STUDYING SEEPAGE IN A BODY OF EARTH-FILL DAM BY (ARTIFICIAL NEURAL NETWORKS) ANNs

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ABSTRACT

Dams are structures that are used especially for water storage, energy production, and irrigation. Dams are mainly divided into four parts on the basis of the type and materials of construction as gravity dams, buttress dams, arch dams, and embankment dams. There are two types of embankment dams: earthfill dams and rockfill dams.

In this study, seepage through an earthfill dam's body is investigated using an artificial neural network model. Seepage is investigated since seepage both in the dam's body and under the foundation adversely affects dam's stability. This study specifically investigated seepage in dam's body. The seepage in the dam's body follows a phreatic line. In order to understand the degree of seepage, it is necessary to measure the level of phreatic line. This measurement is called as piezometric measurement.

Piezometric data sets which are collected from Jeziorsko earthfill dam in Poland were used for training and testing the developed ANN model. Jeziorsko dam is a non-homogeneous earthfill dam built on the impervious foundation.

Artificial Neural Networks are one of the artificial intelligence related technologies and have many properties. In this study the water levels on the upstream and downstream sides of the dam were input variables and the water levels in the piezometers were the target outputs in the artificial neural network model.

In the line of the purpose of this research, the locus of the seepage path in an earthfill dam is estimated by artificial neural networks. MATLAB 6 neural network toolbox is used for this study.

ÖZ

Barajlar, özellikle suyu biriktirmek, enerji üretmek ve sulama yapmak için kullanılan yapılardır. Barajlar başlıca dört gruba ayrılır. Bunlar; Ağırlık barajları, payandalı barajlar, kemer barajlar ve dolgu barajlardır. Dolgu barajlar ekonomiklikleri açısından daha çok tercih edilir. Dolgu barajlar iki gruba ayrılır. Bunlar toprak dolgu barajlar ve kaya dolgu barajlardır.

Bu çalışmada, bir toprak dolgu baraj gövdesindeki sızma, yapay sinir ağları (YSA) metodu kullanılarak yapılan modelleme aracılığıyla incelenmiştir. Sızmanın incelenme amacı, sızmanın hem baraj gövdesinde hem de temelin altında doğrudan baraj stabilitesine karşı bir tehdit oluşturmasıdır.Bu çalışmada spesifik olarak baraj gövdesindeki sızma incelenmiştir. Baraj gövdesindeki sızma, freatik çizgi denilen bir hattı takip eder. Sızmanın derecesini anlayabilmek için, freatik çizginin seviyesini ölçmek gereklidir. Bu ölçüm piyezometrik ölçüm olarak adlandırılır.

Modellemede kullanılacak, piyezometrik ölçümlerin oluşturduğu veri grubu, Polonya'da bulunan Jeziorsko toprak dolgu barajından elde edilmiş olup, yapay sinir ağları modellemesinde eğitim ve sınama için kullanılmıştır. Bu veri grubu, piyezometrelerdeki su seviyeleriyle, baraj menba ve mansabındaki su seviyelerini kapsamaktadır. Jeziorskobarajı, geçirimsiz zemin üzerine oturmuş, homojen olmayan bir toprak dolgu barajdır.Piyezometrik ölçümler, Varşova'da bulunan, meteoroloji ve su yönetim enstitüsü baraj gözlem merkezince yapılmıştır.

Yapay sinir ağları yapay zeka ile ilgili teknolojilerden biridir ve birçok özelliği vardır.Yapay sinir ağları, örneklerden öğrenir ve veriler arasında fonksiyonel bir ilişki yakalarlar. Bu çalışmada barajın menba ve mansabına ait olan su seviyeleri, giriş değişkenleri olarak kullanılmıştır; piyezometrelerdeki su seviyeleri ise yapay sinir ağları modellemesinde hedef çıktı verisi olarak kullanılmıştır.

Bu çalışmanın amacı, bir toprak dolgu barajdaki sızmanın geometrik yerini yapay sinir ağları metodunu kullanarak hesaplamaktır.

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CHAPTER 1

INTRODUCTION

A dam is an artificial barrier usually constructed across a stream channel to capture water. Dams must have spillway systems to convey normal stream and flood flows over, around, or through the dam. Spillways are commonly constructed of non-erosive materials such as concrete. Dams should also have a drain or other water-withdrawal facility for control the water level and to lower or drain the lake for normal maintenance and emergency purposes. Dams are constructed especially for water supply, flood control, irrigation, energy production, recreation, and fishing. Dams are mainly divided into four parts on the basis of their structure types. These are gravity dams, buttress dams, arch dams, and embankment dams. Embankment dams are more preferable due to being more economical. Embankment dams are two types- Earthfill dams and rockfill dams. This study is an investigation about earthfill dams, especially about seepage through the earthfill dam's body.

An earthfill dam is an embankment dam, constructed primarily of compacted earth, either homogeneous or zoned, and containing more than 50% of earth. The materials are usually excavated or quarried from nearby sites, preferably within the reservoir basin. If the remaining materials consist of coarse particles, there is gradation in fineness from the core to the coarse outer materials. According to the materials located in the body of dam, there is a seepage through the dam's body. Seepage can occur under the dam foundation, too. In this research, seepage through the dam's body was investigated.

Seepage is very important, as seepage affects the stability of dam. Because of its importance, the determination of the seepage through an earthdam has received a great deal of attention. Of primary concern is the location of the surface seepage on the downstream toe of the dam. There is seepage in the dam's body following a phreatic line. This seepage must be limited, and phreatic line is important in order to understand the degree of seepage. If the surface seepage intersects the face of the dam, erosion may result and possible failure of the dam. Thus, it is necessary to measure the level of phreatic line and rockfills are used at the downstream toe or gravel blankets to intersect the line of seepage before it reaches the downstream toe.

Up to now, seepage under the dam foundation is usually investigated. However, in this research seepage through the earthfill dam's body was investigated. An artificial neural network (ANN) model was developed for simulating seepage through a non-homogeneous porous body of an earthfill dam.The model was calibrated and verified using the piezometer data collected on a section of Jeziorsko earthfill dam in Poland. The water levels on the upstream and downstream sides of the dam were input variables and the water levels in the piezometers were the target outputs in the artificial neural network model. Jeziorsko dam is a non-homogeneous earthfill dam built on the impervious foundation. Piezometric measurements were made by the Institute of Meteorology and Water Management, Dams Monitoring Centre located in Warsaw.

Artificial Intelligence (AI) is the field of Computer Science that attempts to give computers humanlike abilities. The human brain is the ultimate example of a neural network. The human brain consists of a network of over a billion interconnected neurons. Neurons are individual cells that can process small amounts of information and then activate other neurons to continue the process. A computer can be used to simulate a biological neural network. This computer simulated network is called an artificial neural network (ANN). Artificial Neural Networks have many properties. They are non-linear structures shown to be highly flexible function approximators for the cases, especially where the data relationships are unknown. Artificial Neural Networks are data-driven self-adaptive methods. They learn from examples and capture functional relationships among the data. This modeling approach with the ability to learn from experience is very useful since it is often easier to have data set; Furthermore, artificial neural networks are particularly adapt at solving problems that cannot be expressed as a series of steps. Artificial neural networks are useful for recognizing patterns, classification into groups, series prediction and data mining. Artificial neural network training methods fall into the categories of supervised, unsupervised, and various hybrid approaches. The most common form of neural network that is used in applications is the feedforward back-propagation neural network.

The purpose of this research is to estimate the locus of the seepage path in an earthfill dam using artificial neural network. MATLAB 6 neural network toolbox is used for this study. The ANN model was a feedforward three layer neural network employing a sigmoid function as activator and a back-propagation algorithm for network learning. The water levels on the upstream and downstream sides of the dam were input variables and the water levels in the piezometers were the target outputs in the artificial neural networks model. The water levels computed by the models compared with the measured levels in the piezometers satisfactorily. The model results also revealed that the artificial neural network (ANN) performed as good as did the site observation and measured field data. In addition, sensitivity analysis was carried out trying different scenarios.

CHAPTER 2

DAMS

Dams are barriers built across a river to hold back water. The main function of a dam is to store water. It is designed to make the most effective use, at reasonable cost, of the available supply of the water in a stream. More than 52% of the world's dams are located in China, 16% in the United States, and 6% in Japan (Bequette, 1997). Figure 2.1. is a sketch showing main components of a dam.

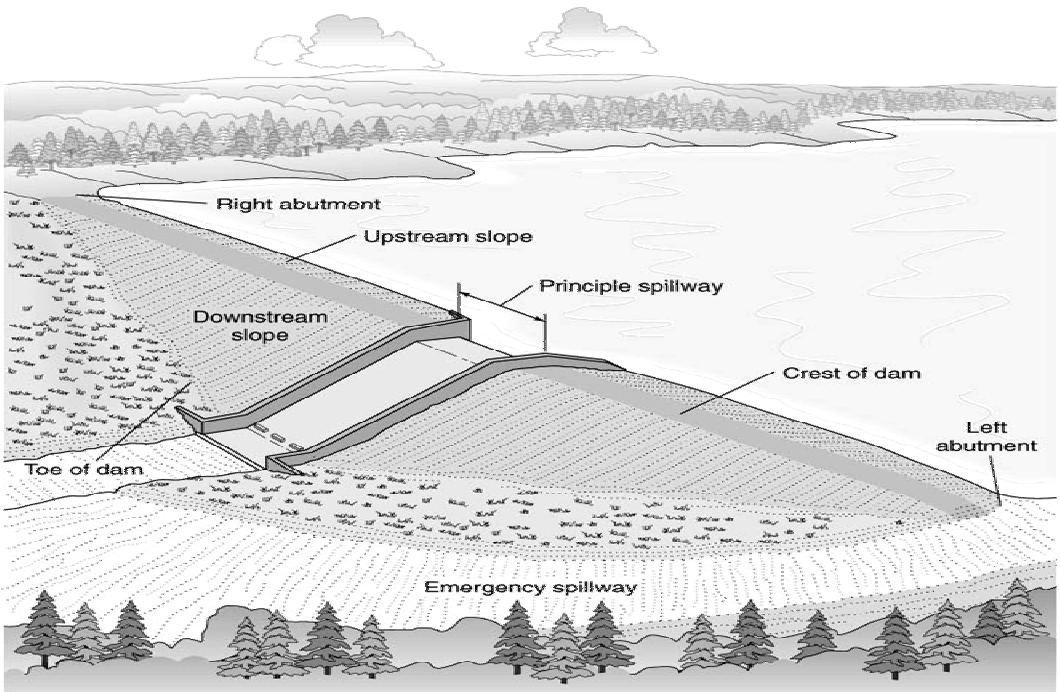


Figure 2.1. Main components of a Dam.
(Source:Web_1 2004)

2.1. Main Functions of the Dams

Main functions of dams can be summarized as follows:

Water storage;

Flood control;

Water supply;

Power production;

Industrial water supply;

Emergency domestic water supply;

Irrigation; and

Recreation.

Figure 2.2. shows main construction purposes of a dam.

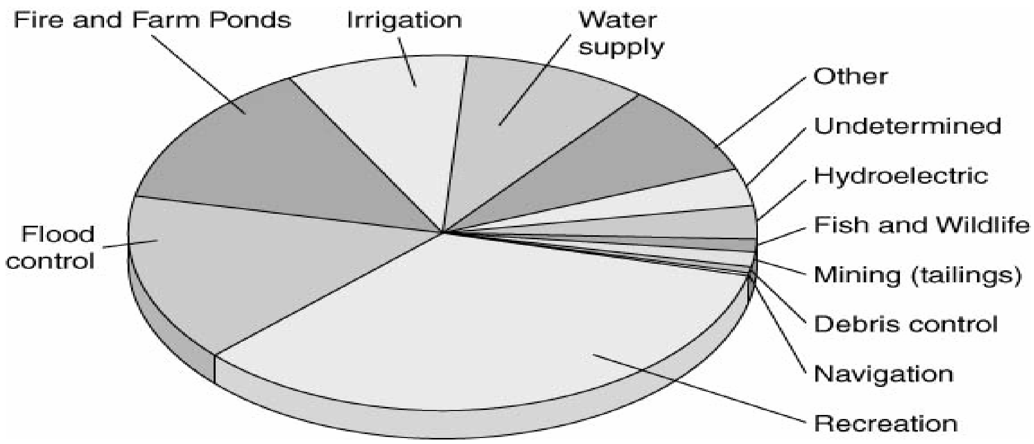


Figure 2.2. Graphical representation of construction purposes of a Dam.
(Source: Web_2 2004)

2.2. History of the Dams

The first dam for which there are reliable records was built in Jordan 5,000 years ago to supply the city of Jawa with drinking water. During the reign of the Pharaoh Amenemhet III, around 1800 B.C., the Egyptians constructed a reservoir with the amazing storage capacity of 275 million [m.sup.3] in Al Fayyum Valley, some 90 km southwest of Cairo. A large dam was built by an Arabian king called Lokman about 1700 B.C.; the flood caused by its collapse is recorded in Arabian history. Thousands of dams have been built in India from the earliest days to the present time. The oldest existing dams in Europe are the Almanza and Alicante dams in Spain; they were built some time before 1586. In time, materials and methods of construction have improved, making possible the erection of large dams such as the Nurek Dam which is being

constructed on the Vaksh River near the border of Afghanistan. This dam is designed 1017 ft
(333 m) high, of earth and rock fill. The failure of dam may cause serious loss of life and property; consequently, the design and maintenance of dams are commonly under government surveillance. In the United States over 30000 dams are under the control of state authorities(Grolier Incorporated, 1970); (Güney, 2002); (Beuqette, 1997).

The General Directorate of State Hydraulic Works (DSI in Turkish acronym) with a legal entity and supplementary budget is the primary executive state agency of Turkey for Nation overall water resources planning, managing, execution, and operation**.** The main objective of DSI is to develop all water and land resources in Turkey. It aims at all the wisest use of the principal natural resources. DSI was established by Law 6200 in December 18, 1953 as legal entity and brought under the aegis of the Ministry of Energy and Natural Resources. It is charged with "single and multiple utilization of surface and groundwaters and prevention of soil erosion and flood damages". For that reason, DSI is empowered to plan, design, construct, and operate dams, hydroelectric power plants, domestic water, and irrigation schemes**.** DSI's purpose "to develop water and land resources in Turkey" covers a wide range of interrelated functions. These include irrigation, hydroelectric power generation; domestic and industrial water supplies for large cities; recreation and research on water-related planning, design, and construction materials. Projects, master plan, and feasibility reports are prepared for the development of water resources. In this respect, required main data are collected by DSI from the river basin surveys which are related with flow and meteorological, soil classification, agricultural economy, erosion, maps, geological conditions etc. issues (Web_3, 2004). Table 2.1 shows main embankment dams especially earthfill dams in Turkey, with their construction purposes and capacities.

Table 2.1. Tables about the embankment dams at (a), (b), (c), (d), (e), (f), (g), (h), (i), (j), (k), (l), (m), (n), (o), (p), (q). These dams are constructed by DSI. Tables are given according to the chronological construction year.

(a) GÖLBAŞI DAM

Location	Bursa
River	Aksu
Purpose	Irrigation, Flood control
Construction (starting and completion) year	1933-1938
Embankment type	Earthfill
Dam volume	320 000 m^3
Height (from river bed)	10.70 m
Reservoir volume at normal water surface elevation	12.75 hm^3
Reservoir area at normal water surface elevation	1.74 km^2
Irrigation Area	2 100 ha

(b)DEMİRKÖPRÜ DAM

Location	Manisa
River	Gediz
Purpose	Irrigation, Flood control Energy
Construction (starting and completion) year	1954 - 1960
Embankment type	Earthfill
Dam volume	4 300 000 m^3
Height (from river bed)	74.00 m
Reservoir volume at normal water surface elevation	1 320.00 hm^3
Reservoir area at normal water surface elevation	47.66 km^2
Irrigation Area	99 220 ha
Capacity	69 MW
Annual generation	193 GWh

(Cont. on next page)

Table 2.1.(cont.)

(c) KESİKKÖPRÜ DAM

Location	Ankara
River	Kızılırmak
Purpose	Irrigation, Energy
Construction (starting and completion) year	1959 - 1966
Embankment type	Earthfill-Rockfill
Dam volume	900 000 m^3
Height (from river bed)	49.10 m
Reservoir volume at normal water surface elevation	95.00 hm^3
Reservoir area at normal water surface elevation	6.50 km^2
Irrigation Area	11 860 ha
Capacity	76 MW
Annual generation	250 GWh

(d) DAMSA DAM

Location	Nevsehir
River	Damsa
Purpose	Irrigation
Construction (starting and completion) year	1965 -1971
Embankment type	Earthfill
Dam volume	862 000 m^3
Height (from river bed)	31.50 m
Reservoir volume at normal water surface elevation	7.12 hm^3
Reservoir area at normal water surface elevation	0.82 km^2
Irrigation Area	1 390 ha

(Cont. on next page)

Table 2.1.(cont.)

(e) ATIKHİSAR DAM

Location	Çanakkale
River	Sarıçay
Purpose	Irrigation, Flood control
Construction (starting and completion) year	1967 -1973
Embankment type	Earthfill
Dam volume	1 990 000 m^3
Height (from river bed)	37.20 m
Reservoir volume at normal water surface elevation	40.00 hm^3
Reservoir area at normal water surface elevation	3.30 km^2
Irrigation Area	5 200 ha

(f) KORKUTELİ DAM

Location	Antalya
River	Korkuteli
Purpose	Irrigation, Flood control
Construction (starting and completion) year	1968 -1975
Embankment type	Earthfill+Rockfill
Dam volume	1 940 000 m^3
Height (from river bed)	47.20 m
Reservoir volume at normal water surface elevation	47.50 hm^3
Reservoir area at normal water surface elevation	2.20 km^2
Irrigation Area	5 986 ha

(Cont. on next page)

Table 2.1.(cont.)

(g) AFŞAR DAM

Location	Manisa
River	Alaşehir
Purpose	Irrigation, Flood control
Construction (starting and completion) year	1973 - 1977
Embankment type	Earthfill
Dam volume	3 166 000 m^3
Height (from river bed)	43.50 m
Reservoir volume at normal water surface elevation	69.00 hm^3
Reservoir area at normal water surface elevation	5.25 km^2
Irrigation Area	13 500 ha

(h) AĞCASAR DAM

Location	Kayseri
River	Yahyalı
Purpose	Irrigation
Construction (starting and completion) year	1979-1986
Embankment type	Earthfill
Dam volume	239 10^3 m^3
Height (from river bed)	25,00 m
Reservoir volume at normal water surface elevation	66,06 hm^3
Reservoir area at normal water surface elevation	4,17 km^2
Irrigation Area	15500 ha

(Cont. on next page)

Table 2.1.(cont.)

(i) KAYABOĞAZI DAM

Location	Kütahya
River	Koca
Purpose	Irrigation, Flood conrtol
Construction (starting and completion) year	1976 -1987
Embankment type	Earthfill+Rockfill
Dam volume	628 000 m^3
Height (from river bed)	38.00 m
Reservoir volume at normal water surface elevation	38.00 hm^3
Reservoir area at normal water surface elevation	3.00 km^2
Irrigation Area	7 080 ha

(j) KOVALI DAM

Location	Kayseri
River	Dündar
Purpose	Irrigation
Construction (starting and completion) year	1983 -1988
Embankment type	Earthfill
Dam volume	3 589 000 m^3
Height (from river bed)	42.00 m
Reservoir volume at normal water surface elevation	25.10 hm^3
Reservoir area at normal water surface elevation	1.67 km^2
Irrigation Area	3 317 ha

(Cont. on next page)

Table 2.1.(cont.)

(k) UZUNLU DAM

Location	Yozgat
River	Kozanözü
Purpose	Irrigation, Flood control
Construction (starting and completion) year	1979 - 1989
Embankment type	Earthfill
Dam volume	4 145 000 m^3
Height (from river bed)	50.00 m
Reservoir volume at normal water surface elevation	49.00 hm^3
Reservoir area at normal water surface elevation	2.75 km^2
Irrigation Area	7 800 ha

(l) İKİZCETEPELER DAM

Location	Balıkesir
River	Kocadere
Purpose	Irrigation, Domestic and industrial water supply
Construction (starting and completion) year	1986 – 1990
Embankment type	Earthfill
Dam volume	1200 000 m^3
Height (from river bed)	47.00 m
Reservoir volume at normal water surface elevation	164.56 hm^3
Reservoir area at normal water surface elevation	9.60 km^2
Irrigation Area	1 700 ha
Annual domestic water	72 hm^3

(Cont. on next page)

Table 2.1.(cont.)

