AN ARTIFICIAL NEURAL NETWORK MODEL OF THE CROCODILE RIVER SYSTEM FOR LOW FLOW PERIODS

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DECLARATION

I declare that this research report is my own, unaided work. It is submitted for the Degree of Master of Science in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in any other University.

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(Signature of candidate)

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ABSTRACT

With increasing demands on limited water resources and unavailability of suitable dam sites, it is essential that available storage works be carefully planned and efficiently operated to meet the present and future water needs.This research report presents an attempt to: i) use Artificial Neural Networks (ANN) for the simulation of the Crocodile water resource system located in the Mpumalanga province of South Africa and ii) use the model to assess to what extent Kwena dam, the only major dam in the system could meet the required $0.9m^3/s$ cross border flow to Mozambique. The modelling was confined to the low flow periods when the Kwena dam releases are significant.

The form of ANN model developed in this study is the standard error backpropagation run on a daily time scale. It is comprised of 32 inputs being four irrigation abstractions at Montrose, Tenbosch, Riverside and Karino; current and average daily rainfall totals for the previous 4 days at the respective rainfall stations; average daily temperature at Karino and Nelspruit; daily releases from Kwena dam; daily streamflow from the tributaries of Kaap, Elands and Sand rivers and the previous day's flow at Tenbosch. The single output was the current day's flow at Tenbosch. To investigate the extent to which the $0.9m^3/s$ flow requirement into Mozambique could be met, data from a representative dry year and four release scenarios were used. The scenarios assumed that Kwena dam was 100%, 75%, 50% and 25% full at the beginning of the year. It was found as expected that increasing Kwena releases improved the cross border flows but the improvement in providing the $0.9m^3/s$ cross border flow was minimal. For the scenario when the dam is initially full, the requirement was met with an improvement of 11% over the observed flows.

DEDICATION

This report is dedicated to my late father.
May his soul rest in peace.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude and indebtedness to Dr. J.G. Ndiritu for guiding this entire research effort and particularly for making critical but valuable comments that informed this research. It is difficult to figure out how this could have been achieved without his guidance and contribution. I also wish to extend my gratitude to the Department of Water Affairs and Forestry for allowing me to carry out this research and for the data they availed for me. I also take notice of the contribution from my colleagues and office mates; Mthokozisi Ncube, Paulo Kagoda and Zacharia Katambara for proof-reading most of the chapters in this report and for the moral support they extended to me.

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η	learning rate
α	momentum factor
n	epoch number
δ	a factor depending on whether neuron j is an output or hidden neuron
$Q_j^{(t)}$	output response from the neural network
Q_j	observed response
$\widehat{Q}$	mean of the calculated flow values
Q_{ave}	mean value of the observed flows
Q_{obs}	observed flows
Q_{cal}	computed flows
f	transfer function
q	number of neurons in the output layer
T_m	available total monthly abstraction
R_i	catchment wetness for i^{th} day of the month
R_T	wetness threshold
nd	number of days in the month where the catchment wetness is zero

CHAPTER 1

1. INTRODUCTION

Activities associated with the planning and operation of the components of a water resource system require knowledge of expected future performance. In the hydrologic component of the water resource, there is a need to know how the system will behave in both the short and long term in order to optimise the system or to plan for future modification i.e. decommissioning of system components or expansion. Many of these water resource systems are large in spatial extent and therefore their hydrometric data collection network is also very sparse with the result that there is almost always a considerable uncertainty in the available hydrologic information. This problem is also compounded by the non-linearity among the hydrologic variables, which makes the required modelling difficult.

The ability to simulate river flows quickly and accurately is of crucial importance in forecasting operations. Physically based hydrologic and hydraulic mathematical modelling approaches have been proposed for streamflow predictions, but there are complexities and difficulties in these modelling processes associated with obtaining the data they require. These have limited the scope and applicability of these traditional methods (Khalil *et al*., 2005). While conceptual models are important in understanding hydrologic processes, there are many practical situations such as streamflow forecasting where the main concern is making accurate predictions at specific watershed locations. In such a situation, a hydrologist may prefer not to expend the time and efforts required in developing and implementing a conceptual model or numerical model, but instead implement a simpler system theoretic model, such as Artificial Neural Networks (ANNs) (Eslami and Mohammadi, 2002; Dibike and Solomatine, 2001). There is therefore, a need to develop modelling approaches that capture the behaviour of the system using available data, are computationally robust, and could be used in real practical applications. Hydrodynamic models provide a good basis for this since they have the capability to simulate a wide range of flow situations (Shrestha *et al*., 2005). However, these models require accurate geometry of the river which may not always be available or easy to obtain in many locations. The other problem is that with hydrodynamic models, it is not possible to integrate observed data directly at desired locations to improve model results (Shrestha *et al*., 2005). During recent years, new technologies and algorithms have arisen as powerful tools for modelling several problems in hydrology and water resources. *Artificial Neural Networks* (ANNs) is one of them. ANNs have been used to successfully solve many different kinds of hydrological problems. A recent review can be found in the ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000). ANNs, being conceptually analogous to the biological neural network controlling the functions of the human brain, are highly interconnected networks of basic processing units, called neurons, and have weights associated with the links (or information pathways) between the neurons (Goswami and O'Connor, 2005). The ANN approach is essentially data driven and considered to be appropriate in situations where the overall transformation process and its sub-processes are not explicitly defined and satisfactory explanations of the physical relationships involved cannot be advanced (Coulibaly *et al*., 2000).

ANNs are beginning to have an impact on water resources and hydrologic modelling. According to Maier and Dandy (1997), ANNs were first introduced to the water resources community by Daniell (1991) who used them to predict monthly water consumption and to estimate flood occurrence. Since then, ANNs have been used for a variety of water resource applications. These include time-series prediction for rainfall forecasting (French *et al.*, 1992), reservoir inflow time series forecasting (Raman and Sunilkumar, 1995; Coulibaly *et al*., 2000), and rainfall-runoff processes (Riad *et al*., 2004, Hsu *et al.,* 1995 and Shamseldin, 1997), watershed sediment loss prediction (Saraingi and Battacharya, 2005). Khalil *et al*., 2005 used ANNs for forecasting basin water management and developed a model for predicting a seasonal streamflow, daily-required reservoir releases and hourly streamflow in the Sevier River Basin in Utah. ANNs have also been applied to areas such as deriving a general operating policy for reservoirs (Raman and Chandramouli, 1996), and prediction of water quality parameters (Maier and Dandy 1996). Odhiambo *et al.,* 2001 used neural networks fused with fuzzy logic to estimate daily evapotranspiration. They reported that the results found were comparable to those obtained using the FAO Penman–Monteith equation. Goswami and O'Connor, (2005) used ANNs for river flow simulation and forecasting in three catchments in North-West France, compared its performance with five "system-theoretic" models and one conceptual model. The ANN model was found to be the best performing for those catchments.

Eslami and Mohammadi (2002) applied ANNs for reservoir inflow forecasting in the Karaj river catchment in Iran. Using the results of the ANN model the inflow to the Amir Kabir reservoir was predicted fairly accurately. The other objective was to compare the ANN model with other two methods: Auto Regressive Integrated Moving Average (ARIMA) and regression analysis using forty years of data. Of the three methods the ANN performed best i.e. had smaller of errors than the others.

