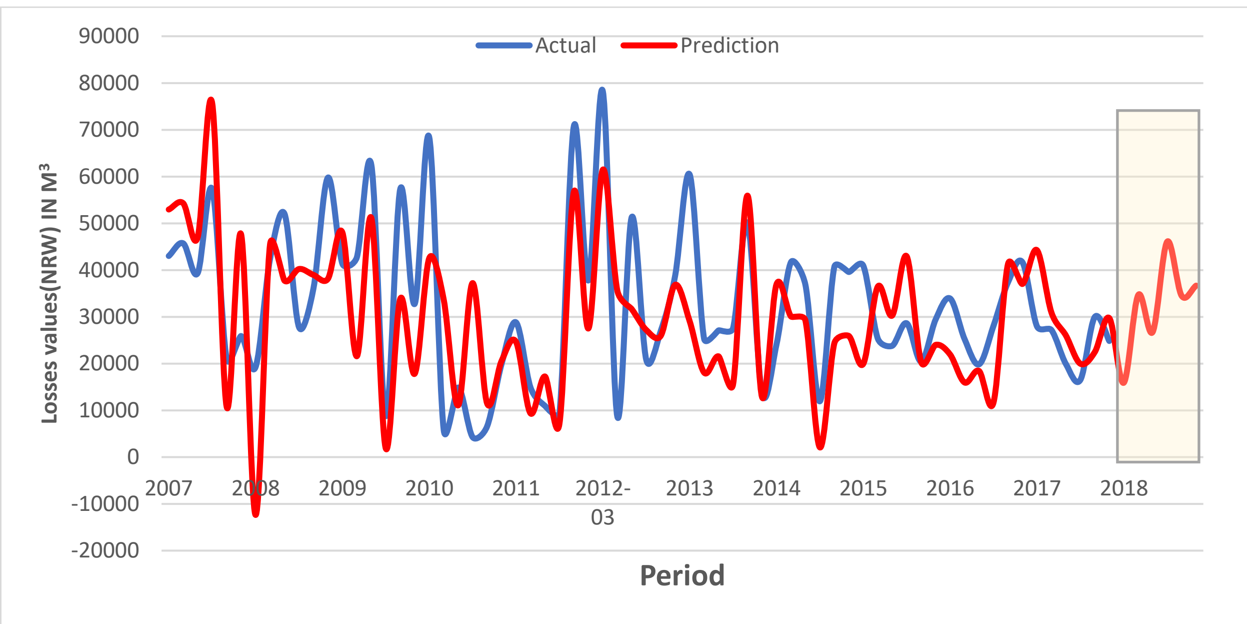

Figure 4.6: Actual and predicted losses values using ARIMA for the Flash region

In addition, Figure 4.6 demonstrates the forecast future values of water losses for Flash region for 6 periods of the year 2018. As shown in figures 4.5, 4.6 and table 4.4, it's obvious that the proposed intervention model gives some good results based on the values of MSE testing and training, which leads that the model is appropriate in such cases of water losses prediction in the Flash region.

4.3.1.4 ARIMA NRW Result for Sunuqrot Region

In Sunuqrot area, water losses data is stationary at the level, so there is no need for differencing, we will apply the correlogram to identify and select the elements of ARIMA (MA and AR). As shown in figure 4.7 the ACF is positive and has no negative significant values or lags and the PACF is positive at the first lag so the best and fitted model is ARIMA (1,0,0).

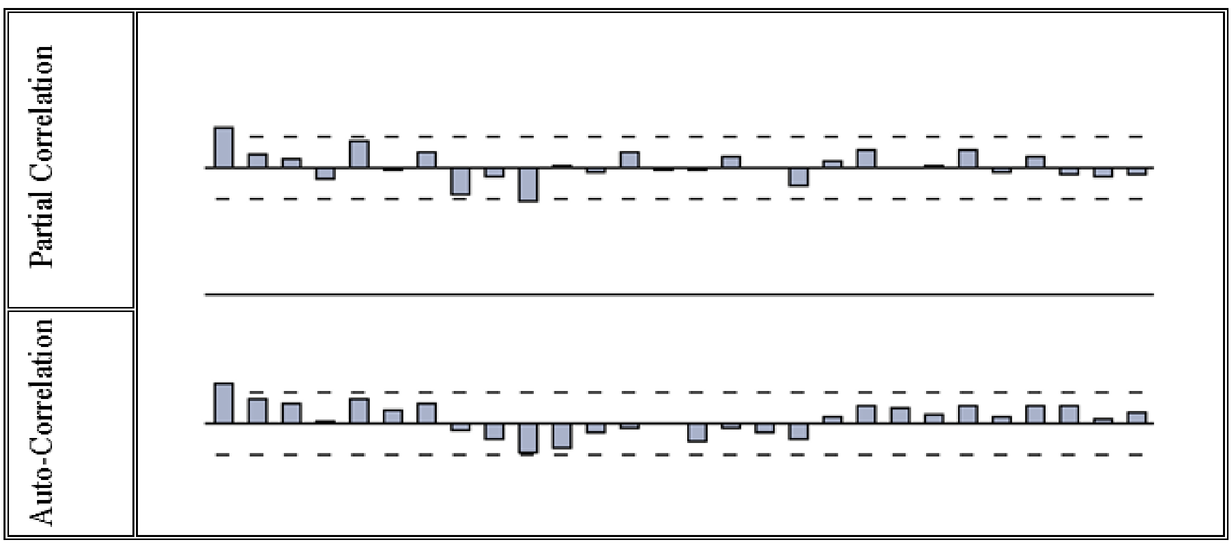

Figure 4.7: ACF and PACF Function for Water Losses (NRW) for the Sunuqrot region.

Tables 4.5 shows the Mean Square Error of the ARIMA model after selecting the best ARIMA model (1,0,0). moreover, as shown in in the highlighted in area 4.8, we forecast future quantities of water losses for the Sunuqrot region for 6 periods of the year 2018.

Table 4.5: MSE of NRW for the Sunuqrot region using ARIMA.

MSE $_{Training}$	MSE $_{Testing}$
1.32E-01	2.52E-01

The comparison between the actual and prediction value produced by the ARIMA model is illustrated in figure 4.8. As we can see in table 4.5 and figures 4.7 and 4.8 that ARIMA model (1,0,0) based on MSE values did not give good future prediction result of water losses in the Sunuqrot region.

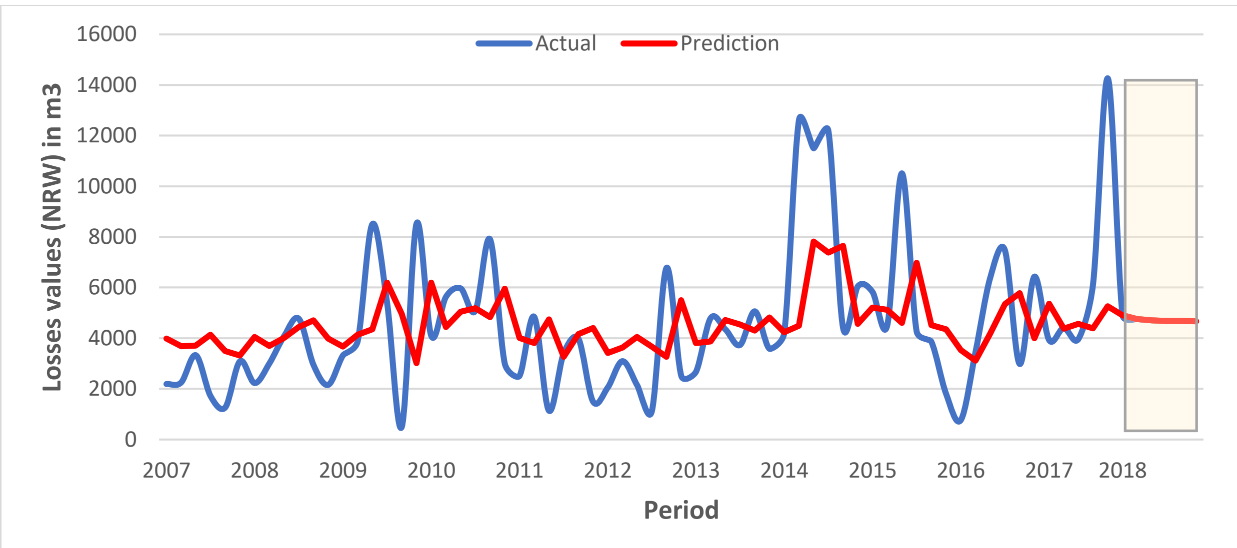

Figure 4.8: Actual and predicted losses values using ARIMA for Sunuqrot region

As shown in figures and tables of using the statistical ARIMA model on the data of water losses for the whole city and for the other three regions (College, Flash and Sunuqrot), we can see that ARIMA in the whole city and Sunuqrot was unable to find a suitable model because in these regions data series sufferers from pattern interruption. While ARIMA was able to find a suitable model in the other regions. Where, it can be concluded that ARIMA model gives good results in the area of College and Flash which leads that the model is appropriate in such cases of water losses prediction in the College and Flash.

4.3.2 ARIMA Demand Prediction Result

In the following sections, we will show the result of the ARIMA model of water demands for all regions of Beitunia city.

4.3.2.1 ARIMA Demand Result for the Whole City Region

The unit root test shows that the whole city water demands data is nonstationary and this fact implies the necessity to use the first difference form data. So, we apply the correlogram of the first difference to identify the MA and AR terms, as shown in figure 4.9 the ACF is negative at lag 3 MA(3) and the PACF has the negative value at lag 3 and does not have a positive lag value. It is clear that the third lag autocorrelation is statistically significant while all following autocorrelations are not. So, we will reduce the difference and the MA levels by one so the fitting ARIMA model will be ARIMA (0,1,2).

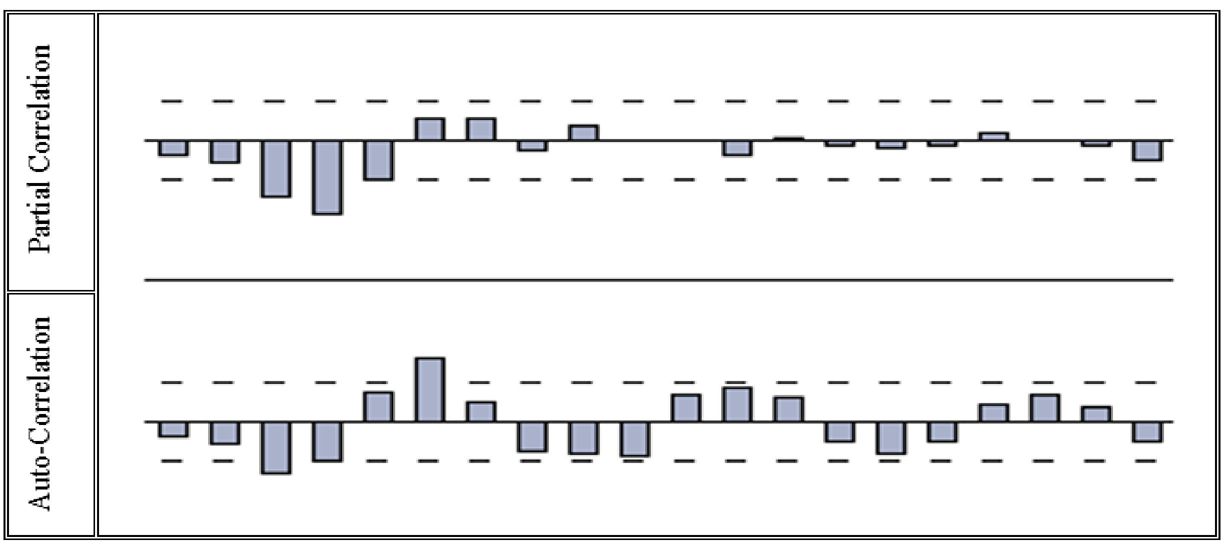

Figure 4.9: ACF and PACF Function for Water demands for the whole city region.

Tables 4.6 shows the Mean Square Error of the ARIMA model after selecting the best model (0,1,2). Furthermore, according to these values of MSE, we can see that ARIMA (0,1,2) model gives a good result so we can use it in water demands prediction in the whole city region. Figure 4.10 illustrates the comparison between the actual and prediction value produced by the ARIMA model.

Table 4.6: MSE of demands for the Whole City region using ARIMA.

MSE $_{Training}$	MSE $_{Testing}$
9.12E-02	1.17E-01

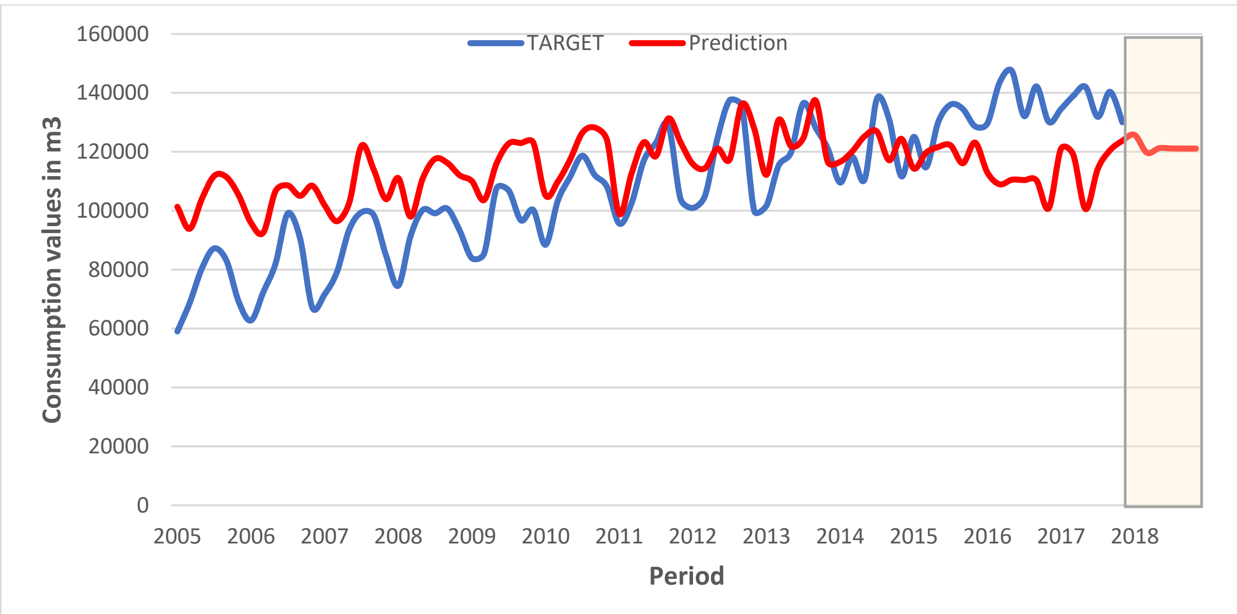

Figure 4.10: Actual and predicted demands values using ARIMA for the whole city region.

Additionally, using the best model, ARIMA (0,1,2) as shown in the highlighted area in the figure 4.10, we forecast future quantities of water losses for the whole city region for 6 periods of the year 2018. As shown in figures 4.10, 4.9 and table 4.6, it's obvious that the proposed model gives some good results based on the values of MSE testing and training, which leads that the model is appropriate in such cases of water losses prediction for the Whole City region.

4.3.2.2 ARIMA Demand Result for the College Region.

The unit root test shows that the water demands data of College is stationary at the first difference, this indicator to apply the Correlogram of the first difference in order to find and select ARIMA elements (MA and AR). The lag values as appear in figure 4.11, ACF is negative at the first term this means that MA=1, while the PACF is, has no positive values above the dashed line so AR=0, so the best ARIMA model according to these values is ARIMA (0,1,1). Tables 4.7 shows the Mean Square Error of the ARIMA model after selecting the best model (0,1,1), which illustrate that the model gives a good result in water demand prediction for the Collage region.

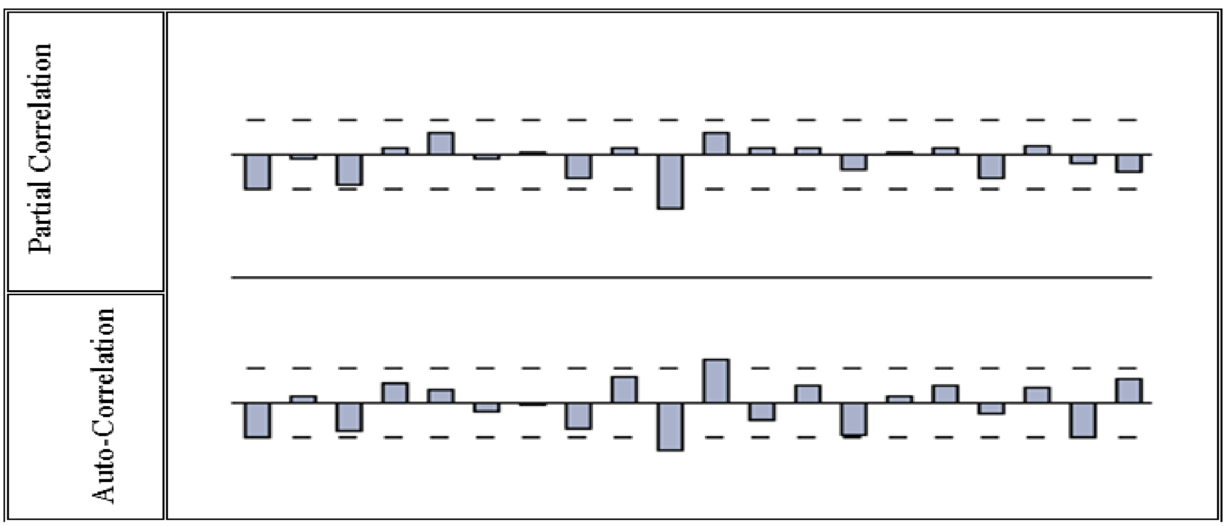

Figure 4.11: ACF and PACF Function for Water demands for the College region.

Table 4.7: MSE of demands for the College region using the ARIMA model

MSE $_{Training}$	MSE $_{Testing}$
1.80E-02	1.82E-01

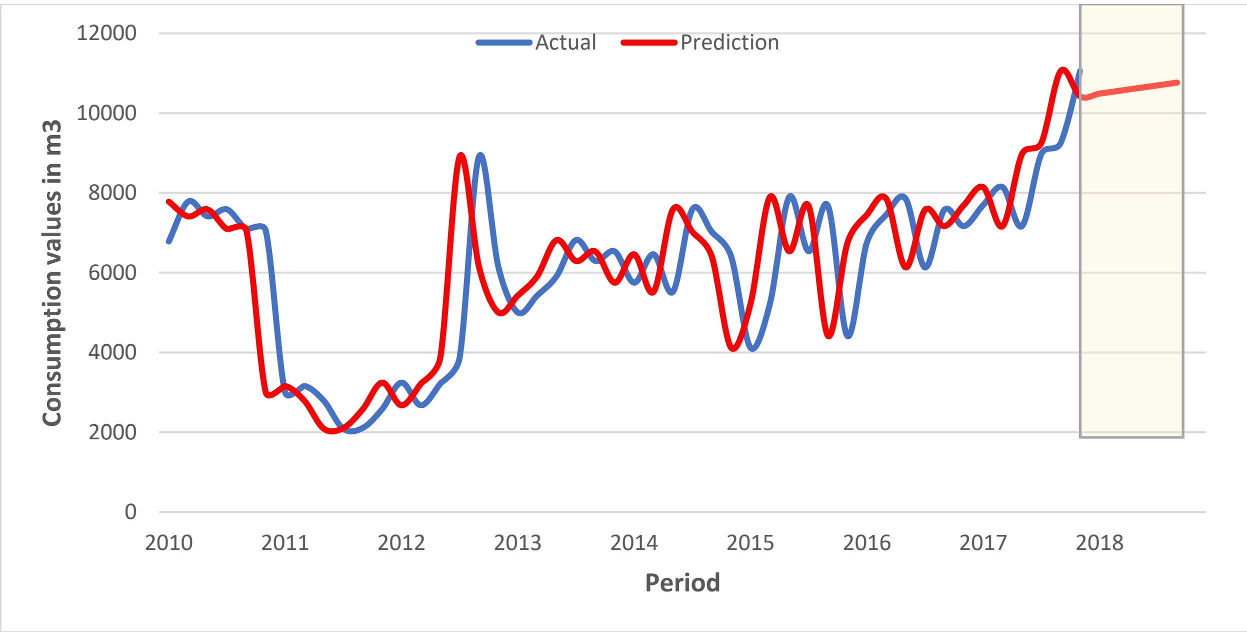

Figure 4.12: Actual and predicted demands values using ARIMA for College region

Furthermore, figure 4.12 illustrates the comparison between the actual and prediction value produced by the ARIMA model. Also, in the figure 4.12 as illustrated in the highlighted area, we forecast future quantities of water demands of the College region for 6 periods of the year 2018 using the best model, ARIMA (0,1,1).

4.3.2.3 ARIMA Demand Result for the Flash Region

The unit root test shows that the water demands data of the Flash region is nonstationary and this fact implies the necessity to use the first difference form data. So, we apply the Correlogram of the first difference to identify the MA and AR terms, as illustrated in figure 4.13 the ACF is negative at lag 3 MA(3) and the PACF also has a negative value at lag 3 and does not have a positive lag value AR(0). It is clear that the third lag autocorrelation is statistically significant while all following autocorrelations are not. So, we will reduce the difference and the MA levels by one so the fitting ARIMA model will be ARIMA (0,0,2).

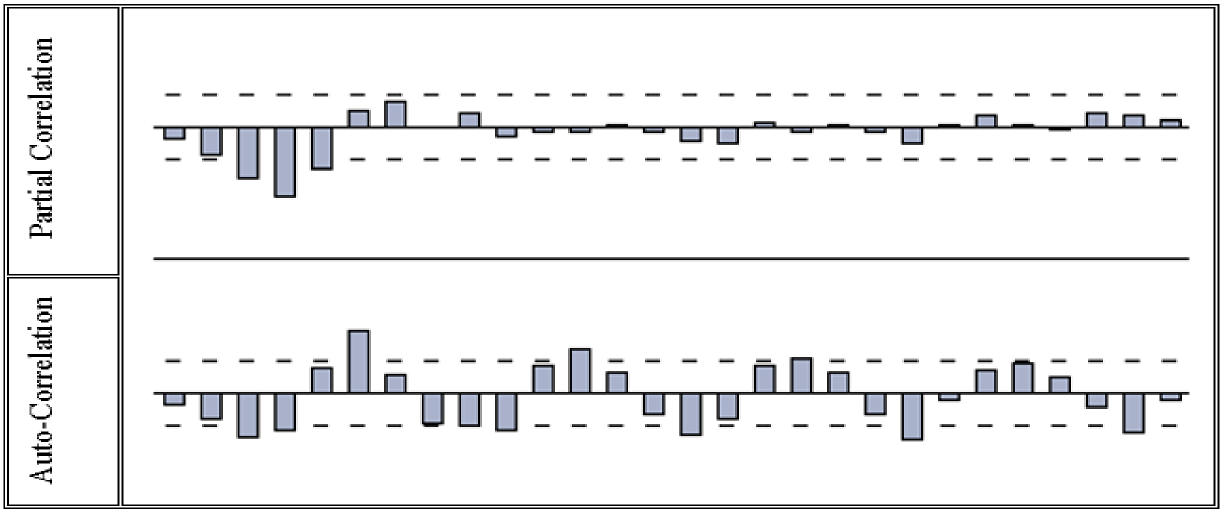

Figure 4.13: ACF and PACF Function for Water demands for the Flash Region in 2018.

Table 4.8: MSE of demands for the Flash region using ARIMA.

MSE $_{Training}$	MSE $_{Testing}$
7.24E-02	2.06E-01

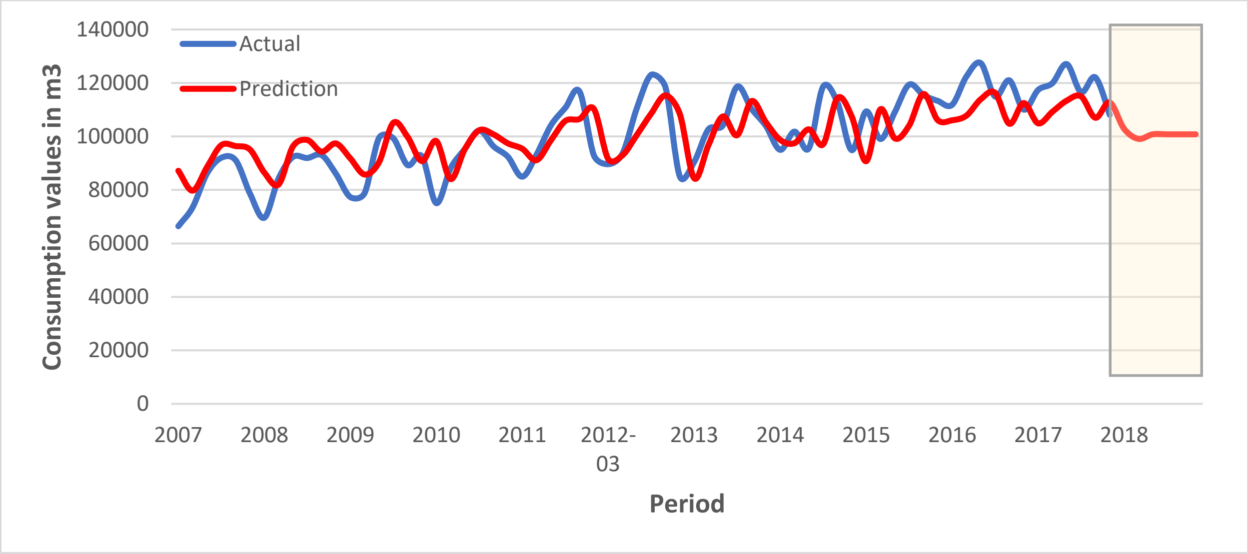

Figure 4.14: Actual and predicted demands values using ARIMA for the Flash Region in 2018.

Tables 4.8 shows the Mean Square Error of the ARIMA model after selecting the best model (0,0,2), it's clear that the proposed ARIMA model gives some good results according to the values of MSE testing and training. Furthermore, figure 4.14 illustrates the comparison between the actual and prediction value produced by the ARIMA model.

Using the best model, ARIMA (0,0,2) as illustrated in the highlighted area in the figure 4.14, we predict future quantities of water demands for the Flash for 6 periods (12 months) of the year 2018.

4.3.2.4 ARIMA Demands Result for the Sunuqrot Region

The unit root test shows that the Sunuqrot is stationary at the level so it is not necessary to perform differencing, we apply the Correlogram of the first difference to identify the MA and AR terms. As shown in figure 4.15, the PACF is positive at the first lag this means the value of AR=1 and the ACF is decaying so the best model is ARIMA (1,0,0) according to the value of AR, differencing and MA.

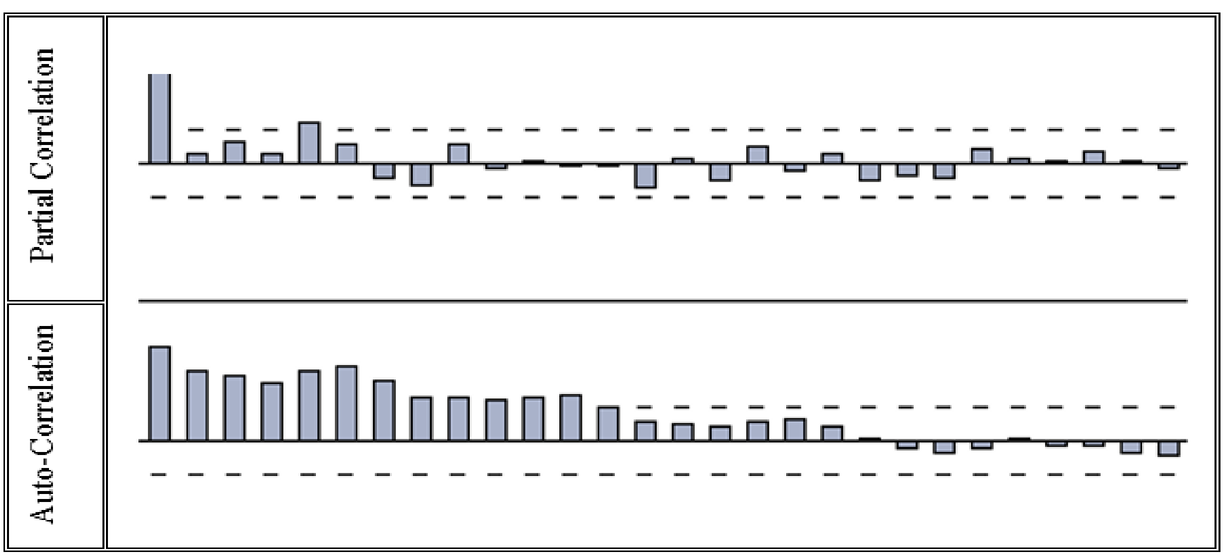

Figure 4.15: ACF and PACF Function for Water demands for the Sunuqrot region.

Table 4.9: MSE of demands for the Sunuqrot region using ARIMA.

$MSE_{Training}$	$MSE_{Testing}$
9.35E-02	2.54E-01

Tables 4.9 shows the Mean Square Error of the ARIMA model after selecting the best model (1,0,0). Furthermore, figure 4.16 illustrates the comparison between the actual and prediction value produced by the ARIMA model.