(m) KRALKIZI DAM

Location	Batman
River	Dicle
Purpose	Energy
Construction (starting and completion) year	1985 - 1997
Embankment type	Earthfill + Rockfill
Dam volume	12 700 000 m^3
Height (from river bed)	113.00 m
Reservoir volume at normal water surface elevation	1 919.00 hm^3
Reservoir area at normal water surface elevation	57.50 km^2
Irrigation Area	90 MW
Annual domestic water	146 GWh

(n) ÇAMLIGÖZE DAM

Location	Sivas
River	Kelkit
Purpose	Energy, Flood control
Construction (starting and completion) year	1987 - 1997
Embankment type	Earthfill+ Rockfill
Dam volume	2 086 000 m^3
Height (from river bed)	32.00 m
Reservoir volume at normal water surface elevation	50.00 hm^3
Reservoir area at normal water surface elevation	4.70 km^2
Irrigation Area	33 MW
Annual domestic water	88 GWh

(Cont. on next page)

Table 2.1.(cont.)

(o) KARAOVA DAM

Location	Kırşehir
River	Manahozu
Purpose	Irrigation
Construction (starting and completion) year	1991 - 1997
Embankment type	Earthfill
Dam volume	1 717 000 m^3
Height (from river bed)	53.00 m
Reservoir volume at normal water surface elevation	65.00 hm^3
Reservoir area at normal water surface elevation	3.50 km^2
Irrigation Area	3 646 ha

(p) ERZİNCAN DAM

Location	Erzincan
River	Gönye
Purpose	Irrigation
Construction (starting and completion) year	1991 - 1997
Embankment type	Earthfill
Dam volume	3 000 000 m^3
Height (from river bed)	73.00 m
Reservoir volume at normal water surface elevation	8.39 hm^3
Reservoir area at normal water surface elevation	0.46 km^2
Irrigation Area	4 722 ha

(Cont. on next page)

Table 2.1.(cont.)

(q) GÖKPINAR DAM

Location	Denizli
River	Gökpınar
Purpose	Irrigation+domestic water supply
Construction (starting and completion) year	1995-2002
Embankment type	Earthfill
Dam volume	1 245 000 m^3
Height (from river bed)	43.00 m
Reservoir volume at normal water surface elevation	23.70 hm^3
Reservoir area at normal water surface elevation	1.98 km^2
Irrigation Area	6 522 ha

2.3. The Types of Dams

The basic types of the dams are classified on the basis of the structure type and materials of construction. The dams which are classified on the basis of the structure type are gravity dams, arch dams, buttress dams and embankment dams. Embankment dams can be divided into two types as embankment earthfill dams and embankment rockfill dams. The gravity, arch and buttress dams are usually constructed of concrete. Dams that are classified on the basis of materials of construction are masonry dams, filling dams, both masonry and filling dams, and framed dams. Masonry dams can be divided into four parts as stone and brick dams, concrete dams, reinforced concrete dams, and prestressed concrete dams. Filling dams can be divided into two types as earthfill dams and rockfill dams. Lastly, framed dams can be divided into two parts as steel dams and timber dams. Dams can also be classified according to usage purposes. These are drinking water dams, industrial water dams, irrigation water dams, hydroelectric power dams, and flood control dams. The most common type of dam is embankment earthfill dams. The following summarize structure types of dams.

2.3.1. Gravity Dams

A gravity dam depends on its own weight for stability and is usually straight in plan although sometimes slightly curved. It looks like a retaining wall, set across a river. Keban dam on the Fırat river (Figure 2.3.) is an example of a gravity dam in Turkey.

Figure 2.3. Keban Dam.

(Source:Web_4 2005)

2.3.2. Arch Dams

Arch dams transmit most of the horizontal thrust of the water behind them to the abutments by arch action and may have comparable thinner cross-sections than gravity dams. Arch dams can be used only in narrow canyons where the walls are capable of withstanding the thrust produced by the arch action. Karakaya dam on the Fırat river (Figure 2.4.) and Oymapınar dam on the Manavgat river are examples of arch dams in Turkey.

Figure 2.4. Karakaya Dam.
(Source: Web_5 2005)

2.3.3. Buttress Dams

Buttress dams are dams in which the face is held up by a series of supports. Buttress dams can take many forms. The face may be flat or curved. A buttress dam is supported by a series of buttress walls, set at right angles to the dam on the downstream side. There are several types of buttress dams, the most important ones are flat-slab and multiple-arch buttress dams. Flat- slab and buttress dams are particularly adapted to wide valleys where a long dam is required and foundation materials are of inferior strength. The multiple-arch dam is more rigid than the flat-slab type and consequently requires a better foundation. Elmalı dam on the Göksu river is an example of a buttress dam in Turkey. Figure 2.5. shows a buttress dam.

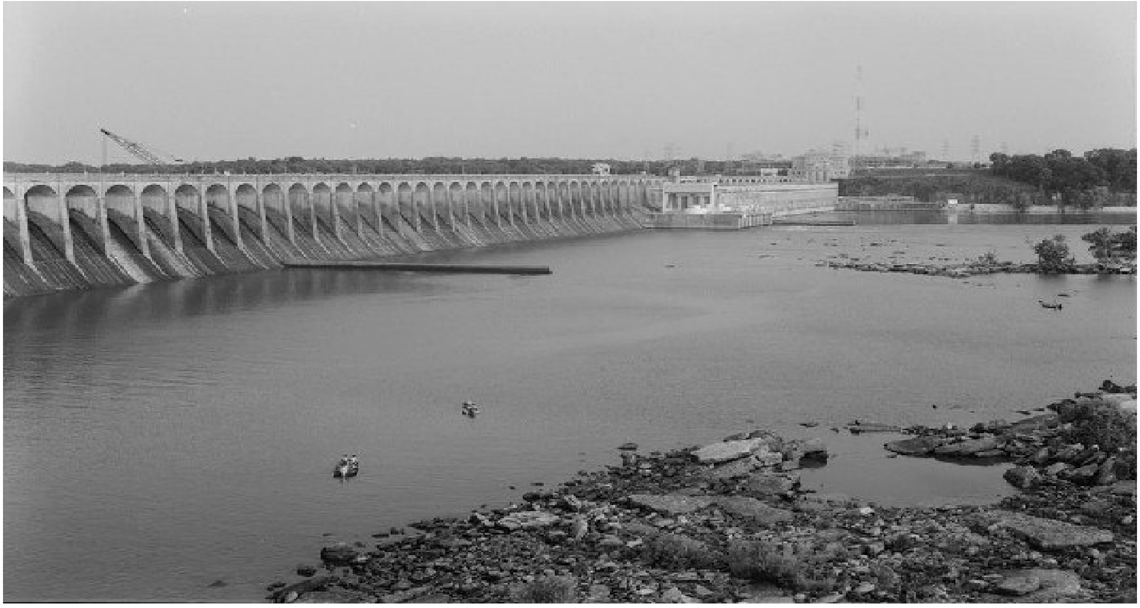


Figure 2.5. A buttress dam in the USA.

(Source: Web_6 2005)

2.3.4. Embankment Dams

Embankment dams can be divided into two types as earthfill dams and rockfill dams.

2.3.4.1. Earthfill Dams

An earthfill dam is made up partly or entirely of pervious material which consists of fine particles usually clay, or a mixture of clay and silt or a mixture of clay, silt and gravel. They are principally constructed from available excavation material. The dam is built up with rather flat slopes. Fine, impervious material of an earthfill dam occupies a relatively small part of the structure, it is known as the core. The core is located either in a central position or in a sloping position upstream of the center. If the remaining materials consist of coarse particles, there is a gradation in fineness from the core to the coarse outer materials. Some earth dams have a large proportion of rock in the outer zones for the purpose of stability. In a later section in this thesis, the importance of the stability in an earthfill dam especially in the dam's body, will be given in more detail. Most new earthfill dams are roll fill type dams, which can be further classified as homogenous, zoned, or diaphragm (U.S. Bureau of Reclamation, 1987). Homogenous earthfill dams are composed of only one kind of material, besides the slope protection material. The material used must be impervious enough to provide an adequate water barrier and the slope must be relatively flat for stability. It is more common today to build modified homogeneous sections in which pervious materials are placed to control steeper slopes. When pervious material is used in order to drain the material three methods are used. Rockfill toe, horizontal drainage blanket, inclined filter drain with a horizontal drainage blanket. Pipe drains are also used for drainage on small dams in conjunction with a horizontal drainage blanket or a pervious zone. For diaphragm-type earthfill dams, the embankment is constructed of pervious materials(sand, gravel, or rock). A thin diaphragm of impermeable material is used to form a water barrier. The diaphragm may vary from a blanket on the upstream face to a central vertical core. Diaphragms may consist of earth, portland cement concrete, bituminous concrete, or other materials. In addition, the diaphragm must be tied into bedrock or a very impermeable material if excessive underseepage is to be avoided. Zoned embankment-type earthfill dams have a central impervious core that is flanked by a zone of materials considerably more pervious, called shells. These shells enclose, support, and protect the impervious core (Linsley and Franzini, 1964). Demirköprü dam on the Gediz river and Aslantaş dam on the Ceyhan river are examples of earthfill dams in Turkey.

Figure 2.6. Anita Dam.

(Source: Web_7 2005)

Figure 2.6. shows the Warm Springs earthfill dam in the USA.

2.3.4.2. Rockfill Dams

The main body of a rockfill dam consists of a mass of dumped rock, which is allowed to take its own angle of repose. That is to setle naturally. This results in a slope of about 36 degrees. A rockfill dam consists of rock of all sizes to provide stability and an impervious core membrane. Membranes include an upstream facing of impervious soil, a concrete slab, asphaltic concrete paving, steel plates, other impervious soil (U.S. Bureau of Reclamation, 1987). Hirfanlı dam on the Kızılırmak river and Hasan Uğurlu dam on the Yeşilırmak river (Figure 2.7.) are examples of rockfill dams in Turkey.

Figure 2.7. Hasan Uğurlu Dam.

(Source: Web_8 2005)

Table 2.2. Classification of the dams.

On the basis of the structure	On the basis of the materials of construction	According to usage purpose
a. Gravity Dams b Arch Dams c. Buttress Dams d Embankment Dams - Earthfill Dams - Rockfill Dams	a. Masonry Dams -Stone and Brick Dams -Concrete Dams -Reinforced Concrete Dams -Prestressed Concrete Dams b. Filling Dams -Earthfill Dams -Rockfill Dams c. Masonry and Filling Dams d. Framed Dams -Steel Dams -Timber Dams	a. Dams for drinking water b. Dams for Industrial water c. Dams for irrigation d. Dams for flood control e.Dams for Hydroelectric Power f. Cofferdams

Table 2.2. shows the classification of dams.

2.4. The Forces acting on dams

Main forces which are acting on dams can be summarized as follows.

2.4.1. Water Pressure

Water pressure is the most obvious force that is exerted by the water that presses upon the upstream face of structure. In designing a dam, when silt builds up against the lower part of the dam, it acts as a liquid that is denser than water. Engineers must take this factor also in dam design.

2.4.2. Weight

The weight of the dam itself is another force that acts on dam structures. This factor is important mainly in the case of gravity dams and very high arc dams. Concrete can withstand pressure such as the vertical downward pressure. To reduce the stress on weak foundations, a limit must be set to the height of the dam, and the upstream face must be sloped so as to spread the load. The weight of the water pressing down on the slope will act as a satabilizing factor.

2.4.3. Earthquakes

Earthquakes may exert considerable pressure on dams. The action is like that of pulling a rug from under a person who is standing on it. The horizontal force exerted by an earthquake may be equal to as much as a tenth of the weight of the dam; hence earthquake forces are usually taken into account in the design stage of a dam.

2.4.4. Forces like Ice, Rain, Waves

Ice is another factor that must be considered. In cold climates a thick sheet of ice may form on the reservoir surface. Such a sheet of ice may be warmed by the sun. The tendency to expand may then cause a huge force near the top of the dam. Hence this part of the structure must be made thick enough to withstand the pressure. Seasonal and daily changes in temperature may cause internal stresses in dams . These changes must be carefully analyzed. Waves striking against the face of a gravity or arch dam have little effect on the stability of the structure. In the case of an earthfill dam, however, the waves would soon erode the surface material if it were not protected by a facing of heavy rock laid on a bed of gravel. Such rock is known as riprap. The erosive forces of nature – winds, rain, running water etc. – are always at work. To be able to keep these forces in check, periodic maintenance work is required on all dams.

2.5. Seepage in Earthfill Dams and the Importance of Seepage in Dam’s Body

An earthfill dam’s body prevents the flow of water from dam’s back to downstream. However, with the most impermeable materials used in the dam’s body, some amount of water seeps into dam’s body and goes out from downstream of body slope until it meets an impermeable barrier. So if the water level at the upstream side is rapidly lowered, the water-soaked material may become unstable. This has to be considered in the design of earthfill dams. Earthfill dams are usually designed pervious, and some seepage flow through the dam body must be expected.

Seepage flow which occurs in the earthfill dam's body has a top surface. This surface is called as phreatic line or zero pressure curve. However the upper zone of phreatic line can be wet or saturated because of capillarity. There is a pore water pressure under the phreatic line. According to the analysises, value of pore water pressure depends on the type tightness degree, humidity, and impermeability of soil, and load on soil etc. Pore water pressure decreases the shearing resistance of earth mass. If the rate of pore water pressure drop resulting from seepage exceeds the resistance of a soil particle to motion, that particle will tend to move . This results in piping, the removal of the finer particles from the dam' s body. Piping usually occurs near the downstream toe of a dam when seepage is excessive (Linsley and Franzini, 1964). According to these reasons for stability of dam the level of seepage flow especially phreatic line must be limited. In this thesis, there are measurement results for determination of seepage flow using piezometers, in this thesis in a later section there are model results which are obtained according to these piezometric measurement results.

In addition, seepage in the dam's body is important due to two reasons. First one is that, phreatic line cuts downstream slab. The higher cutting of the dam slab because of phreatic line is the more dangereous condition for the slab, because the soil under that point will be saturated, when the soil saturation increases, pore water pressure increases too and due to the quantity of saturation, collapse probability increases. That makes the body of dam unstable. Second reason is maximum reservoir position that contains the body's maximum saturation degree is the most critical condition for the downstream slab's stability after the construction. The most critical condition for upstream slab's stability is the sudden drop in the water level in the reservoir. That makes the body of dam unstable.

2.6. Piezometric Measurement of Seepage in an Earthfill dam' s Body

Seepage path in an earthfill dam can be monitored through piezometric measurements. Piezometer is a device for a measurement of static pressure. Measuring the static pressure in a flowing fluid requires that the measuring device fits the streamlines as closely as possible. This is required so that no disturbance in the flow will occur. For straight reaches of pipe conduit, the static pressure is usually measured by using a piezometer. Measuring the static pressure in a flow field requires the use of a static tube. For this device, the pressure is transmitted to a gauge or a manometer through piezometric hole that are evenly spaced around the circumference of the tube. The device must be perfectly aligned with the flow (Mays, 2001).

CHAPTER 3

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are mathematical modeling tools and computing systems that are especially helpful in the field of prediction and forecasting in complex settings. (Hamed et al.,2003). These computing systems are made up of a number of simple and highly interconnected processing elements that process information by their dynamic state response to external inputs (Caudill M.,1987). Mathematically, an artificial neural network can be treated as a universal approximator which has an ability to learn from examples without the need of explicit physics (ASCE Task Committee, 2000a, b). It is well known that the artificial neural network can be envisaged as a non-linear black box model. That is given an input it produces an output, without revealing the physics of the process (Rajurkar et al., 2003). ANNs have been recently employed for the solution of many hydrologic, hydraulic and water resources problems ranging from rainfall and runoff (Rajurkar et al. 2002) to sediment transport (Tayfur, 2002) to dispersion (Tayfur and Singh, 2005).

Artificial neural networks are first developed in the simplest form by Widrow and Hoff in the beginning of 1960's which consist of two layers, input layer and output node but only the output node has an activation function, which is a linear function and it can only solve linearly separable problems. This simple architecture named ADALINE (Adaptive Linear Neuron) Neural Networks. After ADALINE NN, new architectures are developed like Multi Layer Perceptrons (MLP). In Multi Layer Perceptrons some new activation functions are utilized like sigmoid or Gaussian activation functions. Artificial intelligent methods are divided into three main categories as supervised, unsupervised and reinforcement algorithms. MLPs are the most popular and widely used supervised algorithms. Supervised algorithms need input-output pairs. With these pairs, through the error propagation, network approximates a function. Apart from supervised algorithms in unsupervised algorithm there is no error to back propagate and there is no target to reach, instead, this type of algorithms only works on input pairs and tries to arrange inputs according to pre-specified rules. Reinforcement learning (RL) attempts to learn from its past experience and it is expected that after each trial it is going to respond more rationally. In this research Backpropagation Neural Network is used as MLP.

3.1. Historical Development of Artificial Neural Networks

The history of neural network development has been eventful, and exciting. The history of neural networks shows the interplay among biological experimentation, modeling, and computer simulation / hardware implementation. Thus, this field is strongly interdisciplinary. Back in the 1940's, first studies about neural networks began. Warren McCulloch and Walter Pitts designed what are generally regarded as the first neural networks (McCulloch & Pitts, 1943).

At the end of 1940's, Donald Hebb, a psychologist at McGill University, designed the first learning law for artificial neural networks (Hebb, 1949). He thougt that if two neurons were active, then the strength of the connection between them should be increased. This idea is closely related to the correlation matrix learning developed by Kohonen (1972) and Anderson (1972) among others.

Frank Rosenblatt (1958, 1959, 1962) introduced and developed a large class of artificial neural networks called perceptrons, together with several other researchers (Block, 1962; Minsky & Papert, 1988). The most typical perceptron consisted of an input layer connected by paths with fixed weights to associator neurons. In the beginning of 1960's, Bernard Widrow and his student, Marcian Ted Hoff (Widrow & Hoff, 1960) developed a learning rule that is closely related to the perceptron learning rule. The Widrow – Hoff learning rule for a single – layer network is a precursor of the backpropagation rule for multilayer nets. Despite Minsky and Papert's demonstration of the limitations of perceptrons (i.e.,single – layer nets), research on neural networks continued. In 1970's, the early work of Teuvo Kohonen (1972), of Helsinki University of Technology, dealt with associative memory neural nets.His more recent work (Kohonen, 1982) has been the development of self – organizing feature maps. James Anderson, of Brown University, also started his research in neural Networks with associative memory nets (Anderson, 1968, 1972). In 1980's, Gail Carpenter has developed a theory of self – organizing neural networks called adaptive resonance theory (Carpenter & Grossberg, 1985, 1987a, 1987b, 1990). Nobel prize winner John Hopfield has developed a number of neural networks based on fixed weights and adaptive activations together with a researcher, David Tank (Hopfield & Tank, 1985, 1986). In 1980's, Kunihiko Fukushima and his colleagues have also developed a series of specialized neural nets for character recognition (Fukushima et al., 1983).

Table 3.1 shows a brief summary about the development of the artificial neural networks.

Table 3.1. A brief history of neural networks (Nelson & Illingworth, 1991)

Conception	1890	James, Psychology (Briefer Course)
Gestation	1936 1943 1949	Turing uses brain as computing paradigm McCulloch & Pitts paper on neurons Hebb, The Organization of Behaviour
Birth	1956	Darmouth Summer Research Project
Early Infancy	Late 50's, 60's	Research efforts expand
Stunted Growth	1969	Some research continues Minsky & Papert ' s critique, Perceptrons
Late Infancy	1982	Hopfield at National Academy of Sciences
Present	Late 80's to now	Interest explodes with conferences, simulations, new companies, government funded research .

3.2. Fundamentals of Neural Networks

Neural networks are one of the few Artificial Intelligence – related technologies that have a mathematical foundation. An artificial neural network is a flexible mathematical structure which motivates from the operation of human nervous system. It has many advantages and treats the arbitrary complex non – linear relationship between the input and the output of any system (Rajurkar et al., 2003). Artificial neural networks can be considered as non – linear function approximating tools (i.e.,linear combinations of non – linear basis functions) having an ability to learn from examples, where the parameters of the networks should be found by applying optimisation methods. The optimisation is done with respect to the approximation error measure.

Neural networks are noted for mathematical basis, parallelism, distributed associative memory, fault tolerance, adaptability, pattern recognition, intuition, and statistical pattern recognition (Nelson & Illingworth, 1991). Neural networks are particularly adept at solving problems that can not be expressed as a series of steps and useful for recognizing patterns, classification into groups, series prediction, and data mining.

Artificial Neural Networks can be divided particularly in two parts.

1) Architecture (it defines the structure of the network)
2) Neurodynamics (it includes properties as to how the network learns, recalls, associates, and continously compares new information with existing knowledge.)