Coulibaly *et al*., (2000) used ANNs for daily reservoir inflow forecasting of Chute-du-Diable in Canada and compared it with two other methods: Auto Regressive Moving Average with exogenous inputs (ARMAX) and a conceptual model called PREVIS. The comparison of the results of the methods showed that in general the proposed ANN model had substantially better prediction accuracy. Shrestha *et al*., (2005), Bazartseren *et al*., (2003) and Imrie *et al*., (2000) applied the ANNs for flood flow prediction. Dawson *et al*., (2006) extended the application of ANNs in water resources to flood estimation in 850 ungauged catchments in the UK. When compared with multiple regression models, ANNs provide improved flood estimates that can be used by engineers and hydrologists. ANNs are data dependent and therefore do not impose any functional relationship between the independent and dependent variables. Instead, the functional relationship is determined by the data in the training process. Neural Networks have been used in water resources systems because they are able to learn relationships between input and output variables even when the underlying physical laws are unknown, use simple mathematical equations and easily adapt to solutions over time. When developing ANN models the statistical distribution need not be known (Zealand *et al*., 1999) and non-stationarities in the data such as trends and seasonal variations are implicitly accounted for by the internal structure of the ANNs (Maeir and Dandy, 1996). ANNs also have the advantage of being able to determine which model inputs are critical so that there is no need for prior knowledge about the relationships amongst the variables being modelled. Once they have been trained, they are easy to use and work well even when the training sets are incomplete. A thorough and extensive review of ANN applications in water resources can be found in Maier and Dandy (2000).

1.1 Problem Statement

Kwena dam is the major storage dam on the Crocodile River catchment in South Africa. The dam is used to support water supply to mainly irrigation at the same time maintaining a portion of the cross-border flow to Mozambique. The historical firm yield for the dam is only 71 million cubic metres per annum against irrigation demand of 403.6million m^3/annum mainly supplied from the run-of-river (Knight Piesold Consulting, 2005). Releases from the Kwena dam have to be made to supplement incremental catchment flow shortfalls to meet both the Ecological Water Requirements (EWRs) and the cross border flow.

The governments of South Africa and Mozambique have through the Inco-Maputo Agreement 29 agreed on $2.0m^3/s$ of flow at Komatipoort into Mozambique. $0.9m^3/s$ (45%) of this flow is expected to be supplied from Crocodile River while $1.1m^3/s$ (55%) is to be supplied from the Komati River. However, the Crocodile River does not meet its contribution of $0.9m^3/s$ most of the time. The current operation of the Kwena Dam seems to be adhoc and based mostly on the dam operator’s experience. Several modelling approaches have been used for the Crocodile system such as the hydraulic routing and the Water Resources Yield Model (WRYM). The hydraulic model is both data and computation intensive. While the WRYM obtains the long term yields working at a monthly time interval, the cross border requirement is specified at a daily time interval. This computational intensiveness coupled with the difficulty to integrate the WRYM with the hydraulic model for system operation optimization, has triggered the need to try some other modelling methods that could be less computation and data intensive and yet help as effectively in decision support.

1.2 Objectives

The main objective of this research project is to model the Crocodile River system using Artificial Neural Networks and to apply the developed model to investigate the extent to which Kwena Dam can be used to meet the $0.9 m^3/s$ required trans-boundary flow to Mozambique at the downstream end of the Crocodile River.

1.3 Methodology

Chapter 4 presents the detailed methodology and only a brief description is presented here.

The main steps followed were:

- Identification of the hydrometric variables required to meet the objectives. These then became the input and output components of the ANN model. The identified variables were streamflow, rainfall, temperature, river abstractions, and release from the Kwena dam.

- Development of the ANN model. This included the selection of the specific inputs, the number of hidden layers and the number of neurons in each hidden layer. As there are no fixed rules, the conceptual understanding of the system and consideration of how the ANN may be used in practice guided the development. There is no algorithm to use in selecting the number of hidden layers. Therefore, they were selected by a process of trial and error. One hidden layer has been found to be adequate in most situations. Several ANN topologies were experimented with before deciding on the final one. The experimentation included training and testing in which the performance of each topology was evaluated.

- Applying the model to evaluate the ability of Kwena dam in meeting the required 0.9 m^3/s cross border flow to Mozambique.

CHAPTER 2

2. STUDY AREA AND CURRENT OPERATING SYSTEM

2.1 Description of the Study Area

The Crocodile River catchment in Mpumalanga Province of South Africa is drained by the Crocodile River and its tributaries mainly Elands, Sand, White and Kaap rivers. The Crocodile River originates North of Dullstroom in the western parts of the catchment area and flows through mountainous terrain into the grasslands of the Lowveld. It then flows eastwards past Nelspruit and into the Komati River where it is called the Inkomati River at Komatipoort, just upstream of the Mozambique border. The Elands River on the other hand originates near Belfast. These two rivers join at Nelspruit, from where the Crocodile River flows further eastwards. The confluence of the Kaap and Crocodile Rivers is near Kaapmuiden in eastern Mpumalanga. Mountain ranges in the north and the south separate this sub region from the upper Komati River catchment and the Sabie River catchment.

The Crocodile River catchment (Figure 2.1) covers an area of 10450 km^2. Kwena dam, the only major storage in the catchment, commands about 10% of the catchment's runoff (DWAF, 2004) with a storage capacity of 159 million cubic meters. The catchment is dominated by irrigation and forestry. There is an estimated 42300 hectares of irrigation in the catchment and an estimated 1 775 km^2 of exotic forests. These two activities are also the major users of water in the catchment. Industrial water use in the catchment is limited and consists mostly of the Sappi paper mill at Ngodwana and the sugar mills at Malelane and Komatipoort. The water requirements of the Ngodwana paper mill are supplied from the Ngodwana Dam, which is situated in the Elands catchment, while the water requirements of the Malelane sugar mill are abstracted from the Crocodile

River. The urban requirements of the Crocodile sub-area are also mostly supplied from direct abstractions from the Crocodile River.

Rainfall varies from over 1 200 mm per annum to as low as 400 mm per annum in the lower eastern part of crocodile catchment (DWAF, 2004). The major dams found within the catchment are the Kwena dam on the Crocodile River, Witklip on the Sand River, Klipkopjes, Longmere and Primkop dams on the White river. Table 2.1 shows these dams and their capacities. The water resources of the dammed tributaries i.e. Sand and White rivers are already fully utilised and have very little contribution to the flow in the Crocodile River (Knight Piesold Consulting, 2005; http://www.dwaf.gov.za/). The Kaap and the Elands Rivers therefore have a direct contribution to both the irrigation requirements in their respective sub-catchments and flow at Tenbosch.