Using the best model, ARIMA (1,0,0) as shown in the highlighted area in figure 4.16, we forecast future quantities of water demands for the sunburst for 6 periods of the year 2018.

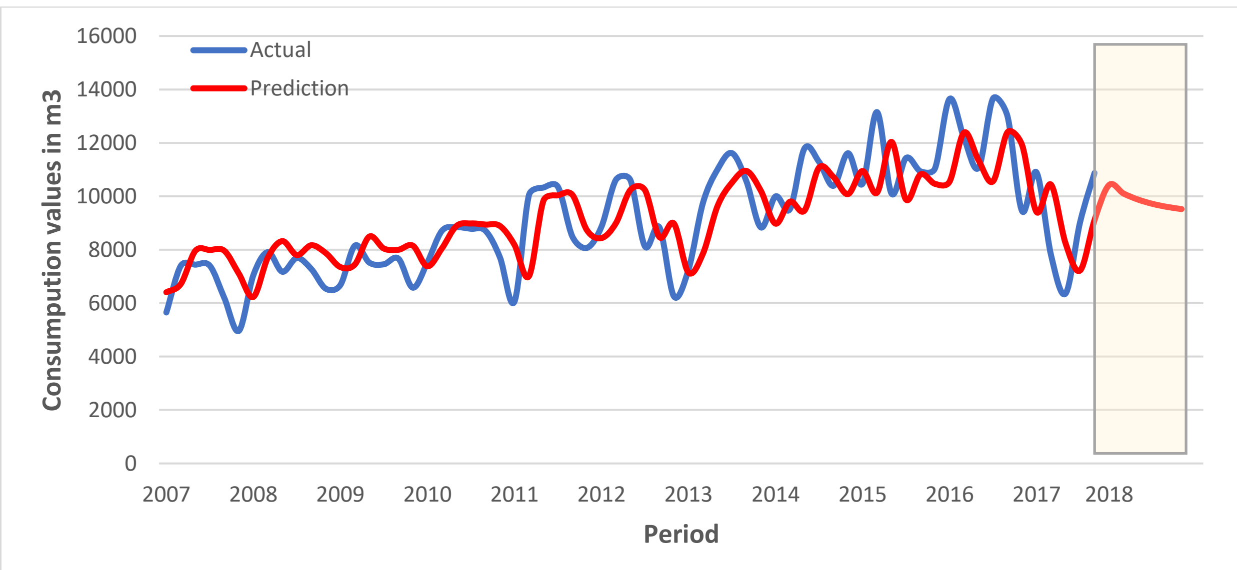

Figure 4.16: Actual and predicted demands values using ARIMA for the Sunuqrot region

As shown in figures and tables of using the statistical ARIMA model on the data of water demands for the whole city and for the other three regions (College, Flash, and Sunuqrot), we can see that ARIMA was able to find a suitable model for regions of the city. This leads that ARIMA model gives good results for regions of the city which leads that the model is appropriate in such cases of water demands prediction in Beitunia city.

4.4 MLPNN-LM Prediction Model

In this model, we have resulted in water losses and demands prediction for the whole city and for the other three regions. In order to predict the water losses (NRW) and water demands using the MLPNN-LM model, we obtained the real losses and consumption values from all regions of Beitunia city for 13 years. We have used MATLAB 14a to perform the predicting, the outcomes of values are given a number of neurons, epochs or number of Iterations that represent the number of the execution cycle, and the Mean Squared Error for the training and the testing (**$MSE_{Training}$** and **$MSE_{Testing}$).** We have divided the data into two sets based on cross-validation model, for the training part the value of the set is 70% and 30% for the testing set.

4.4.1.1 MLPNN- LM NRW Prediction Result

In this section, all predictions resulted from applying the MLPNN model of water losses (NRW) are illustrated for each region of Beitunia city.

4.4.1.2 Water Losses (NRW) Prediction for the Whole City Region

In experiencing different models on the purpose of selecting the best one, table 4.10 and diagram 4.17 show the best results of predicting water losses of data which were preprocessed in prior. The table shows the Mean Square Error (MSE) calculations, a number of iterations, and the number of neurons; ranges from 5 to 90 neurons, with an incremental step of 5 neurons.

According to table 4.10 and figure 4.17, it can be seen that MLPNN-LM produces a good result of NRW Prediction; by neuron 65, the model achieves the best (lowest) MSE training of value

Table 4.10: MLPNN-LM NRW Prediction for the whole city region.

Number of Neurons	MSE $_{Training}$	MSE $_{Testing}$	Number of Iteration
5	3.909E-02	7.108E-02	12
10	3.019E-02	1.140E-01	11
15	2.369E-02	1.111E-01	8
20	2.681E-02	1.567E-01	13
25	1.784E-02	1.520E-01	7
30	2.263E-02	1.083E-01	7
35	1.715E-02	1.401E-01	7
40	9.971E-03	2.636E-01	8
45	1.987E-03	2.897E-01	14
50	2.126E-03	2.288E-01	10
55	1.027E-02	2.387E-01	7
60	9.826E-03	2.183E-01	7
65	**6.17E-07**	2.75E-01	6
70	8.208E-03	2.054E-01	7
75	5.772E-05	1.592E-01	9
80	4.370E-03	1.609E-01	5
85	3.885E-03	1.855E-01	4
90	3.613E-03	3.985E-01	4

6.17E-07 this value can be viewed as small which results in high quality of prediction for the future of water losses. Having presented the model results, it can be noticed that the prediction process is not highly dependent on the number of iterations of the MLPNN-LM. For instance, with number of neurons = 45, the process duration is 14 iterations which achieved an MSE value acknowledged by 1.987E-03, which is not as good fit compared to the previous values. One more other observation is that the increase in the number of neurons does not necessarily generate more reasonable predictions (least error metrics).

Moreover, as shown in figure 4.18 we can see the comparison produced by MLPNN-LM model between the real and predicted of water losses up to the year 2017, also the figure shows the

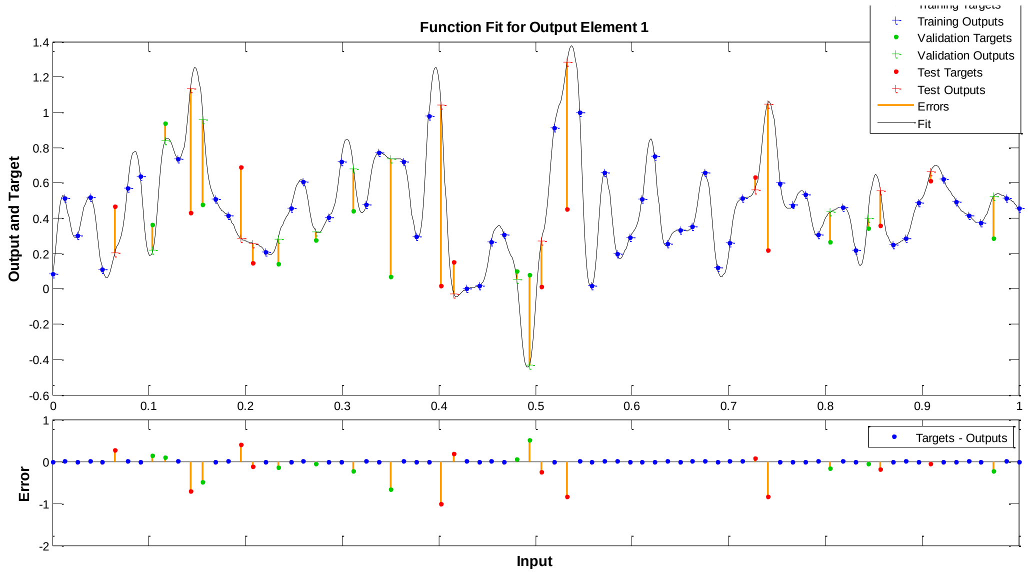

Figure 4.17: MLPNN-LM Best NRW Prediction Result for the whole city region when number of neurons = 65.

predicted water losses values of the year 2018 as shown in the highlighted area in the graph.

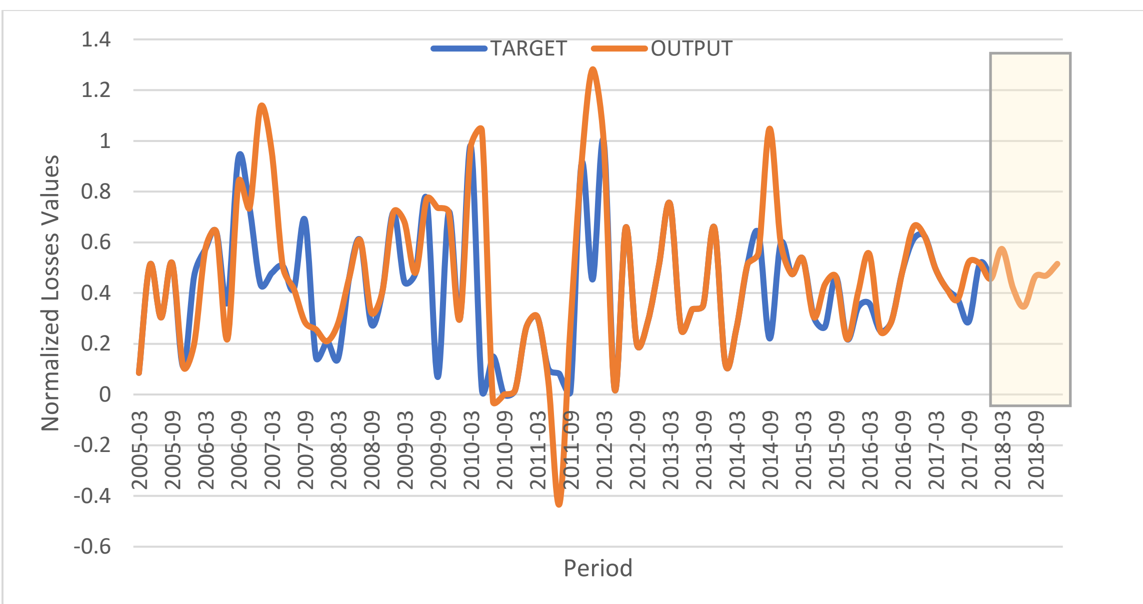

Figure 4.18: Comparison between real and predicted water losses values for the whole city region when number of neurons = 65.

Having such results shown in figures 4.17, 4.18 and table 4.10, which show that the model is one of the promising models for the future forecasting of water losses in the whole city region.

4.4.1.3 Water Losses (NRW) Prediction for the College Region.

Table 4.11: MLPNN NRW Prediction for the College region

Number of Neurons	MSE $_{Training}$	MSE $_{Testing}$	Number of Iteration
5	7.936E-03	4.938E-02	12
10	1.050E-02	3.961E-02	7
15	3.872E-03	9.725E-03	9
20	4.999E-04	3.486E-02	9
25	2.601E-04	3.014E-02	25
30	**2.04E-04**	1.30E-01	11
35	2.10-E-03	6.357E-02	7
40	1.604E-03	1.213E-01	4
45	2.534E-04	7.416E-02	6
50	1.708E-03	9.650E-02	4
55	4.051E-05	8.256E-02	5
60	2.148E-05	2.509E-01	4
65	4.873E-04	1.432E-01	3
70	9.739E-04	1.587E-01	4
75	6.334E-04	6.211E-01	3

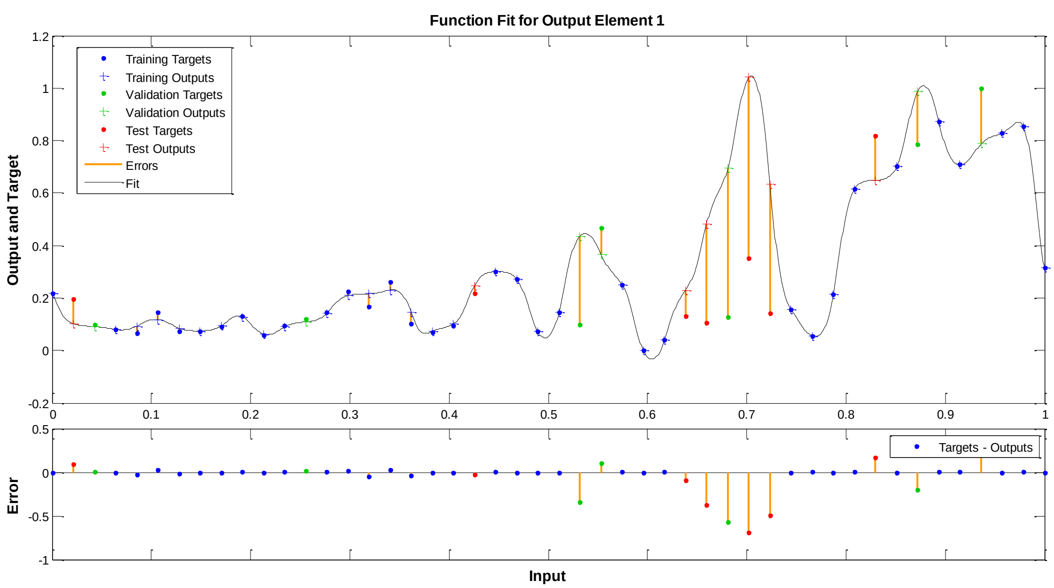

Figure 4.19: MLPNN-LM Best NRW Prediction Result for the College region when number of neurons = 30

As shown in table 4.11 and figure 4.19, it can be noticed that the MLPNN-LM model also generates highly accurate predictions with a suitable number of neurons in the hidden layer, this leads that the model is highly appropriate in such cases of water losses in the college region.

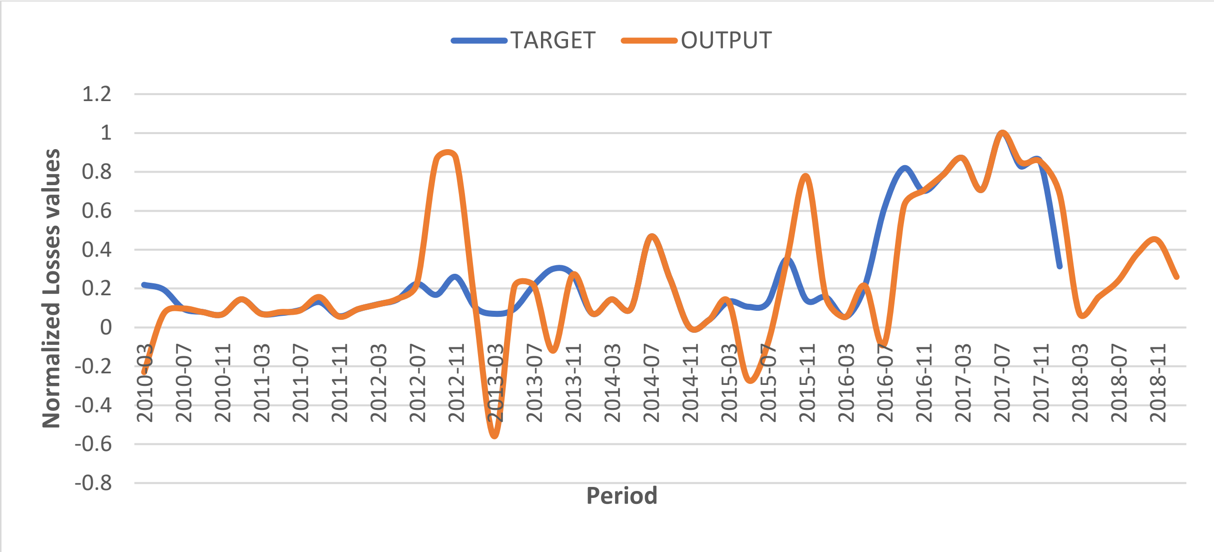

Figure 4.20 :Over-fitting Prediction NRW Result for the College region when number of neurons = 60.

The MSE value, with a number of neurons = 30, has caused a precise result for the NRW. Therefore, increasing the number of neurons does not ultimately result in acceptable model performance; the model suffers from the over-fitting problem when increasing the number of neurons as shown in Figure 4.20.

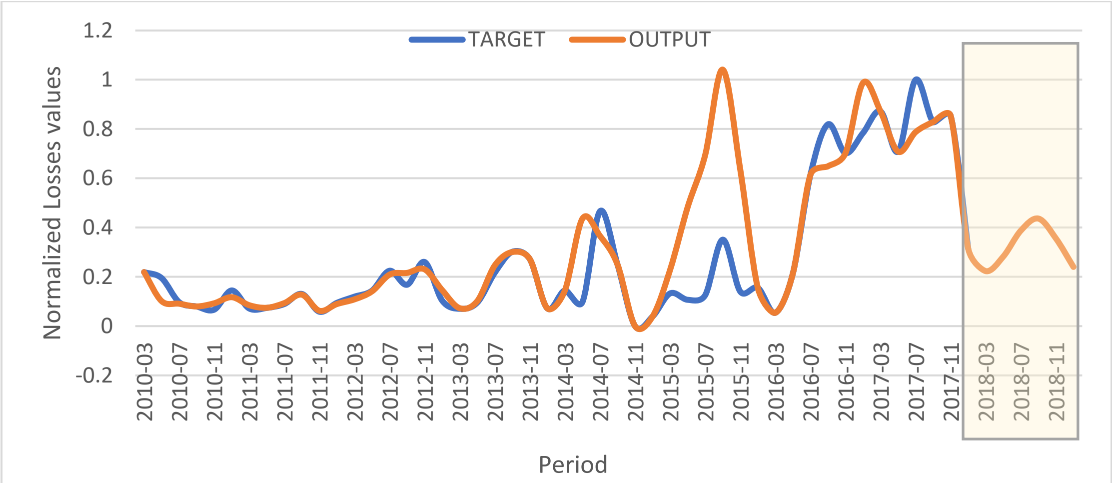

Figure 4.21: Comparison between real and predicted water losses values for the College region when number of neurons = 30

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Furthermore, in this model, we have produced the predicted values of NWR for the year 2018 as illustrated in the highlighted area in figure 4.21. Also, the figure shows a comparison between the actual and predicted water losses.

4.4.1.4 Water Loss (NRW) Prediction for Flash Region

According to the result shown in table 4.12 and figure 4.22, it's clear that the proposed MLPNN-LM model produces accurate and fewer MSE values, which means that the model is suitable for NRW Prediction in the Flash region. As we mentioned before the prediction process does not depend on the number of iterations, although we have 13 iterations with number of neurons = 20, the captured MSE value is 1.517E-02 which could be not acceptable.

Table 4.12: MLPNN-LM NRW Prediction for the Flash region

Number of Neurons	**MSE $_{Training}$**	**MSE $_{Testing}$**	**Number of Iteration**
5	2.881E-02	1.426E-01	7
10	2.709E-02	6.610E-02	11
15	2.869E-02	4.025E-02	7
20	1.517E-02	1.406E-01	13
25	1.792E-02	2.373E-01	9
30	1.698E-02	8.094E-02	9
35	9.816E-04	1.849E-01	9
40	1.663E-02	6.695E-02	7
45	1.106-E-03	6.159E-02	10
50	8.722-E-03	1.455E-01	7
55	6.852E-04	4.322E-01	12
60	**2.711E-05**	4.163E-01	5
65	3.662E-04	3.265E-01	7
70	2.277E-03	1.600E-01	4
75	1.409E-03	1.574E-01	5

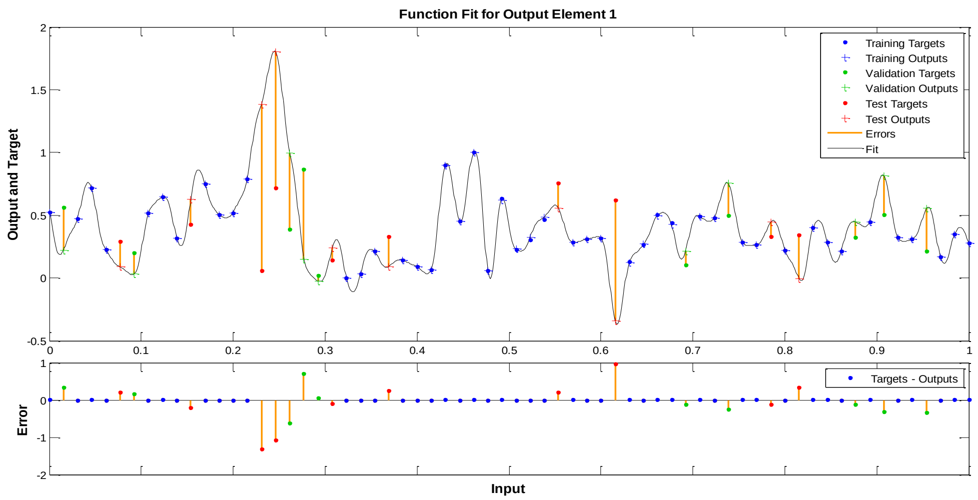

Figure 4.22: MLPNN-LM Best NRW Prediction Result for the Flash region when number of neurons = 60

In order to forecast the losses values and comparing those values with the real losses in the College Region, the produced predicted values for the year 2018 are depicted in figure 4.23.Also, the figure shows the comparison produced by the MLPNN-LM model between the real and predicted water losses

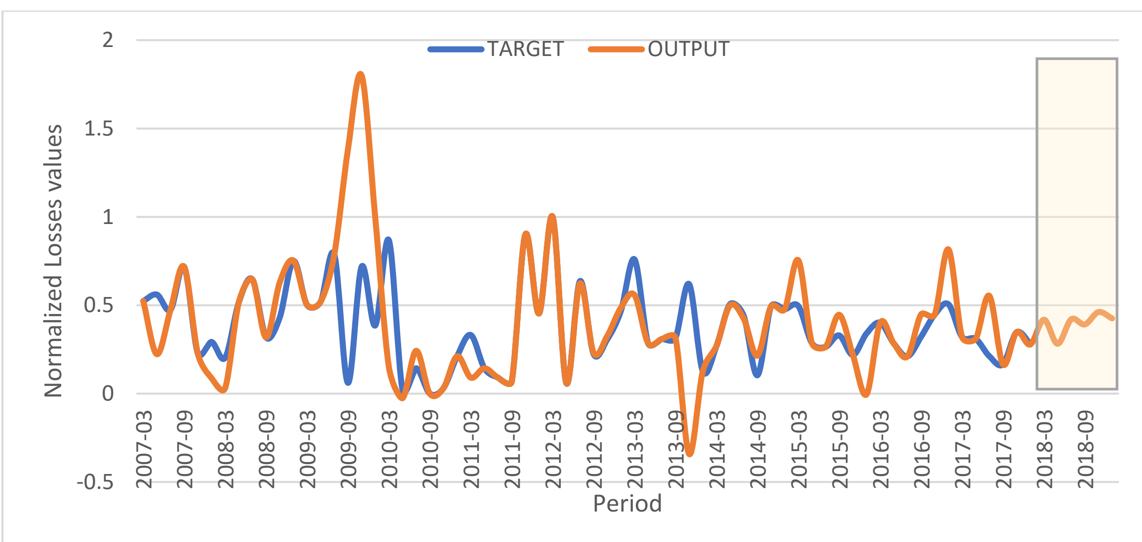

Figure 4.23: Comparison between real and predicted water losses values for the Flash region when number of neurons = 60.

4.4.1.5 Water Losses (NRW) Prediction for the Sunuqrot *Region*

Table 4.13: MLPNN-LM NRW Prediction for the Sunuqrot region

Number of Neurons	MSE Training	MSE Testing	Number of Iteration
5	1.910E-02	2.553E-02	26
10	1.122E-02	7.534E-02	27
15	7.012E-03	1.347E-01	24
20	1.161E-02	3.206E-02	9
25	6.857E-03	5.082E-02	9
30	1.757E-03	8.016E-02	14
35	7.155E-03	3.102E-02	8
40	**2.99E-04**	3.87E-02	35
45	3.967E-03	6.787E-02	7
50	3.958E-04	1.650E-01	9
55	2.402E-05	5.479E-02	6
60	1.940E-05	1.169E-01	5
65	1.541E-03	1.494E-01	4

Likewise, as illustrated in table 4.13 and figure 4.24, it can be seen that with number of neurons = 40; the model has shown the best performance with the least error value in prediction.

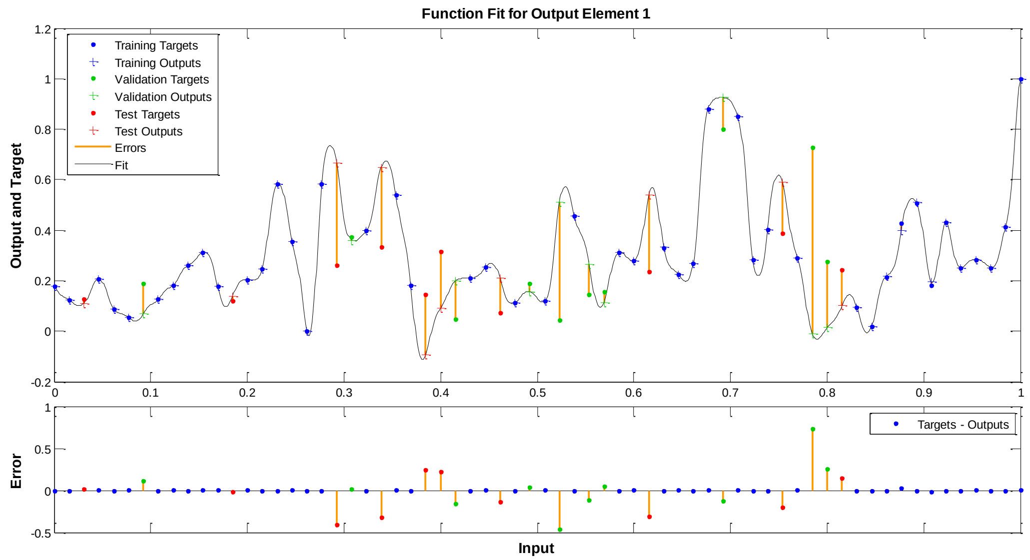

Figure 4.24: MLPNN-LM Best NRW Prediction Result for the Sunuqrot region when number of neurons = 40.

On the other hand, the experiment shows that an increasing number of neurons does not cause more accurate result but overfitting as shown in Figure 4.25.

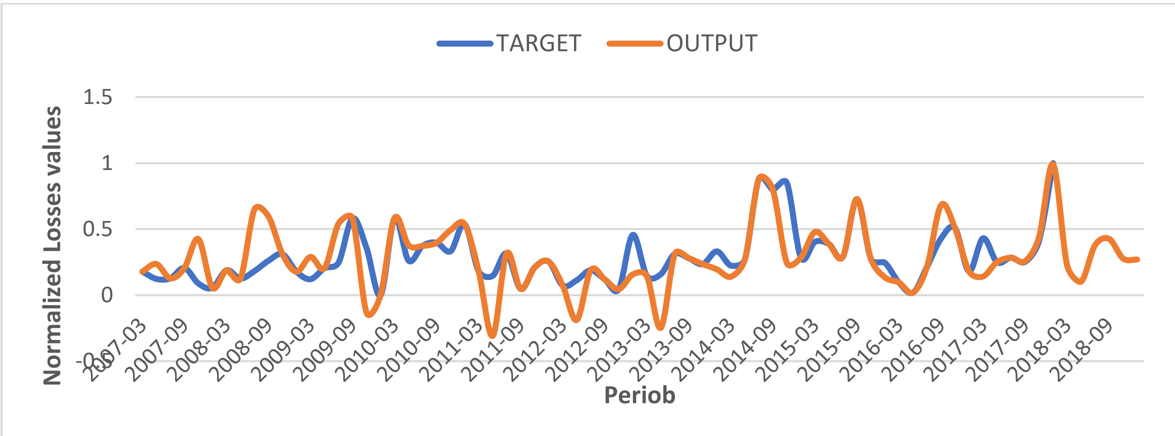

Figure 4.25: Over-fitting Prediction NRW Result for the Sunuqrot region when number of neurons = 60.

As illustrates figure 4.26, we can see the comparison produced by the MLPNN-LM model between the real and predicted water losses values for the Sunuqrot region, besides the predicted losses water values (NWR) for the year 2018 as shown in the highlighted area in figure 4.26.

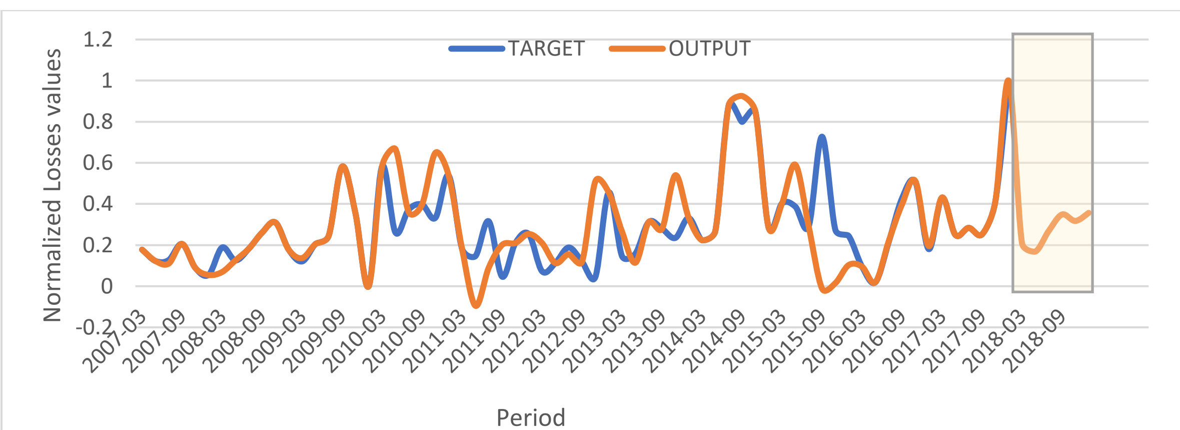

Figure 4.26: Comparison between real and predicted water losses values for the Sunuqrot region when number of neurons = 40.