3.3. Artificial Neuron and the Basic Components of Artificial Neuron

Artificial neural networks are inspired by the learning processes that take place in biological systems. To understand what is placed behind this inspiration, biological neurons will be briefly discussed. Artificial neural Networks are made up of individual models of the biological neuron (Figure 3.1.) that are connected together to form a network. The neuron models used are much simplified versions of the actions of a real neuron (Page et al., 1993). The human brain is very complex capable of thinking, remembering, and solving. Fundamental unit of the brain's nervous system is "neuron". This "neuron" is a simple processing element that receives and combines signals from other neurons through input paths called "dendrites". An artificial neuron (Figure 3.2.) is a model whose components have direct analogies to components of biological neuron. Due to two main reasons, artificial neural network is like human brain:

1) It stores knowledge through synaptic weights.
2) It learns from experiments and / or experience.

The most commonly used neuron model is based on the model proposed by McCulloch and Pitts in 1943.

Biological Neuron

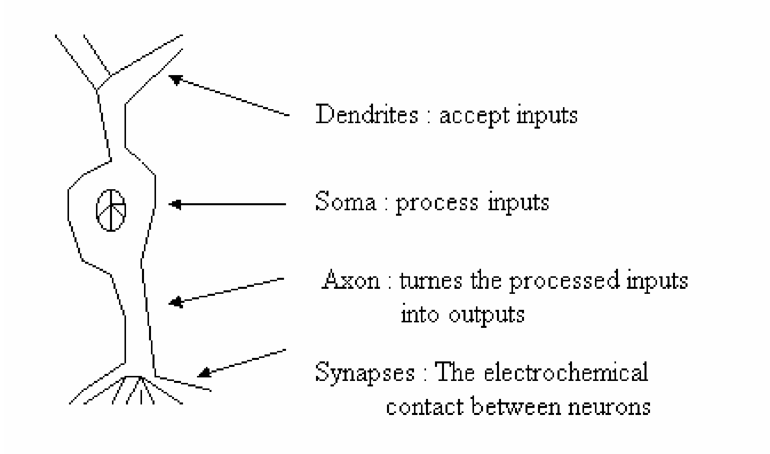


Figure 3.1. A biological neuron and its components.

Artificial Neuron

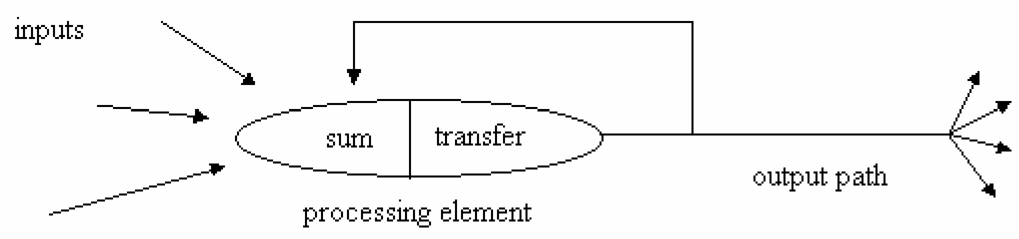


Figure 3.2. An artificial neuron and its structure.

An artificial neuron receives input, process it and then produce an output. It can be called a processing element. It consists of mainly five parts.

1) Inputs and Outputs

There are many inputs (stimulation levels) to a neuron, there should be many input signals to processing element. There may be many inputs to the neuron, but there is only one output from the neuron. Just as real neurons are affected by things other than inputs, some networks provide a mechanism for other influences. Sometimes this extra input called a bias term (Nelson and Illingworth, 1994). There is bias node in the input and hidden layers but not in the output layer. This one output is disributed by the synaptic weights to each neuron in the next layer .

2) Weighting Factors

Each input will be given a relative weighting, which will affect the impact of that input. Weights are adaptive coefficients within the network that determine the intensity of the input signal (Nelson and Illingworth, 1994). The product of the inputs and synaptic weights obtains every information carried to neuron (i.e. $\alpha_I W_{IJ}$). In a way each input is weighted before reaching the neuron .

3) Transfer (Activation) Functions

Transfer functions are functions that transform the net input to a neuron into its activation. Also they are known as a transfer, or output function (Fausett, 1994). They are usually non-linear. If the problem is non-linear, then non-linear is employed. Commonly used non-linear functions are as follows:

- Linear Function

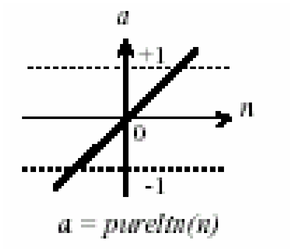


Figure 3.3. Linear transfer function.

The linear transfer function calculates (Figure 3.3.) the neuron's output by simple equation, where α is a constant.

$$a(n) = \alpha x \quad (3.1)$$

This neuron can be trained to find a linear approximation to a nonlinear function.

- Step (Hard Limiter) Function

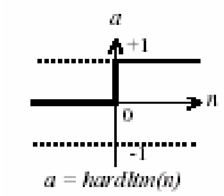


Figure 3.4. Step transfer function.

The hard limiter transfer function (Figure 3.4.) forces a neuron to output a β if its net input reaches a threshold, otherwise it outputs α. This allows a neuron to make a decision or classification (Tsoukalas and Uhrig, 1997). It can say yes or no. This kind of neuron is often trained with the perceptron learning rule, and generally parameters are chosen as $\beta = 1$ and $\alpha = 0$ or 1 in the literature.

- Ramping or Rampage Function

For inputs less than -1 ramping function produces -1. For inputs in the range -1 to +1 it simply returns to the linear function. For inputs greater than +1 it produces +1, but this function is not a continuous function at the intersection points (Tsoukalas and Uhrig, 1997). This network can be tested with one or more input vectors which are presented as initial conditions to the network. After the initial conditions are given, the network produces an output which is then fed back to become the input. This process is repeated over and over until the output stabilizes.

- Gauss Function

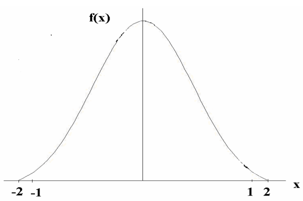


Figure 3.5. Gaussian transfer function.

- Sigmoid Function

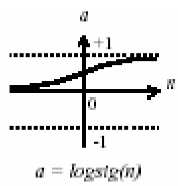


Figure 3.6. Sigmoid transfer function.

The sigmoid transfer function (Figure 3.6) takes the input, which may have any value between plus and minus infinity, and squashes the output into the range 0 to 1. This transfer function is commonly used in backpropagation networks, in part because it is differentiable (Nelson and Illingworth, 1994). The mathematical expression of the sigmoid function is:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3.2}$$

- Hyperbolic Tangent Function

Alternatively, multi-layer networks may use the hyperbolic tangent transfer function. Hyperbolic tangent functions output range is [-1, 1] and also its derivative is continuous (Fu, 1994). The mathematical expression of the hyperbolic tangent function is:

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \tag{3.3}$$

3.4. Artificial Neural Networks and Their Architecture (Topology)

An artificial neural network can be defined as a data processing system consisting of a large number of simple, and highly interconnected processsing elements in an architecture inspired by the structure of the human brain (Tsoukalas and Uhrig, 1997). Network topology is generally defined by the number of hidden layer nodes and the number of nodes in each of these layers. It determines the number of model parameters that need to be estimated (Maier and Dandy, 2001). Neural networks perform two major functions: *Learning* and *Recall*. Learning is the process of adapting the connection weights in an artificial neural network to produce the desired output in response to data presented to the input buffer. Recall is the process of accepting an input stimulus and producing an output response in accordance with the network weight structure (Corchado and Fyfe, 1999). There are two types of learning: *Supervised Learning* and *Unsupervised Learning* . In the supervised case, user decides on the training set, training type, network architecture, learning rate, and number of iterations. In the unsupervised case, the model decides on the things such training set, training type etc.

3.5. Learning Laws

- **Hebbian Learning Rule (Without a Teacher)**

The first learning rule was introduced by Hebb (1949) as:

$$\Delta W_{ij} = \eta \, . \, a_i . o_j \tag{3.4}$$

where η is a constant of proportionally representing the learning rate; o_j is output from unit j, and is connected to the input of unit i through the weight W_{ij}; a_j is the state of activation and the output o_j is a function of the activation state. According to this rule, where unit i and j are simultaneously excited, the strength of the connection between them increases in proportion to the product of their activations.

- **The Delta Rule " Widrow – Hoff Rule " (With a Teacher)**

This rule is based on the simple idea of continuously modifying the strengths of the connections to reduce the difference (the delta) between the desired output and the current output. This learning rule is also referred as last mean square (LMS) learning rule because it minimizes the mean squared error (Spellman, 1999).

$$\Delta W_{ij} = \eta[t_j - y_j] \, x_i \tag{3.5}$$

where η is the learning rate, x as training input, t is the target output for the input x.

- **The Kohonen Learning Rule (Without a Teacher)**

This rule was inspired by learning in biological systems. In this procedure, the processing elements compete for the opportunity of learning. The processing element with the largest output is declared the winner and has the capability of inhibiting its competitors as well as exciting its neighbors; for this reason, sometimes this rule is also referred as the competitive learning rule (Bose and Liang, 1996).

$$W_{new} = W_{old} + \eta(x - W_{old}) \quad (3.6)$$

where x is the input vector, W_{new} is the new weight factor and η is the learning rate.

- **The Hopfield Minimum Energy Rule**

Hopfield's study concentrates on the units that are symmetrically connected. The units are always in one of two states: +1 or -1. The global energy of the system is defined as :

$$E = -\Sigma W_{ij} . S_i . S_j + \Sigma \theta_i . S_i,\ i \langle j \quad (3.7)$$

$$\Delta E_k = \Sigma W_{ki} . S_i - \theta_k \quad (3.8)$$

where S_i is the state of the i th unit (-1 or 1), θ_i is the threshold, and ΔE_k is the difference between the energy of the whole system with the kth hypothesis false and its energy with the kth hypothesis true (Bose and Liang, 1996).

- **The Boltzmann Learning Rule**

The Boltzmann learning algorithm is designed for a machine with symmetrical connections. The binary threshold in a perceptron is deterministic, but in a Boltzmann machine it is probabilistic (Reich et al., 1999).

- **The Back-propagation Learning Rule**

The back-propagation of errors technique is the most commonly used generalization of the Delta Rule. This procedure involves two phases. The first phase, called the " forward phase", occurs when the input is presented and propagated forward through the network to compute an output value for each processing element (Bose and Liang, 1996). In the second phase, called the "backward phase", the recurrent difference computation (from the first phase) is performed in a backward direction. Only when these two phases are completed then new inputs can be presented.

3.6. Back-Propagation Algorithm

This method is simply a gradient descent method to minimize the total squared error of the output computed by the net. Back-propagation is a systematic method for training multiple (three or more layer) artificial neural systems. Back-error propagation is the most widely used of the neural network paradigms and has been applied successfully in applications in a broad range of areas. Back – Propagation network is usually layered, with each layer fully connected to the layers below and above. When the network is given an input, the updating of activation values propagates forward from the input layer of processing units, through each internal layer, to the output layer of processing units. The output units then provide the networks response. When the networks corrects its internal parameters, the correction mechanism starts with the output units and back- propagates backward through each internal layer to the input layer. Hence, it is named as “back-error propagation”, or “back-propagation”.

3.6.1. Background and Topology of the Backpropagation Algorithm

Back-propagation and its architecture was the first developed multi-layer perceptron architecture that can contain more than one output and more than one middle layer. BP algorithm is needed because so far only the linear separator was used (Figure 3.7.) and from the classification point of view, they can only separate the clusters that can be divided by a line. However in real life problems there are too many complex situations exist that we have to use more intricate lines. MLP structure and algorithm gives us that opportunity.

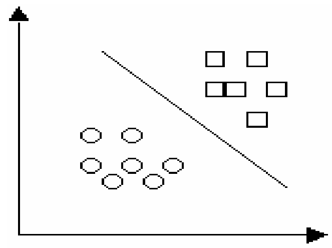


Figure 3.7. Linearly separable two clusters.
(Source: Karakurt 2003)

To train a MLP, Gradient Descent method can be used. This method provides us a tool to direct the middle layer nodes to follow the appropriate direction to minimize the distance between the target value and the actual output.
To train the network, input values and target values are used in which represented by “x” and “t” symbols respectively.

In BP algorithm every middle and output layer uses an activation function. Mostly sigmoid activation functions are used, hence the output of the network will be between 0 and 1. Also Gaussian distribution can be used as an activation function because of the formation of the function this structure is named as Radial Basis NN.

In MLP (Figure 3.8.) every input layer node is connected to the every hidden layer node and every hidden layer node is cooperated to the every output layer node. Process begins when the input data is presented to the input layer. Consequently, these data is multiplied by the corresponding link value which is called weight. This multiplication is used to weight the input values. After the multiplication is done, summation of this value is presented to the activation function and this process goes on to the end of the output layer. After this procedure output value compared with the expected output value and the distance between them are taken as an error to back propagate. Hence, it is called back propagation. The predetermined error function is:

$$E = \sum_{j=1}^{J} (t_j - z_j)^2 \qquad (3.9)$$

“E” represents the total error term and “z” is the actual output for the input “j”.

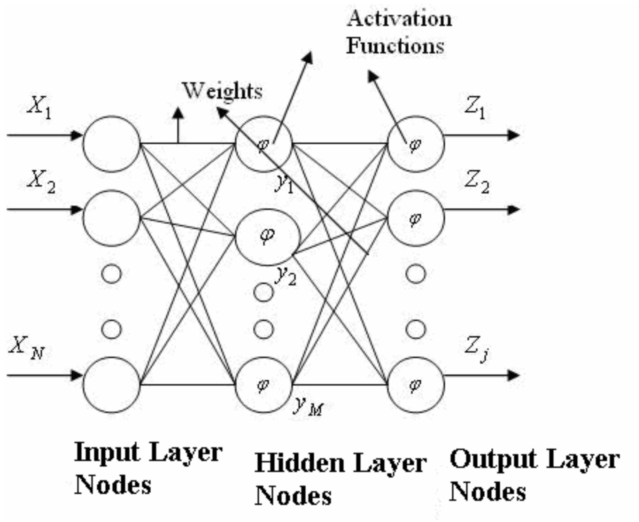


Figure 3.8. Structures of MLPs.

(Source: Karakurt 2003)

The BP scheme is in the following form:

The derivative of the error with respect to the weight connecting i to j is;

$$\frac{\partial E}{\partial W_{ij}} = \delta_j y_i \tag{3.10}$$

To change weights from unit i to unit j by;

$$\Delta W_{ij} = -\eta \delta_j y_i \tag{3.11}$$

where; η is the learning rate ($\eta > 0$); δ_j is the error for unit j; y_i is the input from unit i.

Every middle layer node employs an activation function. In BP process, a sigmoid function can be used because sigmoid function can easily be calculated and differentiated.

$$y = f(a) = \frac{1}{1 + e^{-a}} \tag{3.12}$$

And its derivative is;

$$f^{'}(a) = f(a)(1 - f(a)) \tag{3.13}$$

Every input value is calculated in weighted form;

$$y(x) = w^{T} f(x) \tag{3.14}$$

It is crucial to compute the error term for both output units and the middle units.
For output unit

$$\delta_k = (y_k - y_{\text{target}}) \tag{3.15}$$

For hidden unit

$$\delta_j = y_j(1 - y_j)\sum_k W_{ij}\delta_k \tag{3.16}$$

Gradient descent algorithm physically means that, magnitude of error and the direction is calculated so as to minimize the error, new weight values are driven in the opposite direction. The learning rate determines the amount of update in the specified direction.

This study employed the BP algorithm as a training tool and sigmoid function as a activation function.

CHAPTER 4

MODEL APPLICATION

Seepage path through the dam's body is important for planning and implementing economically and technically remedial stability measures, since an extraordinary seepage may cause a threat to the stability of the dam. That is why, seepage in an earthfill dam. is investigated in this study.

Most of the past studies have involved seepage under the dam foundation (Turkmen, 2002; Al-Homoud et al., 2003). However, in embankment dams there is seepage in the dam body following a phreatic line. An earthfill dam's body prevents the flow of water from dam's back to downstream. However, with the most impermeable materials used in the dam's body, some amount of water seeps into dam's body and goes out from downstream of body slope. This movement is called as seepage. Seepage flow which occurs in the earthfill dam's body has a top surface. This surface is called as phreatic line or zero pressure curve. In order to understand the degree of seepage, it is necessary to measure the level of phreatic line. This measurement is called as piezometric measurement. Seepage in the dam's body is important for dams for two reasons: First one is that, phreatic line can cut downstream slab, that is an unwanted situation and second one is that amount of seepage water. The excess of seepage water can cause erosion. The higher cutting of the dam slab because of phreatic line constitutes a more dangerous situation for the slab, because when the soil under that point gets saturated the probability of collapse increases. Due to these reasons it is necessary to draw phreatic line and to estimate amount of seepage. Figure 4.1. shows seepage path through an earthfill dam and Figure 4.2. shows the downstream toe or gravel blankets to intersect the line of seepage before it reaches the downstream toe for the reason that erosion may take result.

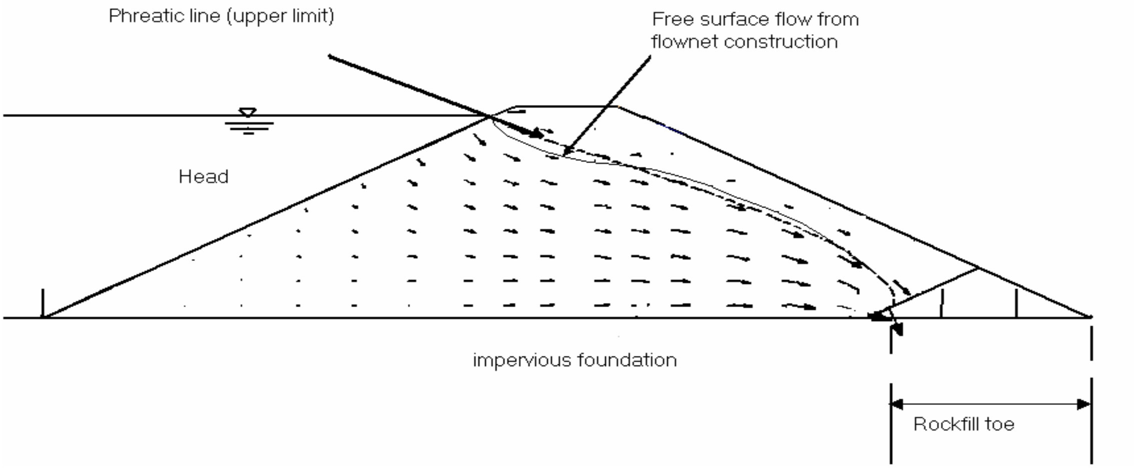


Figure 4.1. Example of seepage path through an earthfill dam.

(Source: Web_9 2005)

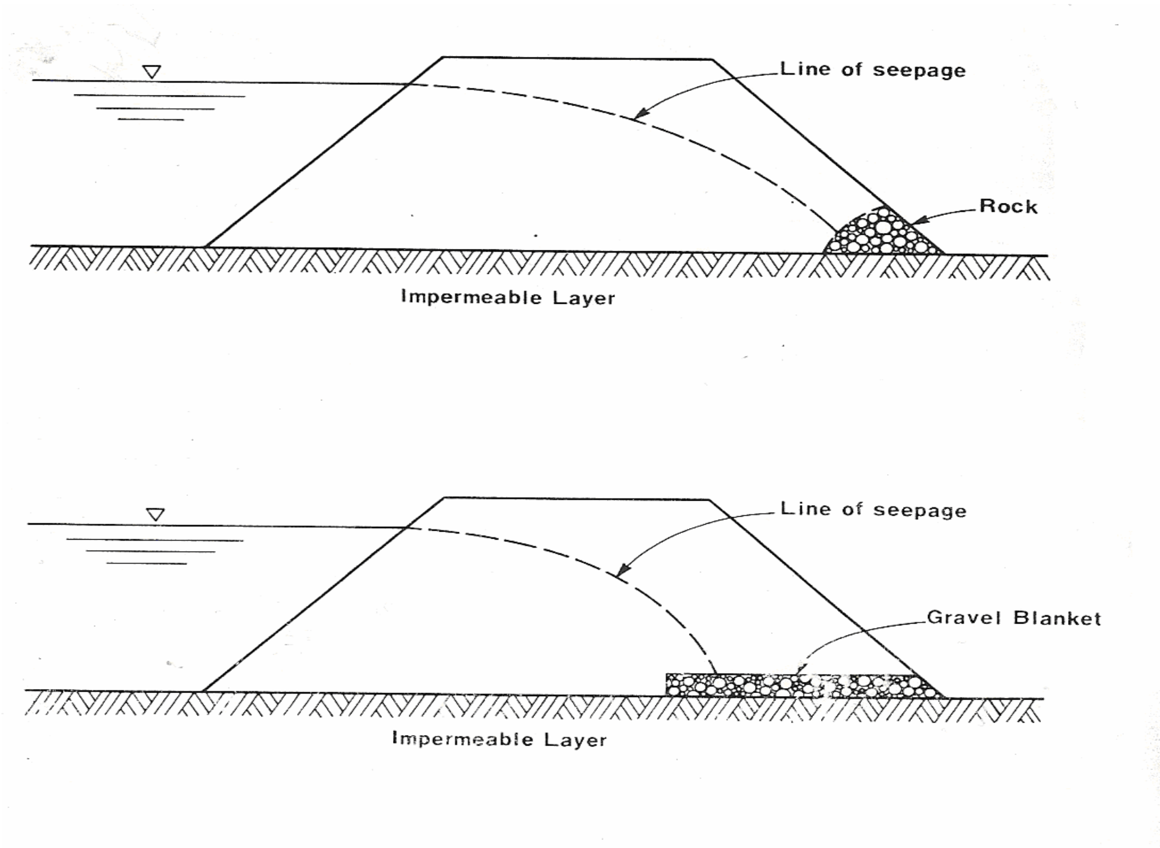


Figure 4.2. Seepage through a dam embankment with rock toe or gravel blanket.