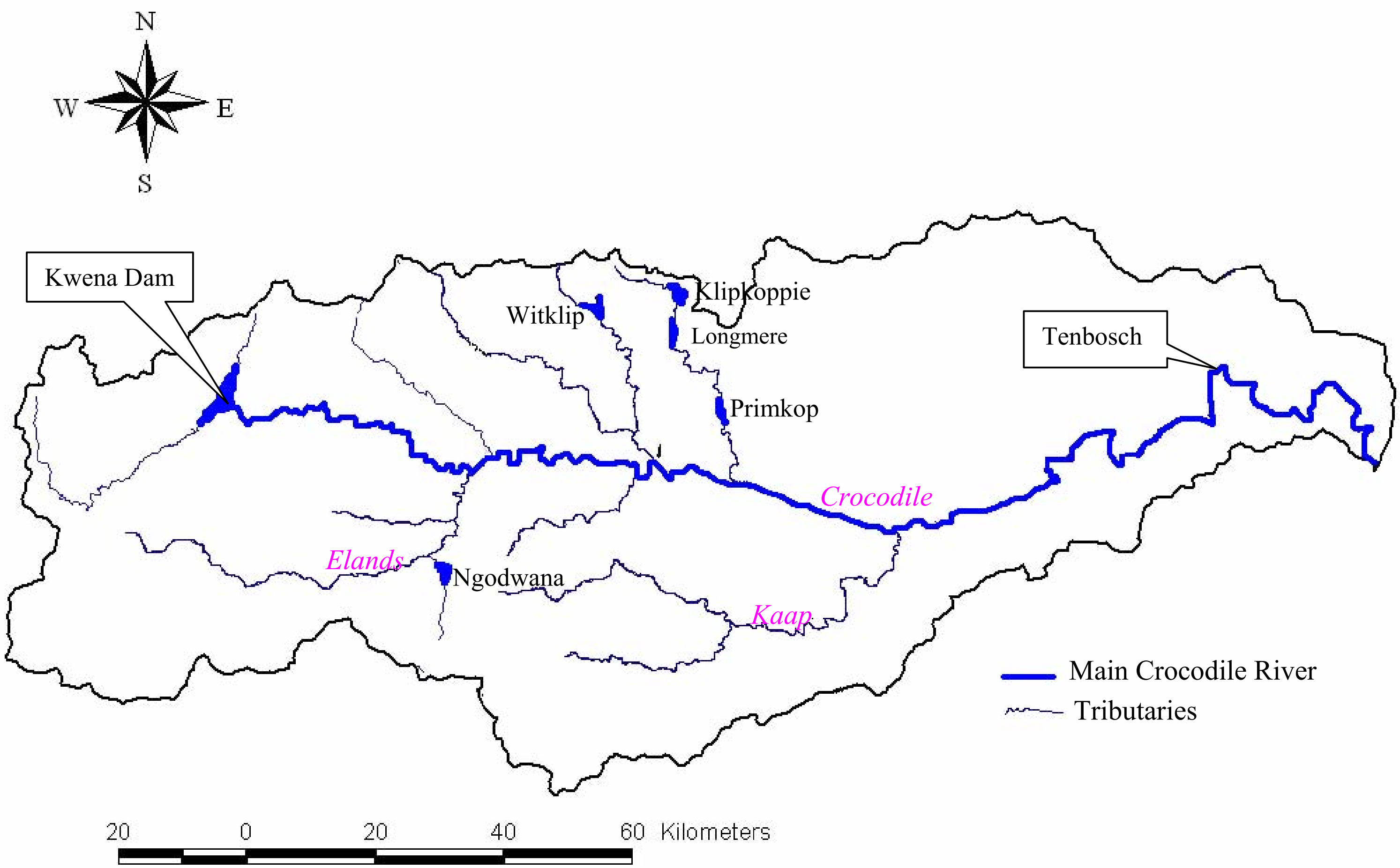

Figure 2.1: The Crocodile River catchment area

The development of water related infrastructure in the Crocodile River catchment has been dominated by agriculture while commercial afforestation has also had a significant indirect effect on the availability of water. Sugarcane and citrus and sub-tropical fruits are the main irrigated crops cultivated in the catchment.

The Crocodile River drainage area is the most developed of the four sub-regions within the Inkomati Water Management Area (IWMA). Large residential areas, agricultural development and forestry are the main features of this sub region. The greater part of the Lowveld is undeveloped and is situated in the Kruger National Park.

Table 2.1: Crocodile River Catchment dam and capacities

Dam name	**Capacity (million m^3)**
Kwena	159.00
Klipkopjes	29.63
Longmere	26.92
Primkop	16.32
Witklip	11.93

2.1.1 Temperature

The mean annual temperature in the Crocodile catchment area is approximately 17 °C. Maximum temperatures are experienced in January and minimum temperatures usually occur in June.

2.1.2 Rainfall

Peak rainfall months are December through January. The average hail day frequency for the IWMA ranges from 5 per annum in the west to less than 1 per annum in the east (DWAF, 2004). The mean lightning flash density ranges from 8 flashes per km^2 per annum in the south-western parts to 2 flashes per km^2 per annum in the eastern parts of the IWMA.

The highest annual rainfall occurs in the central parts, decreasing uniformly to the east and west. The maximum Mean Annual Precipitation (MAP) in the central parts is in excess of 1 200 mm, decreasing to a low of 600 mm in the west and 400 mm in the eastern parts with a coefficient of variation for the MAP of 24 % (DWAF, 2004).

2.1.3 Humidity

Humidity is generally highest in January and February (the daily mean relative humidity for the area is 69.8 % for these months) and lowest in July with a daily mean relative humidity of 58.6 %. In accordance with the rainfall pattern, the relative humidity is higher in summer than in winter.

2.1.4 Evaporation

Average potential mean annual evaporation (as measured by A-pan) for the area ranges from 1 600 mm in the southwest to a high of 2 000 mm in the eastern parts, with a mean value of around 1 900 mm. The highest A-pan evaporation is in January (approximately 203 mm) and the lowest in June (101 mm).

2.2 Catchment Water Demands

Water use in the Crocodile catchment is mainly for irrigation which accounts for almost 90% of total water demand in the catchment (National Water Resource Strategy, 2004). The urban and industrial demands are small compared to the irrigation demands. Table 2.2 shows a summary of the estimated irrigation demand imposed on the main Crocodile River (Knight Piesold Consulting, 2004).

Table 2.2: Summary of irrigation demands for Crocodile Catchment

Area	Area (ha)	Water allocation (million m^3/a)
Upstream Kwena dam	-	9.64
Montrose River Irrigation	12 000	95.71
Crocodile Poort (Karino)	8 200	65.52
Riverside Irrigation	14 600	116.85
Tenbosch Irrigation	10 500	115.88

Urban and industrial demands are summarised in Table 2.3.

Table 2.3: Summary of Urban and Industrial demands for crocodile catchment

Description	Water allocation (million m^3/a)
Urban Demands upstream of Kwena Dam	0.85
Nelspruit Municipality	10.10
Tenbosch Urban Demands	0.716

2.3 Current System Operation

The irrigation demand within the crocodile catchment area is supplied from the run-of-river. Releases are made from Kwena dam to supplement the available water from the run-of-river to meet the irrigation demands. Due to the long lag times for releases to reach the main irrigators, problems have been experienced in determining the correct releases from the dam to ensure all requirements are met without excess water crossing the border. At present releases from the dam to supply users along the river are based on the experience of the dam operators. The current irrigation demand imposed on the Crocodile catchment is estimated to be 403.6million m^3/annum. The decisions on water supply to consumers in the Crocodile catchment are made in May of each year with operating decisions based on 99.5% assurance of supplying the allocation for the next year.

The historical firm yield from Kwena Dam is estimated to be about 71million m^3/annum (Knight Piesold Consulting, 2005), which implies that farmers along the river are operating at a very low assurance of supply due to low tributary flows during times of drought. The Irrigation Board uses a spreadsheet mass balance model that determines the irrigation usage on a weekly basis. Irrigation allocation is based on the storage level in Kwena dam maintaining a minimum storage capacity in the reservoir. If the storage is low then there will be little or no irrigation allocation at all.

When river flow is less than the maximum irrigation demand, farmers are restricted to a maximum pumping rate of 120 hours per week. The maximum abstraction is not determined by the rate of flow but by the maximum number of hours. This however has the disadvantage that it favours farmers with high capacity engines who would not feel the impacts of the restrictions as they can still abstract the same amount of water within the 120 hours. Depending on the river flow levels, the irrigation restrictions can be adjusted every one or three days to match the varying river flow. These restrictions are lifted when a storm event increases runoff to above the local irrigation demand so that farmers can use as much water as possible to minimise spillage over and above the minimum required for the system. The minimum requirement from the Crocodile River and Komati River at the border with Mozambique is $0.9m^3/s$ and $1.1\ m^3/s$ respectively giving a combined minimum of $2.0m^3/s$. To obtain the required minimum flow at the border there is need to restrict irrigation and to increase water releases from Kwena Dam as the $0.9m^3/s$ requirement is not met all the time. Currently, management of the system focuses more on adjusting the irrigation demands than on adjusting releases from the Kwena Dam.