4.5 MLPNN-LM Demand Prediction Result

In this section, we will illustrate the result of MLPNN-LM model water demands prediction for each region of Beitunia city.

4.5.1.1 MLPNN-LM Water Demand Prediction for the whole city Region

Table 4.14: MLPNN-LM Demand Prediction for the whole city region.

Number of Neurons	MSE_{Training}	MSE_{Testing}	Number of Iteration
5	1.06E-02	2.32E-02	22
10	8.69E-03	2.37E-02	8
15	4.87E-03	2.92E-02	26
20	5.20E-03	1.88E-02	10
25	2.45E-03	8.75E-03	14
30	8.31E-04	1.74E-02	10
35	2.82E-04	1.98E-03	12
40	1.29E-03	1.06E-01	8
45	2.87E-04	8.92E-02	11
50	1.46E-04	2.89E-02	15
55	4.69E-04	3.54E-02	9
60	8.88E-05	7.29E-02	7
65	7.30E-04	1.77E-01	7
70	**2.94E-05**	7.25E-02	7
75	3.88E-05	1.00E-01	5
80	6.43E-05	6.61E-02	6

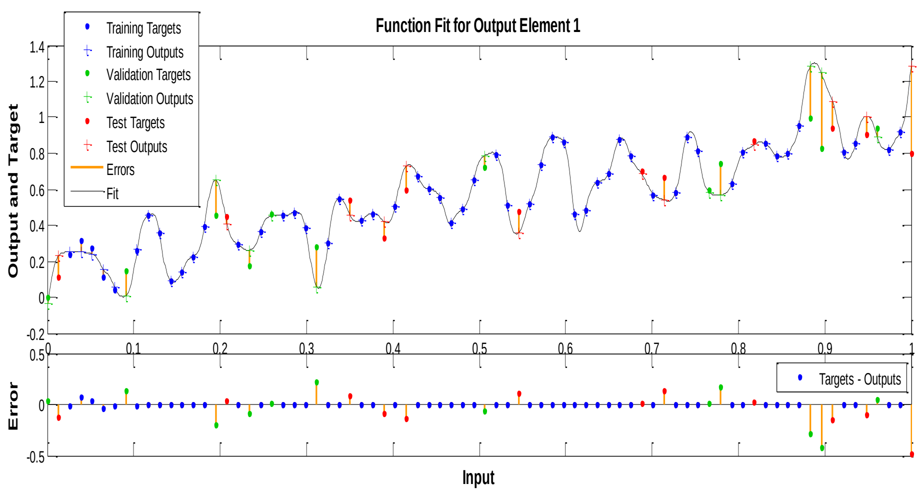

Figure 4.27 :MLPNN-LM Best Demand Prediction Result for the whole city when number of neurons 70.

Table 4.14 and figure 4.27 also show that MLPNN-LM produces highly accurate results of the forecasting of water demand for the whole city. As seen, the best model is achieved with number of neurons = 70, by which the MSE obtained is 2.94E-05. As we mentioned before the prediction process does not depend on the number of iterations, although we have 26 iterations with neuron 15, the captured MSE value is 4.87E-03 which could be not acceptable compared to the result of neutron number 70.

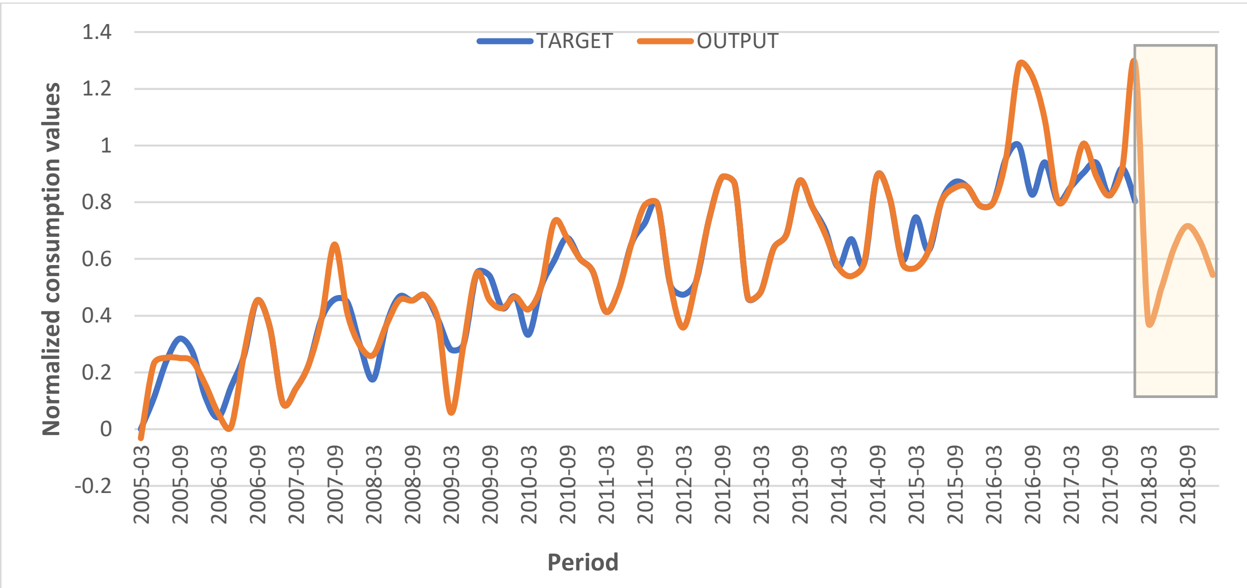

Figure 4.28 :Comparison between real and predicted water consumption values for the whole city region when number of neurons = 70.

In figure 4.28, we can see the comparison produced by the MLPNN-LM model between the real quantities of water consumption and the prediction values according to the adopted model, it is noticeable that there is a convergence in the results indicating the accuracy of the used model Moreover, we predicted water demands values for the year 2018 for the whole city region as shown in the highlighted area in figure 4.28.

4.5.1.2 MLPNN-LM Water Demand Prediction for the College Region

Water demand prediction result for the College as illustrated in table 4.15and figure 4.29 shows that the proposed MLPNN-LM model produces more accurate predictions with fewer MSE values, which leads that the model is highly appropriate in such cases of water demands prediction in the College region. A number of iterations with number of neurons = 35 is 46 iterations which could lead to the conclusion that raising the number of iterations could not necessarily result in more accurate results.

Table 4.15: MLPNN Demand Prediction for the College region.

Number of Neurons	***MSE* Training**	***MSE* Testing**	**Number of Iteration**
5	1.059E-02	2.315E-02	22
10	9.332E-03	1.716E-02	8
15	2.685E-03	4.845E-02	10
20	2.941E-03	2.556E-02	8
25	1.672E-03	1.027E-01	8
30	4.611E-05	4.710E-02	14
35	4.126E-05	1.163E-01	46
40	**1.749E-05**	7.867E-02	6
45	2.356E-05	1.459E-01	5
50	4.371E-05	2.149E-01	5

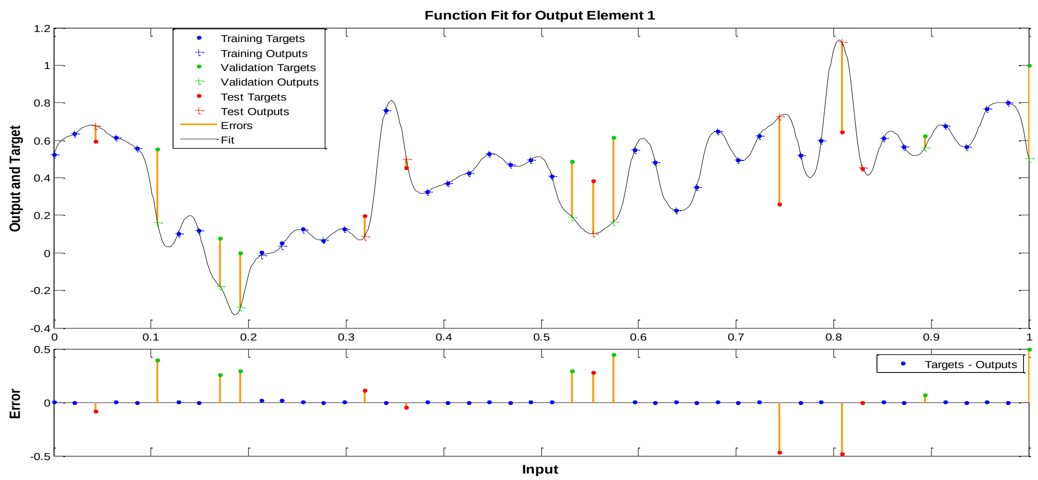

Figure 4.29: : MLPNN-LM Best water Demand Prediction Result for the College region when number of neurons = 40.

Furthermore, in this mode, we have produced the predicted values of water consumption for the year 2018 the College region as illustrated in the highlighted area in figure 4.30. Also, the figure shows a comparison between the actual and predicted water consumption.

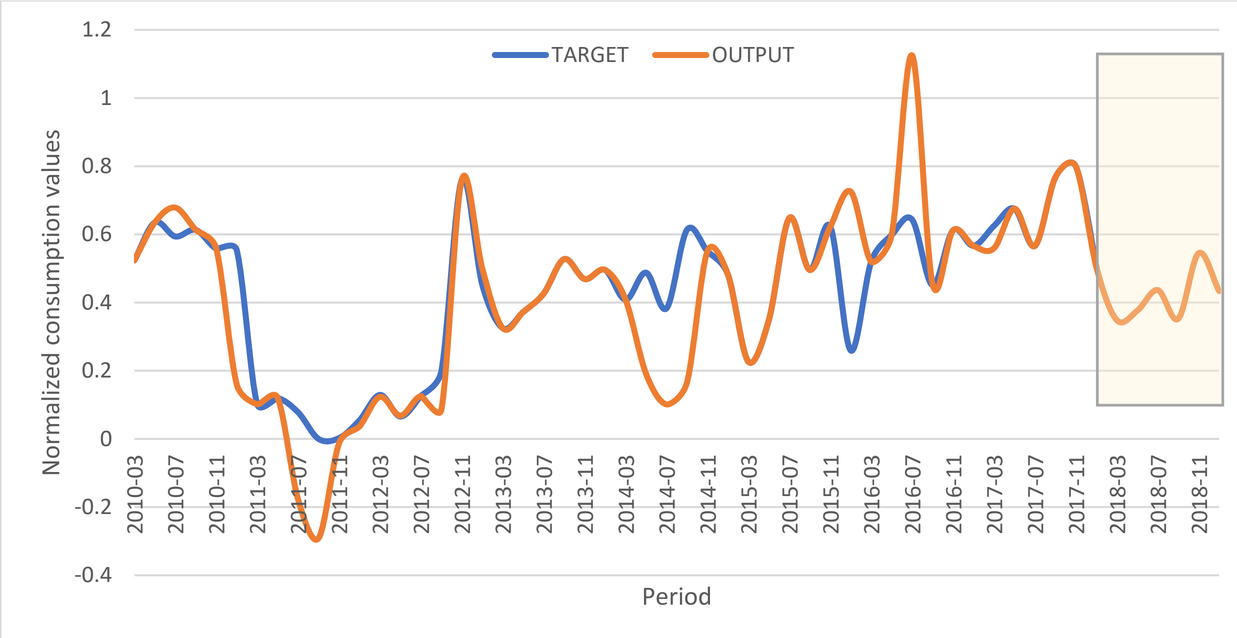

Figure 4.30: Comparison between real and predicted water consumption values for the College region when number of neurons = 40.

As we have seen the accurate prediction results of MLPNN as shown in figures 4.29, 4.30 and table 4.15, which leads that the model is highly appropriate in such cases of water demands prediction in the college region.

4.5.1.3 MLPNN-LM Water Demand Prediction for the Flash Region

According to table 4.16and figure 4.31, it is shown that the MLPNN-LM model produces a good result of the prediction of water demand for the Flash region with a specific number of neurons in the hidden layer. Furthermore, the MSE value with number of neurons = 40 generates a highly correct result for the water demands. The error values for training show that increasing the number of neurons does not cause acceptable results, but it can be seen that the model suffers from overfitting because we get overfitting when number of neurons = 60 as shown in figure 4.32.

To forecast the water consumption in the year 2018 for the Flash region, this model produced the future consumption quantities as shown in the highlighted area in figure 4.33. Similarly, the figure shows a comparison between the actual and predicted water consumption.

Table 4.16: MLPNN-LM Water Demand Prediction for the Flash region.

Number of Neurons	*MSE* Training	*MSE* Testing	Number of Iteration
5	1.365E-02	2.940E-02	11
10	1.422E-02	1.912E-02	17
15	1.402E-02	4.048E-02	10
20	6.256E-03	2.350E-02	11
25	2.883E-03	5.519E-02	8
30	2.402E-03	2.694E-02	8
35	2.601E-04	2.318E-02	13
40	**2.82E-05**	2.11E-02	7
45	3.752E-03	4.413E-02	7
50	3.311E-05	4.906E-02	7
55	1.123E-04	6.615E-02	44
60	2.868E-05	1.184E-01	5
65	1.876E-04	6.096E-02	5
70	2.020E-03	1.387E-01	4
40	2.822E-05	2.106E-02	7

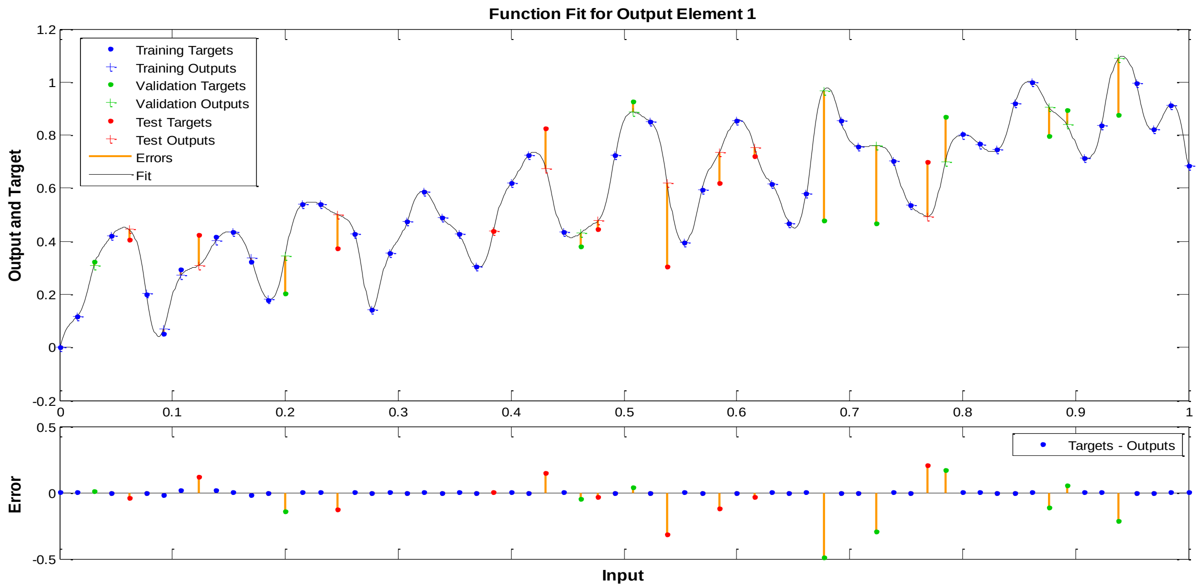

Figure 4.31: MLPNN-LM Best water Demand Prediction Result for the Flash region when number of neurons = 40.

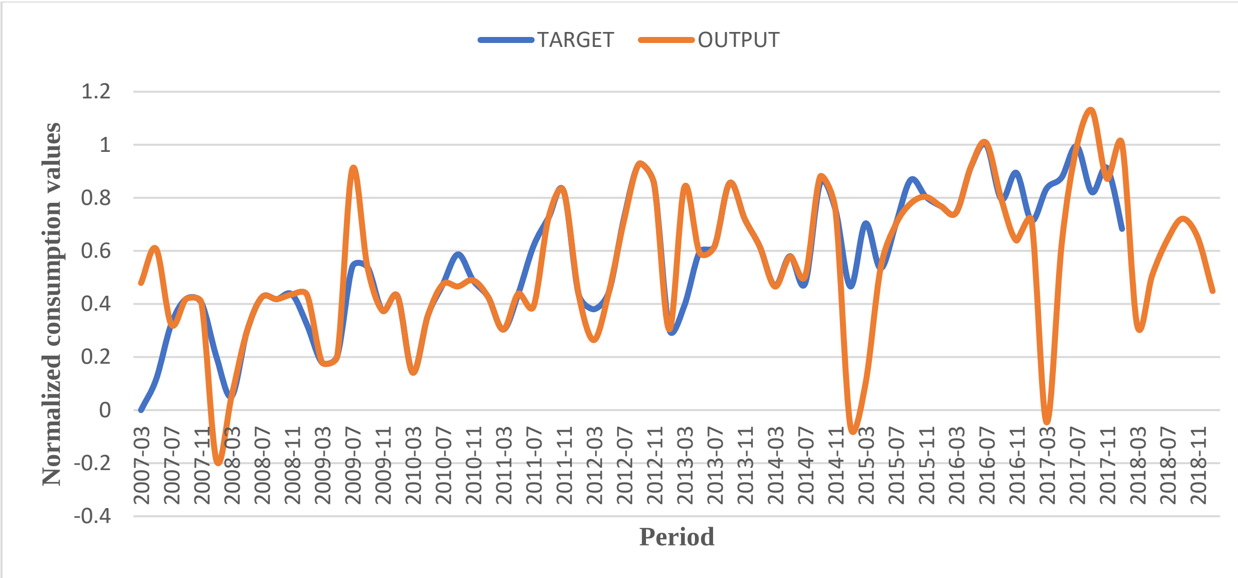

Figure 4.32: Over-fitting of water Demand Prediction Result for the Flash region when number of neurons = 60..

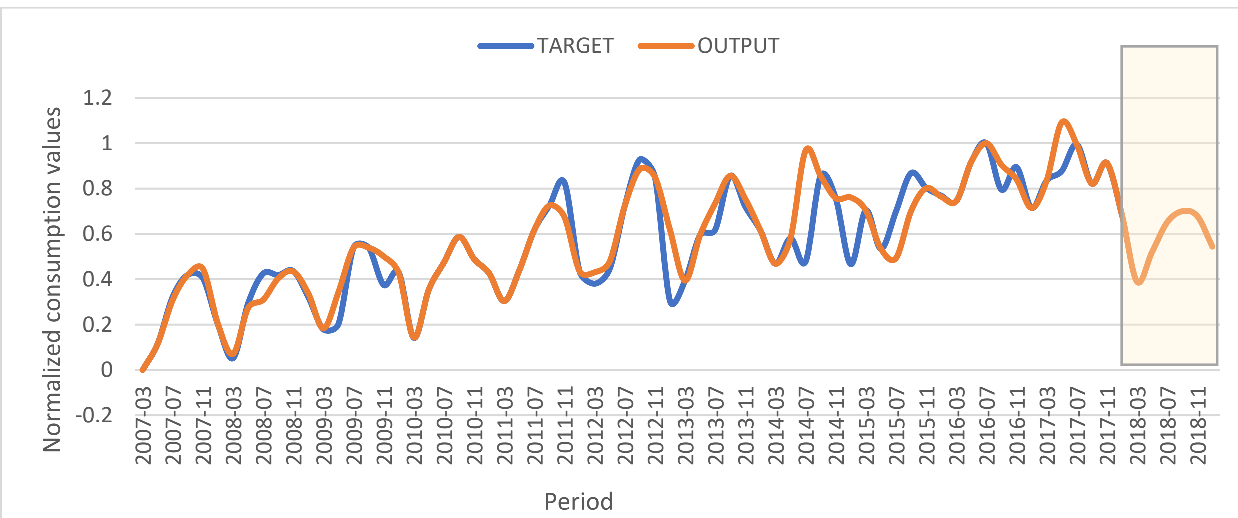

Figure 4.33: Comparison between real and predicted water consumption values for the Flash region when number of neurons = 40.

4.5.1.4 MLPNN-LM Water Demand Prediction for the Sunuqrot Region

As illustrated in table 4.17 and figure 4.34, the best predictions achieved by the MLPNN-LM in Sunuqrot region. When the model used number of neurons = 45 it produces 7.01E-05 MSE value, at which the prediction can be viewed as significantly accurate.

Table 4.17: MLPNN-LM Water Demand Prediction for the Sunuqrot region.

Number of Neurons	*MSE* Training	*MSE* Testing	Number of Iteration
5	1.230E-02	1.450E-01	10
10	9.442-E-3	1.327E-02	28
15	7.377E-03	2.055E-02	11
20	5.995E-03	1.988E-02	42
25	1.345E-03	4.218E-02	19
30	5.137E-02	2.716E-02	8
35	3.568E-03	3.572E-02	8
40	8.012E-04	1.790E-01	14
45	**7.01E-05**	1.210E-01	9
50	2.096E-03	6.156E-02	6
55	7.949E-04	1.024E-01	7
60	6.63E-04	6.20E-02	8
65	3.175E-03	1.513E-01	5
70	1.462E-04	1.459E-01	5
75	1.801E-03	7.039E-02	4

It can also be noticed that the prediction process does not depend on the iteration number of the MLPNN-LM;

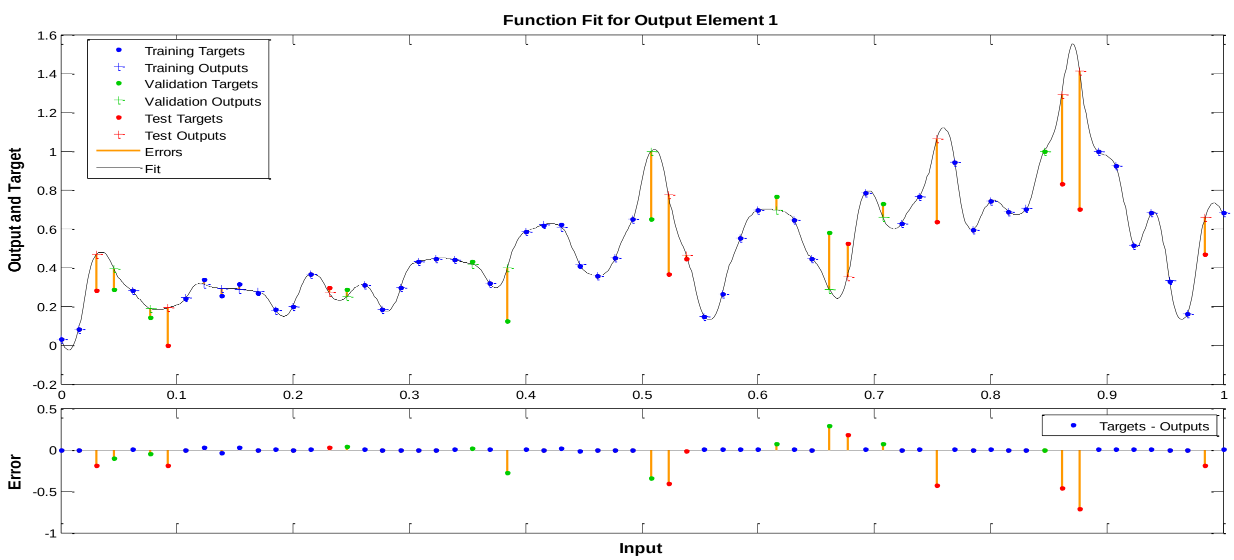

Figure 4.34: MLPNN-LM Best water demand Prediction Result for the Sunuqrot region when number of neurons = 45.

For instance, the model does not perform well with number of neurons = 45 and where number of iterations = 42. Another observation in which the increase in the number of neurons does not necessarily produce the least MSE value.

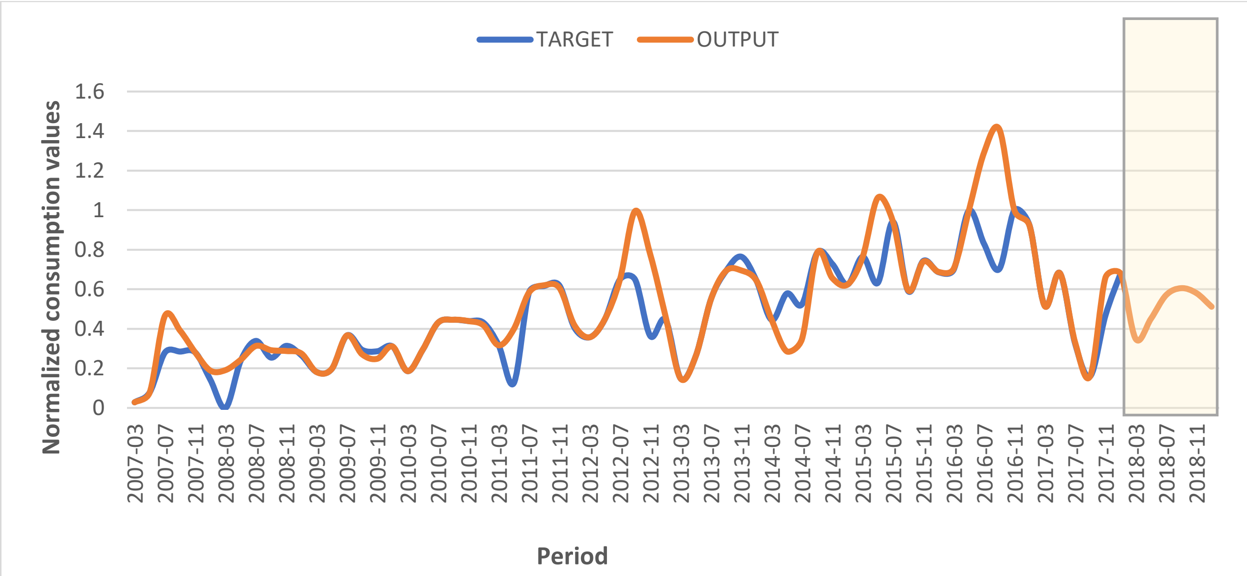

Figure 4.35: Comparison between real and predicted water consumption values for the Sunuqrot region when number of neurons = 45.

As shown in figure 4.35, we can see the comparison produced by the MLPNN-LM model between the Actual and predicted water demands values for the Sunuqrot region, in addition to the predicted water consumption values for the year 2018 illustrated in the highlighted area in the figure 4.35. It’s clear that using MLPNN in Sunuqrot region in order to predict water demands as shown in figures 4.34, 4.35 and table 4.17 produced good results based on the values of MSE testing and training. As a conclusion of using MLPNN-LM model in order to predict the water losses and water demands in Beitunia city as shown in figures and tables in the previous subsections, we observe that the model produced accurate results according to the main square error (MSE). Having such results show that the model is one of the promising models for the future forecasting of water losses and demands.

4.6 RBFNNs (Newrb) Prediction Model

In order to predict water losses and water demands, we applied a proposed model using RBFNN (newrb) fed by real water losses and water consumption quantities of Beitunia city. In the following sections, we will show the result of RBFNNs (newrb) model of water losses (NRW) for all regions of Beitunia city.

4.6.1 RBFNNs (*Newrb*) Prediction Model for Water Losses

In this part of the result, we will present the prediction result of NRW for the whole city and for each region in the city

4.6.1.1 Water Losses (NRW) Prediction for the Whole City Region

The following table and diagram show the best performance results of applying the proposed model for the water losses for the whole city region. The tables below show the MSE (training and testing) values, and the number of neurons used in the experiment; ranging from 5 to 70 neurons, with an incremental step of 5 neurons.

Table 4.18: Newrb NRW Prediction for the whole city region.

Number of Neurons	**MSE $_{Training}$**	**MSE $_{Testing}$**
5	4.43E-02	6.26E-02
10	3.87E-02	7.31E-02
15	3.45E-02	8.77E-02
20	3.13E-02	8.74E-02
25	2.79E-02	8.35E-02
30	2.51E-02	8.44E-02
35	2.34E-02	8.46E-02
40	2.18E-02	8.44E-02
45	2.01E-02	8.59E-02
50	1.71E-02	8.48E-02
55	1.27E-02	8.19E-02
60	5.50E-03	9.35E-02
65	3.78E-03	9.41E-02
70	**2.62E-03**	9.83E-02

According to table 4.10 and figures 4.36, we can see that the behavior of the proposed model in the forecasting process of the nonlinear time series.it can be seen how the newrb model can perform well; achieving fair results for the prediction of water losses. That is, increasing the number of neurons show more accurate values, the model finished with MSE of 0.00262 when number of neurons = 70 in the hidden layer.