(Source: Marino and Luthin 1982)

In this study, ANN Model is developed to estimate the locus of a seepage in an earthfill dam. For the artificial neural network modeling, measured data sets are used to train and test the developed model. Measured data sets used during modeling include water levels in the piezometers and the water levels on the upstream and downstream sides of Jeziorsko earthfill dam in Poland where piezometers for monitoring seepage have been used since 10-2-1995 and measurements were made by the Institute of Meteorology and Water Management, Dams Monitoring Center. Jeziorsko dam is a non-homogeneous earthfill dam built on an impervious foundation. Figure 4.3 shows the places of the piezometers. The first three piezometers are placed in the dam body and P148 is placed in the upper part of the chalk layer.

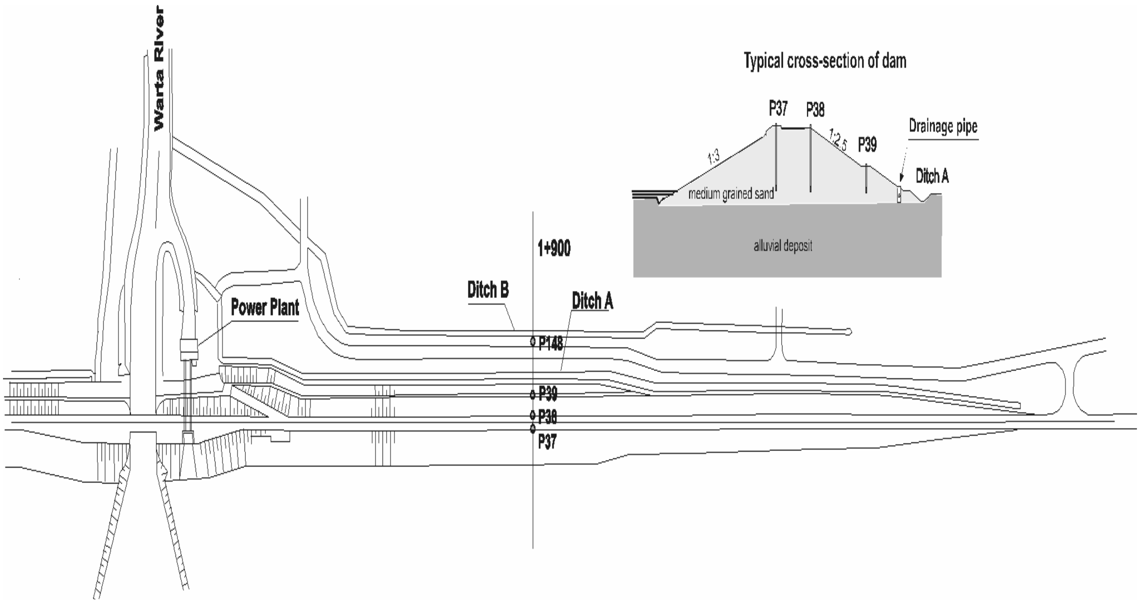


Figure 4.3. Detail Cross-Section Sketch of the Jeziorsko Earthfill dam with depicted soil layers.

For this study, MATLAB 6 neural network toolbox is used. The water levels on the upstream and downstream sides of the dam were input variables and the water levels in the piezometers were the target outputs in the artificial neural network model. The ANN model was a feedforward neural network employing a sigmoid function as activator and a back-propagation algorithm for network learning. Back- propagation algorithm belongs to the supervised learning rule. In the supervised learning, there is an external trainer who decides the size of training and testing sets, training type. In addition to this, different scenarios were modeled by utilizing different layers, activation functions and different inputs. Different scenarios were simulated according to appropriateness of toolbox. Various parameters can be applied using “nntool” command in Matlab. In this study the ANN model had 3 layers: input layer, hidden layer, and output layer. The input layer had 6 neurons and the output layer had one neuron (Table 4.1). However, number of hidden layers and number of neurons in hidden layers can be set. In the toolbox, there are windows including parameters as functions, number of layers etc. Thus, the user can decide to modeling procedure. The optimal number of neurons in the hidden layer was found by trial and error. Also different activation functions were selected randomly. At the dam, four piezometers were placed in order to monitor the flow of water through the dam body. The water levels in the piezometers have been measured every 2 two weeks since 1995. Upstream and downstream reservoir water levels constitute the input data and water levels in piezometers constitute the output data (target data). All the input and output data were compressed to the range 0.1 to 0.9 using Excel. The measured water level data from 4 piezometers were used for training the network. First there were a total of 111 sets of data in the training between 10-02-1995 and 12-20-1999. The training of the model was carried out with the learning rate, the 0.02 momentum factor and after 10000 iterations. Later, another set of data as a total of 125 sets between 10-2-1995 and 08-14-2000 are used for comparison of different scenarios.

Table 4.1. Schematic representation of the model design.

INPUT VARIABLES

UWL	DWL	P37	P38	P39	P39
117.49	109.06	1	0	0	0
117.49	109.06	0	1	0	0
117.49	109.06	0	0	1	0
117.49	109.06	0	0	0	1

6 input variables

OUTPUT VARIABLE

WLP
114.06
113.83
113.54
113.11

1 output variable

[UWL: Upstream water level, DWL: Downstream water level, WLP: Water level in piezometers]

The correlation coefficient R^2 is important because it measures if the fit is good. If the value of it is close to 1, the slope of the regression line is almost one and the intercept is close to zero. Then the training of the network is successfully accomplished. The trained ANN model was tested by predicting the measured 59 water level data in the piezometers between 12-20-1999 and 5-20-2002.

The general procedure for the network simulation includes:

1. Representation of input and output matrices; (as it is mentioned earlier data are separated into two groups as training set and testing set)
2. Representation of the transfer functions (in other words activation function); sigmoid and hyperbolic tangent function were used.
3. Selection of the network structure; different hidden layers
4. Assigning of the random weights; initial random weights are assigned.
5. Selection of the learning procedure; Back propagation algorithm is used.
6. Presentation of the test pattern and prediction or validation set of data for generalization; training of the network completed after 10000 or 20000 iterations, than testing set is represented to the system.

The learning of weights is done using the following procedure:

1. Selection of random numbers for all weights;
2. Calculation of output vectors and comparison with the target output (referred also as the desired output);
3. If the network output is approximately equal to the desired output, then continue with step 1, and if not, weights are corrected according to the correction rule and then continue with step 1.

Applications:

Data set is divided into two parts. First 111, then 125 water level values constitute the training set used for calibration and first the rest 59 water level values between 01-03-2000 and 5-20-2002, then 45 water level values between 8-28-2000 and 5-20-2002 constitute the testing set used for verification of the methodology. 111 and 125 values were selected randomly, considering the fact that in the training set, the output part must include both maximum and minimum values. An artificial neuron receives an input, process it and then produce an output. Inputs to such neuron may come from system casual variables or outputs of other nodes, depending upon the layer where the node is located. In a way each input is weighted before reaching the neuron. Neural network toolbox assigns weighting factors randomly. Net information is passed through an activation function to produce an output. There may be many inputs to the neuron, but there is only one output from the neuron. This one output is distributed by the synaptic weights to each neuron in the next layer. In toolbox, different parameters such as α, the momentum term, and η, the learning rate can be used. Value of α should be comparable with that of η. Multiple hidden layers can be used. There are input layers, hidden layers, and output layers. Number of neurons in the hidden layers can be increased or decreased. Iteration number can be changed.

CHAPTER 5

RESULTS AND DISCUSSION

The data obtained from the piezometers P37, P38, P39, P148 as shown in Figure 5.1, where used for the model calibration and verification.

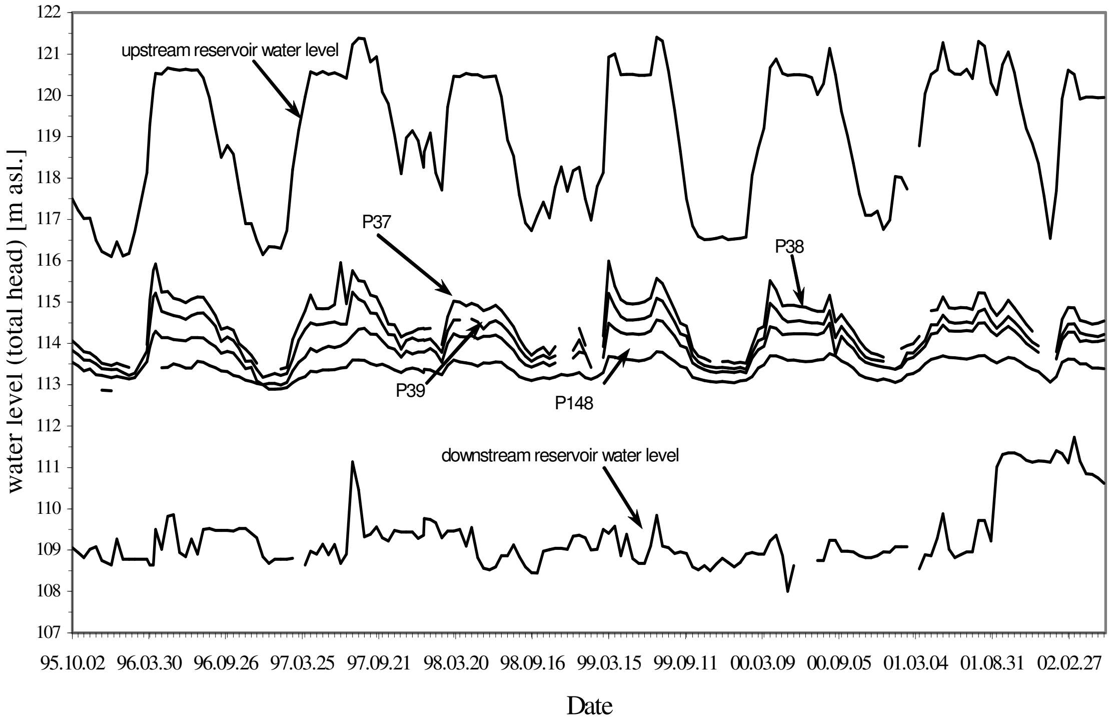


Figure 5.1. Temporal Variations of the Water Level at Piezometers and in Upper and Lower reservoirs.

Figure 5.2 compares the measured output data with the model prediction output data between 10-02-1995 and 12-20-1999. Neuron numbers are 6, 4, and 1 at input, hidden and output layers respectively. Learning rate η is 0.01; Momentum term α is 0.1; Iteration number is 10000; Logsig activation function is used. Number of training data is 111. This stage is called as training stage.

Calibration Run

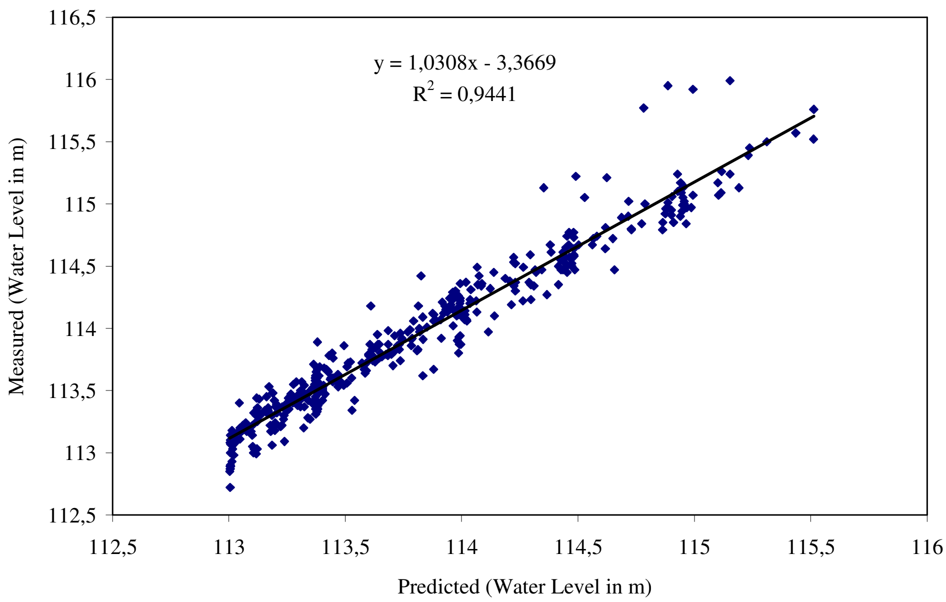


Figure 5.2. Comparison of measured versus ANNs model predicted data. Training Stage.

Figure 5.3 shows the measured water level data versus the model predicted output data for testing. Neuron numbers are 6, 4, and 1 at input, hidden and output layers respectively. Learning rate η is 0.01; Momentum term α is 0.1; Iteration number is 10000; Logsig activation function is used. Number of testing data is 59. This stage is called as testing stage.

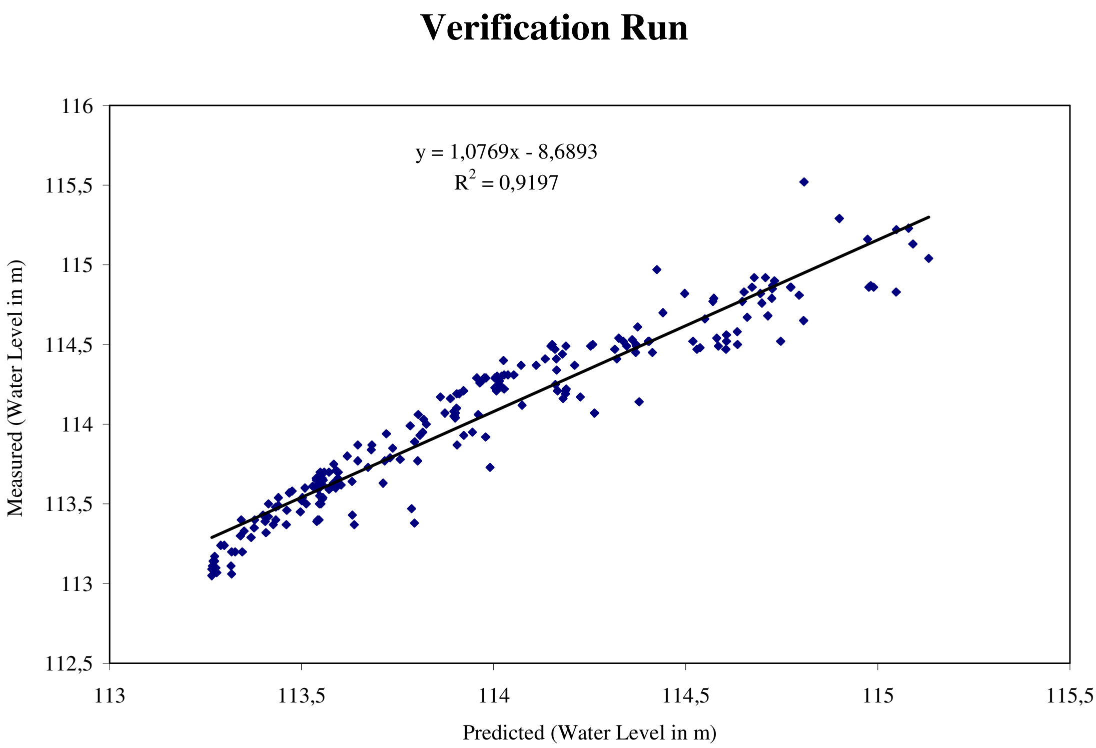
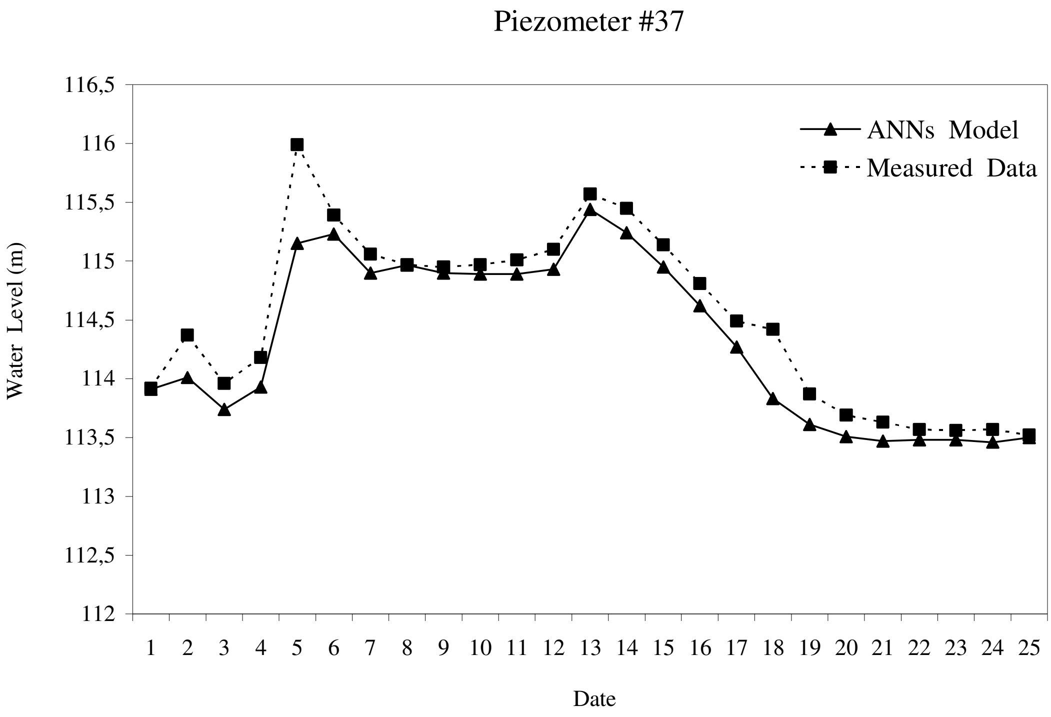


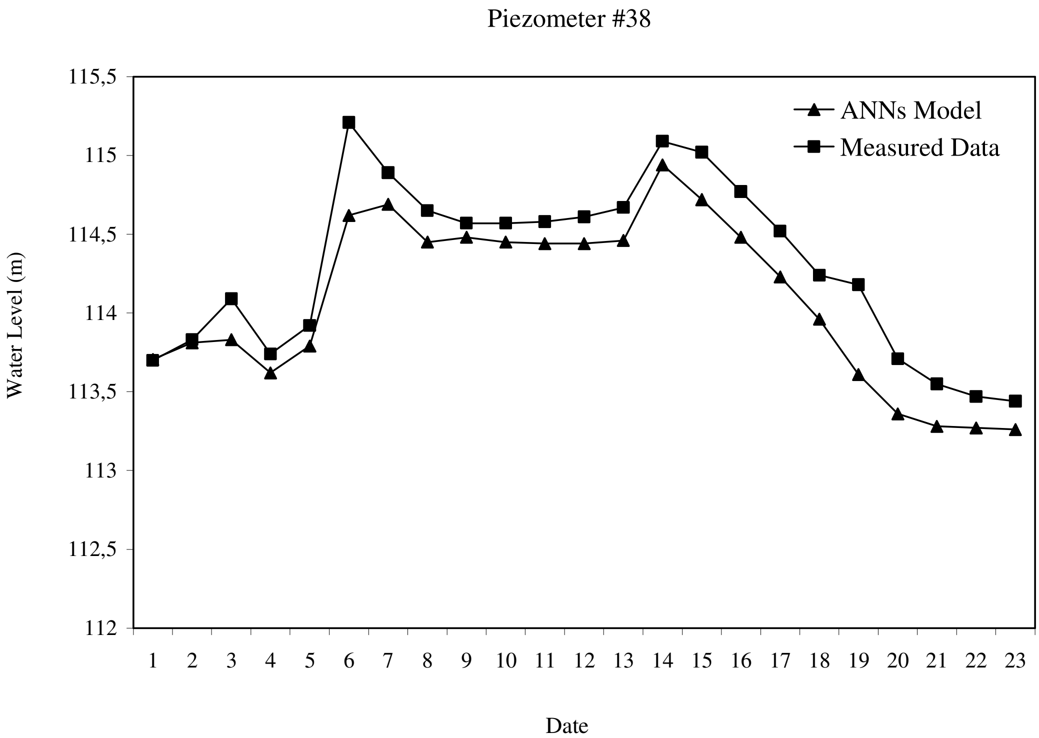
Figure 5.3. Comparison of measured versus ANNs Model Predicted data. Testing Stage.