CHAPTER 3

3. ARTIFICIAL NEURAL NETWORKS

3.1 Introduction

An Artificial neural network is a technique that ‘mimics’ the functioning of the human brain, which contains billions of neurons and their interconnections. Humans can quickly recognise patterns, process data and learn from past experiences. ANNs are adaptive models that can learn from the data and generalise things learned to produce meaningful solutions to problems even when input data contains errors or are incomplete. In the real world, ANNs have been applied in image processing, grouping similar patterns, and solving constrained optimisation problems. In water resources management, ANNs’ applications are gaining momentum because of their power and potential in modelling complex non-linear problems. ANNs are attractive to use because of the following advantages (Jain and Singh, 2003; Zealand, *et al*., 1999; Jain *et al*., 1999)

a) They are able to learn relationships between input and output variables even when the underlying physical laws are unknown
b) Use simple mathematical equations
c) Adapt to solutions over time
d) Once they have been trained, they are easy to use
e) They work well even when the training sets are incomplete

3.2 History

The first theories on ANN techniques were conceived in the 1940s, and various relatively successful neural computers were built during the following two decades. Minsky and Papert (1969) in Dawson *et al*., (2006) showed that networks of any practical size could not be trained effectively. Due to improvements on existing techniques in combination with the increase of computational resources, interest in the applications of ANN increased significantly in the late 1980s. ANNs became popular with researchers when Rumelhart and McClelland (1986) rediscovered a testing method that could be used to train networks of sufficient sizes and complexities to be of practical benefit (Dawson *et al*., 2006). Since then, the field of ANNs has grown quickly, and the widespread applications of ANNs prove that their potential has been recognised in many fields such as earth sciences, engineering, economics, and health sciences.

3.3 Network Topology

Network topology refers to the number and organisation of the computing units, the types of connections between neurons, and the direction of information flow in the network. The node is the basic organisational unit of a neural network, and nodes are arranged in a series of layers to create the ANN. According to their location and function within the network, nodes are classified as input, output, or hidden layer nodes. Input layer nodes receive information from sources external to the neural network, and output layer nodes transmit information out of the neural net. Hidden layer neurons act as the computational nodes in the neural network, communicating between input nodes and other hidden layer or output nodes. The number of nodes in the input layer is equal to the number of independent variables entered into the network. The number of output nodes corresponds to the number of variables to be predicted.

3.4 Architecture of an Artificial Neural Network

The architecture of a single node is shown in Figure3.1.

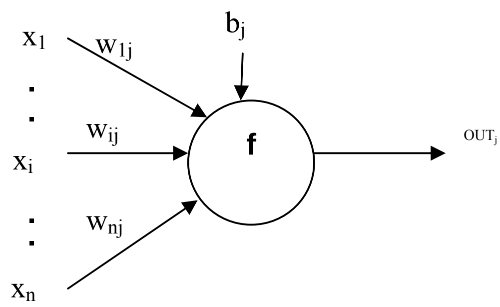

Figure3.1: Architecture of a single neuron

A node can have *n* inputs, x_i labelled from 1 through *n.* Each node has an input that is always equal to 1.0, called the *bias* (or threshold) and b_j is the threshold for node *j*. Each node *j* receives the information from every node *i* in the previous layer. A weight (w_{ji}) is associated with each input (x_i) to node *j* such that the effective incoming information (NET_j) to node *j* is the weighted sum of all incoming information. This is known as the net input and is presented as:

$$NET_j = \sum_{i=0}^{n} w_{ji} x_i \tag{3.1}$$

where x_0 *and* w_{j0} are the bias term and bias weights respectively

3.5 Transfer function

The transfer function, or squashing function, is applied to the net node input and introduces a non-linearity that determines the output of the node. This is achieved by passing the net effective input through a transfer function to produce the outgoing value OUT_j. The most commonly used activation functions are the sigmoid and the hyperbolic tangent function. The sigmoid function 'squashes' and compresses the range of the NET_i so that the OUT_j lies between 1 and 0 whereas the hyperbolic function's output is between -1 and 1. The logistic function which is common (Dibike and Solomatine, 2001; Zealand *et al*., 1999; Hsu *et al*., 1995) is expressed mathematically as (Jain and Singh, 2003):

$$OUT_j = \frac{1}{1+e^{(-NET_j)}} \tag{3.2}$$

The value of the output is bounded between 0 and 1 whereas the value of NET_j can vary from$\pm\infty$. The hyperbolic tangent function on the other hand is expressed as:

$$OUT_j = \frac{e^{(NET)} - e^{(-NET)}}{e^{(NET)} + e^{(-NET)}} \tag{3.3}$$

An ANN is a network of parallel, distributed information processing system that relates an input vector to an output vector. Networks with large number of neurons are frequently used for practical problems. The way the neurons have been structured determines how computations proceed from the input layer through the hidden layers to the output layer. Depending on the number of layers, ANNs can be single layer, bi-layer or multi-layer. The most widely used network structure in water resources is the multi layer and the feed-forward networks (Figure 3.2)

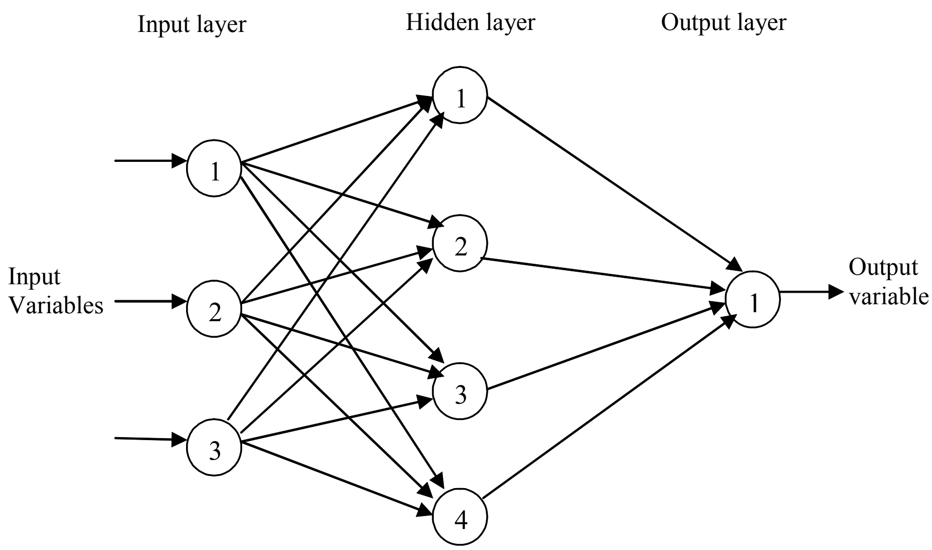

Figure 3.2: A three-layer feed-forward ANN

3.6 Feed-forward Artificial Neural Networks (FNN)

A feed-forward ANN derives its name from its structural makeup. It has an input layer, hidden layer(s) and an output layer. Information passes one way from input to output. Each neuron in one layer is connected to all the neurons of the next layer. The neurons in one layer are only connected to the neurons of the immediate next layer. The information is received by the input layer and, processed and passed on to the hidden layer where it is further processed and passed on to the output layer.