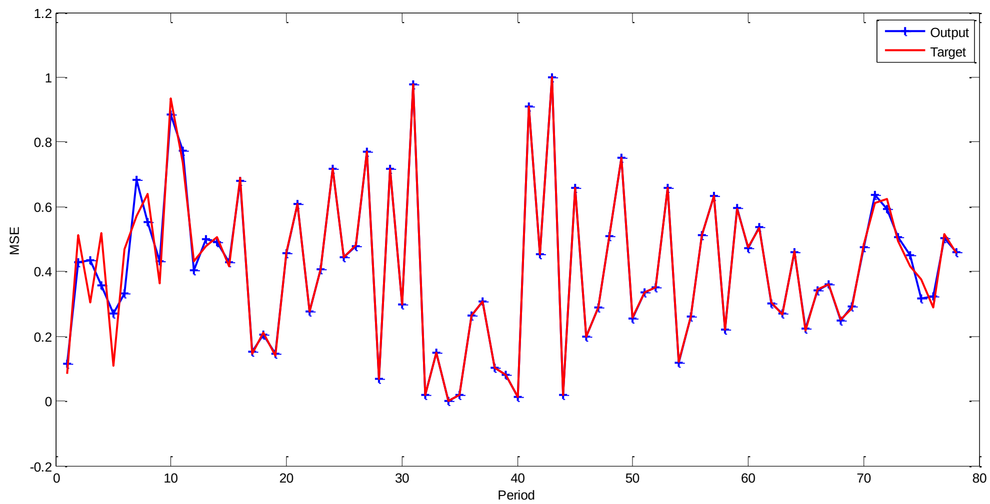

Figure 4.36: Newrb Best NRW Prediction Result for the whole city region when number of neurons = 70.

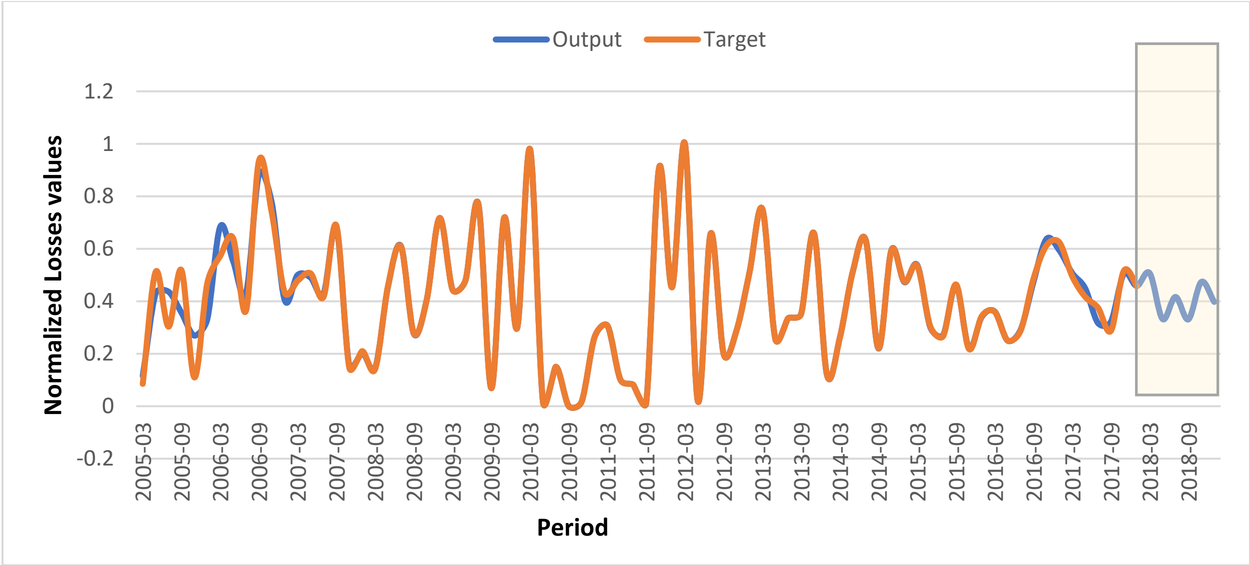

Figure 4.37: Newrb Best NRW Prediction Result for the year 2018 in the whole city Region when number of neurons = 70.

Moreover, from the graph in figure 4.37, we can see the comparison produced by newrb model between the actual and predicted of water losses values (NRW), also the figure shows the predicted water losses values of the year 2018 in the whole city region as illustrated in the highlighted area in the figure.

4.6.1.2 Water Losses (NRW) Prediction for the College Region

Table 4.19: Newrb NRW Prediction for the College Region.

Number of Neurons	**MSE $_{Training}$**	**MSE $_{Testing}$**
5	1.22E-02	8.01E-02
10	1.13E-02	7.89E-02
15	7.51E-03	8.36E-02
20	4.51E-03	8.80E-02
25	3.31E-03	8.91E-02
30	2.07E-03	8.92E-02
35	1.19E-03	8.80E-02
40	1.27E-03	8.86E-02
45	**1.08E-03**	8.82E-02

Similarly, according to table 4.19 and figures 4.38 it is obvious that the newrb model can result in accurate results for the future prediction of water losses with an error goal equal to 0.001.

According to the results, with a number of neurons more than 30, the prediction error will improve; by reducing the error to the minimum as possible, which consequently show the achievement of more accurate results for the future forecasting. therefore, in this prediction model MSE on neuron = 45 give the best result for the future water losses with ($MSE_{training=}$ 0.00108 and $MSE_{testing=}$ 0.0882). Therefore, it can be noticed that the higher the number of neurons, the less the value of the error.

From the figure 4.39, we can see the comparison produced by the newrb model between the actual data which represent the real water losses and the prediction values of the College region according to the adopted model.

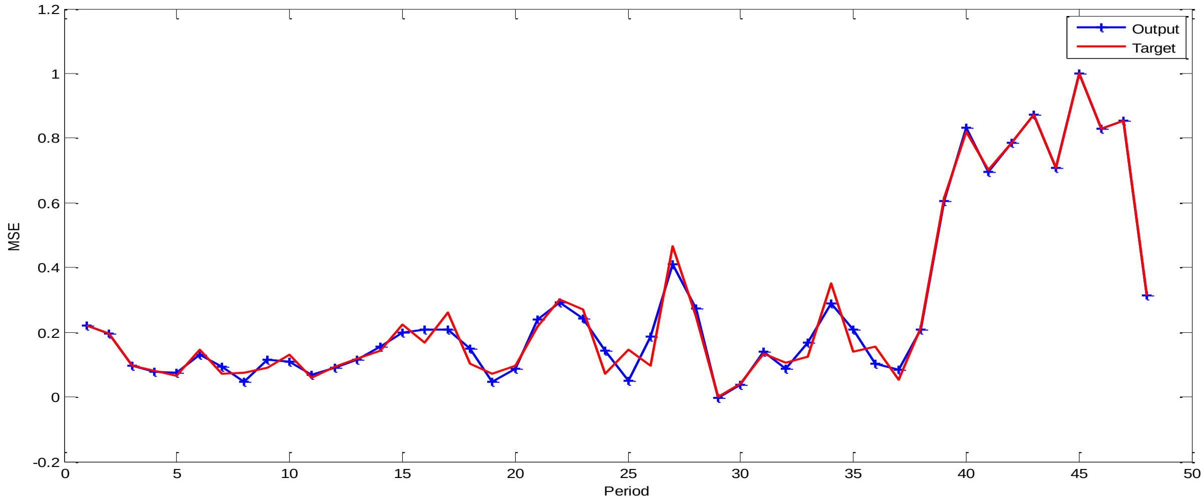

Figure 4.38: Newrb Best NRW Prediction Result for the College Region when number of neurons = 45

Also, figure 4.39 shows the predicted water losses values of College region for the year 2018 as shown in the highlighted area in the figure.

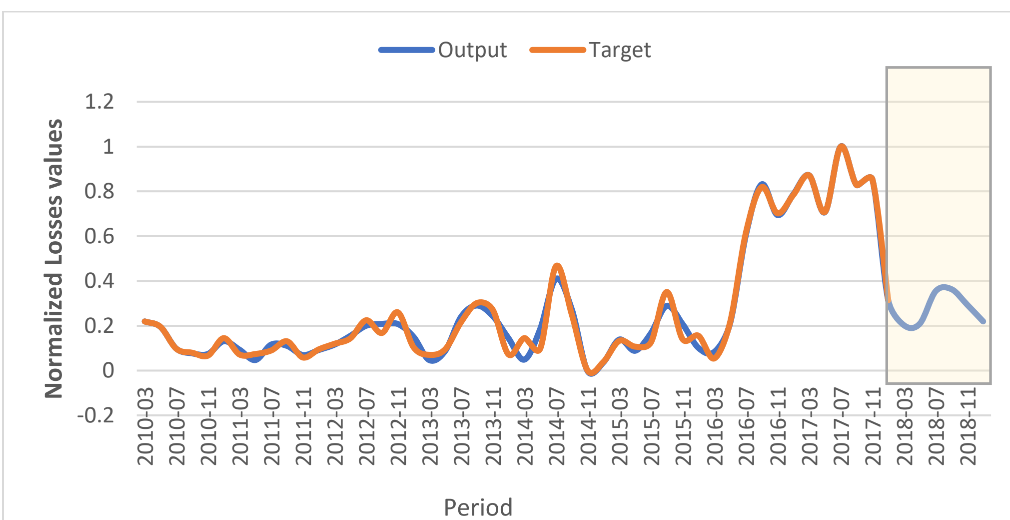

Figure 4.39: Newrb Best NRW Prediction Result for the year 2018 in the College Region when number of neurons = 45.

4.6.1.3 Water Loss (NRW) Prediction for Flash Region

Table 4.20: Newrb NRW Prediction for the Flash Region

Number of Neurons	MSE $_{\text{Training}}$	MSE $_{\text{Testing}}$
5	4.13E-02	5.95E-02
10	3.66E-02	7.40E-02
15	3.36E-02	7.47E-02
20	2.85E-02	8.71E-02
25	2.71E-02	9.04E-02
30	2.44E-02	9.22E-02
35	2.08E-02	9.48E-02
40	1.80E-02	9.38E-02
45	1.70E-02	9.29E-02
50	1.60E-02	9.42E-02
55	9.64E-03	9.98E-02
60	**8.98E-03**	1.25E-01

Moreover, figure 4.40 and table 4.20 show that the newrb model can produce fewer MSE values, which leads that the model is suitable for water losses forecasting in Flash region with an error goal equal to 0.001. It can be also seen that increasing the number of neurons give more acceptable and reasonable predictions. It can also be seen that the least error value was (0.00898) with number of neurons = 60.

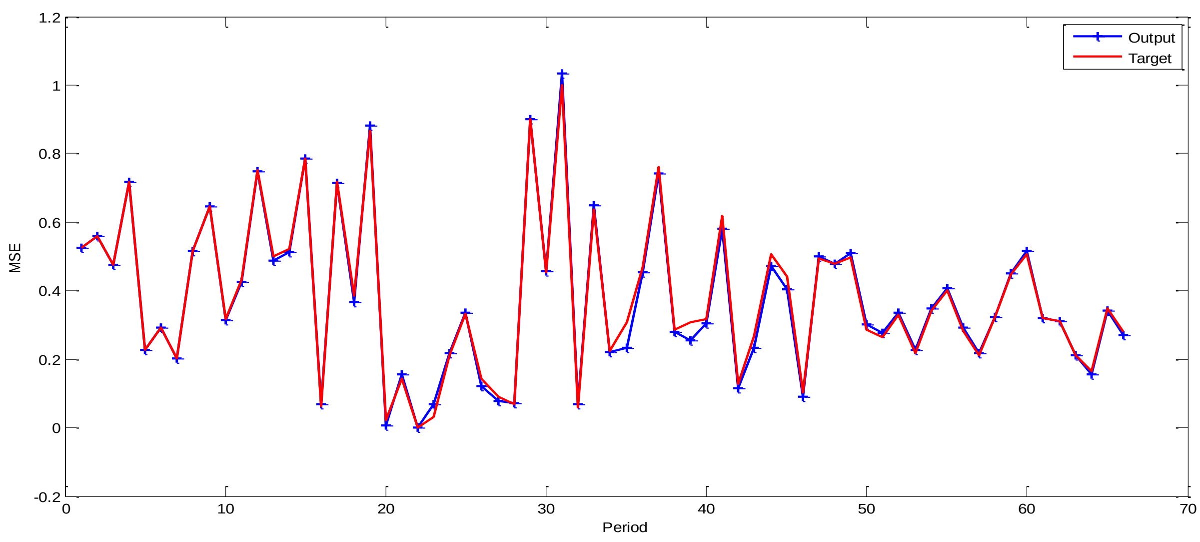

Figure 4.40: Newrb Best NRW Prediction Result for the Flash Region when number of neurons = 60.

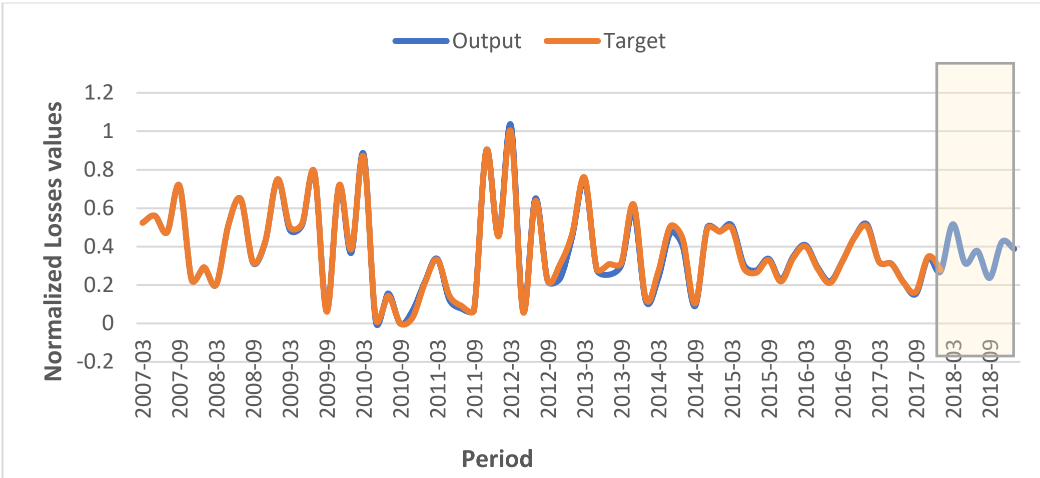

Figure 4.41: Newrb Best NRW Prediction Result for the year 2018 in the Flash region when number of neurons = 60.

Figure 4.41 illustrates the comparison between the actual and prediction value of water losses produced by the newrb model. In addition, this figure demonstrates as illustrated in the highlighted area the forecast future values of water losses for Flash region for 6 periods of the year 2018.

4.6.1.4 Water Loss (NRW) Prediction for the Sunuqrot Region

Table 4.21: Newrb NRW Prediction for the Sunuqrot Region.

Number of Neurons	MSE $_{Training}$	MSE $_{Testing}$
5	1.69E-02	7.99E-02
10	1.30E-02	8.56E-02
15	1.09E-02	8.18E-02
20	9.96E-03	8.45E-02
25	8.70E-03	9.03E-02
30	7.74E-03	9.10E-02
35	6.69E-03	9.24E-02
40	4.56E-03	8.89E-02
45	3.65E-03	8.98E-02
50	**1.83E-03**	9.47E-02

Depending on the previous table 4.21 and figure 4.42 which show that the regression of water losses using newrb model can achieve good performance with a greater number of neurons. As illustrated in the given table, the error was at the minimum value when the network was built with number of neurons = 50.

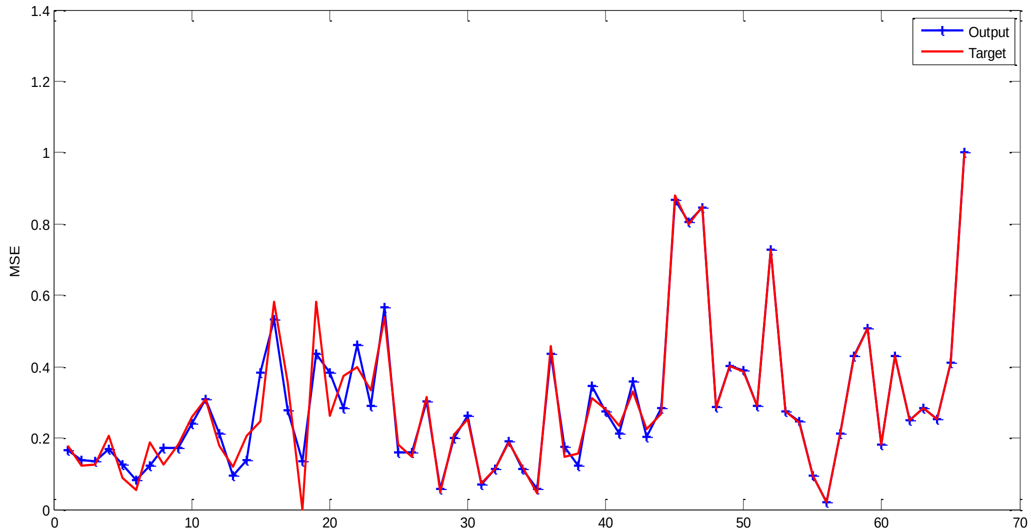

Figure 4.42: Newrb Best NRW Prediction Result for the Sunuqrot Region when number of neurons = 50.

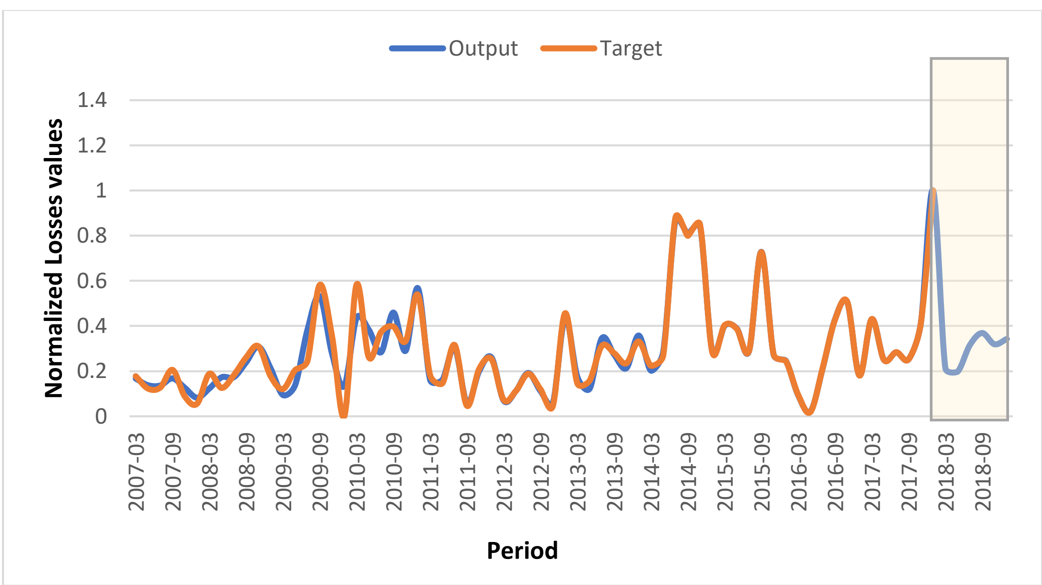

Figure 4.43: Newrb Best NRW Prediction Result for the year 2018 in the Flash Region when number of neurons = 50

As shown in figure 4.43 and illustrated in the highlighted area, we forecast future quantities of water losses for the Sunuqrot region for the year 2018. The comparison between the actual and prediction value produced by the *newrb* model is illustrated in this figure.

4.6.2 RBFNNs (*Newrb*) Prediction Model for Water Demands.

In the following sections, we will show the result of RBFNNs (newrb) model of water demands for all regions of Beitunia city.

4.6.2.1 Water Demands Prediction for the Whole City Region

In table 4.22 and figure 4.44, we can see that the behavior of the newrb model with an error goal of (0.001) in the forecasting process of the nonlinear time series. It is clear that the proposed model converges to the optimum value when the number of neurons equals 50 with better prediction error; the proposed approach performs very well.

Table 4.22: Newrb water demands prediction for the whole city region.

Number of Neurons	$MSE_{Training}$	$MSE_{Testing}$
5	2.55E-02	7.97E-02
10	1.26E-02	1.01E-01
15	1.15E-02	1.15E-01
20	9.26E-03	1.20E-01
25	7.49E-03	1.23E-01
30	3.63E-03	1.21E-01
35	2.58E-03	1.21E-01
40	2.16E-03	1.22E-01
45	2.05E-03	1.22E-01
50	**1.66E-03**	1.22E-01

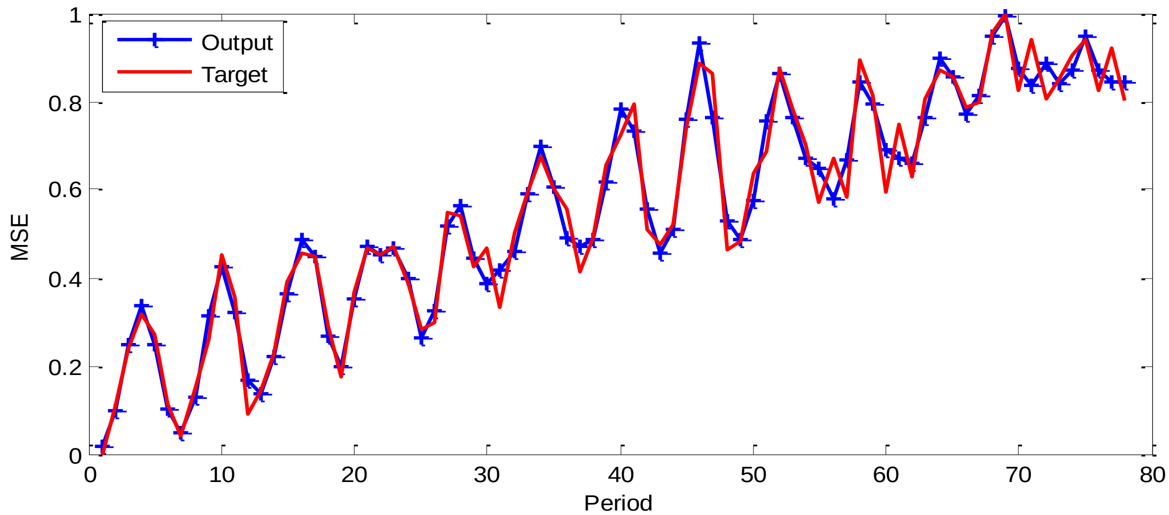

Figure 4.44: Newrb Best NRW Prediction Result for the whole city region when number of neurons = 50.

From figures 4.45 we notice the low difference between actual consumption of water and the predicted values for the whole city region. Also, the figure shows the predicted future values of water demands in the year 2018 as illustrated in the highlighted area.

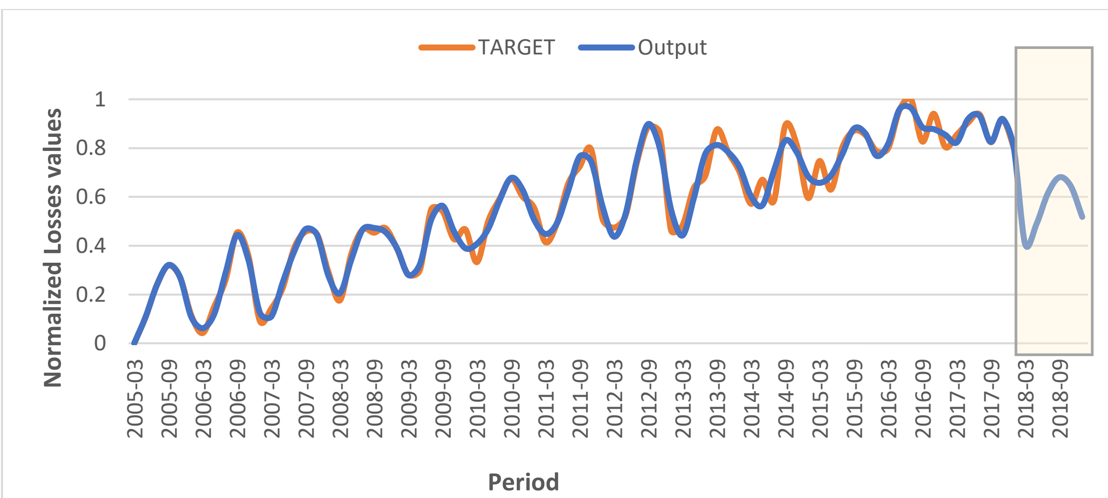

Figure 4.45 :Newrb Best water demand Prediction Result for the year 2018 in the whole city region when number of neurons = 50.

As shown in the figures 4.44, 4.45 and table 4.22, the newrb model can predict water demands for the year 2018 with good accuracy. Also, it’s obvious that newrb model gives a good result based on the values of MSE testing and training, which leads that the model is appropriate in such cases of water demands prediction in the whole city region.

4.6.2.2 Water Demands Prediction for the College Region

The behavior of the newrb model with an error goal of (0.001) is depicted in figure 4.46 and table 4.23 as the number of neurons increases, we get a better fit for the function, and this also shows the best fit was captured when a number of neurons were 45 with MSE value (0.00254).

Table 4.23: Newrb water demands prediction for the College region

Number of Neurons	$MSE_{Training}$	$MSE_{Testing}$
5	2.75E-02	5.23E-02
10	1.12E-02	4.77E-02
15	1.06E-02	5.10E-02
20	7.89E-03	5.47E-02
25	5.52E-03	5.95E-02
30	3.92E-03	5.58E-02
35	3.55E-03	7.08E-02
40	2.55E-03	8.49E-01
45	**2.54E-03**	6.56E-01

To predict the losses values and comparing those values with the actual losses vales in the College region, the produced predicted values for the year 2018 are depicted in the highlighted area in figure 4.47. Also, the figure shows the comparison produced by newrb model between the real and predicted of water losses, where it is noticeable convergence in the results indicating the accuracy of the model used.

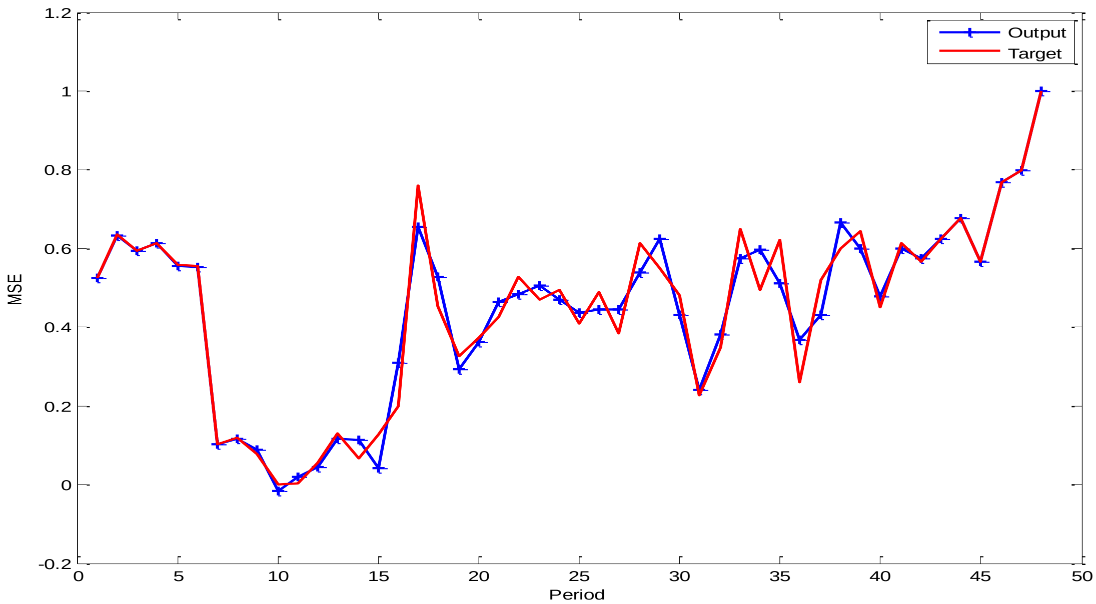

Figure 4.46 :Newrb Best NRW Prediction Result for the College Region when number of neurons =45.

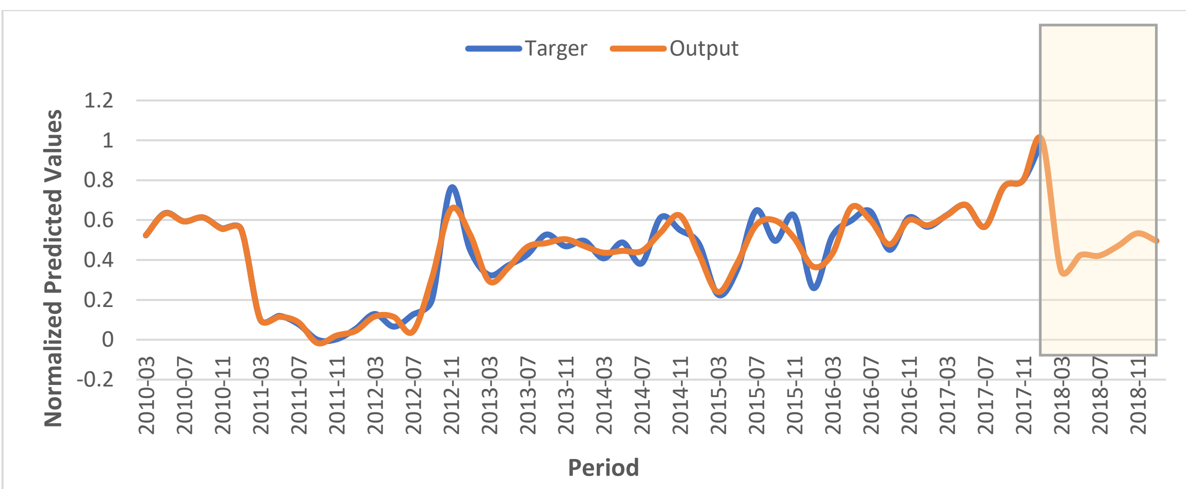

Figure 4.47: Newrb Best water demand Prediction Result for the year 2018 in the College region when number of neurons = 45.