Figure 5.4. presents the calibration runs comparing the predicted model results with the measured water level values of each piezometer. The model was calibrated by comparing the model results against the measured data of one year duration of 10-02-1995 to 12-20- 1999. This time period, which corresponds to the construction, included the possible variations of water rise in the upper reservoir.

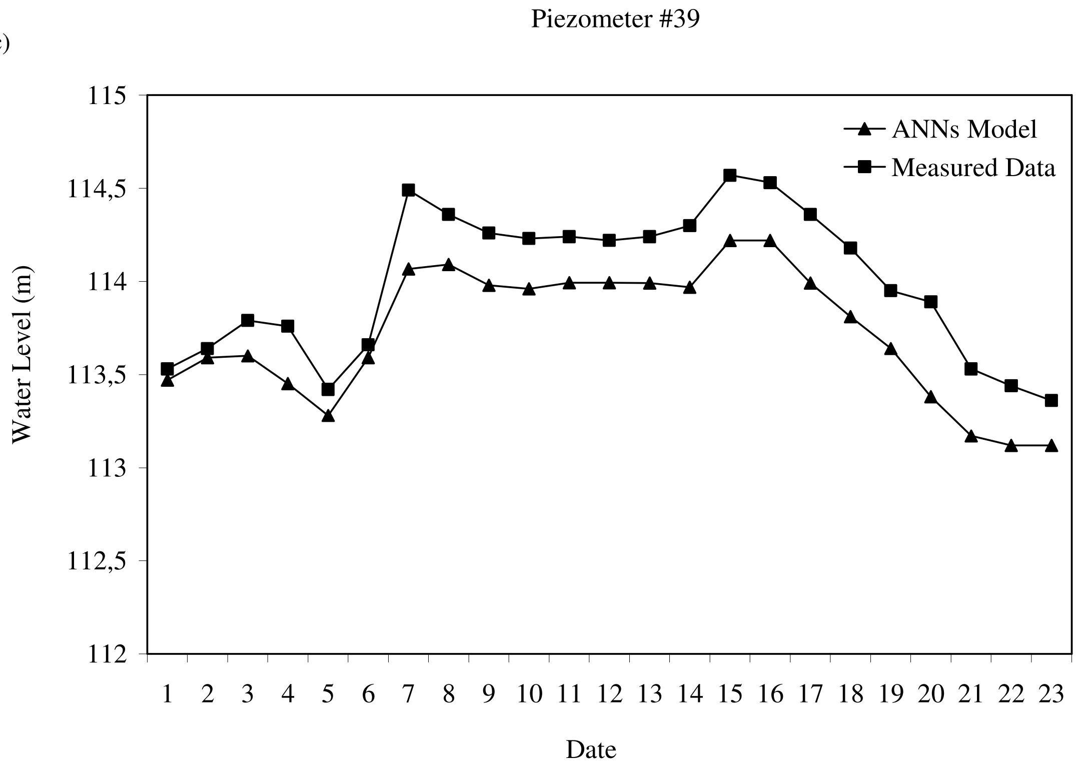
(a)


Piezometer #37
116,5
116
115,5
115
114,5
114
113,5
113
112,5
112
Water Level (m)
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Date
ANNs Model
Measured Data

(b)


Piezometer #38
115,5
115
114,5
114
113,5
113
112,5
112
Water Level (m)
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
Date
ANNs Model
Measured Data

(c)



(d)

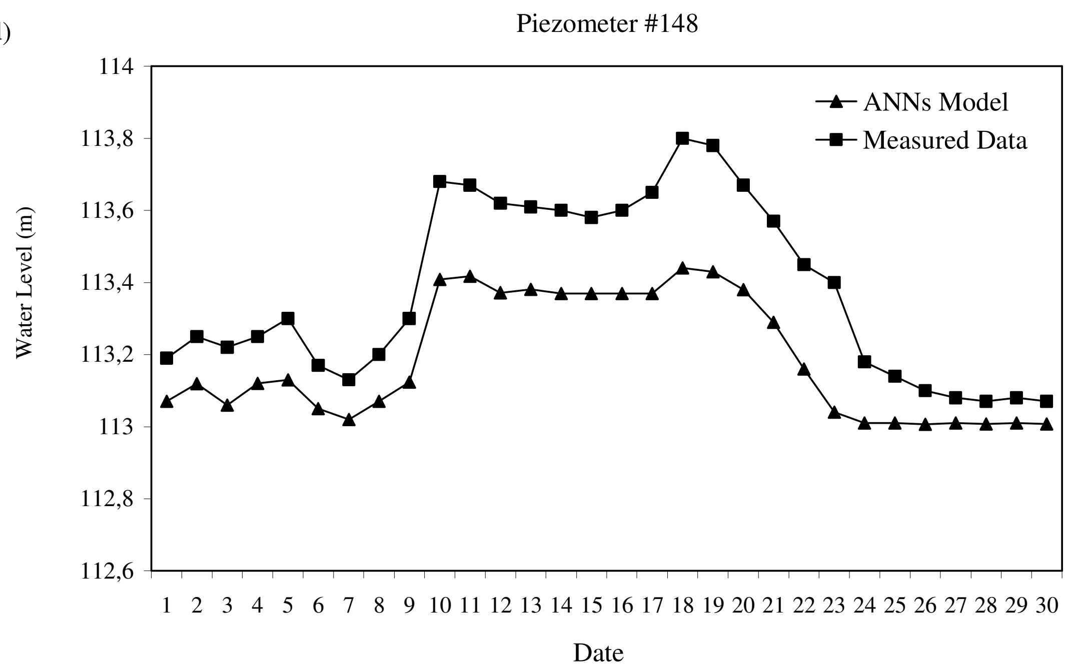
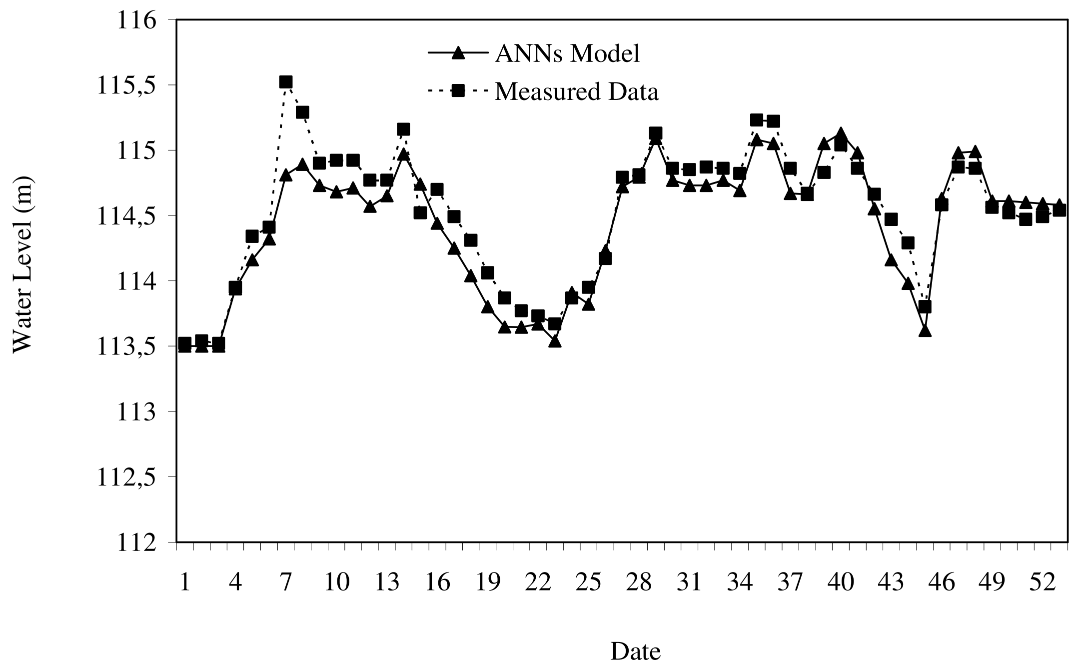


Figure 5.4. Calculated and Measured Water Levels at Piezometers (a) P37, (b) P38, (c) P39, (d) P148 for the Period 02.10.1995-20.12.1999. CALIBRATION RUN.

Figure 5.5. presents the verification runs comparing the predicted model results with the measured water level values of each piezometer. The model was validated using the measured data from 01-03-2000 to 05-20-2002.

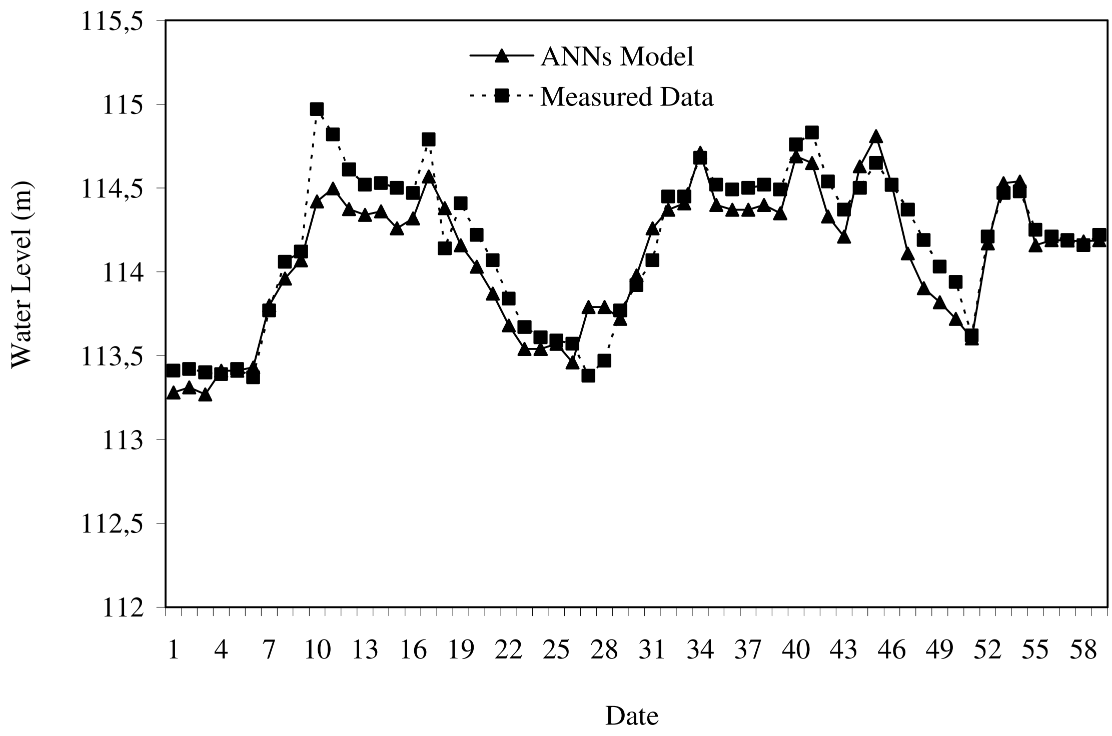
(a)

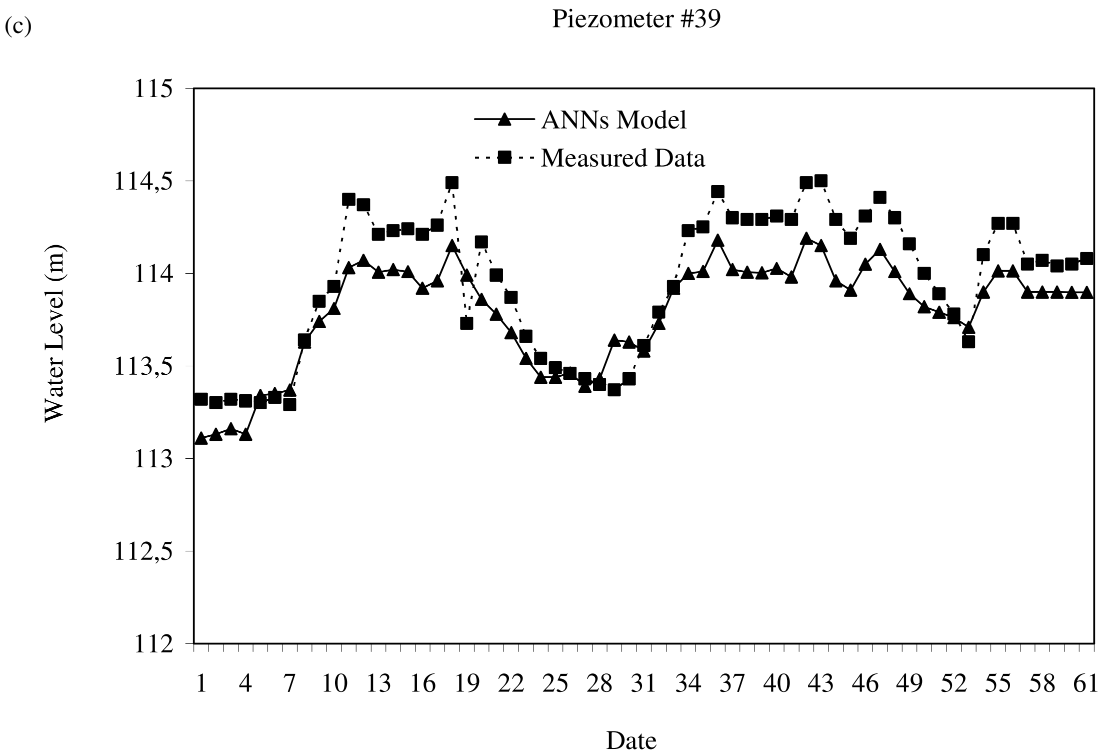
Piezometer #37



(b)

Piezometer #38





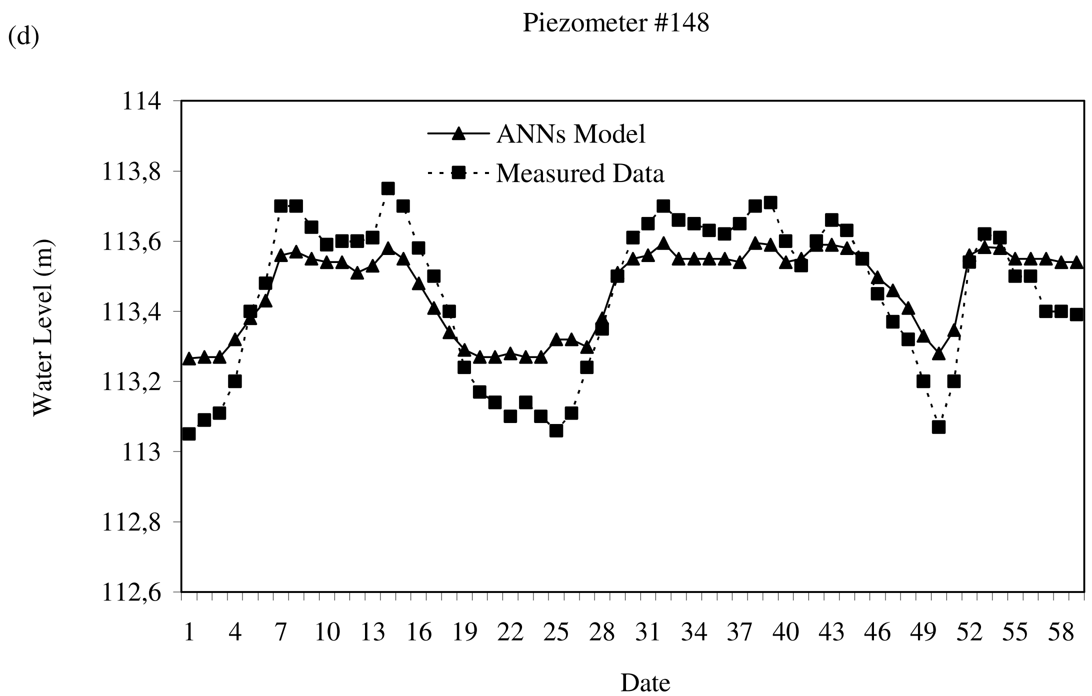


Figure 5.5. Calculated and Measured Water Levels at Piezometers (a) P37, (b) P38, (c) P39, (d) P148 for the Period 03.01.2000-20.05.2002. VALIDATION RUN

For each piezometer case, to be able to evaluate the model performance the most commonly used error measures were computed as summarized in Table 5.1. and Table 5.2. These error measures are the mean absolute error (MAE) and the root mean square error (RMSE). The RMSE and MAE can be defined as (Dolling, and Varas, 2002):

$$\text{RMSE} = \sqrt{\frac{\sum_{i}^{N}(W_{m_i} - W_{p_i})^2}{N}} \tag{5.1}$$

$$\text{MAE} = \frac{\sum_{i}^{N}\left|W_{m_i} - W_{p_i}\right|}{N} \tag{5.2}$$

where W_m = the measured water level; W_p = the predicted water level; and N = the number of observations.

Table 5.1. Calculated Error Measures for the Calibration Run.

Piezometer #	RMSE (m)	MAE (m)
P37	0.26	0.18
P38	0.25	0.21
P39	0.28	0.27
P148	0.20	0.18
Average	0.2475	0.21

Table 5.2. Calculated Error Measures for the Validation Run.

Piezometer #	RMSE (m)	MAE (m)
P37	0.18	0.15
P38	0.17	0.14
P39	0.21	0.19
P148	0.09	0.05
Average	0.1625	0.1325

Figure 5.6. compares the measured output data with the model prediction output data between 10-02-1995 and 12-20-1999. Neuron numbers are 6, 4, and 1 at input, hidden and output layers respectively. Learning rate η is 0.02; Momentum term α is 0.1; Iteration number is 10000; Logsig activation function is used. Number of training data is 111.

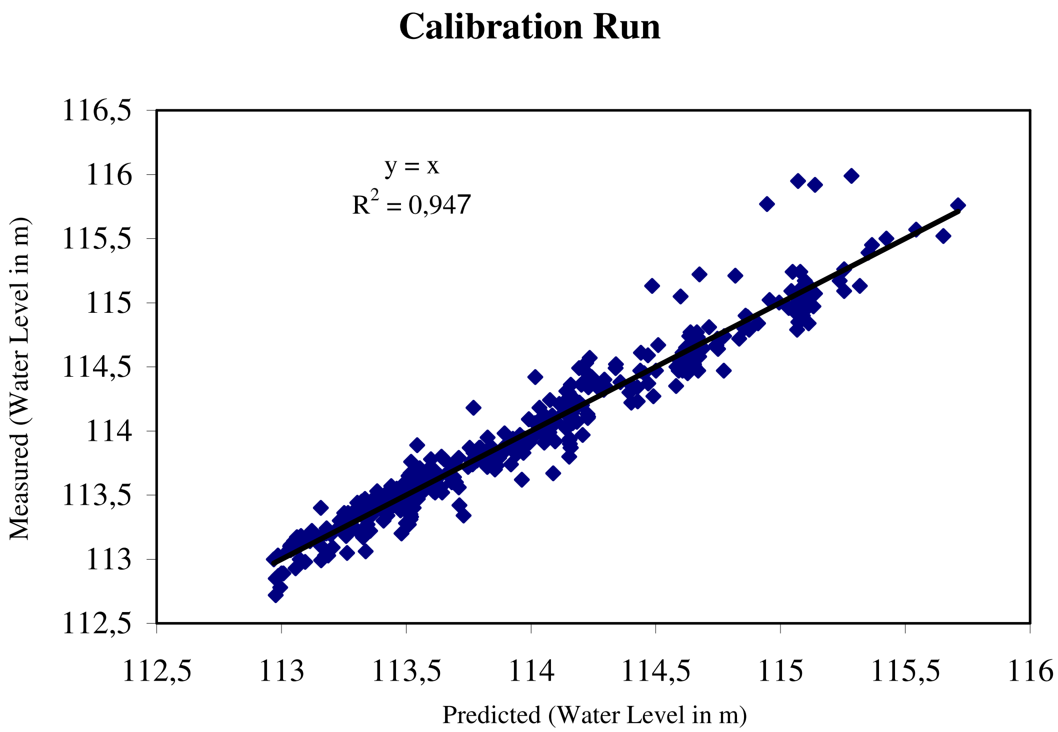


Figure 5.6. Comparison of Measured versus ANNs Model Predicted Data. Training Stage.