3.7 Error Back-propagation (BP) Algorithm

The error back-propagation (BP) is a supervised learning algorithm which is used to find weights in multi-layer feed-forward networks that utilise non-linear transfer functions and is based on a gradient descent algorithm. The back-propagation algorithm is the most practical and commonly used model for neural networks. The total weighted input at any neuron x_j and its output activity OUT_j

based on a selected transfer function is computed. The actual output is subtracted from the target output to find the output layer errors. The weights of all the neurons are adjusted by an amount that is proportional to the strength of the signal in the connection and the total measure of the error. The total error at the output layer is then redistributed backwards from the output layer through the hidden layer to the input layer. This process is continued until some stopping criteria are met. The goal is to find the weights with the smallest sum of squared error. A typical error function can be given as:

$$E = \sum_{p=1}^{N} \sum_{n=1}^{m} (Q_{obs,p,n} - Q_{cal,p,n})^2 \tag{3.4}$$

where $Q_{obs,p,n}$ is the observed value of the n^{th} neuron for the p^{th} data set, $Q_{cal,p,n}$ is the calculated output value of the n^{th} neuron for the p^{th} data set, N is the total number of patterns (observations), and m is the total number of output neurons. In the BP training, minimisation of E is attempted using the steepest descent method and computing the gradient of the error function by applying the chain rule on the hidden layers of the ANN (Coulibaly, 2000). This algorithm updates the interconnection weights Δw_{ji} using the derivative δ_j in the following manner:

$$\Delta w_{ji}(n+1) = -\eta \delta_j x_i + \alpha \Delta w_{ji}(n) \tag{3.5}$$

where η = learning rate; α = momentum factor; n = epoch number; and derivative δ = a factor depending on whether neuron j is an output neuron or a hidden neuron. An epoch is defined as one cycle of training using the considered data set. For the j^{th} neuron in the output layer,

$$\delta_j = \left(\frac{df}{dnet_j} \right) [Q_j^{(t)} - Q_j] \tag{3.6}$$

in which Q_j = observed response and $Q_j^{(t)}$ = output response from the neural network and f = transfer function. For the j^{th} neuron in the hidden layer

$$\delta_j = \left(\frac{df}{dnet_j}\right)\sum_q {}_{qj}\,\delta_q \tag{3.7}$$

where q = number of neurons in the output layer.

The momentum factor controls the speed of training whereas the learning rate steps the weight change and can be adjusted to decrease the chance of the algorithm being trapped in a local minima. The standard error back-propagation, three-layered ANN is depicted in Figure 3.3.

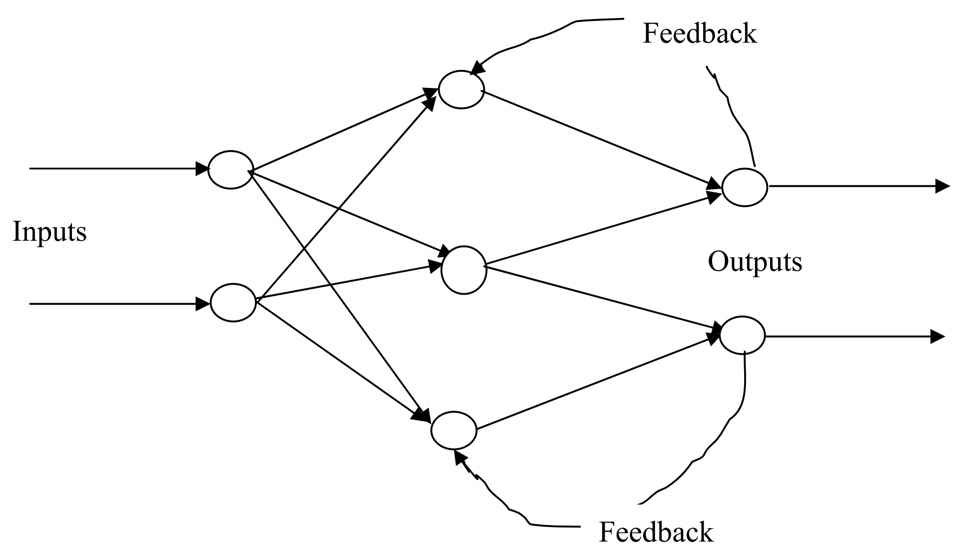

Figure 3.3: Simple error back-propagation ANN

The learning process in the BP is done through sequential or batch mode. In the sequential mode the learning is governed by the error of each data set one by one while for the batch mode weights at each iteration are adjusted after all data sets have been processed.

3.8 Training an Artificial Neural Network

ANNs are trained by applying an optimisation algorithm, which attempts to reduce the error in the network by adjusting the matrix of network weights and the neuron biases (De Vos and Rientjes, 2005). Once a network has been structured for a particular application, that network is ready to be trained. Training a network is a procedure during which an ANN processes a training set (input-output data pairs) repeatedly, changing the values of its weights, according to a predetermined algorithm, to improve its performance (Zealand *et al*., 1999). The objective of training is to determine the set of weights and thresholds such that for an input signal the ANN output is as close to the desired output as possible. To start this process, the initial weights are chosen randomly. Then, the training, or "learning", is initiated. It is assumed that the neural network has no prior knowledge about the problem before being trained. When the network weights are changed, the data transfer through the ANN changes and the network performance changes. Multilayer feedforward neural networks, like other non-linear estimation methods can suffer from either underfitting (where too much hidden nodes fit the noise) or overfitting (insufficient hidden nodes failing to detect regularities in the data set). Underfitting produces excessive bias in the model outputs whereas overfitting produces excessive variance. To avoid overfitting and underfitting, a stop training approach is used. The most popular stopping criterion involves a trade-off between training time and generalisation error (De Vos and Rientjes, 2005; Sivakumar *et al*., 2002, Coulibaly, 2000).

The available data is split into three parts:

a) a *training set*, used to determine the network weights ;
b) a *cross validation set*, these are separate data sets used during the training process to estimate the network performance and decide when the training is to stop
c) a *testing data* set, independent sets of data, not used in training or validation and are used to verify the effectiveness of the stopping criterion and to estimate the expected performance of the ANN.

During training, the output predicted by the network is compared with the actual (desired) output and the mean squared error (MSE) between the two is calculated. As more and more data are presented to the network, the results keep on improving until a suitable weight combination is found and the prediction error of the testing data is minimised. At this stage the ANN is considered trained.
There are two approaches to training: supervised and unsupervised. Supervised training, which is common in water resources applications, involves a mechanism of providing the network with the desired output either by manually grading the network's performance or by providing the desired outputs with the inputs. Unsupervised training is where the network has to make sense of the inputs without outside help. Unsupervised training is used to perform some initial characterisation on inputs.

3.9 Learning Parameters

Learning rate –The learning rate determines the absolute size of the weight change during learning and limits or expands the extent of weight adjustments in a training cycle. A high learning rate reacts quickly to input changes, and can make networks unstable if the rate is too high-the changes can be too extreme and cripple the network's prediction ability. However, if the learning rate is too low, the network training time is substantially increased. A high learning rate is useful to accelerate learning until the weight adjustments begin to plateau. However, the higher learning rate increases the risk that the weight search jumps over a minimum error condition, which could jeopardise the integrity of the network and cause back-propagation learning to fail.

Momentum factor – The momentum factor describes the proportion of the weight change that is added to each subsequent weight change. Low momentum causes weight oscillation and instability, preventing the network from learning. High momentum factor cripples network adaptability. For stable back-propagation, the momentum factor should be kept less than unity. Momentum factors close to unity are needed to smooth error oscillations when they occur. During the middle of training, when steep error slopes often occur, a small momentum factor is optimal, whereas towards the end of training a large momentum factor is desirable.

Training Tolerance -This is the margin of error permitted when training target values are compared with the values generated by the network during supervised training. A training tolerance factor of zero is the most desired since it indicates that the network values exactly match the target values. The higher the training tolerance factor is, the more inaccurate the neural network will be. ANNs generally use more parameters than conventional statistical methods and are therefore susceptible to overtraining when too much data is presented to the network. The network is overtrained when the mean squared error increases as the network trains at predicting the test values. This indicates that the network's ability to recognise new patterns and generalise unknown data sets is hampered. The simplest method of correction to the overtraining phenomenon is to train the model with only part of the data and use the rest to check the network's performance.