4.6.2.3 Water Demands Prediction for the Flash Region

From table 4.24 and figure 4.48, using error goal (0.001) it can be noticed that the error was at the minimum of its values when the network was built with number of neurons = 45. Therefore, increasing the number of neurons does ultimately result in acceptable model performance.

Table 4.24: newrb water demands prediction for the Flash region.

Number of Neurons	MSE $_{Training}$	MSE $_{Testing}$
5	2.24E-02	1.13E-01
10	1.94E-02	1.12E-01
15	1.83E-02	1.14E-01
20	1.64E-02	1.14E-01
25	1.03E-02	1.11E-01
30	5.04E-03	1.21E-01
35	4.83E-03	1.21E-01
40	4.79E-03	1.21E-01
45	**4.30E-03**	1.24E-01

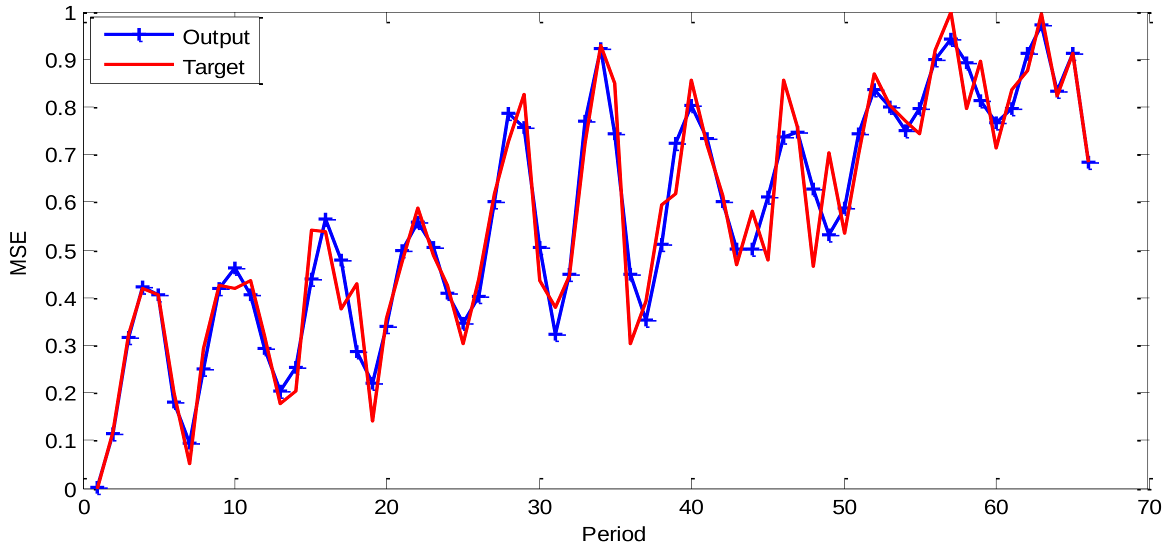

Figure 4.48: Newrb Best NRW Prediction Result for the Flash region when number of neurons = 45.

To predict the losses values and comparing those values with the actual losses values in the Flash region, the produced predicted values for the year 2018 are depicted in the highlighted area in figure 4.49. Also, the figure shows the comparison produced by newrb model between the real and predicted of water losses.

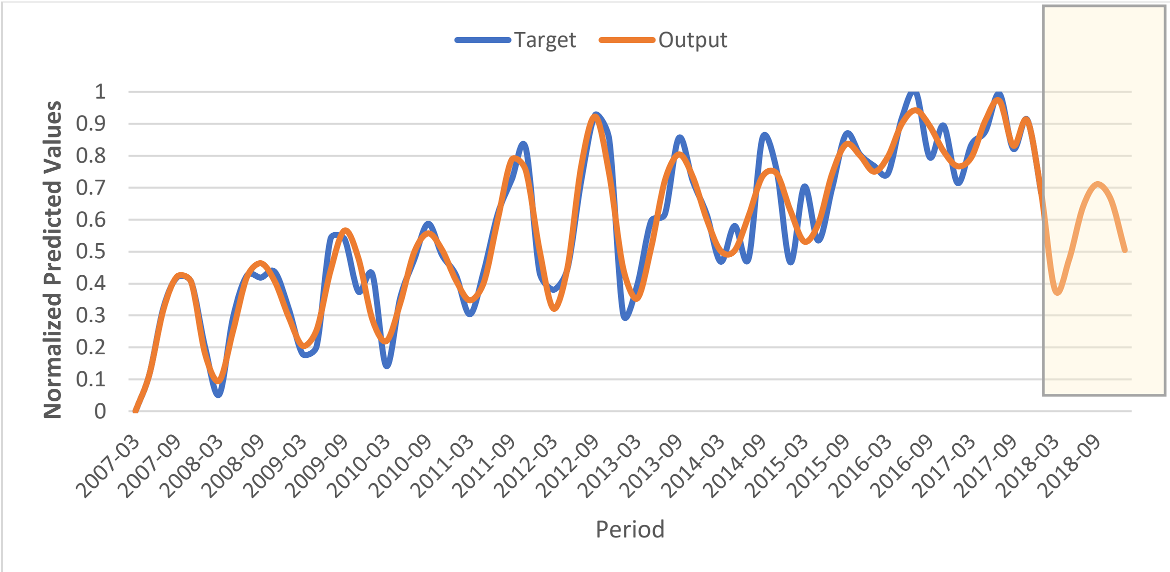

Figure 4.49: Newrb Best water demand Prediction Result for the year 2018 in the Flash region when number of neurons = 45

4.6.2.4 Water demands prediction for the Sunuqrot Region.

Table 4.25: Newrb water demands prediction for the Sunuqrot region.

Number of Neurons	MSE $_{Training}$	MSE $_{Testing}$
5	3.53E-02	6.15E-02
10	2.59E-02	6.12E-02
15	1.75E-02	6.91E-02
20	1.24E-02	6.91E-02
25	1.02E-02	7.16E-02
30	6.16E-03	7.47E-02
35	5.15E-03	7.73E-02
40	3.01E-03	8.24E-02
45	2.36E-03	7.93E-02
50	**1.33E-03**	8.18E-02

furthermore, as illustrated in table 4.25 and figure 4.50, the process of prediction using newrb with error goal = 0.001 shows that by neuron number 50; the model has shown the best performance with least error value in prediction, the error was at its minimum value (0.00133), which is the best error value.

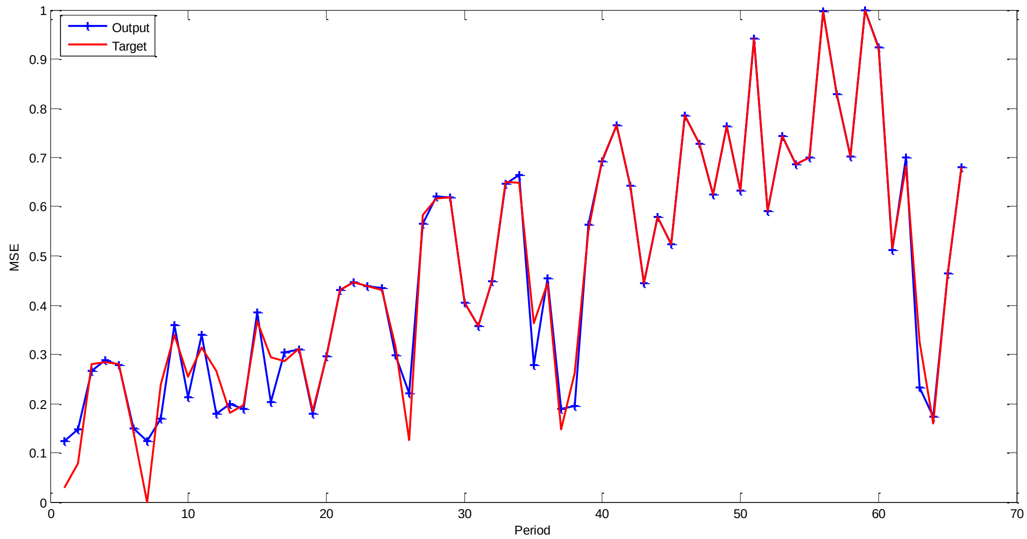

Figure 4.50: Newrb Best NRW Prediction Result for the Sunuqrot Region when number of neurons = 50

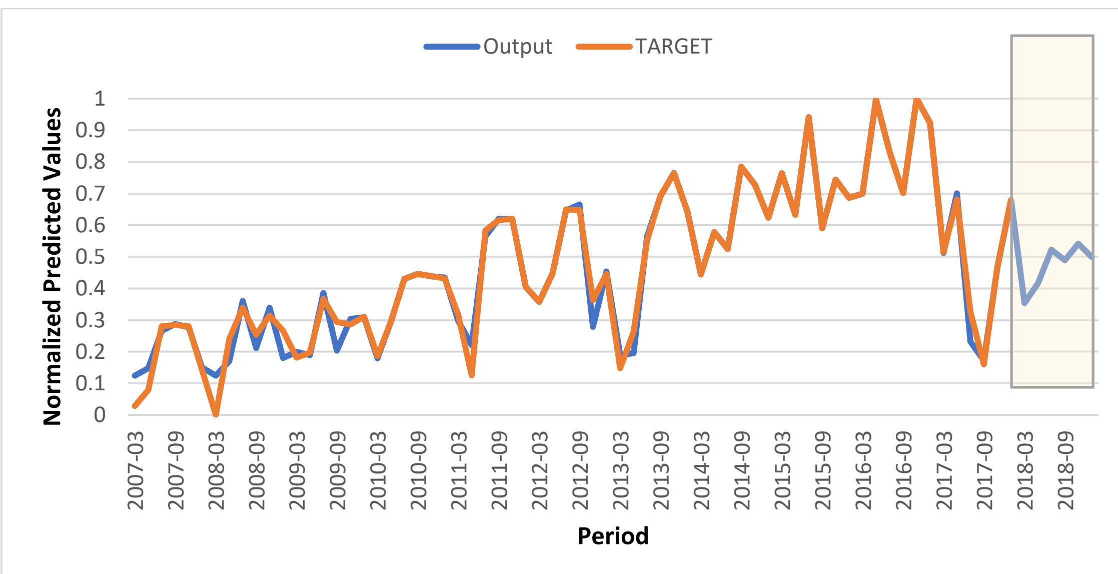

Figure 4.51: Newrb Best water demand Prediction Result for the year 2018 in the Sunuqrot region when number of neurons = 50.

To predict the losses values and comparing those values with the actual losses vales in the Sunuqrot region, the produced predicted values for the year 2018 are depicted as shown in the highlighted area in figure 4.51. Also, the figure shows the comparison produced by newrb model between the real and predicted of water losses, where it is noticeable convergence in the results indicating the accuracy of the model used. As a conclusion of using the newrb model in order to predict water losses and water demands in Beitunia city as illustrated in figures and tables in the previous subsections, we observe that the model produced good results according to the main square error (MSE). Which leads that the model is highly appropriate in such cases of water demands and water losses prediction in Beitunia city.

4.7 GAs-MLPNNs Prediction Model

In the following section, we will discuss the result of GAs-MLPNNs model for each region of Beitunia city.

4.7.1 GAs-MLPNNs Prediction for Water Losses (NRW)

First, we will discuss the result of GAs-MLPNNs model for Prediction for Water loss (NRW) for each region of Beitunia city.

4.7.1.1 Water loss (NRW) Prediction for the Whole City

Table 4.26: GAs-MLPNNs NRW Prediction for the whole city.

Number of Neurons	*MSE* Training	*MSE* Testing
5	4.32E-02	6.22E-02
10	3.80E-02	4.60E-02
15	3.76E-02	6.20E-02
20	3.62E-02	6.11E-02
25	3.47E-02	7.80E-02
30	2.79E-02	1.31E-01
35	2.51E-02	1.81E-01
40	2.67E-02	1.11E-01
45	2.22E-02	1.56E-01
50	2.60E-02	1.56E-01
55	2.31E-02	1.74E-01
60	1.85E-02	2.08E-01
65	**1.73E-02**	2.02E-01
70	1.80E-02	3.47E-01
75	1.92E-02	2.02E-01
80	1.81E-02	2.16E-01

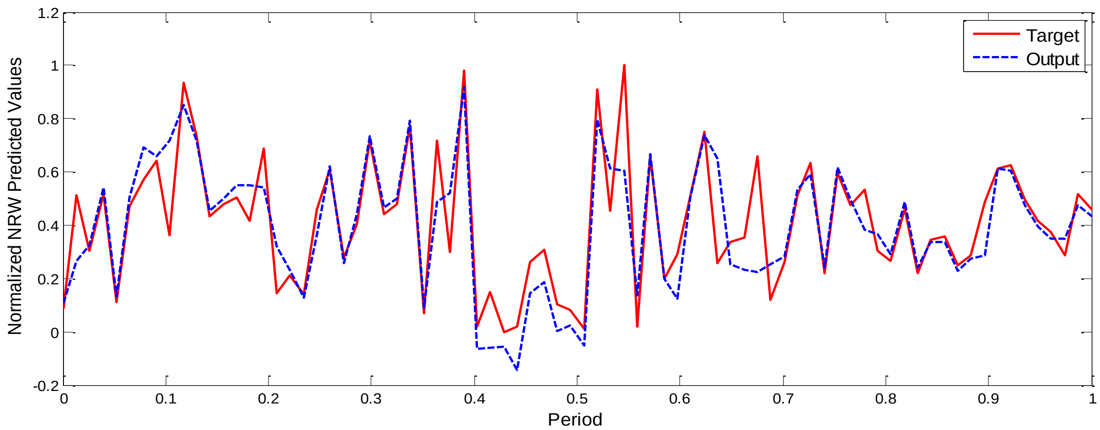

Figure 4.52: GAs-MLPNNs Best NRW Prediction Result for the whole city region when number of neurons = 65.

As shown in figure 4.52 and table 4.26, while the number of neurons increases, the model performs with fewer MSE values. The best result was achieved with number of neurons = 65 with value (0.0173). However, the model shows that the model does not perform well with neurons number more than 65; that is, the MSE value increases with more than 65 neurons.

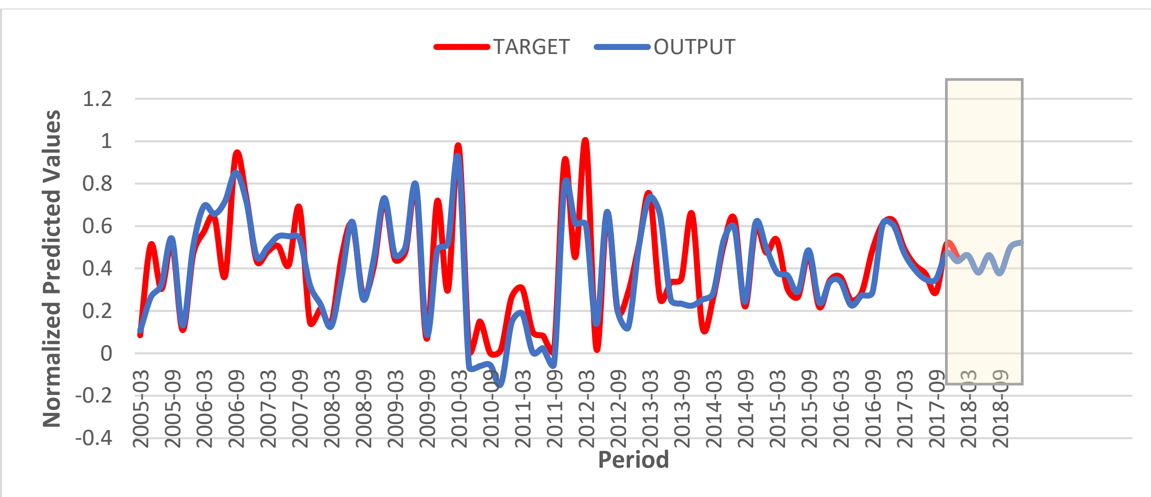

Figure 4.53: GAs-MLPNNs NRW Prediction Result for the year 2018 in the whole city region when number of neurons = 65.

By using the graph and as illustrated in the figure 4.53, we can see a good comparison result produced by the GAs-MLPNNs model between the real quantities of water losses and the prediction values according to the adopted model. Moreover, in this model, we predicted water losses values for the year 2018 as depicted in the highlighted area in figure 4.53.

4.7.1.2 Water Loss (NRW) Prediction for the College

Table 4.27: GAs-MLPNNs NRW Prediction for the College Region.

Number of Neurons	MSE Training	MSE Testing
5	7.10E-03	1.27E-02
10	7.70E-03	7.90E-02
15	4.80E-03	5.40E-03
20	2.90E-03	8.00E-03
25	3.10E-03	8.10E-03
30	2.80E-03	3.50E-03
35	2.60E-03	8.00E-03
40	2.40E-03	3.90E-03
45	1.90E-03	3.40E-03
50	2.00E-03	8.00E-03
55	**1.60E-03**	2.70E-03
60	2.50E-03	5.20E-03
65	2.30E-03	6.00E-03

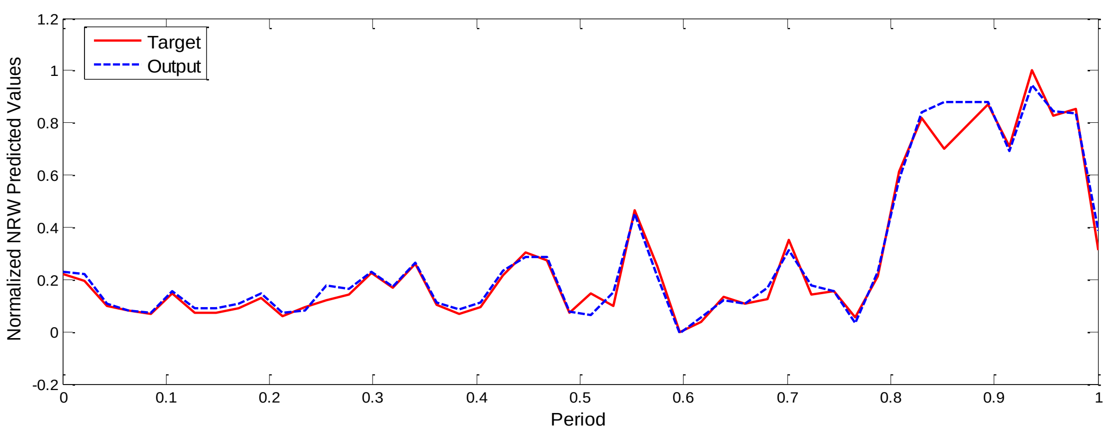

Figure 4.54: GAs-MLPNNs Best NRW Prediction Result for the College Region when number of neurons = 55.

On the other hand, the MSE value decreases by increasing the number of neurons. For instance, the proposed GAs-MLPNNs model produces a good MSE value in the prediction of water losses as shown in figure 4.54 and table 4.27, where the MSE training was at the minimum of its values (0.0016) and MSE testing (0.0027) when the network was built when number of neurons = 55.

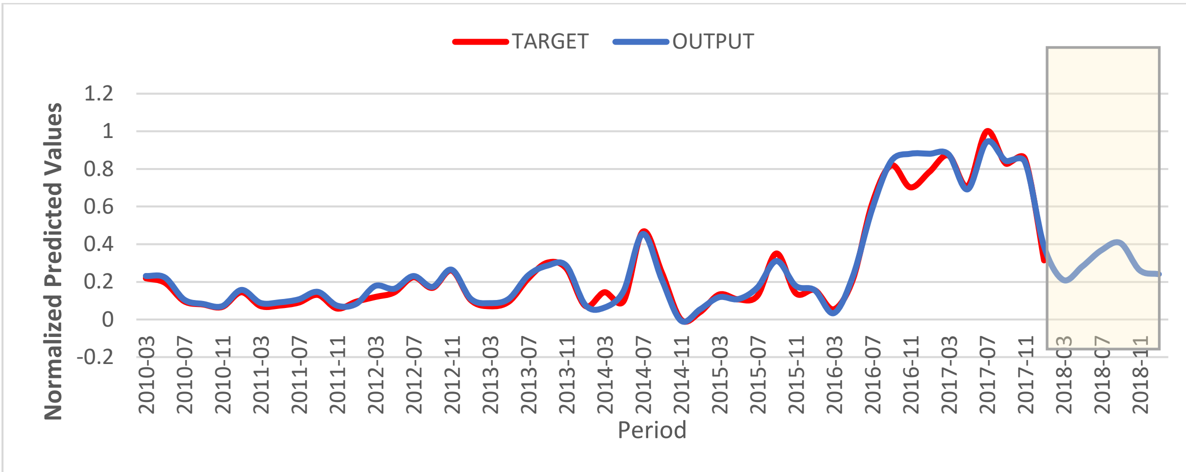

Figure 4.55: GAs-MLPNNs NRW Prediction Result for the year 2018 in the College region when number of neurons = 55.

Furthermore, in this model, we have produced the predicted values of water losses for the year 2018 as illustrated in the highlighted area in figure 4.55. Also, the figure shows the comparison between the actual and predicted of water losses where it is noticeable convergence in the results indicating the accuracy of the model used.

4.7.1.3 Water Loss (NRW) Prediction for Flash Region

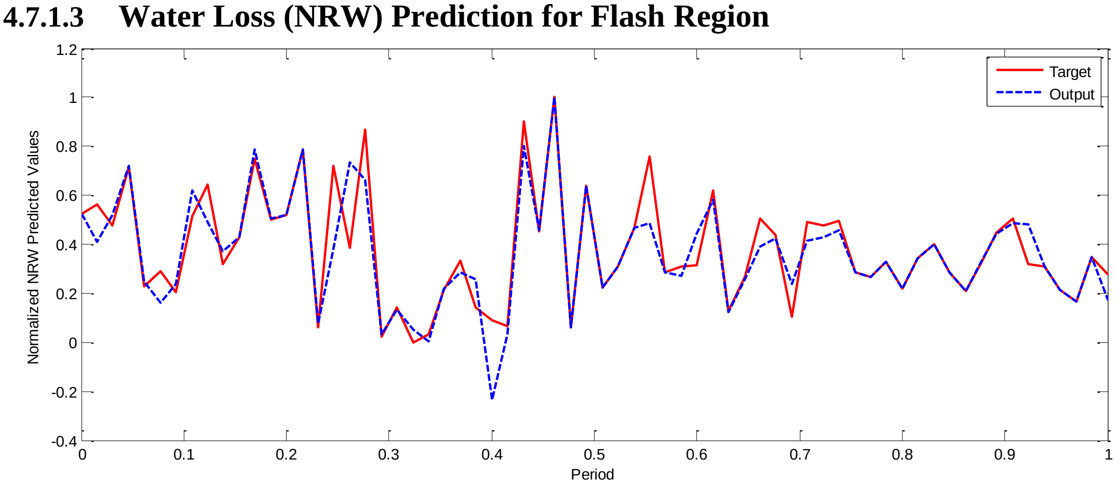

Figure 4.56: GAs-MLPNNs Best NRW Prediction Result for the Flash Region with number of neurons = 65.

Table 4.28: GAs-MLPNNs NRW Prediction for the Flash Region.

Number of Neurons	*MSE* Training	*MSE* Testing
5	3.92E-02	6.54E-02
10	3.83E-02	5.05E-02
15	3.23E-02	6.33E-02
20	2.82E-02	9.94E-02
25	2.91E-02	8.75E-02
30	2.71E-02	9.51E-02
35	2.15E-02	1.27E-01
40	2.06E-02	1.41E-01
45	1.78E-02	1.49E-01
50	1.40E-02	3.04E-01
55	1.60E-02	3.55E-01
60	1.27E-02	3.88E-01
65	**1.01E-02**	1.93E-01
70	1.48E-02	1.93E-01

As shown in table 4.28 and figure 4.56, the result shows that GAs-MLPNNs gives an improvement in training errors values as the number of neurons increased while testing error value become worst after number of neurons =30 . It's clear that the proposed GAs-MLPNNs model produces some good results to some extent based on the Mean Squared Error of training that obtained for the future prediction of water losses.

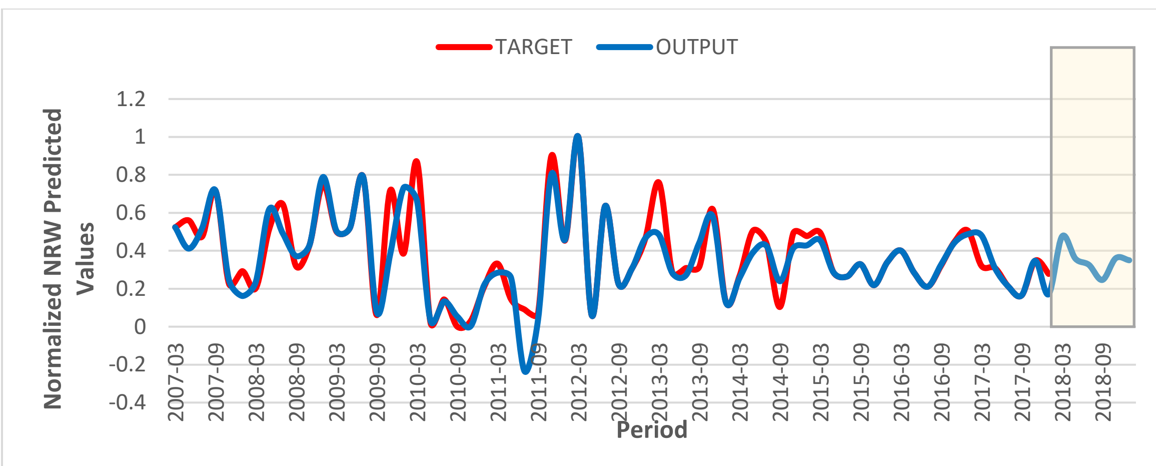

Figure 4.57: GAs-MLPNNs NRW Prediction Result for the year 2018 in the Flash region with number of neurons = 65.

To predict the water losses in the year 2018 in the Flash region, GAs-MLPNNs model produced the future losses quantities as shown in the highlighted area in figure 4.57. Similarly, the figure shows the comparison between the actual and predicted of water losses, as we can see the results are close, which indicate the accuracy of the model.

4.7.1.4 Water Loss (NRW) Prediction for the Sunuqrot Region

Table 4.29: GAs-MLPNNs NRW Prediction for the Sunuqrot Region.

Number of Neurons	***MSE* Training**	***MSE* Testing**
5	1.95E-02	5.56E-02
10	1.89E-02	4.97E-02
15	1.51E-02	1.24E-01
20	1.34E-02	1.91E-01
25	1.04E-02	1.56E-01
30	1.01E-02	1.36E-01
35	5.60E-03	3.33E-01
40	9.30E-03	5.13E-01
45	7.90E-03	4.08E-01
50	**2.70E-03**	4.28E-01
55	7.00E-03	4.24E-01
60	6.00E-03	4.53E-01
65	7.90E-03	1.14E-01
70	6.80E-03	1.60E-01
75	6.00E-03	1.14E-01

From table 4.29 and figure 4.58 the process of water losses prediction using GAs-MLPNNs gives good errors values for MSE training when using more number of neurons. It’s clear that after number of neurons = 50 we do not get good training values of MSE, also we noticed that by adding more neuron we did not get good testing values of MSE.

As shown in figure 4.59, we can see the comparison produced by the GAs-MLPNNs model between the real and predicted water losses values for the Sunuqrot region, we can see that the model performs well in the prediction.

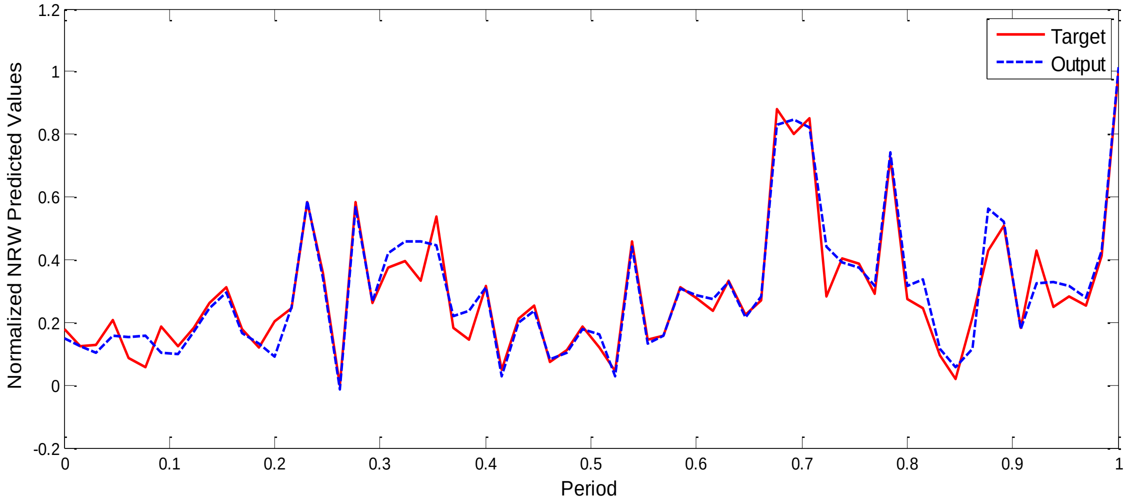

Figure 4.58: GAs-MLPNNs Best NRW Prediction Result for the Sunuqrot Region when number of neurons = 50.