Figure 5.7. shows the measured water level data versus the model predicted output data for testing. Neuron numbers are 6, 4, and 1 at input, hidden and output layers respectively. Learning rate η is 0.02; Momentum term α is 0.1; Iteration number is 10000; Logsig activation function is used. Number of testing data is 59.

Verification Run

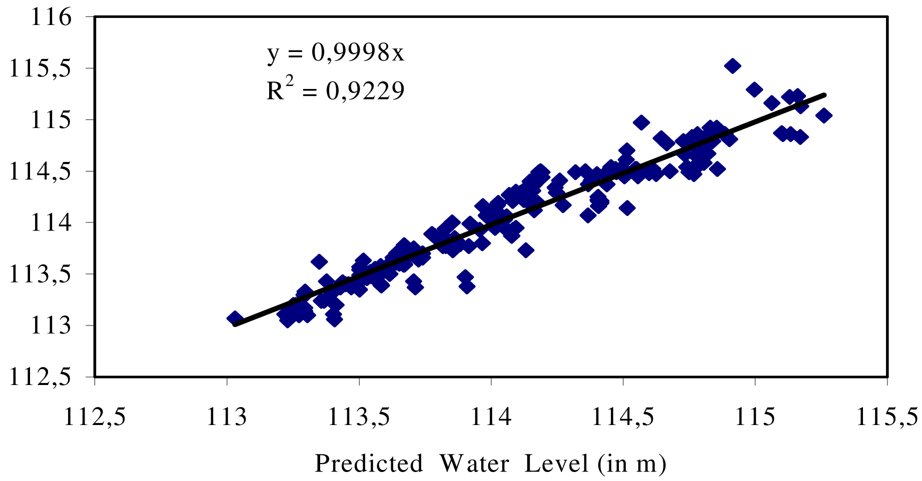
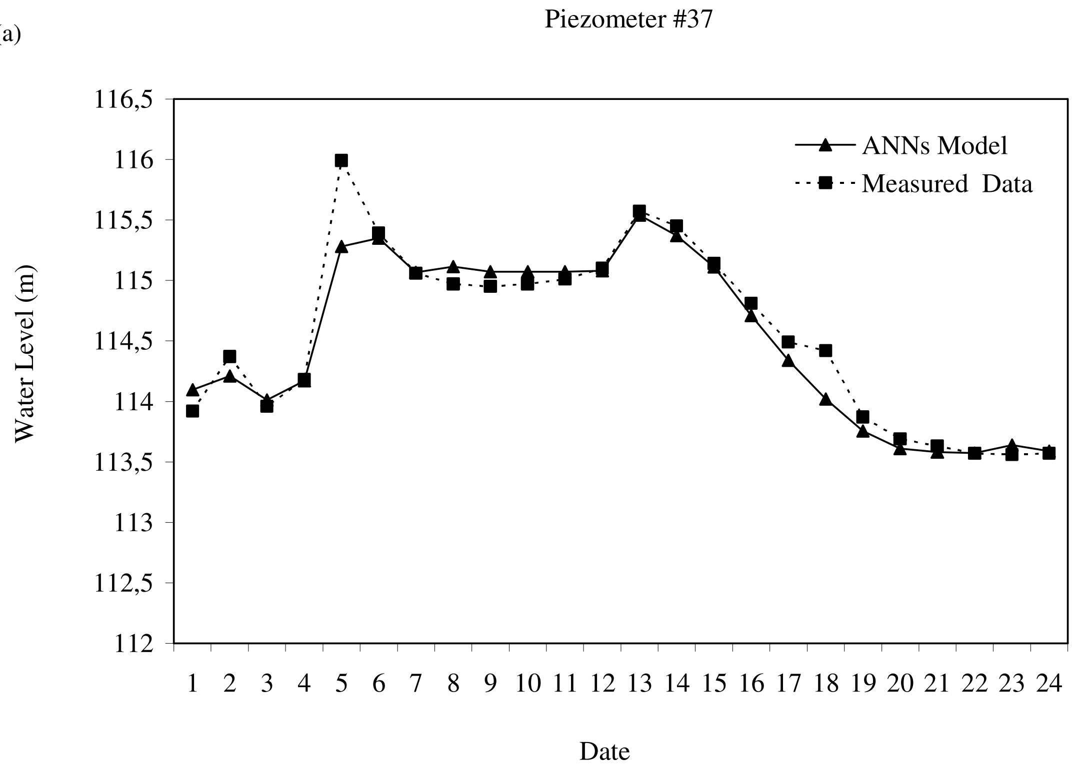


Figure 5.7. Comparison of Measured versus ANNs Model Predicted Data. Testing Stage.

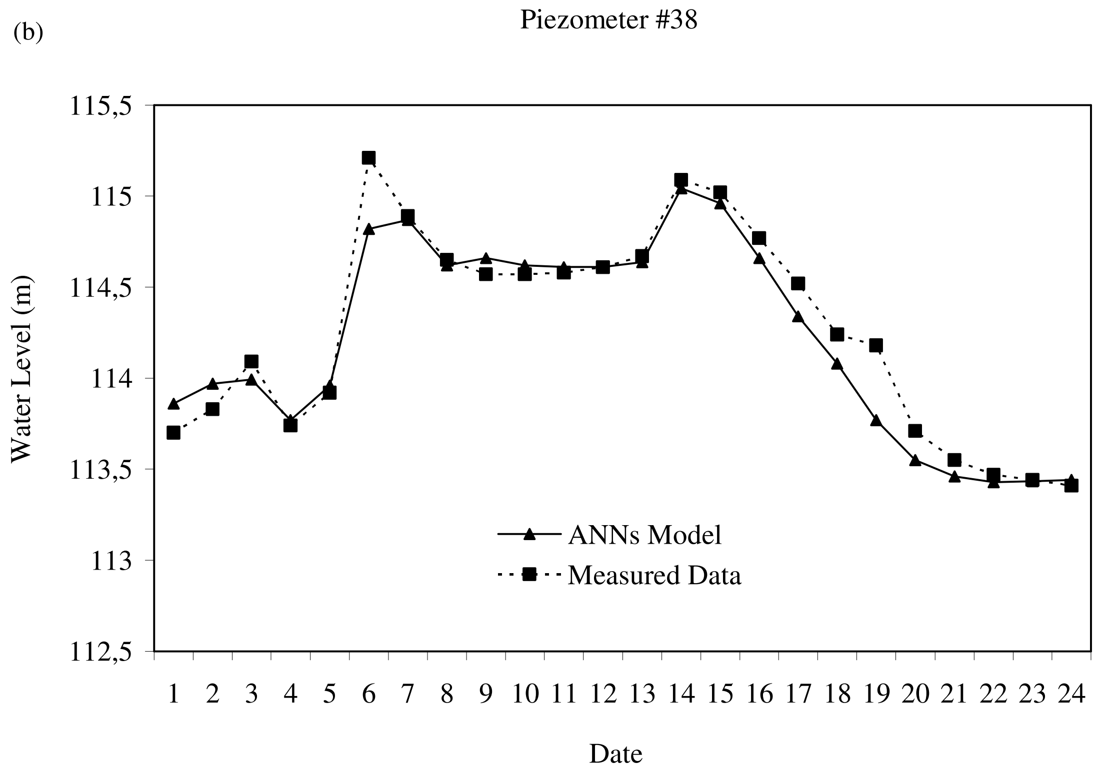
Figure 5.8. presents the calibration runs comparing the predicted model results with the measured water level values of each piezometer. The model was calibrated by comparing the model results against the measured data of one year duration of 10-02-1995 to 12-20- 1999.

(a)



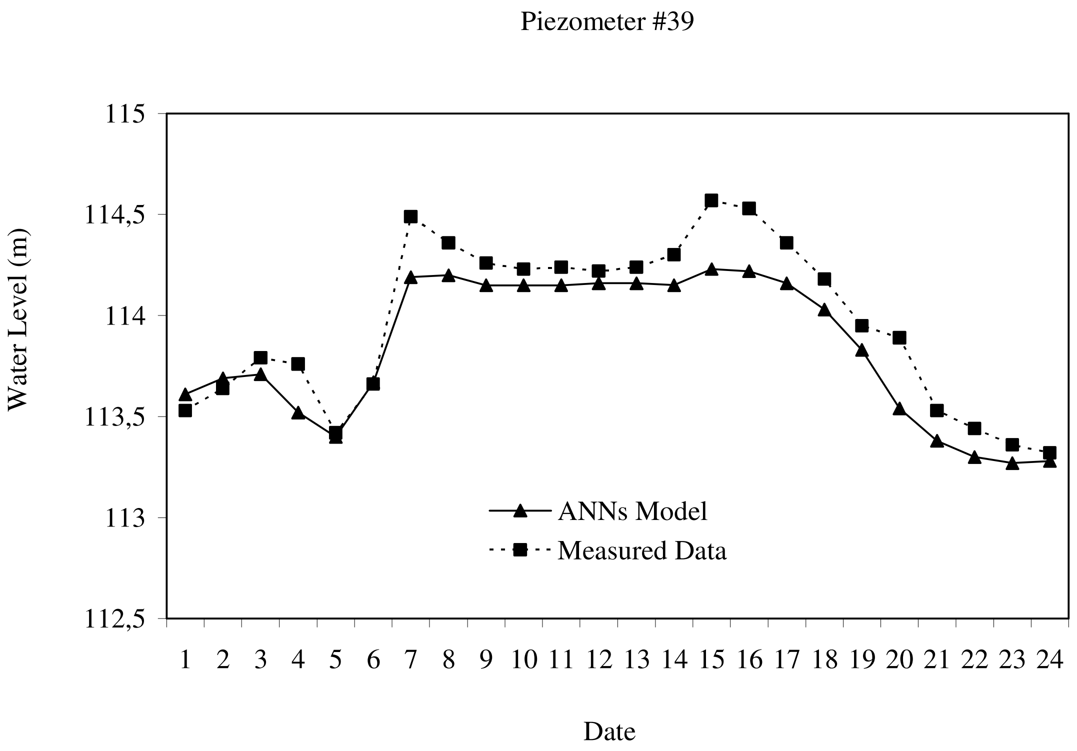
Piezometer #37
116,5
116
115,5
115
114,5
114
113,5
113
112,5
112
Water Level (m)
ANNs Model
Measured Data
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Date

(b)



Piezometer #38
115,5
115
114,5
114
113,5
113
112,5
Water Level (m)
ANNs Model
Measured Data
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Date

(c)



(d)

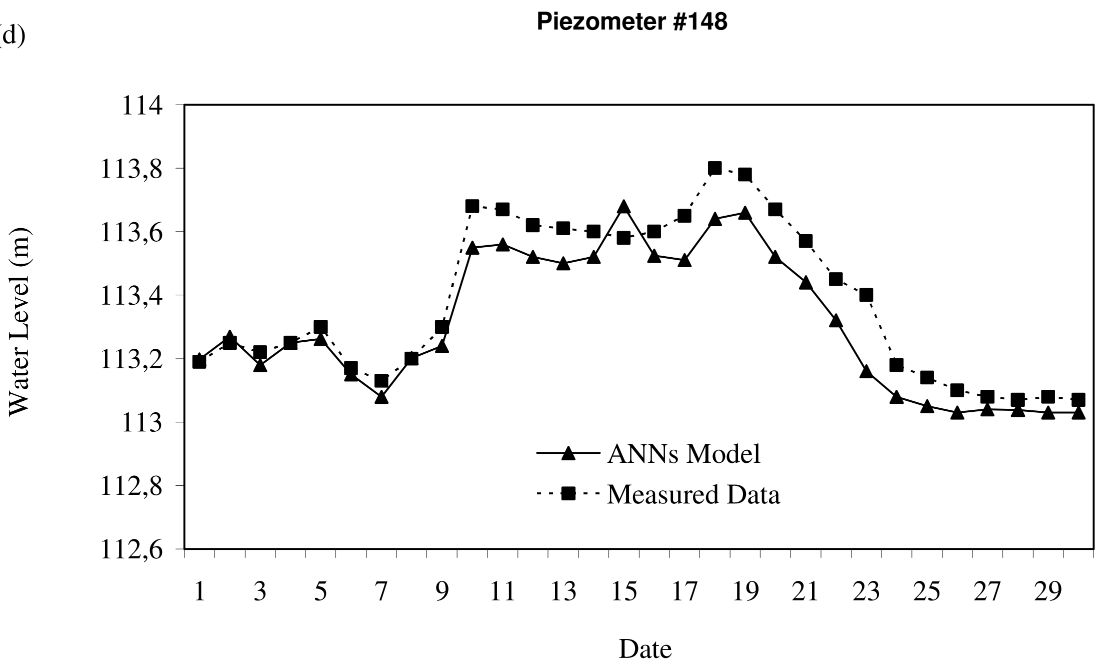
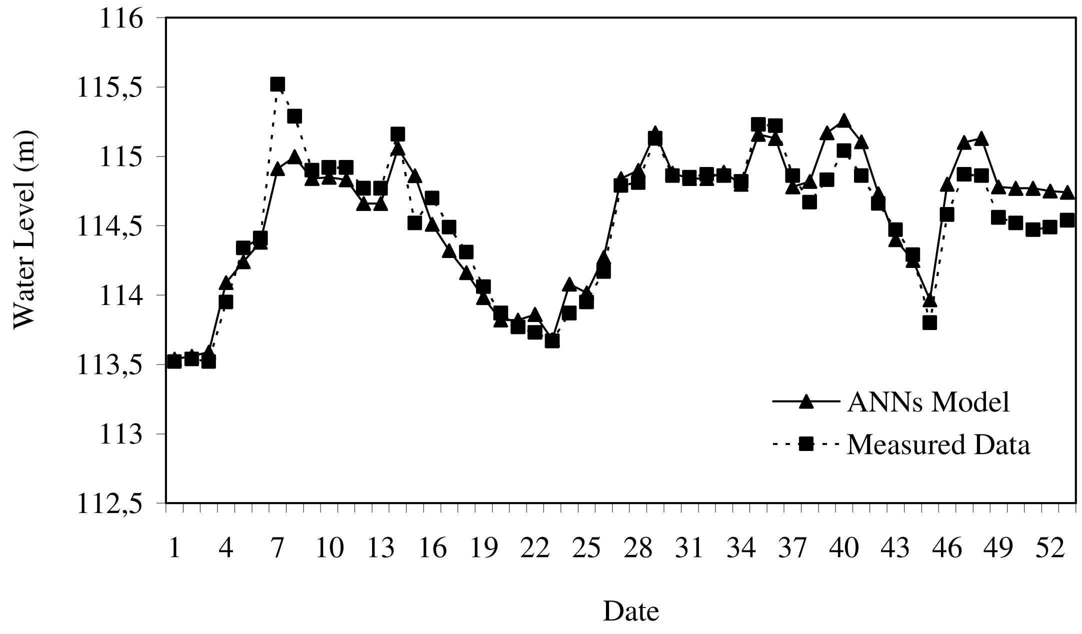


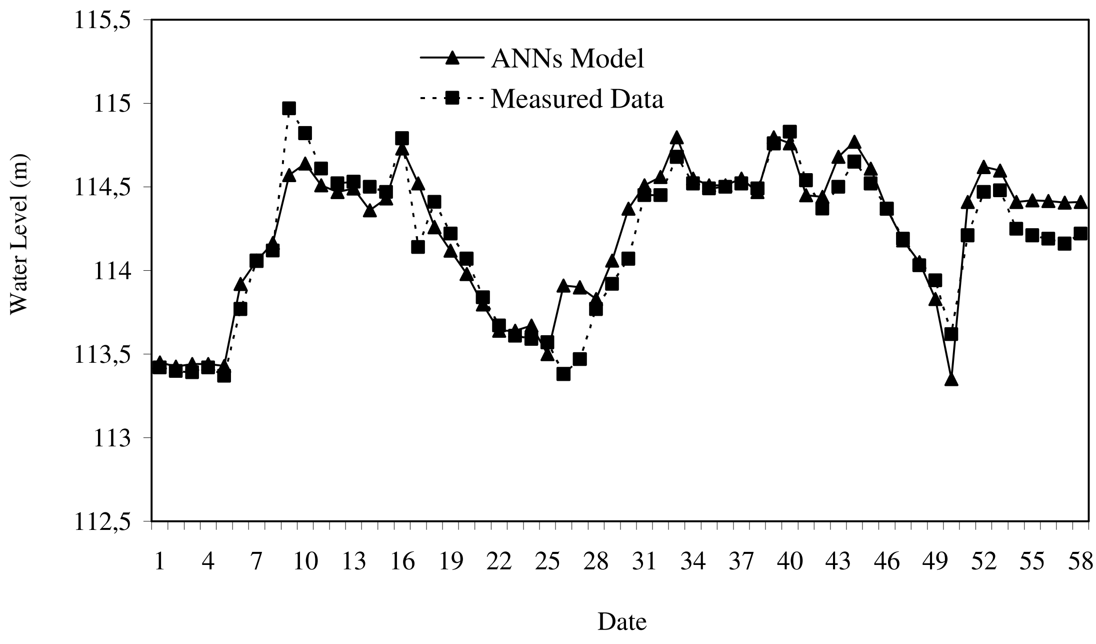
Figure 5.8. Calculated and Measured Water Levels at Piezometers (a) P37, (b) P38, (c) P39, (d) P148 for the Period 02.10.1995-20.12.1999. CALIBRATION RUN.

Figure 5.9. presents the verification runs comparing the predicted model results with the measured water level values of each piezometer. The model was validated using the measured data from 01-03-2000 to 05-20-2002.

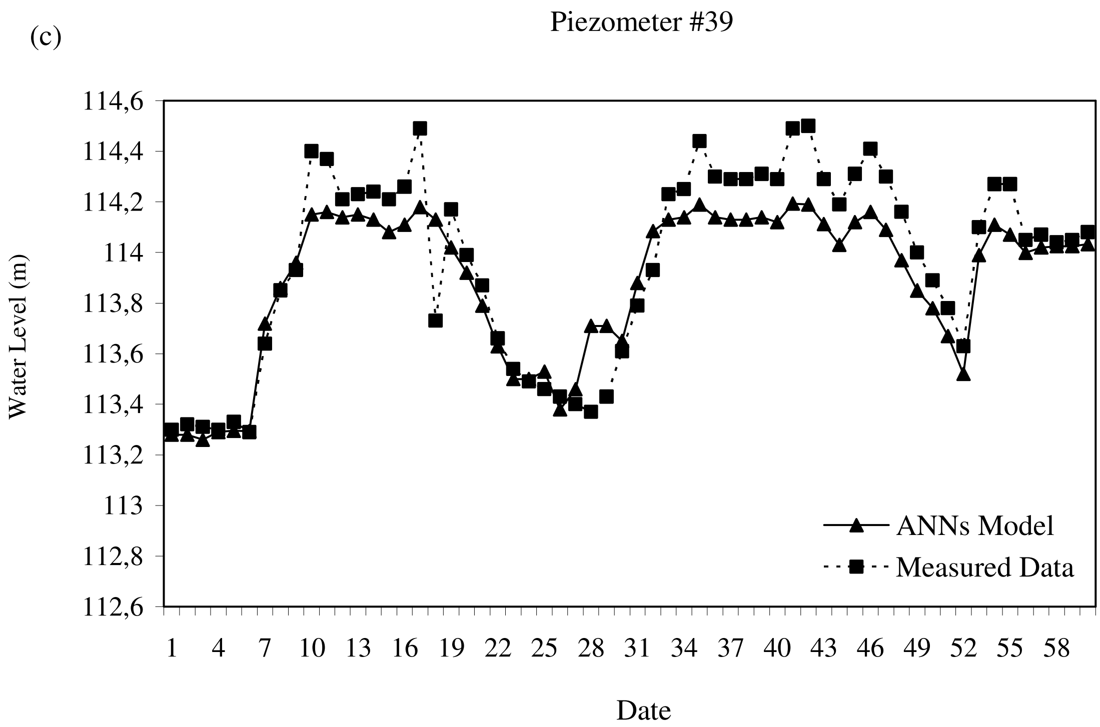
(a) Piezometer #37



(b) Piezometer #38



(c)



(d)

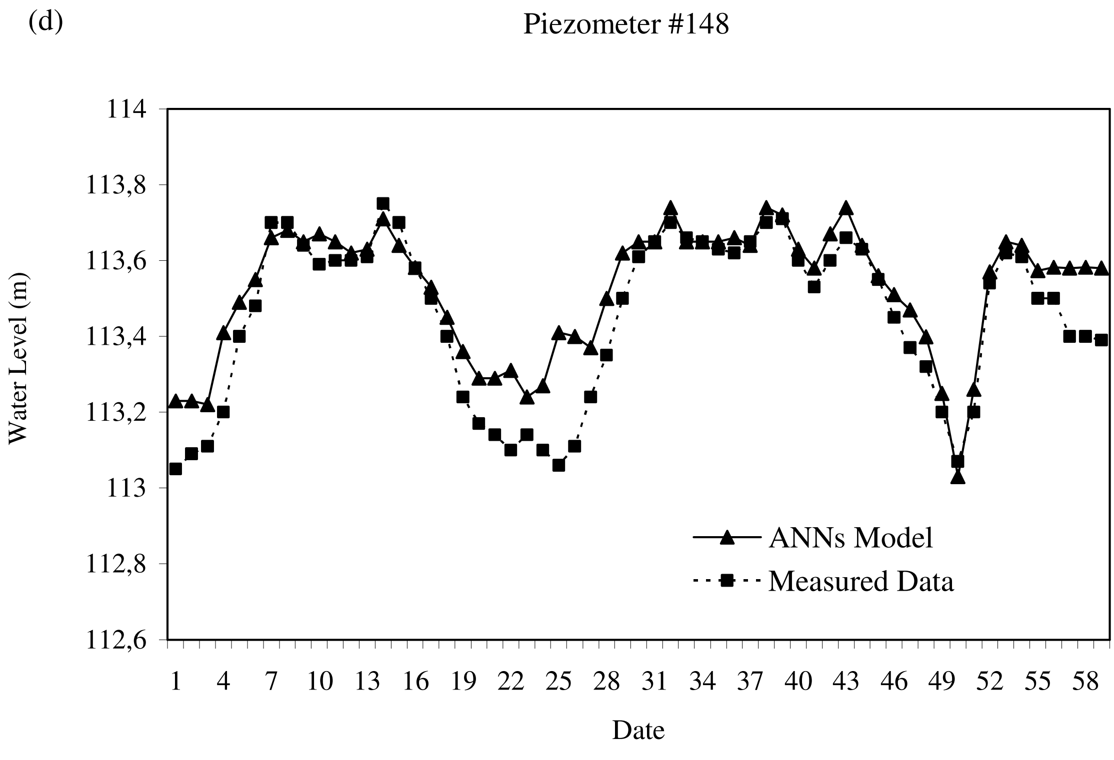


Figure 5.4. Calculated and Measured Water Levels at Piezometers (a) P37, (b) P38, (c) P39, (d) P148 for the Period 03.01.2000-20.05.2002. VALIDATION RUN.