3.10 Summary of computational functions of ANN elements

The computational functions of the neural network consist of the operations of the individual neurons and the way they are connected. Individual neurons calculate an output using the sum of inputs and a selected activation function. These nodes specifically perform the following functions:

1. Signals are received from other neurons [x_0, x_1, x_2, x_i x_n] (Figure 3.3)
2. The signals are multiplied by their corresponding weights [w_0x_0, w_1x_1, w_2x_2, w_ix_i.. … w_nx_n]
3. The weighted signals are summed [Sum=$w_0w_0+w_1x_1+w_2x_2 +\ldots+w_ix_i+ \quad w_nx_n$]
4. The calculated sum is transformed by an activation function [f(sum)]
5. The transformed sum is sent to other neurons and steps 1-4 above are repeated for those neurons.

The input into a node or neuron is either the direct input from a source exterior to the network or the weighted sum of the outputs from nodes in the layer above. If weight (w_{ji}) is negative, the output from the node will generally decrease. A positive (w_{ji}) excites the neuron. OUT_j (Eqn. 3.2) is an output from node j, and b_j is the threshold for node j. The threshold term is the input to a node when no other input exists. The threshold term is also known as the bias term.

3.11 Performance criteria

A survey of recent literature describing ANNs applications to rainfall-runoff modelling exhibits a general lack of a modelling protocol (Dawson and Wilby, 1999). There is no convention for the error measures that are employed (e.g. mean squared error, relative errors etc). The objective of training in the building of the ANNs is to produce a set of connection weights that cause the outputs to match themselves as closely as possible to the observed system outputs for every set of the training data sets. Achievement of this objective is measured in many different ways e.g. the Nash-Sutcliffe coefficient of efficiency (R^2) (Nash and Sutcliffe, 1970), which is formulated as:

$$R^2 = 1 - \frac{F}{F_0} \tag{3.8}$$

where

$$F = \sum_{n=1}^{N} (Q_{obs}(i) - Q_{cal}(i))^2 ; \tag{3.9}$$

$$F_0 = \sum_{n=1}^{N} (Q_{obs}(i) - Q_{ave})^2 \tag{3.10}$$

where F_0 is the initial variance for the flows and F is the residual model variance. In the equations, N is the total number of data sets, Q_{obs} and Q_{cal} is the observed and computed flows respectively at the nth interval, Q_{ave} is the mean value of the observed flows.

The accuracy of the model simulation can also be evaluated using other error indicators such as: mean absolute error (MAE), defined as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(Q_{obs}(i) - Q_{cal}(i)\right|; \tag{3.11}$$

To quantify the errors in terms of the units of the variable, the Root Mean Square Error (RMSE) is used and is defined as:

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}\left[Q_{obs}(i) - Q_{cal}(i)\right]^2\right]^{1/2} \tag{3.12}$$

and coefficient of correlation which is formulated as:

$$r = \left\{\frac{\sum_{i=1}^{N}(Q_{obs}(i) - Q_{ave})(Q_{cal}(i) - \widehat{Q})}{\left[\sum_{i=1}^{N}(Q_{obs}(i) - Q_{ave})^2\right]^{1/2}\left[\sum(Q_{cal} - \widehat{Q})^2\right]^{1/2}}\right\} \tag{3.13}$$

where $\widehat{Q}$ is the mean of the simulated values. The correlation coefficient is not a measure of the predictive capabilities of the model since it is sensitive to outliers and spurious data.

To overcome susceptibility to extreme values, the index of agreement, *d,* which is less sensitive to large values (Khalil *et al*., 2005), can also be used and is defined as:

$$d = 1 - \frac{\sum_{i=1}^{N} \left| (Q_{obs}(i) - Q_{cal}(i) \right|}{\sum_{i=1}^{N} \left[(Q_{obs}(i) - \hat{Q}) + (Q_{cal}(i) - \hat{Q}) \right]} \tag{3.14}$$

The other physical performance measure used is the bias, which is the average of the differences between observed and predicted values. A complete assessment of the model should also include scatter plots. The magnitude of the scatter of observed versus simulated about a 45 degree line can be examined using error bounds to assess the deviation of simulated outputs from observed system behaviour.

3.12 Advantages and Disadvantages of Artificial Neural Networks

Advantages

a) ANNs can learn similarities among patterns directly from input-output data sets presented to them and can modify their behaviour in response to the environment i.e. they self-adjust to produce consistent responses.

b) They are good at abstracting essential characteristics from inputs containing irrelevant data

c) They can easily derive solutions from data without prior knowledge of the regularities in the data; they extract the patterns empirically

d) ANNs are non-linear and can solve some complex problems more accurately than linear techniques do

e) ANNs can generalise from previous examples to new ones, a feature that is important since for many practical problems, data are noisy and often incomplete

f) Due to their structural make up, they have relatively low computational demands and can easily be integrated with other techniques. They contain many identical, independent operations that can be executed at the same time thereby making them faster than alternative methods.

Disadvantages

a) A disadvantage of ANNs is that the optimal form of most design parameters such as the number of processing elements in the hidden layer can differ for each application and cannot be theoretically defined. They are commonly found by a trial and error procedure. As a result they may fail to produce a satisfactory result, perhaps because there is no learnable function or the data sets are insufficient.

b) The other problem is that at the training phase, the minimisation of the error does not necessarily imply good operational performance.

c) ANNs cannot cope with major changes in the system for which they were not trained since they use historical data. If there are major changes in the system they will have to be adjusted for the new environment.

CHAPTER 4

4. DATA ACQUISITION AND PROCESSING

The Department of Water Affairs and Forestry (DWAF) is the custodian of all hydrological data in South Africa. In carrying out this research, available hydrological and meteorological data from the DWAF and South African Weather Service were used as inputs to the neural network model. The software used for this study is NeuroSolutions (version 5.0) developed by NeuroDimension, Inc. The particular version used to run the simulation is the NeuralExpert environment module.

4.1 Relevant Data Sets

In line with achieving the objectives, the following data were considered necessary

4.1.1 Rainfall

Daily rainfall measurements are available at different locations across the catchment. Within the whole catchment there are many rainfall measuring stations. However, some stations have been deserted and are closed and no longer used whereas some are not in the South African Weather Service database as they belong to individual farmers. They are available in the report to the Water Research Commission by Schultze and Maharaj (2004). For this study, only rainfall measurements at the stations shown in Table 4.1 and Figure 4.1 were used. These stations were selected on the basis of their good length of record and were considered representative of most of the catchment area.

Table 4:1: Rainfall stations used for investigation

Station No.	Place	Coordinates (E , S)
0557710S	Tenbosch	-25.33°,31.90°
0556178W	Montrose	-25.47°,31.07°
0554682W	Karino	-25.37°,31.40°
0557115W	Riverside	-25.42°,31.60°

4.1.2 Streamflow

Continuous daily historical streamflow data for different gauge stations within the catchment were obtained from the Department of Water Affairs and Forestry (DWAF).These stations are shown in Figure 4.1. A description of the station selection criteria is given in section 4.2.

4.1.3 Temperature

Temperature directly affects evaporation, which has a direct impact on streamflow. Its inclusion was to enhance the model performance. Daily minimum and maximum temperatures from Shultze and Maharaj, (2004) were available. These were averaged and their daily averages used as inputs to the model. Temperatures were used instead of evaporation as some stations did not have a complete record of evaporation records. The temperature does not vary much over the catchment and therefore a decision was taken to use only two stations as inputs.

4.1.4 Irrigation Demands

Irrigation demands represent the quantities of water that farmers abstract from the river. However, it was found that daily abstraction data for irrigation is not readily available from DWAF. Some irrigators had some data that may have been useful but were not willing to share it. After spending considerable effort searching for the abstractions data, the only available data was for monthly abstractions for the year 2003/04 which was availed by Professor Basson of the University of Stellenbosch who had previously done hydraulic modelling of the Crocodile River. Although there are more abstraction points, the data was lumped for groups of abstractors and was available for four locations along the river as shown on Figure 4.1. Since the modelling required a daily time step, the monthly abstractions needed to be disaggregated into daily abstractions. A simple model was developed for this purpose (Appendix A).