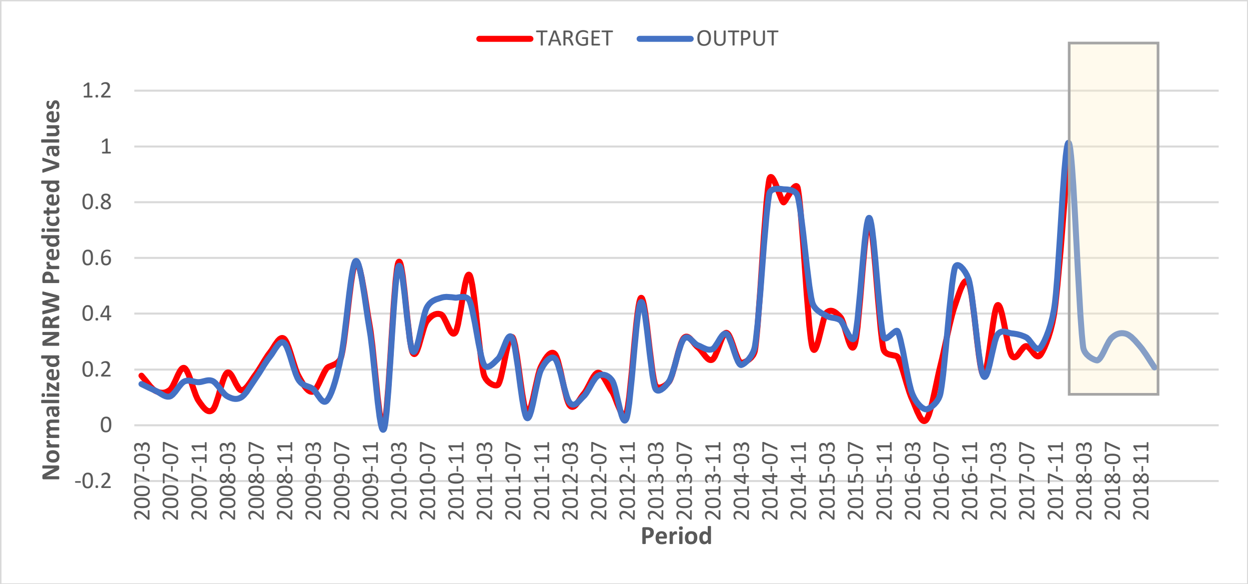

Figure 4.59: GAs-MLPNNs NRW Prediction Result for the year 2018 in the Sunuqrot region when number of neurons = 50.

In addition, in this model, we have predicted the water losses values (NWR) for the year 2018, as shown in the highlighted area in figure.

As shown in figures 4.58, 4.59 and table 4.29, it's obvious that the proposed GAs-MLPNNs model gives some good results based on the values of MSE and comparison values, which leads that the model is appropriate in such cases of water losses prediction in the Sunuqrot region.

4.7.2 GAs-MLPNNs Prediction for Water Demands

In the following section, we will discuss the result of GAs-MLPNNs model for water demands for each region of Beitunia city

4.7.2.1 Water Demand Prediction for the Whole City Region

Table 4.30: GAs-MLPNNs NRW Prediction for the whole city.

Number of Neurons	***MSE* Training**	***MSE* Testing**
5	1.14E-02	2.34E-02
10	1.12E-02	8.50E-02
15	8.00E-03	7.22E-02
20	7.50E-03	2.02E-02
25	4.20E-03	5.43E-02
30	3.60E-03	4.53E-02
35	3.80E-03	2.07E-01
40	3.20E-03	7.67E-02
45	3.00E-03	1.39E-01
50	4.90E-03	2.40E-01
55	**2.30E-03**	1.76E-01
60	3.60E-03	3.51E-01
65	6.80E-03	1.45E-01
70	5.90E-03	2.56E-01

Water Demand Prediction Result for the whole city region as illustrated in table 4.30 and figure 4.60 shows that the proposed GAs-MLPNNs model produces accurate predictions with fewer MSE values, which leads that the model is highly appropriate in such cases of water demands prediction in the whole city region. The error was at the minimum of its values (0.0023) when the network was built with number of neurons = 55.

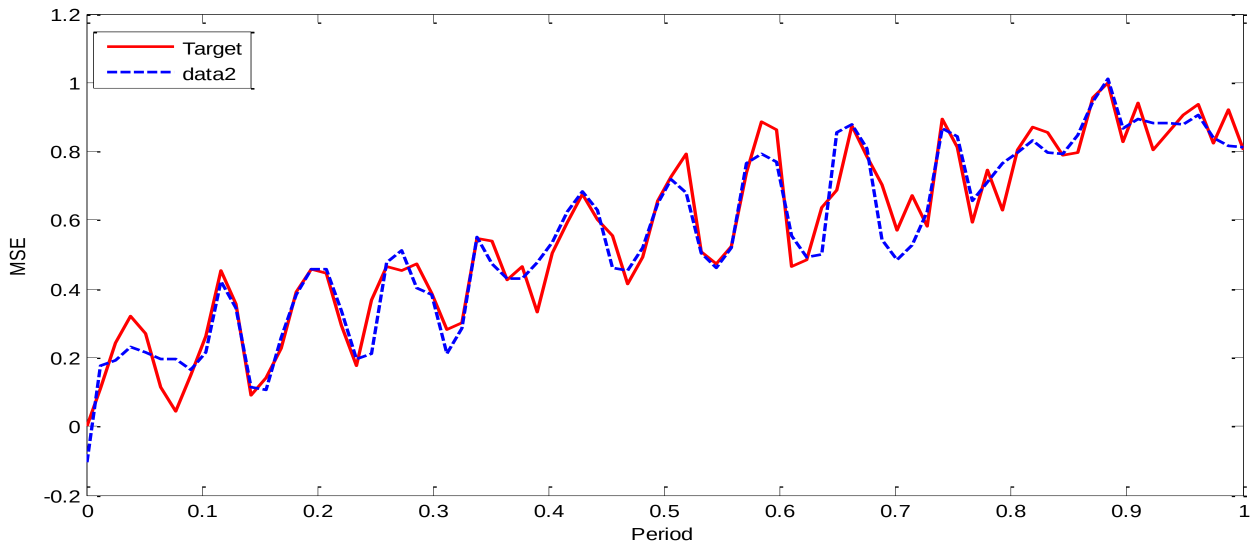

Figure 4.60: GAs-MLPNNs Best demand Prediction Result for the whole city region when number of neurons = 55.

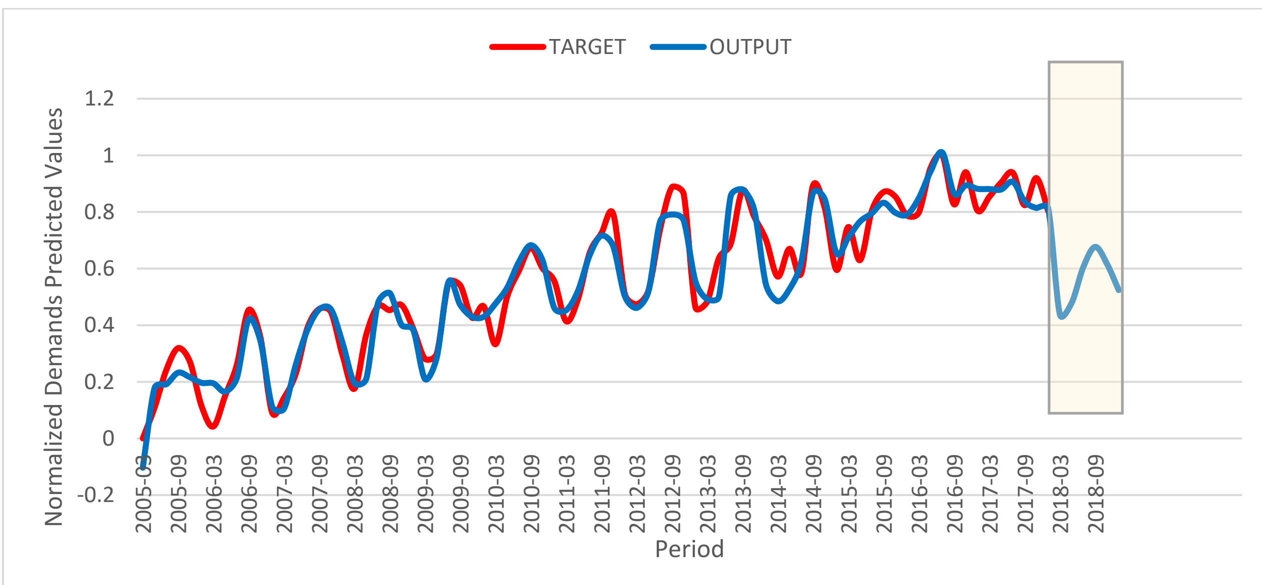

Figure 4.61: GAs-MLPNNs demands Prediction Result for the year 2018 in the whole city region when number of neurons = 55.

Furthermore, in this model, we have produced the predicted values of water demand for the year

2018 for the whole city region as illustrated in the highlighted area in figure 4.61. Also, the figure shows a good comparison result between the real and predicted water consumption.

4.7.2.2 Water demand Prediction for the College Region

According to Table 4.31 and Figures 4.62, it can be seen how the GAs-MLPNNs model can achieve good performance prediction results of water demand with a specific number of neurons in the hidden layer. The best result of the prediction which was achieved when we applied the proposed model with number of neurons = 40 in the hidden layer with MSE for training did not exceed the (0.0025).

Table 4.31: GAs-MLPNNs NRW Prediction for the College region.

Number of Neurons	*MSE* Training	*MSE* Testing
5	8.90E-03	3.58E-02
10	7.80E-03	9.38E-02
15	5.90E-03	1.87E-01
20	4.20E-03	6.59E-02
25	3.50E-03	2.52E-01
30	4.60E-03	1.12E-01
35	3.20E-03	1.41E-01
40	**2.50E-03**	3.39E-01
45	7.70E-03	3.55E-01
50	3.90E-03	2.07E-01
55	2.90E-03	2.54E-01
60	2.60E-03	3.57E-01
65	7.30E-03	3.57E-01

By using the graph and as illustrated in the figure 4.63, we can see the comparison produced by the GAs-MLPNNs model between the actual quantities of water consumption and the prediction values according to the adopted GAs-MLPNNs model for the College region. Also, as shown in the highlighted area in figure 4.63 we can see the predicted values of water demands in the College region for the year 2018.

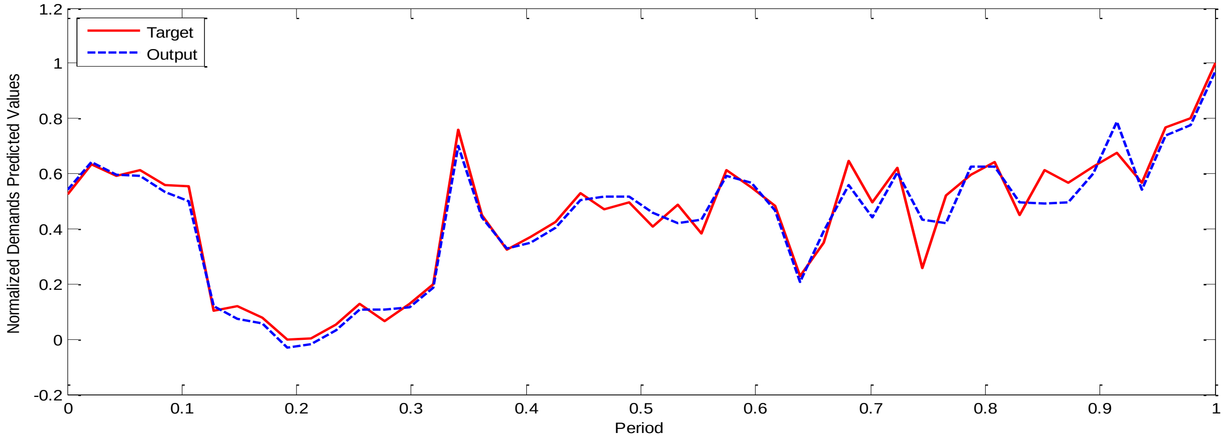

Figure 4.62: GAs-MLPNNs Best demand Prediction Result for the College region when number of neurons = 40.

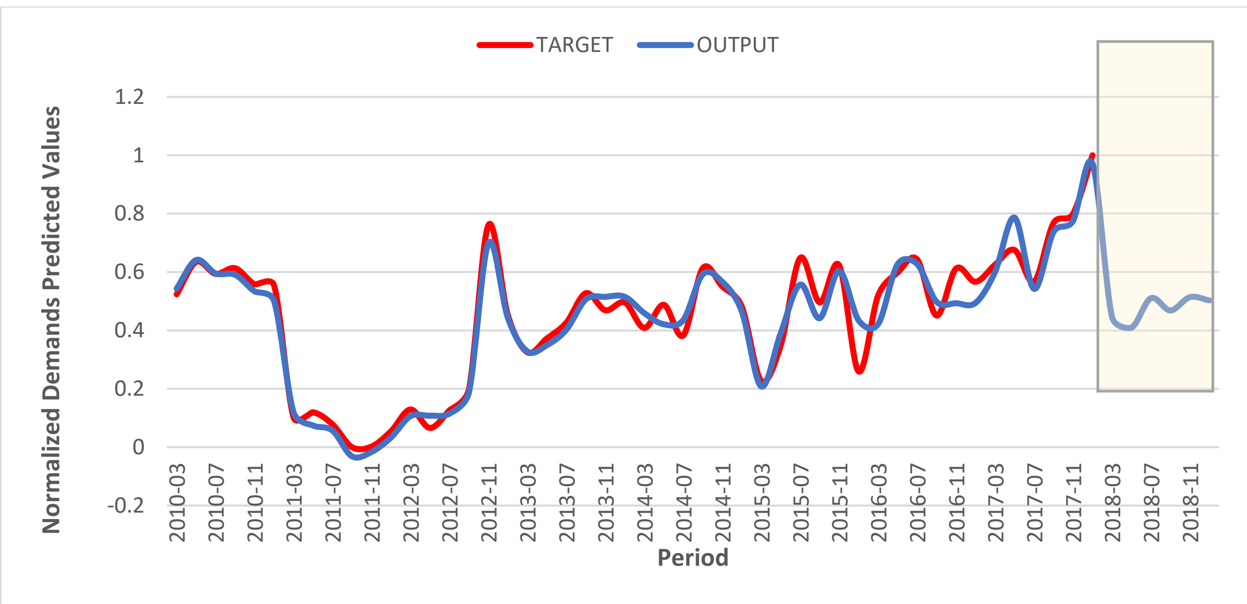

Figure 4.63: GAs-MLPNNs demands Prediction Result for the year 2018 in the College region when number of neurons = 40.

Having such results as shown in figures 4.62, 4.63 and table 4.31, it's obvious that the GAs-MLPNNs model for water demand in prediction the College region is one of the promising models for the future forecasting of water demands in this region.

4.7.2.3 Water demand Prediction for the Flash Region

Table 4.32: GAs-MLPNNs NRW Prediction for the Flash region.

Number of Neurons	*MSE* Training	*MSE* Testing
5	2.02E-02	6.90E-03
10	1.94E-02	4.64E-02
15	1.14E-02	1.20E-01
20	8.30E-03	3.58E-02
25	5.40E-03	5.22E-02
30	4.70E-03	8.21E-02
35	**4.10E-03**	2.00E-01
40	4.20E-03	1.81E-01
45	3.90E-03	1.71E-01
50	5.90E-03	2.28E-01
55	4.40E-03	3.30E-01
60	4.30E-03	1.80E-01
65	4.20E-03	3.80E-01

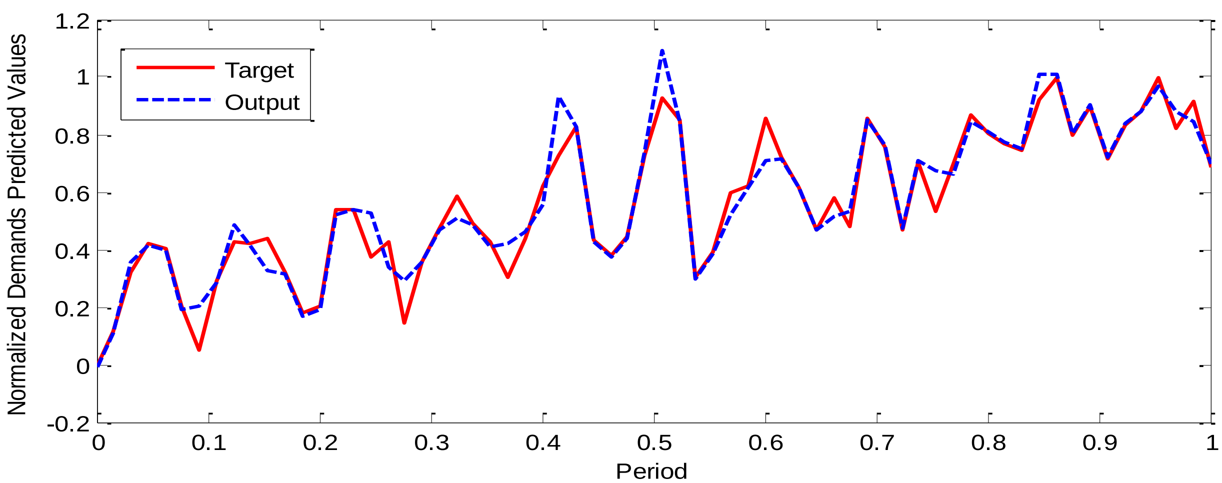

Figure 4.64: GAs-MLPNNs Best demand Prediction Result for the Flash region when number of neurons = 35.

Water demand prediction result for the Flash region as illustrated in table 4.32 and figure 4.64 shows that the proposed model produces more accurate predictions with fewer MSE values, which leads that the model is highly appropriate in such cases of water demands prediction in the Flash region, thus the prediction Mean Square Error on 35 neurons achieves great result for the future of water demand. From figure 4.65, we can see the comparison produced by the GAs-MLPNNs model between the actual and predicted water demands values for the Flash region, also we can see the future predicted water demand values for the year 2018.

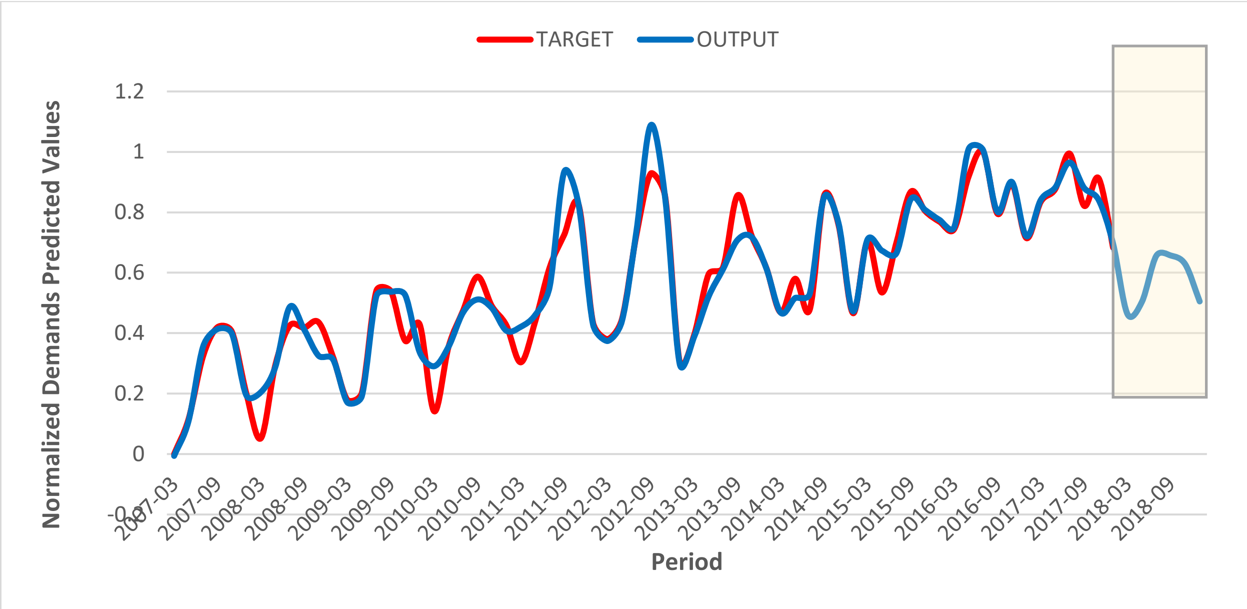

Figure 4.65: GAs-MLPNNs demands Prediction Result for the year 2018 in the Flash region when number of neurons = 35.

4.7.2.4 Water demand Prediction for the Sunuqrot region

Table 4.33: GAs-MLPNNs NRW Prediction for the Sunuqrot region

Number of Neurons	*MSE* Training	*MSE* Testing
5	1.49E-02	5.06E-02
10	1.25E-02	1.01E-01
15	9.80E-03	1.42E-01
20	9.00E-03	1.54E-01
25	7.30E-03	1.18E-01
30	7.20E-03	1.16E-01
35	5.00E-03	1.38E-01
40	5.30E-03	1.06E-01
45	**3.50E-03**	1.15E-01
50	4.90E-03	2.82E-01
55	5.10E-03	1.95E-01
60	4.60E-03	3.10E-01

Likewise, as illustrated in table 4.33 and figure 4.66, it can be seen number of neurons = 45; the model has shown the best performance with the least error value (0.0035) in prediction. On the other hand, the experiment shows that an increasing number of neurons does not cause a more accurate result.

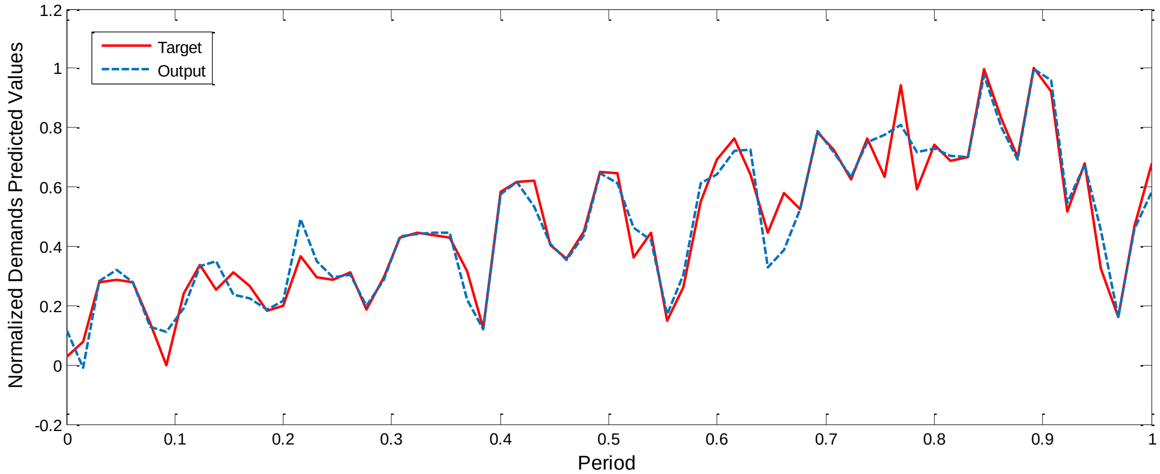

Figure 4.66: GAs-MLPNNs Best demand Prediction Result for the Sunuqrot region when number of neurons = 45.

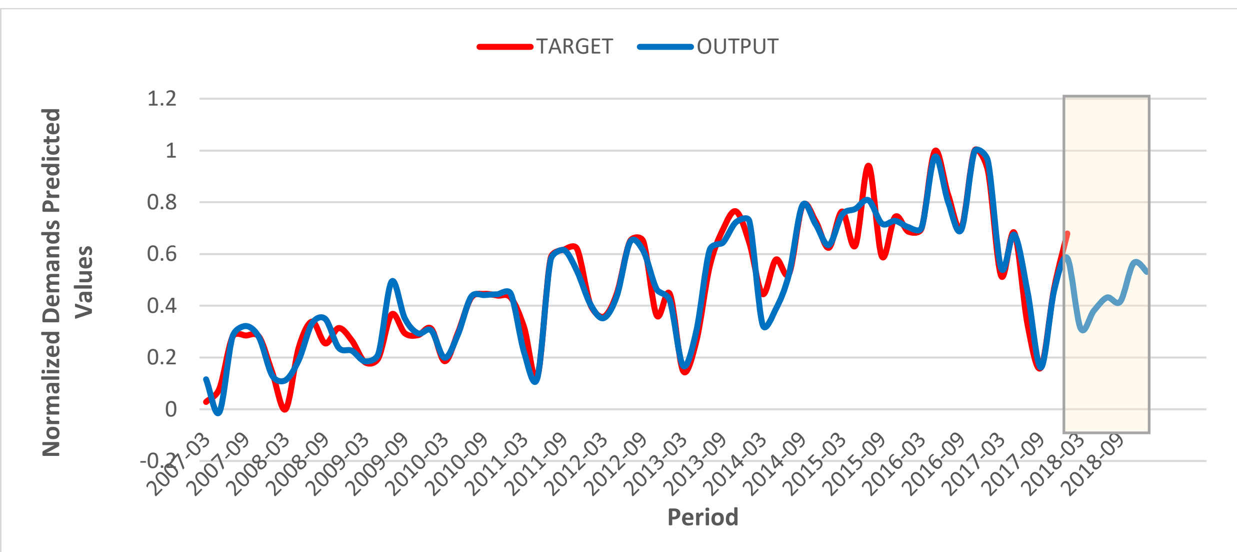

Figure 4.67: GAs-MLPNNs demands Prediction Result for the year 2018 in the Sunuqrot region when number of neurons = 45.

Furthermore, in this model, we have produced the predicted future values of water demand for the year 2018 as illustrated in the highlighted area in figure 4.67. Also, the figure shows a comparison between the actual and predicted water demand. As a conclusion of using GAs-MLPNNs model in order to predict the water losses and demands in Beitunia city as illustrated in figures and tables in the previous subsections, we observe that the model produced good results according to the main square error (MSE). Which leads that the model is highly appropriate in such cases of water demands and losses prediction in Beitunia city.

4.8 Comparison and Discussion

In this section, we show a complete comparison depending to the performance from the viewpoint of the error value against the number of neurons employed of all the results obtained for NN models used in this thesis for NRW and water demands for all Beitunia regions.

4.8.1 Comparison of Water Losses (NRW) for All Regions

Figure 4.68 presents the error values and the number of neurons for the three Models; MLPNN-LM, newrb, and GAs-MLPNNs to observe the performance of each built network using the mentioned models. The supremacy of the MLPNN-LM model can be seen over all models and this has been shown from the first Neuron (5) to last one approximately. It can also be seen that the newrb model performs better than the GAs-MLPNNs model.

Error values are displayed in Figure 4.69 with specific neurons for the three Models; MLPNN-LM, newrb and GAs-MLPNNs, it is noticed that there is a fluctuation in behavior with an advantage to the MLPNN model in overall at the end of the prediction experiments

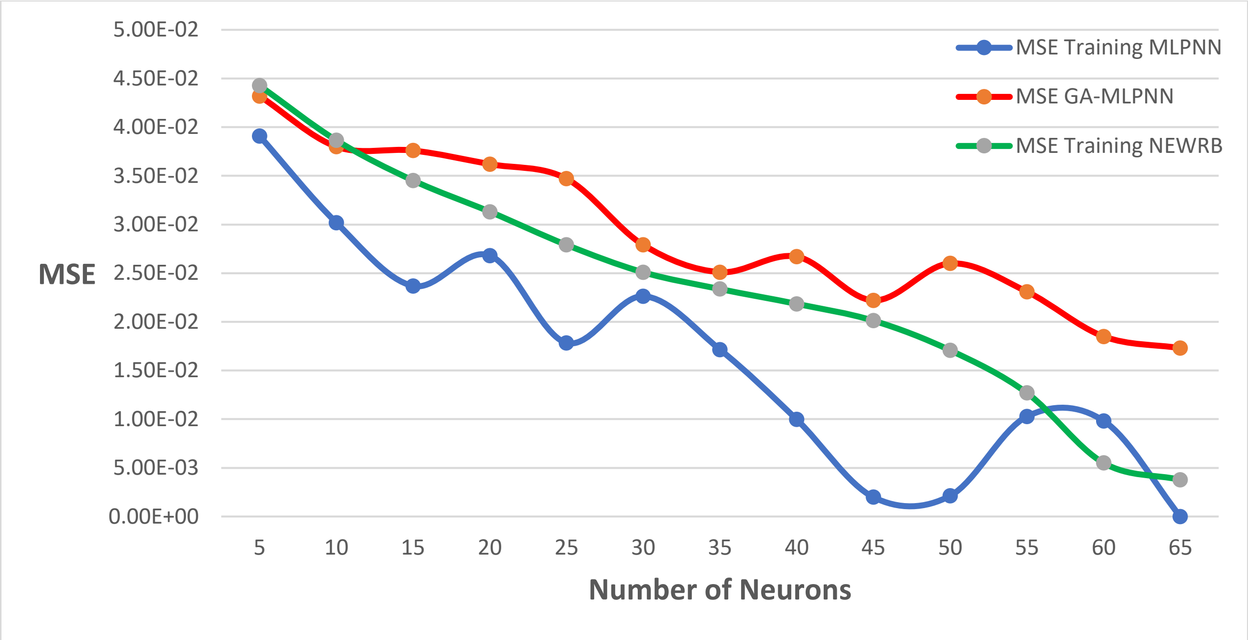

Figure 4.68: MSE Result values of NRW for the Whole City.