For each piezometer case, to be able to evaluate the model performance the most commonly used error measures were computed as summarized in Table 5.3 and Table 5.4. These error measures are the mean absolute error (MAE) and the root mean square error (RMSE).

Table 5.3. Calculated Error Measures for the Calibration Run.

Piezometer #	RMSE (m)	MAE (m)
P37	0.18	0.11
P38	0.14	0.09
P39	0.16	0.12
P148	0,10	0,08
Average	0.145	0.10

Table 5.4. Calculated Error Measures for the Validation Run

Piezometer #	RMSE (m)	MAE (m)
P37	0.18	0.14
P38	0.16	0.12
P39	0.18	0.13
P148	0.11	0.08
Average	0.1575	0.1175

Figure 5.10. shows comparison of correlation coefficient, R^2, with the results which are obtained using different learning rates. Dashed line represents the calibrated data, solid line represents the verified data. Different learning rates were used by the modeling stage. Neuron numbers are 6, 4, and 1 at input hidden and output layers respectively. These neuron numbers were used since they gave best results by modeling stage (Table 5.3). Number of training data is 111 and number of testing data which used in verification part is 59; Momentum term α is 0.1; Iteration number is 10000; Learning rate η is 0.01, 0.02, and 0.03 respectively. Logsig activation function is used. Traingd

training function is used. Traingd is a network training function that updates weight and bias values according to gradient descent.

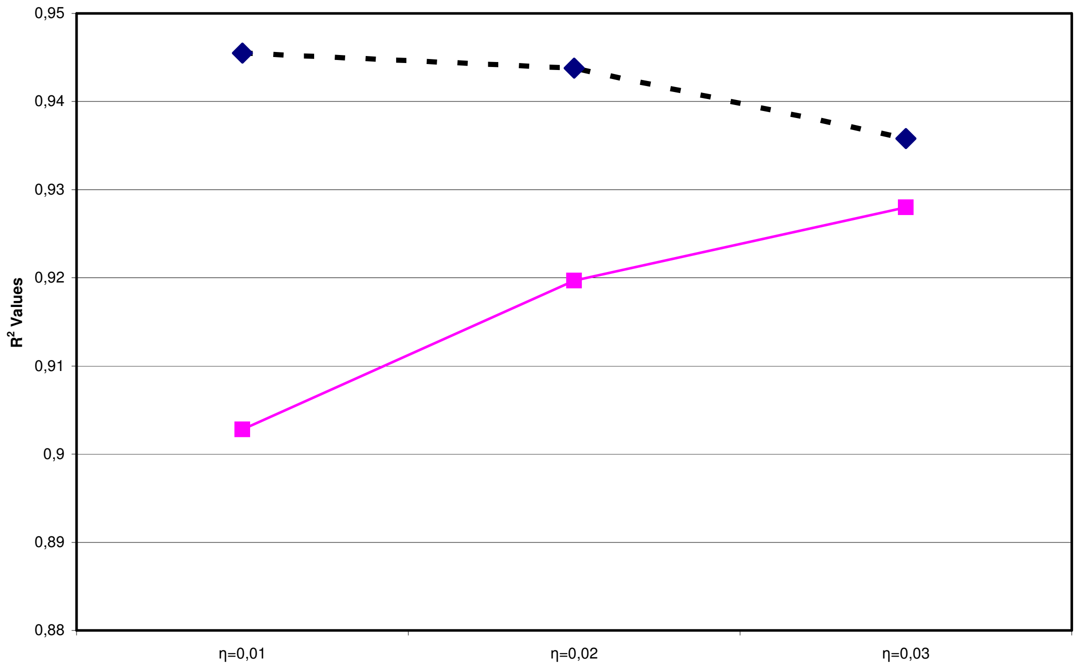


Figure 5.10. Comparison of correlation coefficient, R^2, with the results which are obtained using different learning rates.

Dashed line shows calibrated and the solid line shows verified part. R^2 is correlation coefficient between measured and predicted outputs. Correlation coefficient, R^2, is good if learning rate η is 0.01 at calibration part; and R^2 value is good if learning rate η is 0.03 at verification part. It is wanted that R^2 value is close to 1. Correlation of verified values is more important, η is 0.03 gave better results for these parameters.

Figure 5.11. shows comparison of correlation coefficient, R^2, with the results which are obtained using different iteration numbers. Dashed line represents the calibrated data, solid line represents the verified data. Different iteration numbers were used by the modeling stage. Neuron numbers are 6, 4, and 1 at input hidden and output layers respectively. These neuron numbers were used since they gave best results by modeling stage (Table 5.3). Number of training data is 111 and number of testing data which used in verification part is 59; Momentum term α is 0.1; Logsig activation

function is used. Traingd training function is used. Iteration numbers are 5000, 10000, and 20000 respectively. Learning rate η=0.01. Logsig activation function is used.

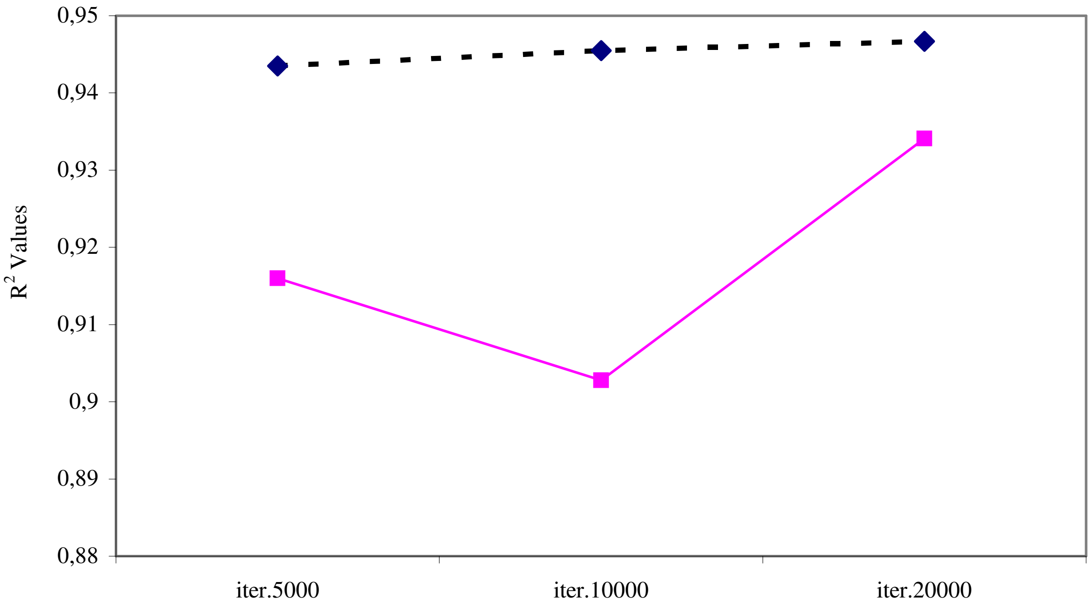


Figure 5.11. Comparison of correlation coefficient, R^2, with the results which are obtained using different iteration numbers.

Dashed line shows calibrated and the solid line shows verified part. The best results are obtained if iteration number is 20000 at calibration part and verification part. The value of iteration number affects R^2 value directly. If iteration number is large, R^2 value is better usually, more close to 1.

If iteration number is 25000, greater than 20000, results are not so different. At calibration part R^2 value is 0.941, at verification part 0.934. These values close to the values which are obtained using 20000 iteration numbers. Sometimes, large iteration numbers affect R^2 values not so good.

Table 5.5. Results of R^2 values with different topologies (tansig:hyperbolic tangent function,logsig:sigmoid function); Number of training data is 111 and number of testing data which used in verification part is 59; Learning rate η is 0.02; Momentum term α is 0.1; Iteration number is 10000. Logsig or tansig activation function is used.

Number of Hidden Layers and Nodes in the Layers	Activation(Transfer) Function	R^2 Value
1 (6-5-1)	tansig	0,85 (Calibrated) 0.83(Verified)
1 (6-5-1)	logsig	0,87 (Calibrated) 0.85(Verified)
2(6-3-3-1)	tansig	0,76 (Calibrated) 0.73(Verified)
2(6-3-3-1)	logsig	0,78(Calibrated) 0.77(Verified)
1 (6-4-1)	tansig	0,88 (Calibrated) 0.86(Verified)
1 (6-4-1)	logsig	0,94 (Calibrated) 0.92(Verified)
3 (6-3-3-3-1)	logsig	0,76 (Calibrated) 0.74(Verified)

According to the results in Table 5.5., using more variables as input leads to the better results. However, sometimes increasing the number of hidden layers could make the system unstable. Network with sigmoid function and network with one hidden layer gave more accurate results than network with two or three hidden layers.

Figure 5.12. compares the measured output data with the model prediction output data between 10-02-1995 and 08-14-2000. Neuron numbers are 6, 4, and 1 at input, hidden and output layers respectively. Learning rate η is 0.01; Momentum term α is 0.1; Iteration number is 10000; Logsig activation function is used. Number of training data is 125. This stage is called as training stage.

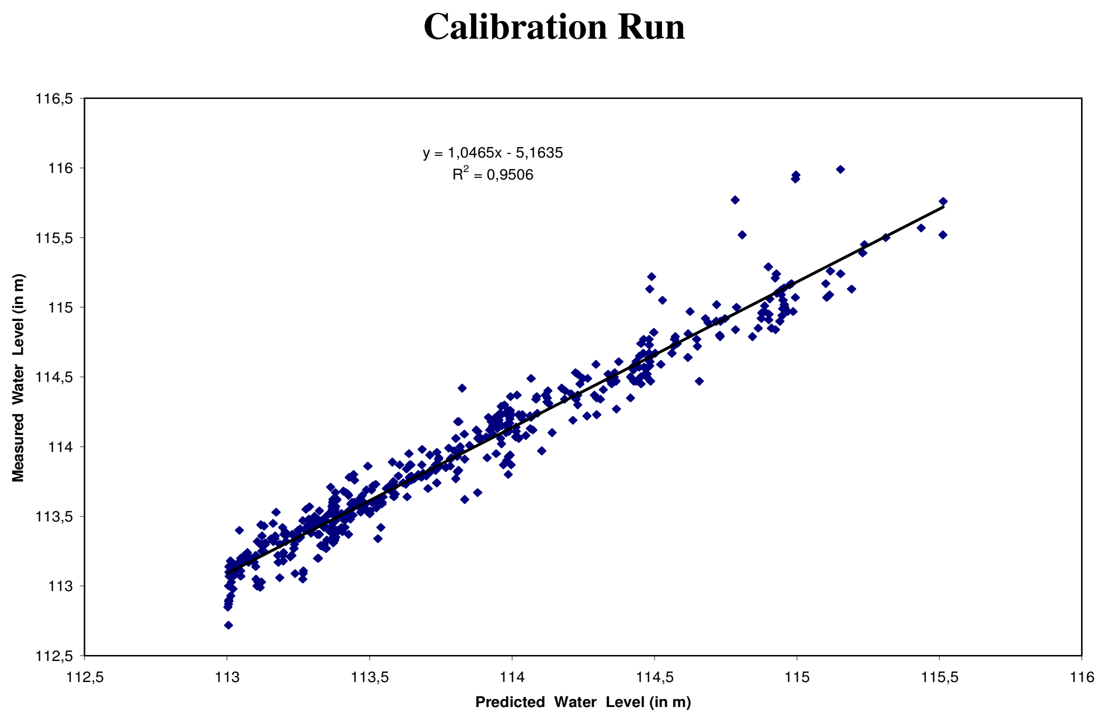


Figure 5.12. Comparison of measured versus ANNs Model Predicted data. Training Stage.

Figure 5.13 shows the measured water level data versus the model predicted output data for testing. Neuron numbers are 6, 4, and 1 at input, hidden and output layers respectively. Learning rate η is 0.01; Momentum term α is 0.1; Iteration number is 10000; Logsig activation function is used. Number of testing data is 45. This stage is called as testing stage.

Verification Run

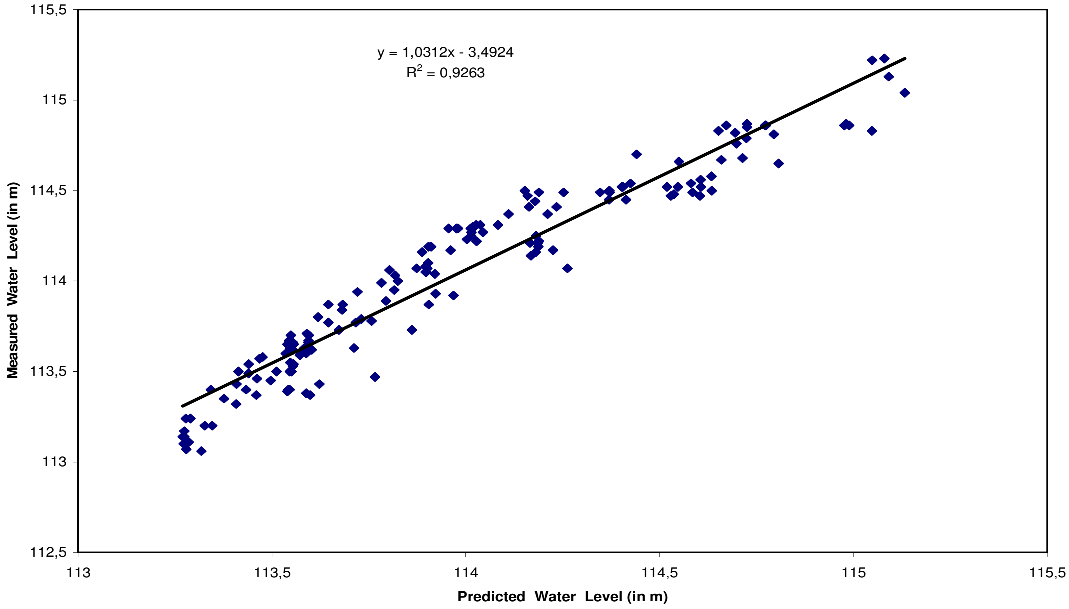
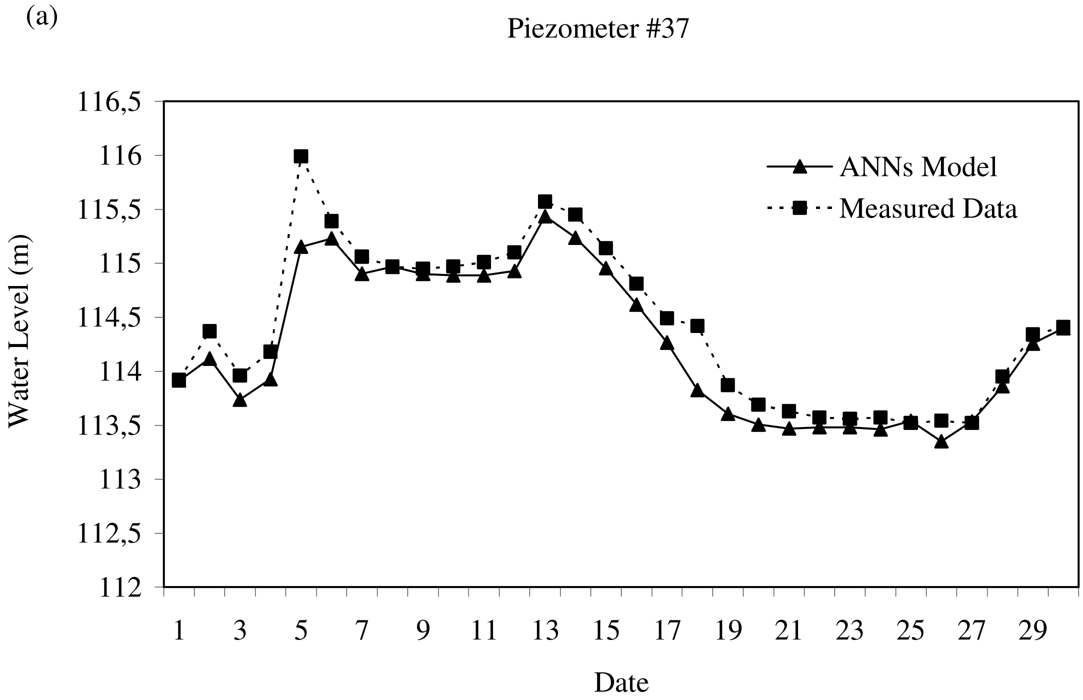


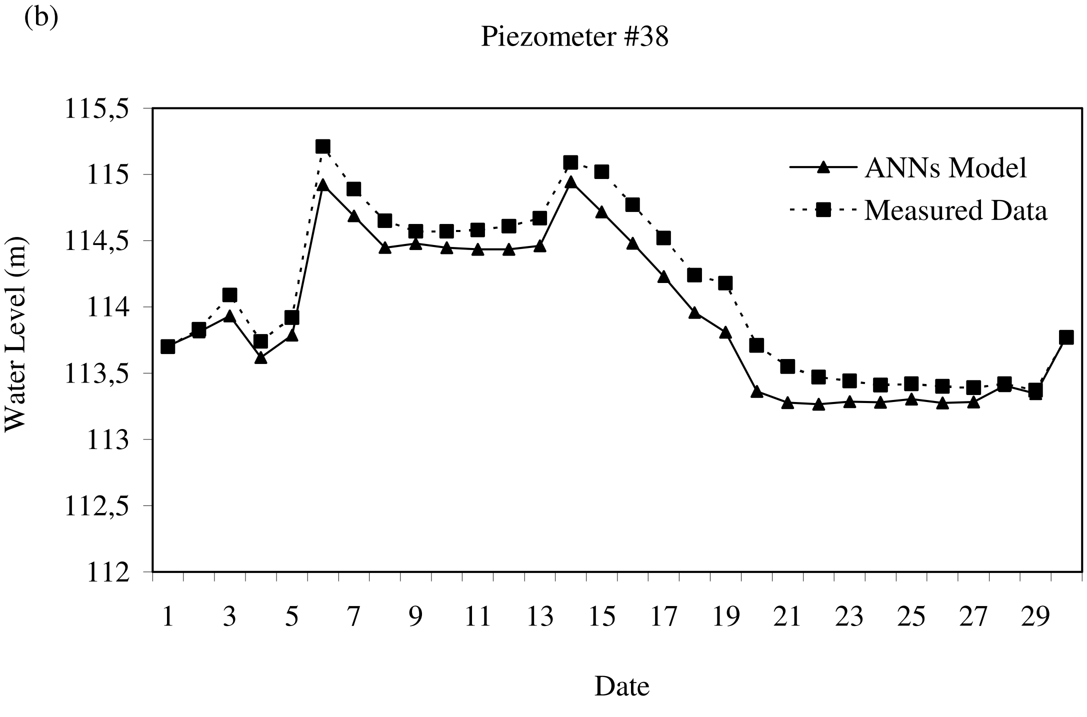
Figure 5.13. Comparison of measured versus ANNs Model Predicted Data. Testing stage.