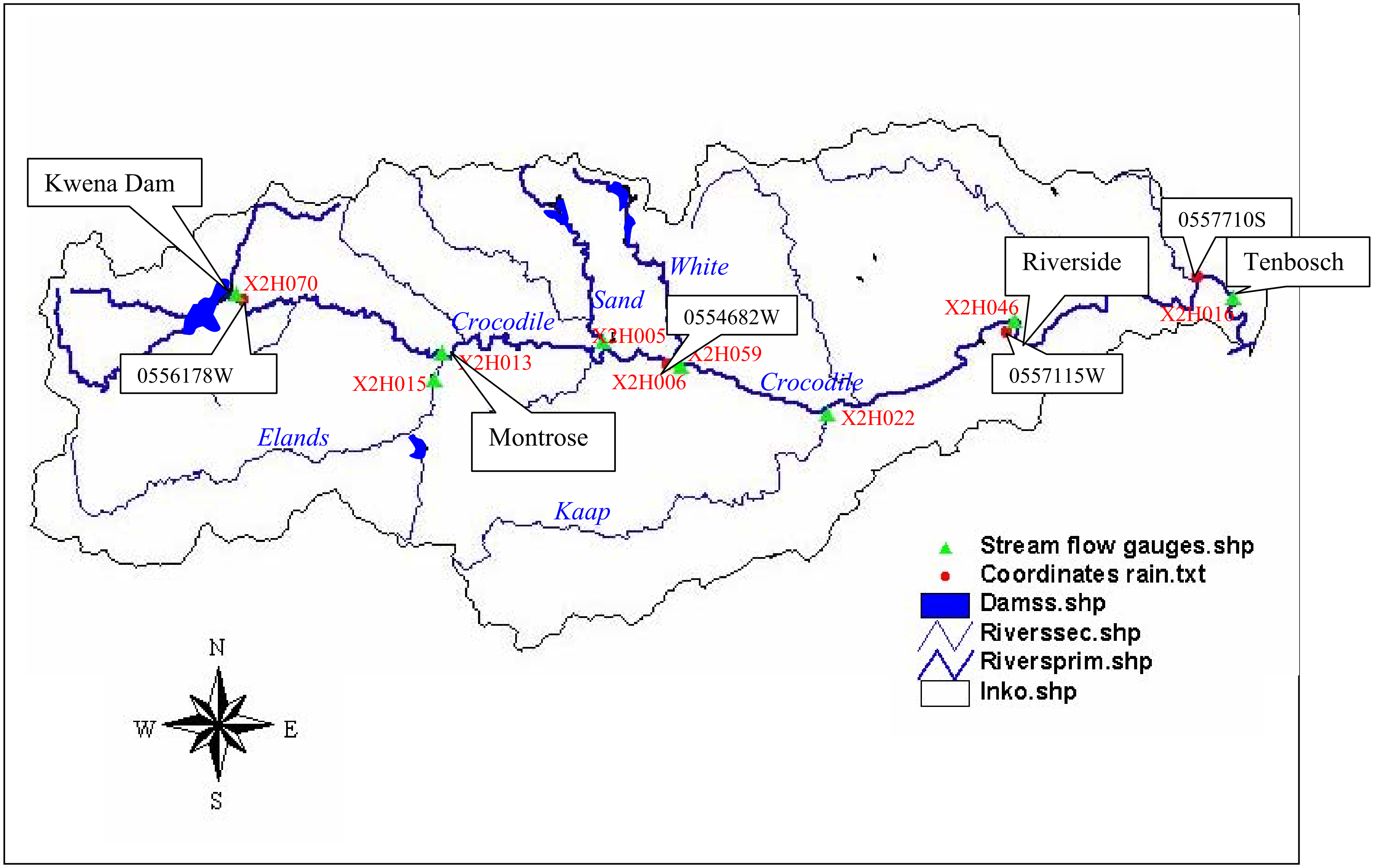

Figure 4.1: Stream flow and rainfall gauge stations within the catchment area

This simple model, which is derived in **Appendix A**, assumes that on a day where the rainfall was more than a threshold, the farms were adequately wet and there was therefore no abstraction. This threshold was considered to depend on the daily crop irrigation demand. Sugarcane, the crop demanding the most water in the Crocodile catchment, has an annual water requirement of approximately 1200mm (Cartwright, 2005, pers. comm.), which translates into 3.28 mm of daily rainfall. A value of 4 mm was subjectively selected as a reasonable threshold. Equations 4.1 to 4.3 describe the model.

$$\text{If } 0 < R_i < R_T \text{ then } Abs_i = \frac{R_T - R_i}{R_T} * Ave*; \qquad (4.1)$$

- If $R_i = 0$; then $Abs_j = Ave*$
- If $R_i \geq R_T$; then $Abs_i = 0$
- Where Abs_i is the daily abstraction, R_i is the catchment wetness for the i^{th} day of the month; and R_T is the wetness threshold.

$$Ave* = \frac{T_m}{\sum_{i=1}^{nr}\left(\frac{R_T - R_i}{R_T}\right) + nd}; \qquad (4.2)$$

- where T_m is the available total monthly abstraction; *nr* is the number of days in the month with catchment wetness greater than zero but less than the threshold R_T, and *nd* is the number of days in the month where the catchment wetness is zero.

The catchment wetness was obtained as

$$R_i = r_i + 0.75r_{i-1} + 0.5r_{i-2} + 0.25r_{i-3} \qquad (4.3)$$

where R_i is the catchment wetness and r_i is the rainfall on the i^{th} day. Figure 4.2 shows an example of the disaggregated Tenbosch abstraction for January 1988.

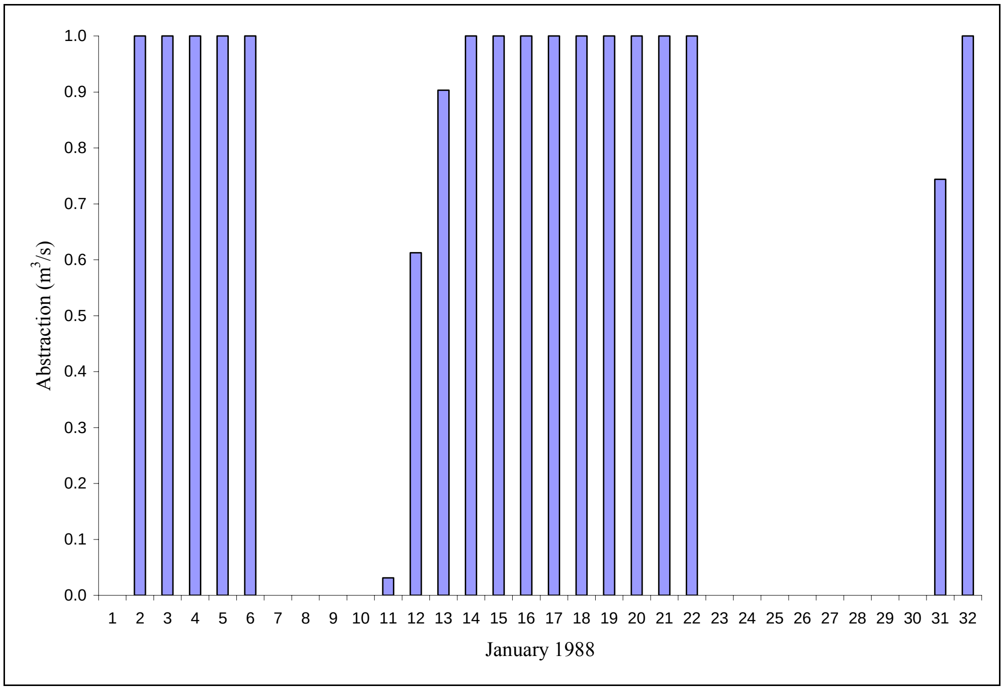

Figure 4.2: Modelled daily river abstractions for Tenbosch January, 1988

4.2 Riverflow Analysis and Selection of Gauge Stations

There are a number of rivers and streams within the Crocodile River Catchment. However, not all of them are gauged. Only the streams and rivers that have gauge stations were used for the analysis. Daily stream flow measurements are available for the different river gauging stations in the respective rivers used in this research. The different river gauging stations have different start dates of flow measurement. Table 4.2 shows the gauging stations and their available records of streamflow measurement and Figure 4.1 shows their locations in the catchment. The stations used for this investigation are the station numbers X2H070 (Kwena Dam outflow), X2H006 at Karino, X2H013 at Montrose, X2H016 at Tenbosch in the Crocodile River, X2H015 at Landenau in the Elands River, X2H022 at Dalton in the Kaap River, X2H005 at Boschrand in the Sand River (X2H005). These stations were selected on the basis of their better records of streamflow measurement. In addition to that, stations X2H022, X2H005 and X2H015 were selected as they are at the confluence of the tributaries with the main river and therefore give the amount of contribution of these tributaries.