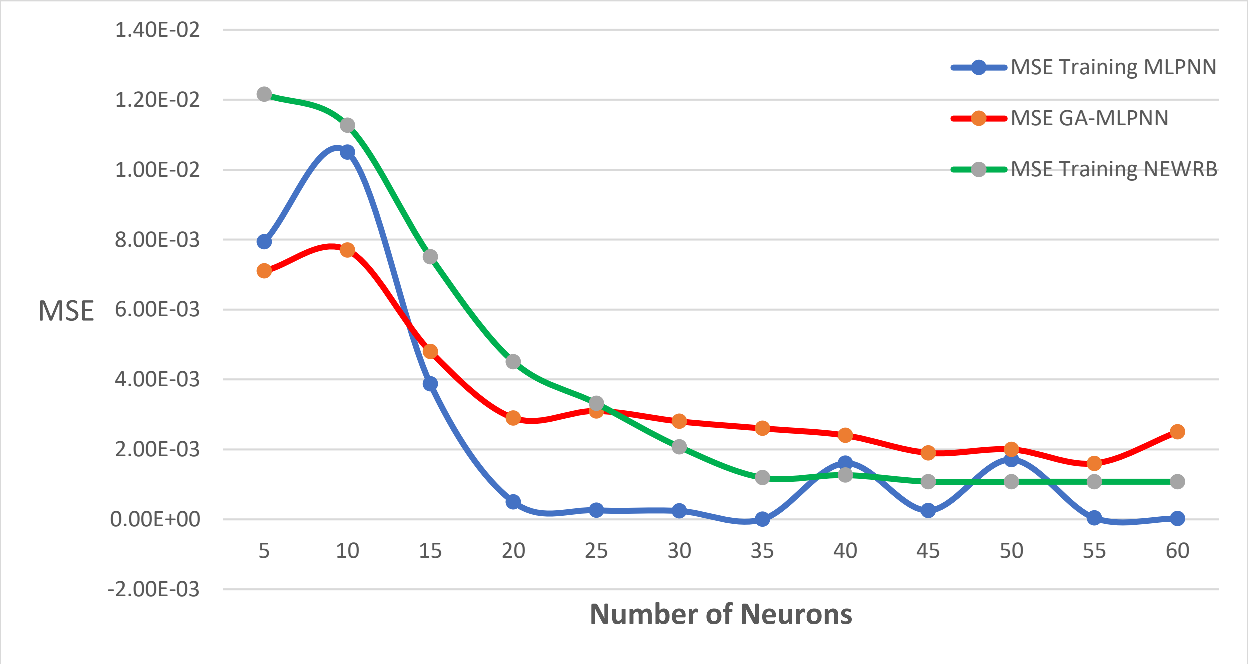

Figure 4.69: MSE Result values of NRW for the College Region.

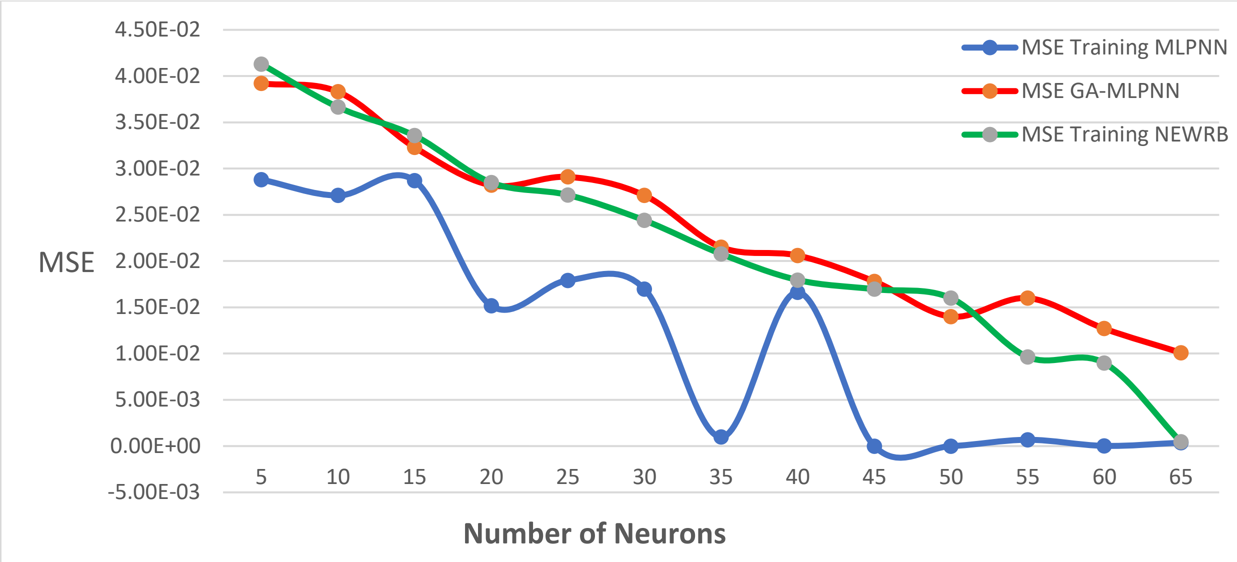

Figure 4.70: MSE Result values of NRW for the Flash Region.

While Figure 4.70 displays the error values and the number of neurons for the three Models; MLPNN-LM, newrb, and GAs-MLPNNs. It can be seen that the MLPNN-LM model clearly surpass the other models. It is also clear that there is a convergence behavior between newrb and GAs-MLPNNs models, but the newrb model can perform better when increasing the number of neurons.

Moreover, MSE values are illustrated in Figure 4.71 which shows that there is fluctuation behavior among the three models, but the MLPNN-LM achieves the best performance when the number of neurons increases. And it is clear that the newrb model can perform better than GAs-MLPNNs when increasing the number of neurons.

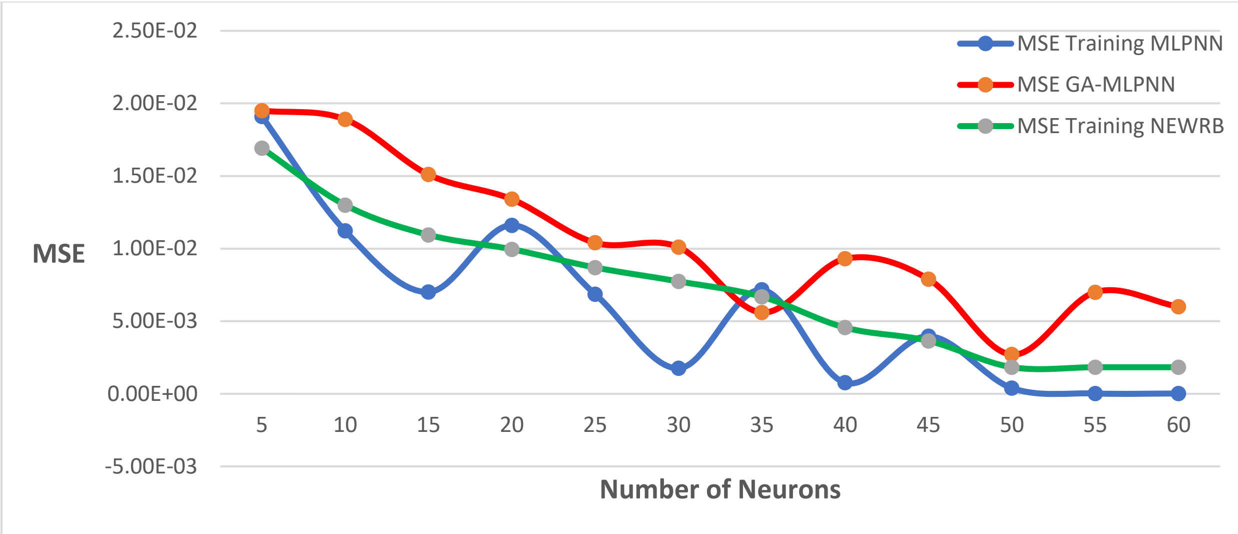

Figure 4.71: MSE Result values of NRW for the Sunuqrot Region.

4.8.2 Comparison of Water Demands for All Regions

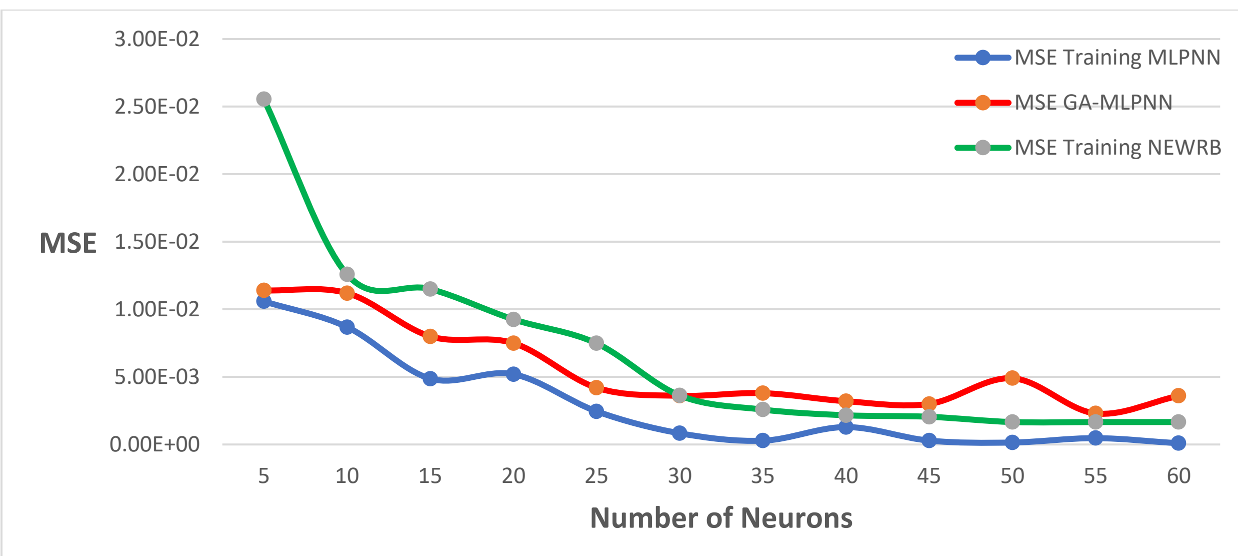

Figure 4.72: MSE Result values of water demands for the Whole City.

Figure 4.72 shows the Error values and specific numbers of neurons for the three Models; MLPNN-LM, newrb and GAs-MLPNNs, it is noticed that there is a fluctuation in behavior with an advantage to the MLPNN-LM model in overall at the end of the prediction experiments.

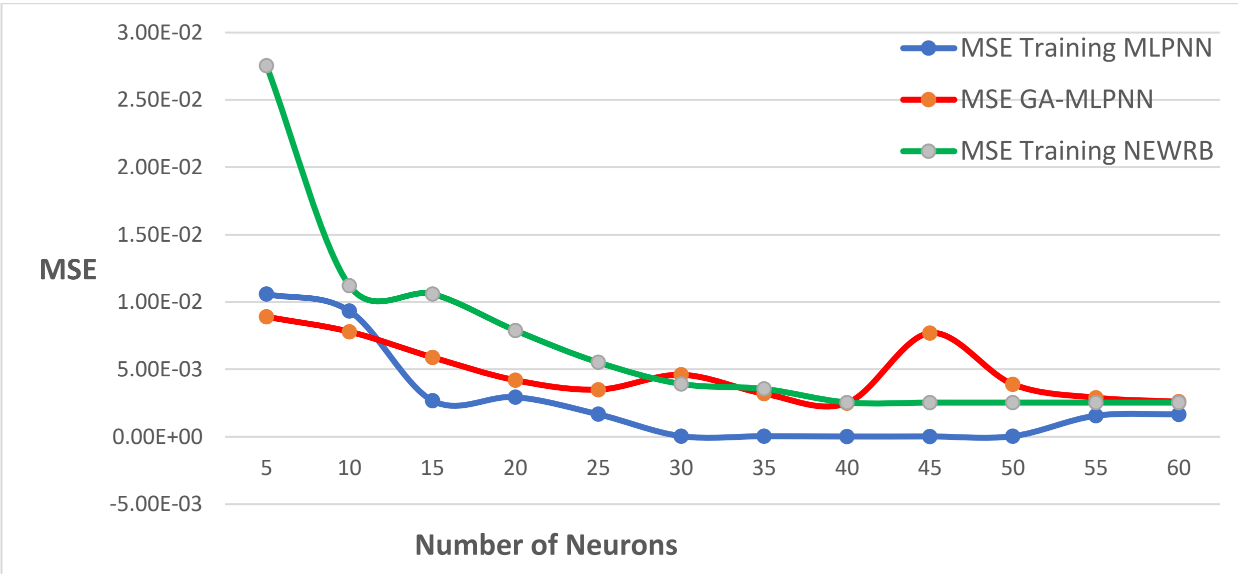

Figure 4.73: MSE Result values of NRW for the College Region.

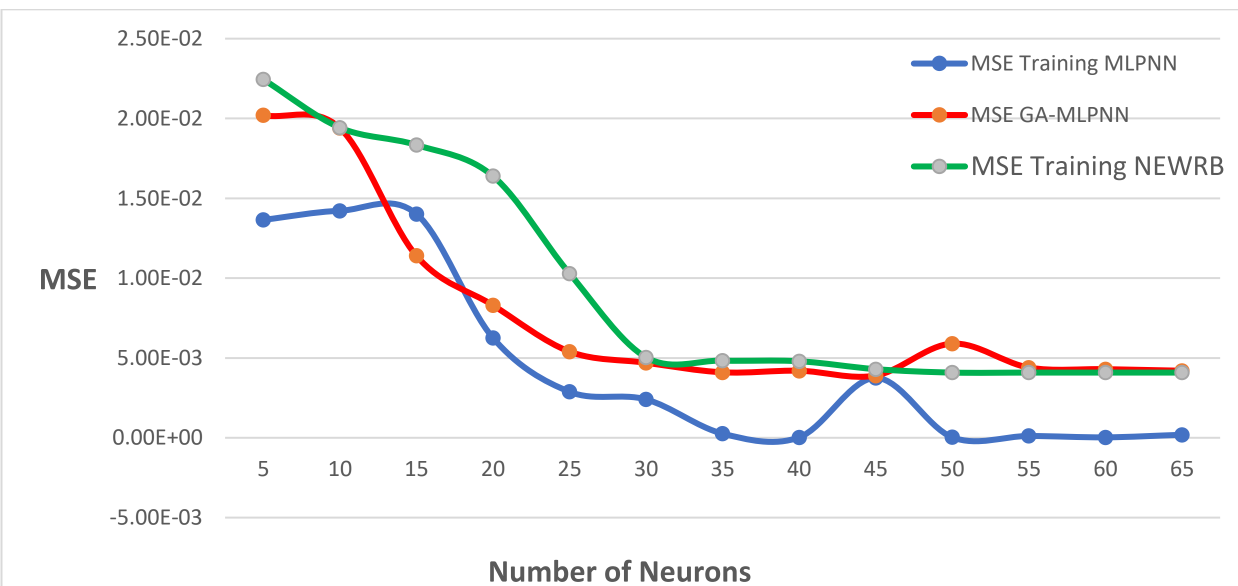

Figure 4.74: MSE Result values of NRW for the Flash Region.

MSE values are illustrated in Figure 4.73 which shows that there is fluctuation behavior among the three models, but the MLPNN-LM achieve the best performance when the number of neurons increases.

Furthermore, error values are displayed in Figure 4.74 with specific neurons for the three Models; MLPNN-LM, newrb and GAs-MLPNNs, it is noticed that there is a fluctuation in behavior with an advantage to the MLPNNs model in overall at the end of the prediction experiments.

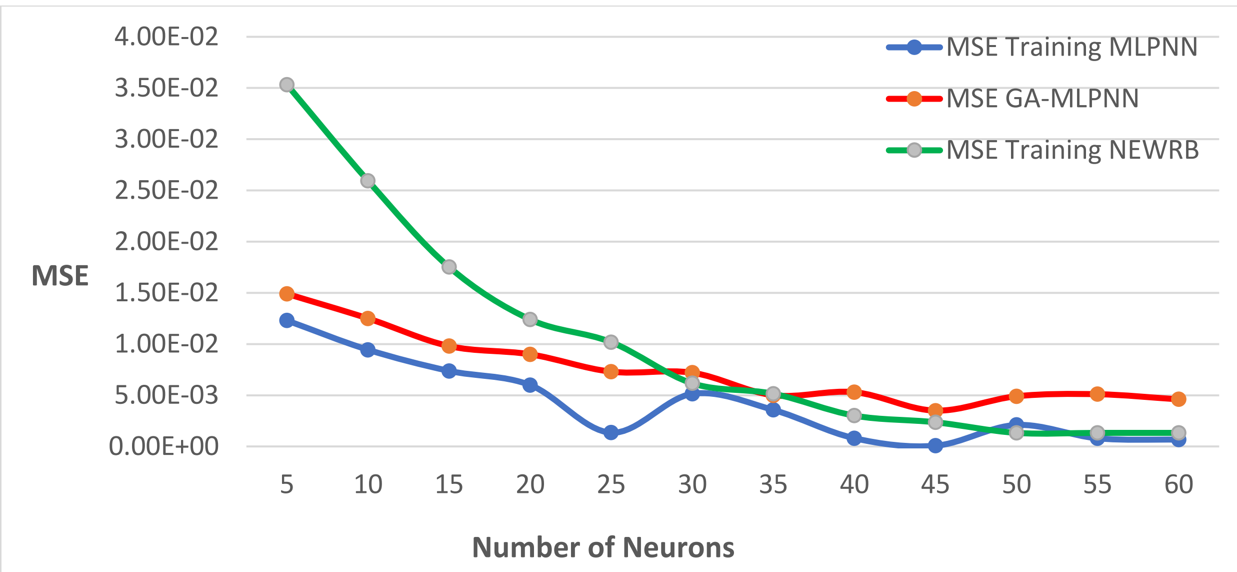

Figure 4.75: MSE Result values of NRW for the Sunuqrot Region.

Figure 4.75 presents the error values and the number of neurons for the three Models; MLPNNs, newrb, and GAs-MLPNNs to observe the performance of each built network using the mentioned models. The supremacy of the MLPNN-LM model can be seen over all models and this has been shown from the first Neuron (5) to last one approximately. It can also be seen that the GAs-MLPNNs model performs better than the newrb model when the number of neurons less than 30 neurons, but newrb model performs better than newrb model when the number of neurons bigger than 30 neurons.

In the previous results and comparison, we have made a comparison between the NNs models as shown in the figures (4.68 - 4.75) in terms of error values in order to predict water losses and demands. The supremacy of the MLPNNs model can be seen approximately over all models and this has been shown from the first Neuron (5) to last one where the error values were decreased as the number of neurons increase. Also, newrb model performing better than GAs-MLPNNs, where the error values in newrb model decreased with the increase in the number of neurons. In addition, we present a comparison of all the results obtained for NN models used in this thesis. In the following two tables (table 4.34 and table 4.35) show the best MSE values for both water losses (NRW) and water demands.

Table 4.34: Comparison of MSE for the four models of NRW.

		MLPNN-LM	**Newrb**	**GAs-MLPNNs**	**ARIMA**
Whole City	**Neuron**	**65**	**70**	**65**	**-**
	MSE	**6.17E-07**	**2.62E-03**	**1.73E-02**	**1.45E-01**
College	**Neuron**	**30**	**45**	**55**	**-**
	MSE	**2.04E-04**	**1.08E-03**	**1.60E-03**	**5.21E-02**
Flash	**Neuron**	**60**	**60**	**65**	**-**
	MSE	**2.71E-05**	**8.98E-03**	**1.01E-02**	**4.40E-02**
Sunuqrot	**Neuron**	**40**	**50**	**50**	**-**
	MSE	**2.99E-04**	**1.83E-03**	**2.70E-03**	**1.31E-01**

Table 4.34 shows the best MSE performance values of the function produced by all models MLPNNs, newrb and GAs-MLPNNs which have been applied for the water losses (NRW) prediction. While Table 4.35 shows the best MSE performance values of the function produced by

all models MLPNNS, newrb and GAs-MLPNNs which have been experienced for the water demands prediction

Table 4.35: Comparison of MSE for the Four Models of Water Demands.

		MLPNN-LM	Newrb	GAs-MLPNNs	ARIMA
WholE-0 City	**Neuron**	**70**	**50**	**55**	**-**
	MSE	**2.94E-05**	**1.66E-03**	**2.30E-03**	**9.12E-02**
College	**Neuron**	**40**	**45**	**40**	**-**
	MSE	**1.749E-05**	**2.54E-03**	**2.50E-03**	**1.79E-02**
Flash	**Neuron**	**40**	**45**	**60**	**-**
	MSE	**2.82E-05**	**4.30E-03**	**4.10E-03**	**7.24E-02**
Sunuqrot	**Neuron**	**45**	**50**	**45**	**-**
	MSE	**7.01E-05**	**1.33E-03**	**3.50E-03**	**9.35E-02**

Result depicted in tables 4.34 and 4.35 of water losses (NRW) and water demands show the achievement of the best performance with the MSE values produced by MLPNN, newrb, GAs-MLPNN, and ARIMA models. According to the MSE values observed, it can be noticed that the MLPNN model outperforms the others in terms of the forecasting of water losses and demands. While the newrb model is the second-best model, which performs better than the hybrid GAs-MLPNN model. On the other hand, the statistical model achieves the worst performance in terms of MSE values when compared to the rest of the models experienced in this study, this is because the ARIMA model relies on linear data to be accurate.

The following tables (4.36-4.37) illustrate the prediction results of water losses and water demands in the year 2018 of all models employed in the experiment of our research.

Table 4.36: Model of water Losses (NRW) Prediction of the year 2018.

Prediction 2018	**Whole-city /MLPNN-LM**	**College /MLPNN-LM**	**Flash /MLPNN-LM**	**Sunuqrot /MLPNN-LM**
03/2018	**48218**	4124	36062	3387
05/2018	**47409**	4907	28361	2818
07/2018	**42001**	6299	28640	4193
09/2018	**38243**	6943	25380	5301
11/2018	**35617**	5879	30175	4867
01/2018	**44627**	4348	35016	5408

Prediction 2018	**Whole-city /newrb**	**College / newrb**	**Flash / newrb**	**Sunuqrot / newrb**
03/2018	47959	3846	42436	3442
05/2018	35698	3943	27410	3220
07/2018	41615	5859	32167	4843
09/2018	35622	5976	21744	5576
11/2018	45613	5052	35618	4892
01/2018	40282	4075	32921	5211

Prediction 2018	**Whole-city /GAs-MLPNNs**	**College / GAs-MLPNNs**	**Flash / GAs-MLPNNs**	**Sunuqrot / GAs-MLPNNs**
03/2018	44833	3702	39434	4367
05/2018	39092	4116	30747	3702
07/2018	44884	5458	28363	4816
09/2018	38826	5390	22480	5015
11/2018	47441	3521	30955	4385
01/2018	48988	4513	30143	3354

Prediction 2018	**Whole-city /ARIMA**	**College /ARIMA**	**Flash /ARIMA**	**Sunuqrot / ARIMA**
03/2018	25959	5153	15902	4904
05/2018	44386	4979	34645	4762
07/2018	36270	4801	26763	4706
09/2018	55368	4620	46064	4684
11/2018	43613	4436	34502	4675
01/2018	45591	4248	36671	4672

Table 4.37: Model of water demands Prediction of the year 2018.

Prediction 2018	Whole-city /MLPNN-LM	College /MLPNN-LM	Flash /MLPNN-LM	Sunuqrot /MLPNN-LM
03/2018	92730	5213	90143	7999
05/2018	102656	5462	98169	8882
07/2018	115384	6005	106145	9925
09/2018	122319	5247	109119	10231
11/2018	117659	6975	107802	10015
01/2018	107101	5979	99606	9415

Prediction 2018	Whole-city /newrb	College / newrb	Flash / newrb	Sunuqrot / newrb
03/2018	95003	5191	89534	8041
05/2018	102294	5891	95388	8583
07/2018	113455	5869	105467	9507
09/2018	119193	6317	109790	9215
11/2018	115958	6874	106889	9675
01/2018	104829	6537	97220	9304

Prediction 2018	Whole-city /GAs-MLPNNs	College / GAs-MLPNNs	Flash / GAs-MLPNNs	Sunuqrot / GAs-MLPNNs
03/2018	97697	6091	38500	7685
05/2018	101365	5759	41519	8276
07/2018	112641	6665	52799	8722
09/2018	118873	6287	52844	8587
11/2018	113596	6697	50691	9879
01/2018	105356	6596	41613	9581

Prediction 2018	Whole-city /ARIMA	College /ARIMA	Flash /ARIMA	Sunuqrot / ARIMA
03/2018	123735	10421	102891	10423
05/2018	119703	10491	99108	10104
07/2018	121241	10560	100804	9877
09/2018	121150	10629	100804	9717
11/2018	121105	10698	100804	9603
01/2018	121093	10767	100804	9522

4.9 Beitunia Water Distribution Network

In this regard, we will talk about the water network in Beitunia city, in terms of the components and infrastructure, related to the pipelines used to supply water in the city, in addition, we will talk about data collected from the GIS system, especially on pipeline data and obstacles encountered in the process of building an important model for predicting water losses based on factors and components present in the pipeline.

4.9.1 Water System in Beitunia

Jerusalem Water Undertaking (JWU), is responsible for providing water for Beitunia and part of Ramallah & Al Bireh Governorate and Jerusalem Governorate. Beside technical operation and maintenance of the water supply systems, it is partly in charge of the revenue collection and other financial issues too. JWU provides and manages the water system for Ramallah and Al Bireh cities besides other municipalities within the Ramallah governorate. JWU also provides water to Beitunia Municipality as a bulk supply via 3 main connection points as follows:

Flash is the main connection point is locating near Al Tari Station which supplies about 125 cubic meters per hour (17 hours/day supply). The second connection point locates near Sunuqrot Company and supplies about 14 cubic meters per hour (24-hour supply) and the third connection point is the College which locates near Al Asryeh collage which supplies about 11 cubic meters per hour (24-hour supply).

According to the water department in Beiutnia municipality, the existing main transmission pipelines supplying the area has different sizes and segment lengths along the main line. The transmission main starting from 24” welded steel pipeline constructed in 2007, reduced to 12” welded steel pipeline constructed in 2013, reduced to 8” welded steel pipeline constructed in 2013 and reduced finally to 6” welded steel pipeline. Figure 4.76 shows the current bulk water system supplies Beitunia City

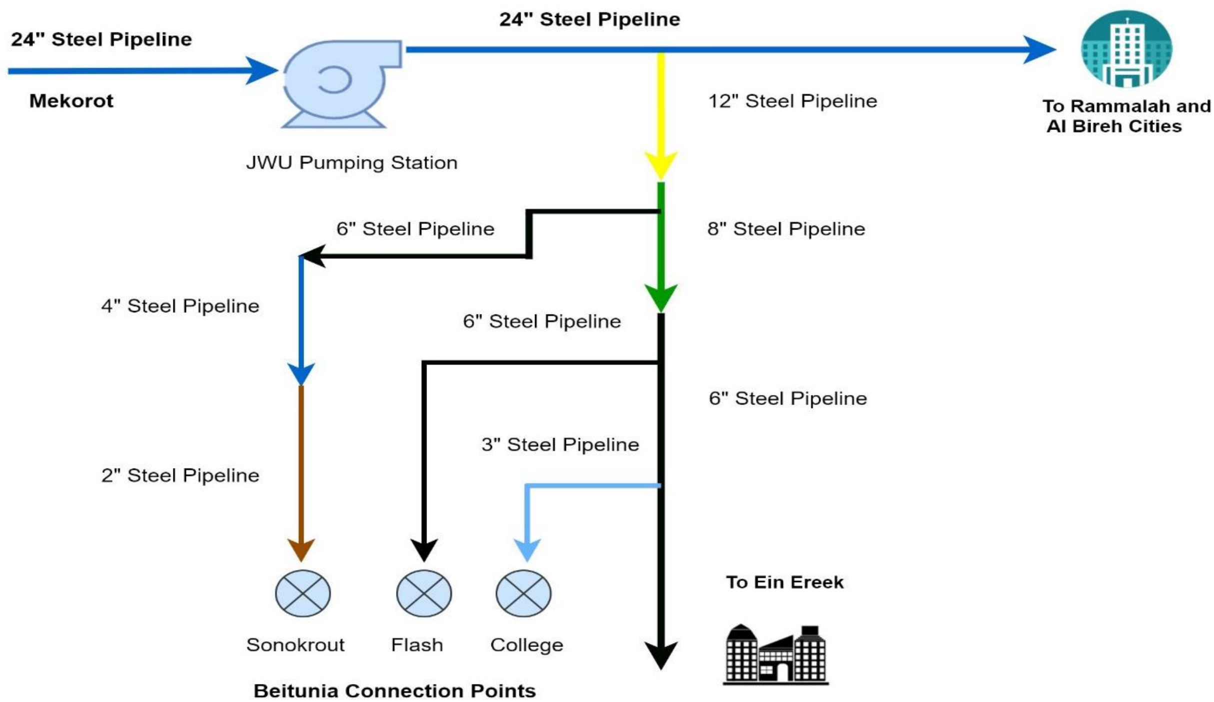

Figure 4.76: Existing water supply system.