Figure 5.14. presents the calibration runs comparing the predicted model results with the measured water level values of each piezometer. The model was calibrated by comparing the model results against the measured data of one year duration of 10-02-1995 to 08-14 2000.

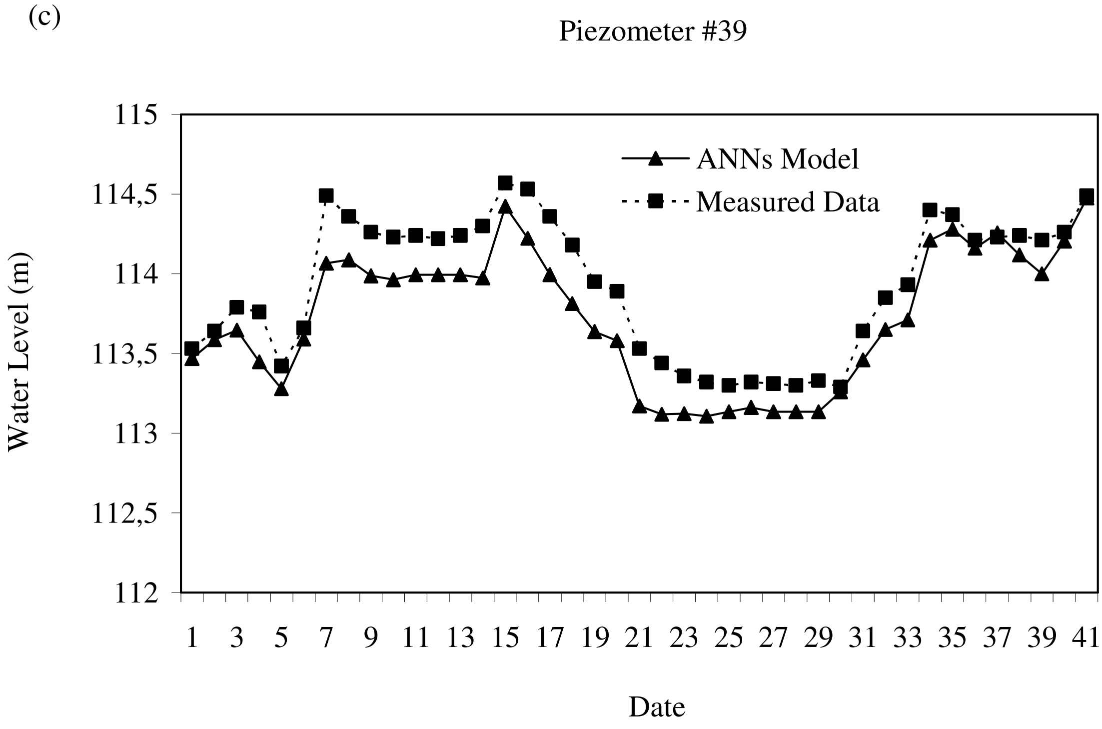
(a)


Piezometer #37
116,5
116
115,5
115
114,5
114
113,5
113
112,5
112
Water Level (m)
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
Date
ANNs Model
Measured Data

(b)


Piezometer #38
115,5
115
114,5
114
113,5
113
112,5
112
Water Level (m)
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
Date
ANNs Model
Measured Data

(c)



(d)

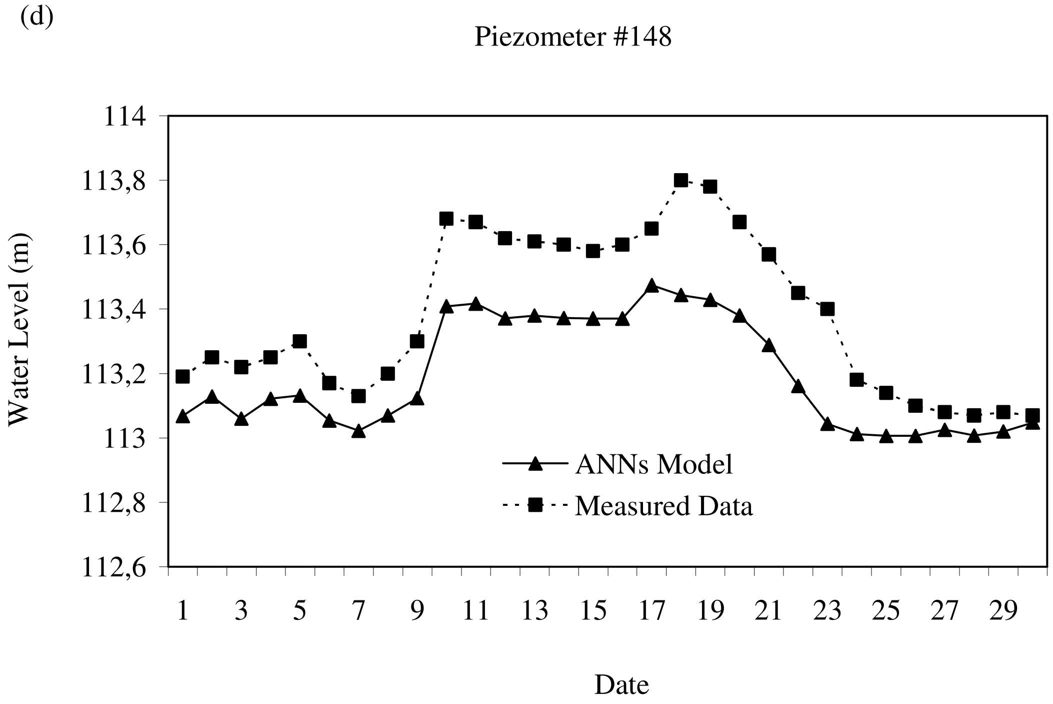
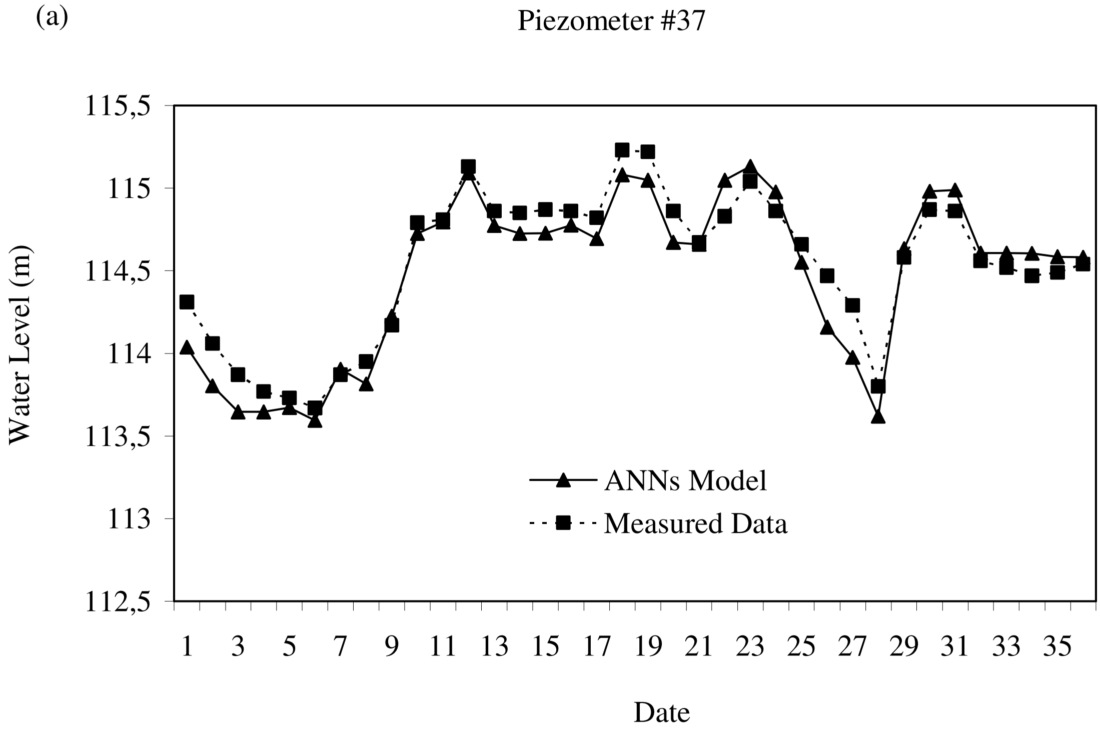


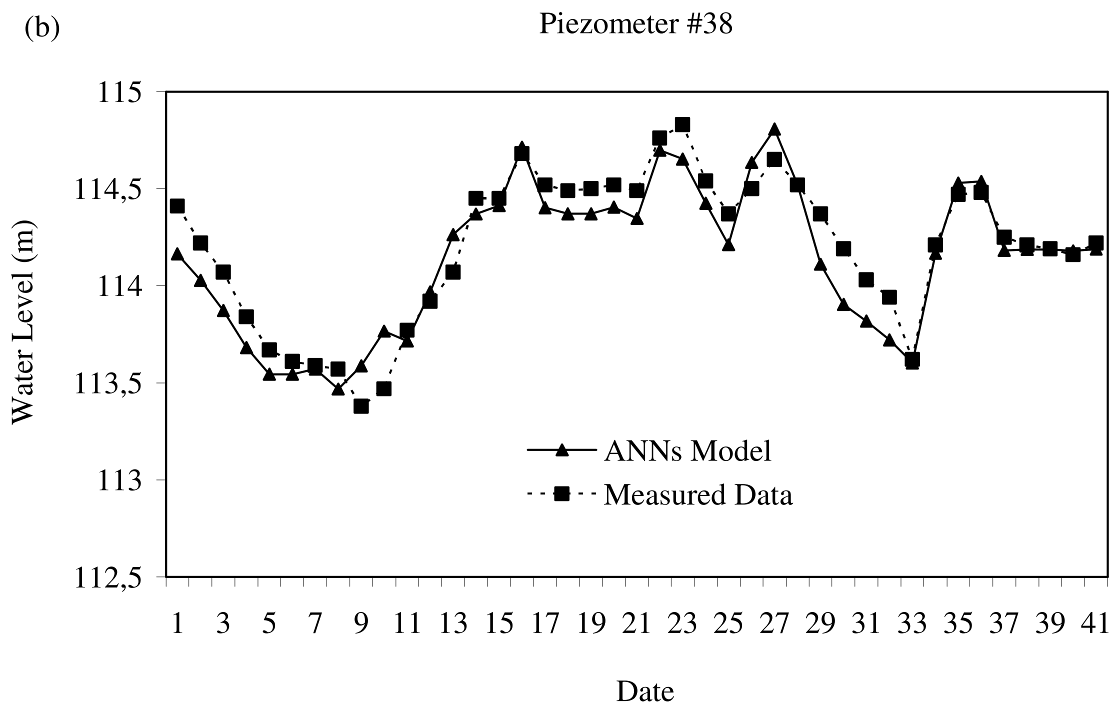
Figure 5.4. Calculated and Measured Water Levels at Piezometers (a) P37, (b) P38, (c) P39, (d) P148 for the Period 02.10.1995-14.08.2000. CALIBRATION RUN.

Figure 5.15. presents the verification runs comparing the predicted model results with the measured water level values of each piezometer. The model was validated using the measured data from 08-28-2000 to 5-20-2002.

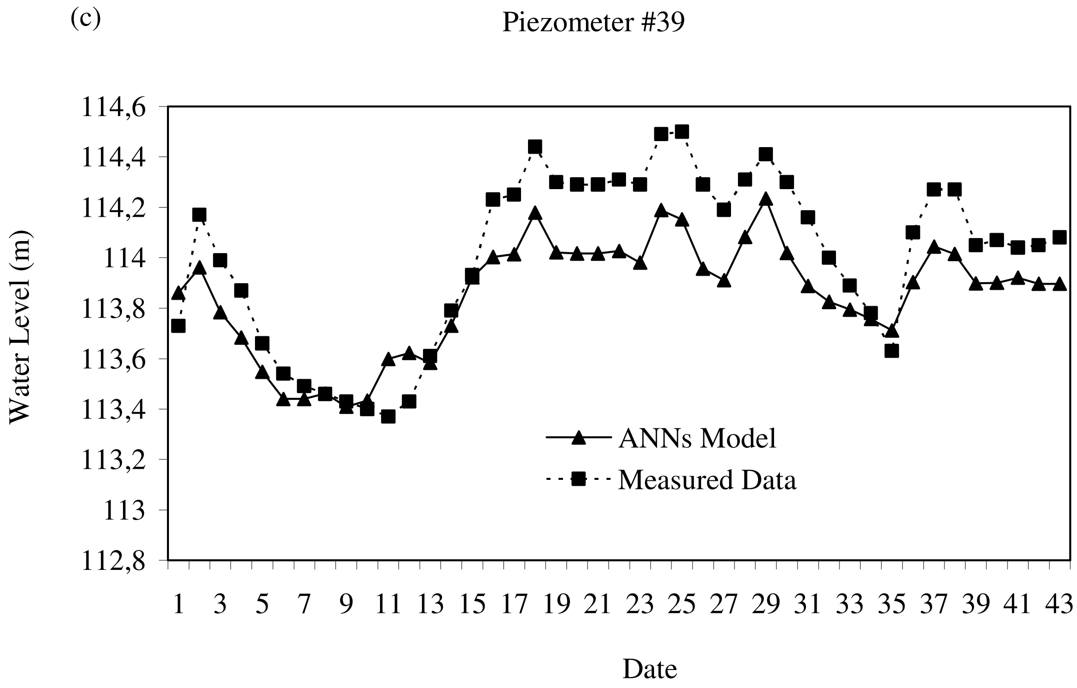
(a)



(b)



(c)



(d)

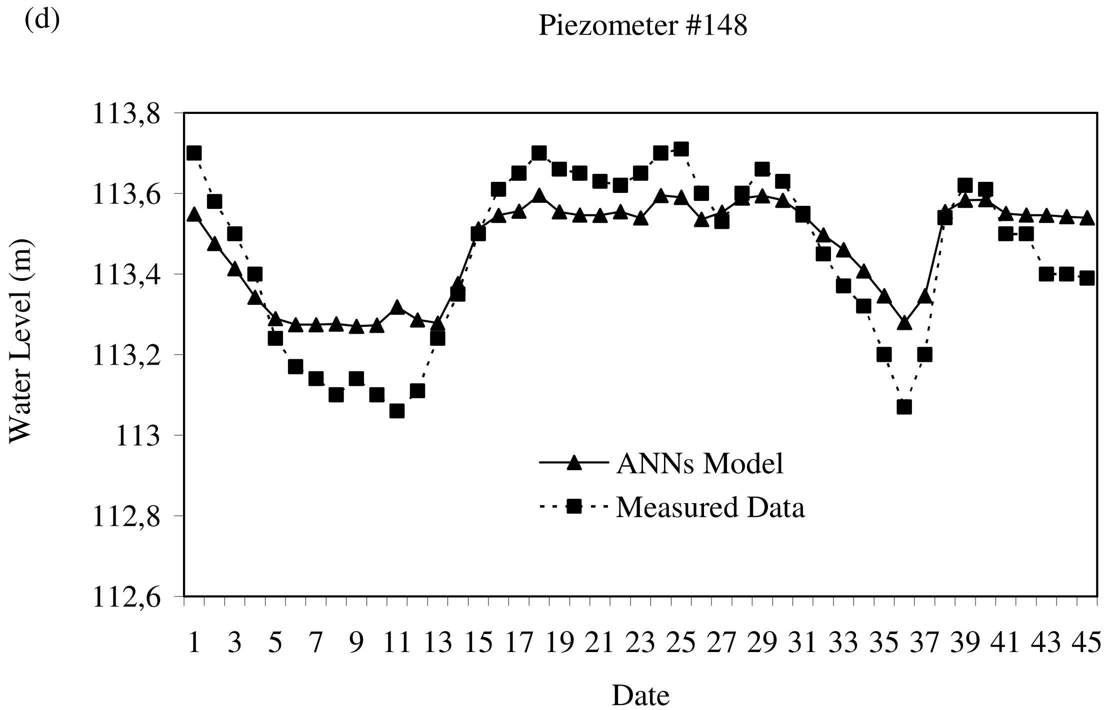


Figure 5.4. Calculated and Measured Water Levels at Piezometers (a) P37, (b) P38, (c) P39, (d) P148 for the Period 28.08.2000-20.05.2002. VALIDATION RUN.

For each piezometer case, to be able to evaluate the model performance the most commonly used error measures were computed as summarized in Table 5.6. and Table 5.7. These error measures are the mean absolute error (MAE) and the root mean square error (RMSE).

Table 5.6. Calculated Error Measures for the Calibration Run.

Piezometer #	RMSE (m)	MAE (m)
P37	0.26	0.20
P38	0.21	0.19
P39	0.26	0.24
P148	0.20	0.19
Average	0.2325	0.205

Table 5.7. Calculated Error Measures for the Validation Run.

Piezometer #	RMSE (m)	MAE (m)
P37	0.14	0.12
P38	0.14	0.11
P39	0.20	0.18
P148	0.11	0.09
Average	0.1475	0.125

Table 5.8. Results of R^2 values with different topologies (tansig:hyperbolic tangent function, logsig:sigmoid function); Number of training data is 125 and number of testing data which used in verification part is 45; Learning rate η is 0.02; Momentum term α is 0.1; Iteration number is 10000. Logsig or tansig activation function is used.

Number of Hidden Layers and Nodes in the Layers	Activation(Transfer) Function	R2 Value
1 (6-5-1)	tansig	0,86 (Calibrated) 0.84(Verified)
1 (6-5-1)	logsig	0,88 (Calibrated) 0.85(Verified)
2(6-3-3-1)	tansig	0,80 (Calibrated) 0.76(Verified)
2(6-3-3-1)	logsig	0,82(Calibrated) 0.79(Verified)
1 (6-4-1)	tansig	0,92 (Calibrated) 0.88(Verified)
1 (6-4-1)	logsig	0,95 (Calibrated) 0.93(Verified)
3 (6-3-3-3-1)	tansig	0,79 (Calibrated) 0.75(Verified)
3 (6-3-3-3-1)	logsig	0,80 (Calibrated) 0.79(Verified)

According to the results in Table 5.8., using 125 data as training set gave more accurate results. Since the system has trained by extra data set.

CHAPTER 6

CONCLUSIONS

In this study, artificial neural networks are used to study seepage through the body of an earthfill dam. For this purpose, MATLAB 6.0 Neural Network Toolbox is used. The water levels on the upstream and downstream sides of the dam were input variables and the water levels in the piezometers were the target outputs in the artificial neural network model. The ANN model was a feedforward neural network employing a sigmoid function as activator.Results generated from the networks are successfully compared with the measured data.

In this thesis several artificial neural networks models are constructed. The best and the most accurate results are found by using six input parameters with one hidden layer or two hidden layers and one output neuron and by using 125 training data set and sigmoid activation function. Using 125 data as training set gave more accurate results. Since the system has trained by extra data set. By using 111 training data set, one hidden layer and one output neuron, it was found good results, too. In this thesis as input six variables were used and using six input variables gave good results. It was found that using more data in the training leads to the better results. Thus, a feedforward three layer neural network model employing a sigmoid function as activation function and a back-propagation algorithm for network learning with an appropriate iteration number as 10000, learning rate as 0.01 is preferable according to the applications. In the future, this model can be applied to the different problems.

In addition, the ANN is a simple and convenient model to recognise the pattern between input and output variables if it is provided sufficient measured field data. The satisfactory prediction in time and space of the seepage path through the dam by the models indicate that these models can be employed to verify the piezometer readings to detect the anomalies in the course of seepage. The ANN has an ability to recognise the pattern between input and output variables. As presented in this thesis, it was able to capture pattern between the water levels in the upper and lower reservoirs and the water levels in the piezometers. Thus predicting the locus of the seepage path in the body of the earthfill dam is possible. However it is noted that the ANN is a black-box model, thus it does not reveal any explicit relation between the input and output variables. It lacks the extrapolation ability for the cases for which it is not trained.

As future work, when longer period of observation and as well as data physical characteristics of the dam become available the performance of the neural network may be further improved.

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