4.9.2 Distribution Networks

The Distribution networks cover most of Beitunia City and consist of various sizes and lengths; 6”, 4”, 3”, 2”, 1” and ¾” for the house connections. The pipe material is threaded and galvanized steel pipes for 2” and less, welded and black steel with internal cement lining for 3” and more. Table 4.38 shows the Sizes, types, and lengths of the existing distribution networks.

The construction phases for the Beitunia distribution network could be divided into the following phases;

- Construction of 4”, 2” and 1” pipelines in the year 1971.
- Construction of 2” pipelines in the year 1986 during the Israeli civil administration control.

- Construction of 500 CM elevated reservoir, 4” and 3” pipelines in the year 1998 by BECDAR.
- Construction of different types of 2” pipelines and less by Beitunia municipality during the years (1995-2016)

Table 4.38: Sizes and lengths of the existing distribution networks

Diameter (inch)	Coated Black Steel, length (m)	Coated Galvanized Steel, length (m)	Galvanized Steel, length (m)	Total, length (m)
(3/4")			307	307
1"		4,491	2,188	6,679
1.25"			669	669
2"		12,364	21,866	34,230
3"	13,291			13,291
4"	3,593			3,593
6"	2,537			2,537
Grand Total	19,421	16,855	25,030	61,306

4.9.3 Pipelines Network in Beitunia

By working on the ArcGIS program, which contains all the information about the water network and all the details of the pipes, and a lot of meetings with the water technicians and municipal engineers, we collected the data related to the water network and pipelines we have divided the data and distributed it by region in order to use it in water losses and demand prediction, at the end of this work we had an Excel file contains data such as, pipeline diameters, pipeline length, and also we got important information about the status of these pipes (good, very good or excellent), in addition to information related to the surface above these pipes, also the file contains data related to the age of the pipelines and the year of installation. However, there is some important information that we cannot obtain, such as water pressure, since water pressure is an important factor needed to build a model for predicting water loss and demand. Another important information that we could not obtain is the information about the leakages in the pipelines such as quantities of water lost due to the leakages, places of leakages and the amount of time it took to repair each leakage.

Table 4.39 shows a sample of the pipelines data, and table 4.40 shows the water losses in cubic meters per area. Looking at these tables, we observe that the data in table 4.39 are spatial data related to information of pipelines, and the information in table 4.40 are temporal data.

Table 4.39: Beitunia pipelines network

Area	Diameter	Material	Condition	Surface	Contractor	Year	SHAPE Length
Flash	3	Coated Black Steel	V.Good	Asphalt	Al Mahole/PICDAR	1998	310.0
Sunuqrot	3	Coated Black Steel	V.Good	Asphalt	Al Mahole/PICDAR	1998	8.1
Sunuqrot	2	Steel	Good	Asphalt	Mun.	1998	166.4
Flash	4	Coated Black Steel	Bad	Asphalt	Al Amour	1971	253.4
Flash	3	Coated Black Steel	V.Good	Asphalt	Al Mahole/PICDAR	1998	4.9
Flash	3	Coated Black Steel	V.Good	Asphalt	Al Mahole/PICDAR	1998	2.8
Flash	6	Coated Black Steel	V.Good	Asphalt	Al Mahole/PICDAR	1998	724.3
Flash	4	Coated Black Steel	Bad	Asphalt	Al Amour	1971	185.8
Flash	4	Coated Black Steel	Bad	Asphalt	Unknown	1971	240.4
Sunuqrot	3	Coated Black Steel	Good	Asphalt	Al Mahole/PICDAR	1998	1.0

If we want to build multiple regression analysis (MRA) model to determine which parameter (parameters) in table 4.39 or in another word, what is the most parameter (parameters) causing water losses in a given region, we need to link the spatial data with the temporal data by adding the amount of loss as a column we need to link the spatial data with the temporal data by adding the amount of loss as a column in table 4.39 (adding the amount of losses to the table of spatial data), after a long search and investigation we could not find a suitable solution even after consulting with experts, this issue prevented us to implement MRA Model.

Table 4.40: water losses quantities (m^3) for Beitunia regions

Flash

2005	214533
2006	332360
2007	232261
2008	237294
2009	245436
2010	119873
2011	172554
2012	224837
2013	204133
2014	194795
2015	168583
2016	186114
2017	146414
Total	24126

Sunuqrot

2007	13697
2008	20123
2009	23764
2010	37199
2011	18882
2012	16685
2013	23121
2014	48505
2015	35023
2016	22859
2017	39164
Total	299022

College

2010	17654
2011	13904
2012	20526
2013	20620
2014	20235
2015	20424
2016	49162
2017	67501
Total	230026

CHAPTER FIVE

CONCLUSION AND FUTURE WORK

5.1 Introduction

In this chapter, we show and summarize the conclusions achieved by what we have experienced in addition to the findings obtained. The conclusions are based on the goal of this research, the research assumptions, in addition to the discussion and analysis of the results obtained from the conducted experiments on different NNs and statistical models. This chapter also offers some recommendations for researchers, the municipality of Beitunia city, water utilities and the local government authority. Finally, it will present important directions for future work.

5.2 Conclusions

This study has drawn some conclusions that can be expressed as follows:

- In this thesis, we have addressed one of the main challenges facing the local governments in Palestine. Water losses problem is concerning the municipalities and water utilities; leading to, sometimes, disruption of services, in addition to affecting the quality of water distribution service. Most importantly, such a problem has caused significant financial losses which has an impact on the development process either on improving water services or developing other important areas. The significance of studying and offering solutions in regards to minimizing (or avoiding) such problems led to building a forecasting tool for the prediction of water losses and water supply demands.
- This research has been supported with an in-depth review in the literature; surveying what research efforts have been made in regards. It can be found that many researchers were motivated to conduct studies in an attempt to predict water loss and water demands; employing different techniques and algorithms such as a statistical and artificial neural network (ANNs).

- This academic work has presented an exploration and investigation in addition to experiencing various AI models. Nonetheless, the importance of resulting of least loss value as possible (approaches to zero), this research finds it important to experiencing models and building what it could be more efficient in forecasting water losses and water demands in Palestine for the scope of this academic work, and, specifically, for the interest of Beitunia city.
- The historical data of water loss and consumption quantities from Beitunia database were used for all models over the period between the years 2005 and 2017. It can be seen that the data changing over time Series.
- In this study, various experiments were conducted, in which different and various ANNs models were used. Three models were used; MLPNN-LM, RBFNNs (newrb) and GAs-MLPNNs, utilizing real data. More importantly, it has been presented how the employed models resulted in highly accurate and precise results. In other words, the models have shown good performance in a form that regression could be done achieving highly precise values compared to the actual readings (data label). This success is led to the conclusion of the success of the prediction experiments concerning the achievement of the goal of this research.
- After a number of modeling iterations, ANNs models can fit better than the ARIMA model for the prediction of water demand and water losses. While the MLPNN-LM model has achieved the best results when it is compared to other ANNs models (newrb and GAs-MLPNNs). Going through results, it has been found that MLPNNs using the Levenberg-Marquardt algorithm revealed great results of water losses and water demands with small Mean Square Error values. The results of the newrb model were also highly precise, despite

being less accurate compared to the MLPNN-LM model. While the GAs-MLPNNs model could also generate predictions with small Mean Square Error value, but it was the least accurate model when it is compared with the other models applied in our experiment. The ARIMA model was less accurate than other NNs models. This is because the ARIMA model relies on linear data to be accurate.

- The evaluation of our experiments was not only conducted using the Mean Square Error calculations as metric for judging the performance and quality of the experienced AI models, but it has also been supported with some statistical methods such as the ARIMA model. This enabled to perform comparisons with the results of the employed NNs models.
- Most importantly, this research has introduced a proof of concept in an attempt to construct a robust and reliable model that can be nationally generalized; over the whole country. This can be achieved by providing such solutions, proposed in this study, for the interest of water utilities and municipalities on the purpose of reducing (or avoiding) water losses (NRW) Thus, it will definitely improve the quality of service and will save one of the key resources.

5.3 Recommendations

In order to improve the efficiency of NNs models, we recommend further studies to be undertaken exploiting more historical water data to validate the obtained results of our model. On a wider level, the dataset should include the complete data of water supply and demands from the JWU, which could help better estimate water losses that will improve the target variable values. In regards, pipe leakages information should also be recorded, thereby, it will improve the accuracy of prediction of water losses.

For the decision makers in the municipality of Beitunia city and the JWU, this study recommends the renewal of the water distribution networks, specifically, in the three regions; Flash, the College, and Sunuqrot. It is believed that this will help reduce (or avoid) water leakages, in one hand. In the other hand, it will increase the municipality revenues by reducing the water losses, discovering illegitimate use of water, replacing broken meters, and employing prepaid water meters.

5.4 Future Work

As future work, we aim to use these models for many municipalities and water services facilities. For the municipality of Beitunia city, we will work together with the municipality staff, who are experts in the domain of water supply services, on purpose of doing more in-depth investigations about the factors that cause water losses in each region. After understanding the most effective factors, we will collect the important information that will work as the dataset. Multiple regression analysis will also be employed in our future models.

It is also possible to work with the municipality to create a smart application to control the pipes leakages in the city in order to reduce NRW quantities, the smart application can monitor the condition of the pipes and alert the control center of the municipality.

Another important future work will be the prediction of unwanted substances in the water. This will be achieved by more cooperation between the municipality of Beitunia city and the Jerusalem Water Undertaking. In other words, we will develop other applications for the prediction of the amounts of chemical substances such as water chlorine for the suitability of human use.

References

1. Authority, P.W., *STATUS REPORT OF WATER RESOURCES IN THE OCCUPIED STATE OF PALESTINE-2012*. 2013. p. 22.
2. El Khateeb, M.E. and M.A. Salaime, *Quality of Drinking Water from Rainwater Harvesting Cisterns of Hebron City and Factors Affecting It.* 2009.
3. Mimi, Z., et al., *Evaluation of water losses in distribution networks: Rammallah as a case study.* Water Science and Technology: Water Supply, 2004. **4**(3): p. 183-195.
4. Msiza, I.S., F.V. Nelwamondo, and T. Marwala, *Water demand prediction using artificial neural networks and support vector regression.* 2008.
5. Jang, D. and G. Choi, *Estimation of non-revenue water ratio using MRA and ANN in water distribution networks.* Water, 2017. **10**(1): p. 2.
6. Al-Zahrani, M.A. and A. Abo-Monasar, *Urban residential water demand prediction based on artificial neural networks and time series models.* Water resources management, 2015. **29**(10): p. 3651-3662.
7. Lourakis, M.I., *A brief description of the Levenberg-Marquardt algorithm implemented by levmar.* Foundation of Research and Technology, 2005. **4**(1): p. 1-6.
8. Broomhead, D.S. and D. Lowe, *Radial basis functions, multi-variable functional interpolation and adaptive networks*. 1988, Royal Signals and Radar Establishment Malvern (United Kingdom).
9. Itano, F., M.A.d.A. de Sousa, and E. Del-Moral-Hernandez. *Extending MLP ANN hyper-parameters Optimization by using Genetic Algorithm*. in *2018 International Joint Conference on Neural Networks (IJCNN)*. 2018. IEEE.
10. Faruk, D.Ö., *A hybrid neural network and ARIMA model for water quality time series prediction.* Engineering Applications of Artificial Intelligence, 2010. **23**(4): p. 586-594.
11. Hu, D., *Water Rights*. 2006: IWA Publishing.
12. UNESCO. *The United Nations World Water Development Report 2016* 2016 [14 09 2018]]; Available from: https://www.unescap.org/sites/default/files/2016%20UN%20World%20Water%20Development%20Report-%20Water%20and%20Jobs.pdf.
13. Thornton, J., *Water Loss Control Manual*. 2002: McGraw-Hill.
14. Butler, D. and F.A. Memon, *Water demand management.* 2005.
15. Assaf, K. *Water as a human right: The understanding of water in Palestine* 2004; Available from: https://www.boell.de/sites/default/files/assets/boell.de/images/download_de/internationalepolitik/GIP11_Palestine_Karen_Assaf.pdf.
16. Undertaking, J.W. *Foundation of JWU*. 2018; Available from: https://www.jwu.org/jwu/?p=1698&lang=en.
17. Authority, P.N. *Water Sector Review West Bank & Gaza*. 2006; Available from: http://www.lacs.ps/documentsShow.aspx?ATT_ID=733.
18. *http://siteresources.worldbank.org/INTWESTBANKGAZA/Resources/WaterRestrictionsReportJuly2009.pdf Accessed [03 09 2018]*.
19. Jabari, S.J., *Non-Revenue Water Management in Palestine.* World Academy of Science, Engineering and Technology, International Journal of Civil, Environmental, Structural, Construction and Architectural Engineering, 2017. **11**(7): p. 953-959.
20. *https://www.wsrc.ps/cached_uploads/download/2018/02/18/english-report-website-1518948893.pdf Accessed [23 09 2018]*.
21. (PHG), U.a.t.P.H.G., *Water for life, Water, Sanitation and Hygiene Monitoring Program (WASH MP) 2010*. 2011.

22. http://www.pcbs.gov.ps/Downloads/book2364.pdf *Accessed [03 09 2018].*
23. Liemberger, R. and P. Marin, *The Challenge of Reducing Non-Revenue Water in Developing Countries--How the Private Sector Can Help: A Look at Performance-Based Service Contracting.* 2006.
24. Bank, A.D., *The Issues and Challenges of Reducing Non-Revenue Water*. 2010: Asian Development Bank.
25. González-Gómez, F., M.A. García-Rubio, and J. Guardiola, *Why is non-revenue water so high in so many cities?* Water Resources Development, 2011. **27**(02): p. 345-360.
26. Chimene, C.A., *Strategies and methods for apparent water loss management in developing countries*. 2013, Unesco-IHE.
27. Frauendorfer, R. and R. Liemberger, *The issues and challenges of reducing non-revenue water*. 2010: Asian Development Bank.
28. Farley, M. and S. Trow, *Losses in water distribution networks: a practitioner's guide to assessment, monitoring and control.* IWA, London, 2003.
29. DAI, *The manager's non-revenue water handbook for Africa: A guide to understanding water losses,* . 2010.
30. https://en.wikipedia.org/wiki/Non-revenue_water*. Accessed [10 10 2018].*
31. Makridakis, S., S.C. Wheelwright, and R.J. Hyndman, *Forecasting methods and applications*. 2008: John wiley & sons.
32. Qi, M. and G.P. Zhang, *Trend time–series modeling and forecasting with neural networks.* IEEE Transactions on neural networks, 2008. **19**(5): p. 808-816.
33. Khashei, M., M. Bijari, and G.A.R. Ardali, *Improvement of auto-regressive integrated moving average models using fuzzy logic and artificial neural networks (ANNs).* Neurocomputing, 2009. **72**(4-6): p. 956-967.
34. Box, G.E., et al., *Time series analysis: forecasting and control*. 2015: John Wiley & Sons.
35. Hipel, K.W. and A.I. McLeod, *Time series modelling of water resources and environmental systems*. Vol. 45. 1994: Elsevier.
36. Zhang, G.P., *Time series forecasting using a hybrid ARIMA and neural network model.* Neurocomputing, 2003. **50**: p. 159-175.
37. Haykin, S., *Neural networks: a comprehensive foundation*. 1994: Prentice Hall PTR.
38. Hagan, M., H. Demuth, and M.B.N.N. Design, *PWS publishing company.* Boston, MA, USA, 1996.
39. Dreiseitl, S. and L. Ohno-Machado, *Logistic regression and artificial neural network classification models: a methodology review.* Journal of biomedical informatics, 2002. **35**(5-6): p. 352-359.
40. Wan, E.A., *Neural network classification: A Bayesian interpretation.* IEEE Transactions on Neural Networks, 1990. **1**(4): p. 303-305.
41. Hepner, G., et al., *Artificial neural network classification using a minimal training set-Comparison to conventional supervised classification.* Photogrammetric Engineering and Remote Sensing, 1990. **56**(4): p. 469-473.
42. Penn, B.S., *Using self-organizing maps to visualize high-dimensional data.* Computers & Geosciences, 2005. **31**(5s): p. 531-544.
43. García-Pedrajas, N., C. Hervás-Martínez, and J. Muñoz-Pérez, *COVNET: a cooperative coevolutionary model for evolving artificial neural networks.* IEEE Transactions on neural networks, 2003. **14**(3): p. 575-596.
44. Haykin, S. and N. Network, *A comprehensive foundation.* Neural networks, 2004. **2**(2004): p. 41.
45. Grothmann, R., *Multi Agent Market Modeling Based on Neutral Networks*. 2003, University of Bremen, Germany.

46. Gardner, M.W. and S. Dorling, *Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences.* Atmospheric environment, 1998. **32**(14-15): p. 2627-2636.
47. Willmott, C.J. and K. Matsuura, *Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance.* Climate research, 2005. **30**(1): p. 79-82.
48. Mikolov, T., et al. *Recurrent neural network based language model*. in *Eleventh Annual Conference of the International Speech Communication Association*. 2010.
49. Orr, M.J., *Introduction to radial basis function networks*. 1996, Technical Report, center for cognitive science, University of Edinburgh.
50. Sangwan, O.P., P.K. Bhatia, and Y. Singh, *Radial basis function neural network based approach to test oracle.* ACM SIGSOFT Software Engineering Notes, 2011. **36**(5): p. 1-5.
51. Bazartseren, B., G. Hildebrandt, and K.-P. Holz, *Short-term water level prediction using neural networks and neuro-fuzzy approach.* Neurocomputing, 2003. **55**(3-4): p. 439-450.
52. Mitchell, M., *An introduction to genetic algorithms*. 1998: MIT press.
53. Jang, D., H. Park, and G. Choi, *Estimation of leakage ratio using principal component analysis and artificial neural network in water distribution systems.* Sustainability, 2018. **10**(3): p. 750.
54. Wibowo, A., S.H. Arbain, and N.Z. Abidin, *Combined Multiple Neural Networks and Genetic Algorithm with Missing Data Treatment: Case Study of Water Level Forecasting in Dungun River-Malaysia.* IAENG International Journal of Computer Science, 2018. **45**(2).
55. Jang, D. and G. Choi, *Estimation of Non-Revenue Water Ratio for Sustainable Management Using Artificial Neural Network and Z-Score in Incheon, Republic of Korea.* Sustainability, 2017. **9**(11): p. 1933.
56. Chang, M. and J. Liu. *Water demand prediction model based on radial basis function neural network*. in *2009 First International Conference on Information Science and Engineering*. 2009. IEEE.
57. Kutyłowska, M., *Comparison of two types of artificial neural networks for predicting failure frequency of water conduits.* Periodica Polytechnica Civil Engineering, 2017. **61**(1): p. 1-6.
58. Farley, M. *Non-revenue water–international best practice for assessment, monitoring and control*. in *12th Annual CWWA Water, Wastewater & Solid Waste Conference*. 2003.
59. Farah, E. and I. Shahrour, *Leakage detection using smart water system: combination of water balance and automated minimum night flow.* Water Resources Management, 2017. **31**(15): p. 4821-4833.
60. Jain, A. and L.E. Ormsbee, *Short-term water demand forecast modeling techniques—CONVENTIONAL METHODS VERSUS AI.* Journal-American Water Works Association, 2002. **94**(7): p. 64-72.
61. Bougadis, J., K. Adamowski, and R. Diduch, *Short-term municipal water demand forecasting.* Hydrological Processes: An International Journal, 2005. **19**(1): p. 137-148.
62. Sebri, M., *ANN versus SARIMA models in forecasting residential water consumption in Tunisia.* Journal of Water Sanitation and Hygiene for Development, 2013. **3**(3): p. 330-340.
63. Ajbar, A. and E.M. Ali, *Prediction of municipal water production in touristic Mecca City in Saudi Arabia using neural networks.* Journal of King Saud University-Engineering Sciences, 2015. **27**(1): p. 83-91.
64. Murrar, A., A. Tamim, and S. Samhan, *The Determinants of Non-Revenue Water & Financial Viability for the Palestinian Water Service Providers.* Journal of Water Resources and Ocean Science, 2017. **6**(2): p. 35-45.

65. Mahmoud, K.O. and D.M.A. Shanab, *Forecasting Monthly Water Production in Gaza City Using a Seasonal ARIMA Model.* Scholars Journal of Physics, Mathematics and Statistics, 2014. **1**(2): p. 61-70.
66. Castillo, P., et al., *G-Prop-II: Global Optimization of Multilayer Perceptrons using G As.*
67. Bhatt, A.K. and K.S. Vaisla, *An analysis of the performance of artificial neural network technique for stock market forecasting.* International Journal on Computer Science and Engineering, 2010. **2**(6): p. 2104-2109.
68. Okasha, M.K. and A.A. Yaseen. *Comparison between ARIMA models and artificial neural networks in forecasting Al-Quds indices of Palestine stock exchange market*. in *The 25th Annual International Conference on Statistics and Modeling in Human and Social Sciences, Departmentof Statistics, Faculty of Economics and Political Science, Cairo University, Cairo*. 2013.
69. Riedmiller, M. and H. Braun. *A direct adaptive method for faster backpropagation learning: The RPROP algorithm*. in *Neural Networks, 1993., IEEE International Conference on*. 1993. IEEE.
70. Hornik, K., M. Stinchcombe, and H. White, *Multilayer feedforward networks are universal approximators.* Neural networks, 1989. **2**(5): p. 359-366.
71. HAMDAN, I., M. AWAD, and W. SABBAH, *SHORT-TERM FORECASTING OF WEATHER CONDITIONS IN PALESTINE USING ARTIFICIAL NEURAL NETWORKS.* Journal of Theoretical & Applied Information Technology, 2018. **96**(9).
72. Jayalakshmi, T. and A. Santhakumaran, *Statistical normalization and back propagation for classification.* International Journal of Computer Theory and Engineering, 2011. **3**(1): p. 1793-8201.
73. Wong, T.-T., *Performance evaluation of classification algorithms by k-fold and leave-one-out cross validation.* Pattern Recognition, 2015. **48**(9): p. 2839-2846.
74. Browne, M.W., *Cross-validation methods.* Journal of mathematical psychology, 2000. **44**(1): p. 108-132.
75. Karayiannis, N.B., M. Balasubramanian, and H. Malki. *Evaluation of cosine radial basis function neural networks on electric power load forecasting*. in *Neural Networks, 2003. Proceedings of the International Joint Conference on*. 2003. IEEE.
76. Huang, G.-B., L. Chen, and C.K. Siew, *Universal approximation using incremental constructive feedforward networks with random hidden nodes.* IEEE Trans. Neural Networks, 2006. **17**(4): p. 879-892.
77. *https://au.mathworks.com/help/deeplearning/ug/radial-basis-neural-networks.html. Accesses [01 11 2018]*.
78. Cherian, M. and S.P. Sathiyan, *Neural network based ACC for optimized safety and comfort.* Int J Comp Appl, 2012. **42**.
79. Seiffert, U. *Multiple layer perceptron training using genetic algorithms*. in *ESANN*. 2001. Citeseer.
80. Awad, M., *Optimization RBFNNs parameters using genetic algorithms: applied on function approximation.* International Journal of Computer Science and Security (IJCSS), 2010. **4**(3): p. 295-307.
81. Alabsi, F. and R. Naoum, *Comparison of selection methods and crossover operations using steady state genetic based intrusion detection system.* Journal of Emerging Trends in Computing and Information Sciences, 2012. **3**(7): p. 1053-1058.
82. Goldberg, D.E., *Genetic algorithms in search, optimisation and machine learning, 1989.* Reading, Addison, Wesley.
83. Hakimi, D., et al., *Comparative analysis of genetic crossover operators in knapsack problem.* Journal of Applied Sciences and Environmental Management, 2016. **20**(3): p. 593-596.

84. Season, D., *Non-linear PLS using genetic programming*. 2005, School of Chemical Engineering and Advanced Materials University of ….
85. Howard Beale, D., Mark, *Neural Network Toolbox For Use with Matlab--User'S Guide Verion 3.0.* 1993.
86. Dogan, I., *Engineering simulation with MATLAB: improving teaching and learning effectiveness.* Procedia Computer Science, 2011. **3**: p. 853-858.
87. *http://www.eviews.com/home.html. Accessed [02 01 2019]*.

يعتمد بحثنا على البيانات التاريخية لإجمالي استهلاك المياه والبيانات الفعلية للفاقد من المياه في مدينة بيتونيا، الهدف الرئيسي من هذا البحث هو استكشاف نماذج الذكاء الاصطناعي (AI) التي يمكن استخدامها بكفاءة أكبر في التنبؤ بفقدان المياه والتنبؤ بالطلب على المياه في فلسطين وبالتحديد لمدينة بيتونيا. في هذه الرسالة ، تتكون منهجية العمل من تقييم الجوانب المختلفة لتصميم الشبكات العصبية التنبؤية ، مثل تضمين خوارزميات تعلم جديدة في أبنية الشبكات العصبية المختلفة. يتم محاكاة الشبكة العصبية ومن ثم يتم مقارنة تنبؤاتها بالبيانات الحقيقية للفاقد والاستهلاك من المياه.

من خلال النتائج التي حصلنا عليها، وجدنا أن خوارزمية التعلم Levenberg Marquardt والتي تستخدم لتحسين نموذج MLPNNs-LM قد اعطت نتائج واعدة لفقدان المياه والطلب عليها مع قيم خطأ صغيرة ومقارنة بالنماذج الاخرى مثل (RBFNN-Newrb and GAs-MLPNNs)، بينما كان نموذج ARIMA أقل دقة من نماذج الشبكات العصبية الأخرى وذلك لأن نموذج (ARIMA) يعتمد على ان تكون البيانات خطية لتكون نتائجه دقيقة.وبالتالي ، فان بلدية بيتونيا ستستخدم نظامًا فعالًا من شأنه تقليل التكلفة فضلا عن الاستفادة المثلي من الموارد المائية وأدارتها. والأهم من ذلك ، فإن هذا النجاح سيساعد في تعميم نموذجنا في العديد من البلديات ومرافق خدمات المياه.

ملخص

يعتبر الماء من الموارد الطبيعية الاستراتيجية النادرة التي لا تضاهى، فهو العنصر الاساسي للحياة والتنمية الاجتماعية. يفتقر بعض الناس إلى مياه الشرب نتيجة التسربات الكبيرة في شبكات المياه. تُعتبر الخسائرفي المياه والطلب على المياه واحدة من أهم المشكلات التي تواجه قطاع المياه في فلسطين. وبشكل أكثر تحديدًا ، تعاني البلديات ومرافق المياه من هذه المشكلة مما يؤدي إلى انقطاع الخدمة وانخفاض جودة الخدمة المقدمة ، بالإضافة إلى التسبب بخسائر مالية كبيرة.لذلك ، يعتبر التنبؤ الدقيق لفقدان المياه والطلب عليها أحد المهام الأساسية التي توفر الدعم الفعال لإدارة الموارد المائية. ان توفر التوقعات الموثوقة على الطلب والخسائر للمياه في المناطق الحضرية هو الأساس لاتخاذ القرارات التشغيلية والتكتيكية والاستراتيجية لمرافق المياه، وهو أمر حاسم وضروري تحتاجه المرافق العامة من اجل معرفة كمية الطلب على المياه لتلبية الاحتياجات الأساسية للناس بالإضافة إلى متطلبات التصنيع والزراعة ، وكذلك لتطوير مصادر مياه جديدة. ان معرفة الاسباب الحقيقية المسبقة لفقدان المياه والاستجابة الاستباقية في معالجتها يمكن أن يقلل من الخسائر ، والأهم من ذلك أنها قد توفر الموارد المالية بطريقة من شأنها أن تعزز قطاع المياه.

يعتبر الفارق الكبير بين كمية المياه التي يتم توفيرها وكمية المياه التي يتم استهلاكها والمعروفة أيضًا باسم "المياه غير المدرة للدخل" من أهم القضايا التي تؤثر على مرافق المياه .[NRW] "يتم النظر في كميات كبيرة من المياه المفقودة من خلال التسريبات، وعدم إصدار الفواتير للعملاء، والوصلات غير القانونية، وعدم عمل عدادات المياه بالشكل الصحيح، والقراءة غير الدقيقة. مما يؤثر بشكل خطير على الجدوى المالية لمرافق المياه.

التنبؤ بالخسائر المائية والطلب على المياه اصبحت أداة مهمة لإدارة وتشغيل أنظمة إمدادات المياه. والذي له الاثر على تطوير النظام وتوسيعه وتقدير حجم وتشغيل الخزانات ومحطات الضخ وسعات الأنابيب، لذلك من الضروري إيجاد آليات تلقائية لتوقع الخسائر في المياه والطلب عليها من خلال استخدام تقنيات الذكاء الاصطناعي لضمان وجود نظام لتوزيع المياه يمكن الاعتماد عليه من جهة ومن جهة اخرى يساعد في حل مشكلة فقدان المياه.