Table 4.2: Streamflow measurement stations within the Crocodile River catchment

Station No.	**Location**	**Available Record**
X2H005	Sand River at Boschrand	1929 - 2004
X2H006	Crocodile River at Karino	1929 - 2004
X2H015	Elands River at Lendenau	1959 - 2004
X2H016	Crocodile at Tenbosch	1960 - 2004
X2H022	Kaap River at Dalton	1960 - 2004
X2H046	Crocodile River at Riverside	1985 - 2004
X2H070	Kwena Dam outflow	1979 - 2004

Table 4.2 shows a staggered pattern in the start dates of the streamflow gauge stations. The Kwena dam, one of the main focus areas in this research project has records starting from 1979. Two other stations, Riverside (X2H046) and Goede Hoop (X2H059), have records starting after the year 1979. Even though some of the stations have long lengths of records, they are not free from what has become a part of streamflow measurement i.e. gaps of missing records. To overcome the problem of gaps, normally the data is patched to generate a good time series of the records. In this case the seasonal means over the considered data range were used to fill up the gaps. The daily runoffs of a particular day of a particular month over the period of interest were summed up and averaged by dividing by their number. The average was then filled into the gaps as flows for those particular days where there was missing data.

The most important points within the catchment are the Kwena dam and the streamflow gauge station at Tenbosch (X2H016). The significance of the Kwena dam is that it is the main surface water storage within the catchment and is used to augment flow at Tenbosch to meet the international agreement with Mozambique. The releases from the dam can be controlled whereas flows from the tributaries cannot be easily controlled with a view to meeting the Tenbosch flow requirements. The Tenbosch station is the last streamflow monitoring station in the Crocodile River and is located approximately 5 kilometres from the confluence of the Komati River which is at the boundary between Mozambique and South Africa. Accurate flow measurements at this station are of critical importance for catchment management and operational purposes.

In order to meet the international agreement with Mozambique, a minimum flow of $0.9m^3/s$ must be sustained at this station to ensure a sufficient contribution towards the cross border requirements. Flow measurements at the Kwena dam started in the year 1979 whereas for Tenbosch they started in 1960. The author, therefore, initially took a decision to use data points from 1979 to 2000 for all the gauging stations. Within this period, there was a very huge variation in terms of the low and the high flows, which is attributed to cycles of droughts and floods respectively. The maximum flow recorded for this station (Tenbosch) was 1169 m^3/s whereas the minimum was $0.00m^3/s$. A preliminary ANN trial testing with these data did not bear any good results i.e. the ANN could not extract any meaningful patterns within them and tended to overestimate low flows. This range was then cut down further to include data series from 1985 to 1996 yielding 4015 data sets; a range that is between two high floods. The consideration was to ensure that all the input data sets start at the same time of record. Within this section of the data, the few gaps were filled with the seasonality means of the time period considered. Figure 4.3 shows flow time series for Tenbosch from 1980 to 1996.

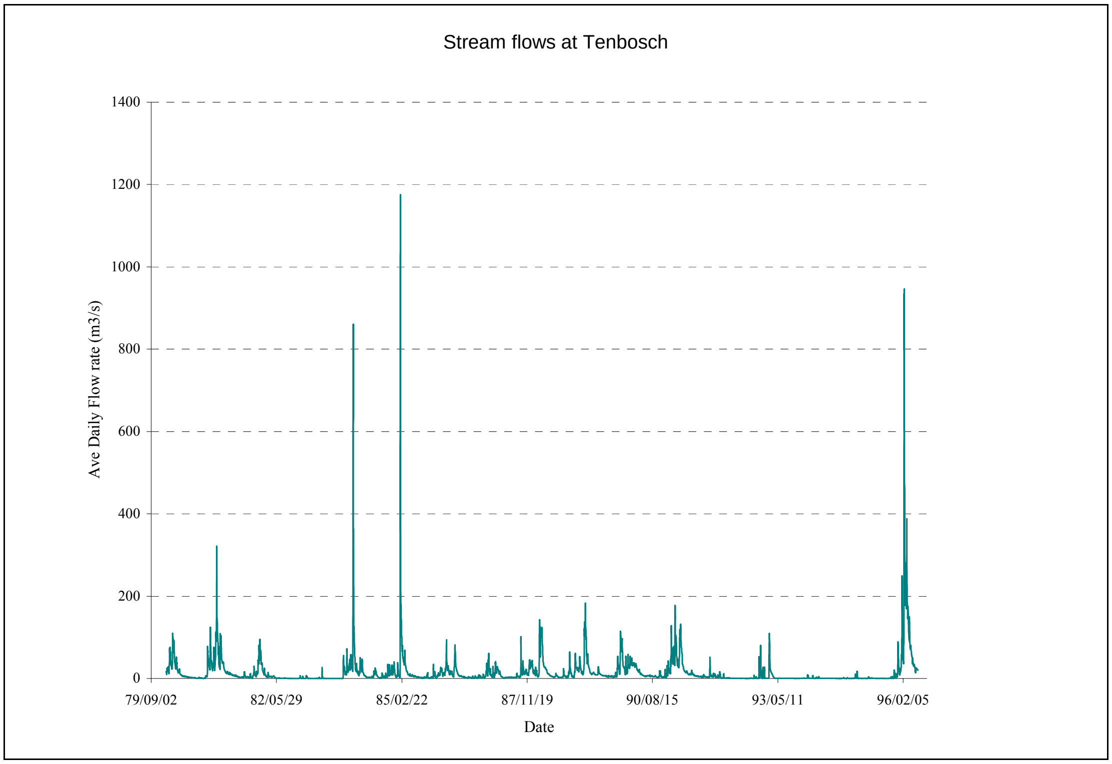

Figure 4.3: Daily River flow series at Tenbosch from 1980 to 1996

As can be seen from the graph, the river flow series exhibits significant variations although an annual cycle is evident. A thorough inspection of the data for this station shows that there are gaps within the series some of them too long to be ignored. Artificial Neural Networks approaches belong to the so-called 'black-box' models, and depend primarily on good training and learning of the data sets to establish relationships between the input and output. As such it is imperative to select a very good training set from the available data series. The best way to do this is to include all or most of the extreme events (high and low flows) in the training sets. The inclusion of biased samples in the training sets is not recommended since these increase the training times without necessarily improving the results (Sivakumar *et al*., 2002).

In so far as meeting the flow requirements at Tenbosch is concerned, Kwena dam only becomes significant in the dry seasons when flows are low and do not meet the minimum flows of 0.9m^3/s into Mozambique. During times of high flows this requirement is met most of the time and all demands are met. Figure 4.4 shows a portion of flow time series at Tenbosch for drought years between 1990 and 1996 and corresponding releases from Kwena dam clearly showing that Kwena releases are significant only in the low flow periods.

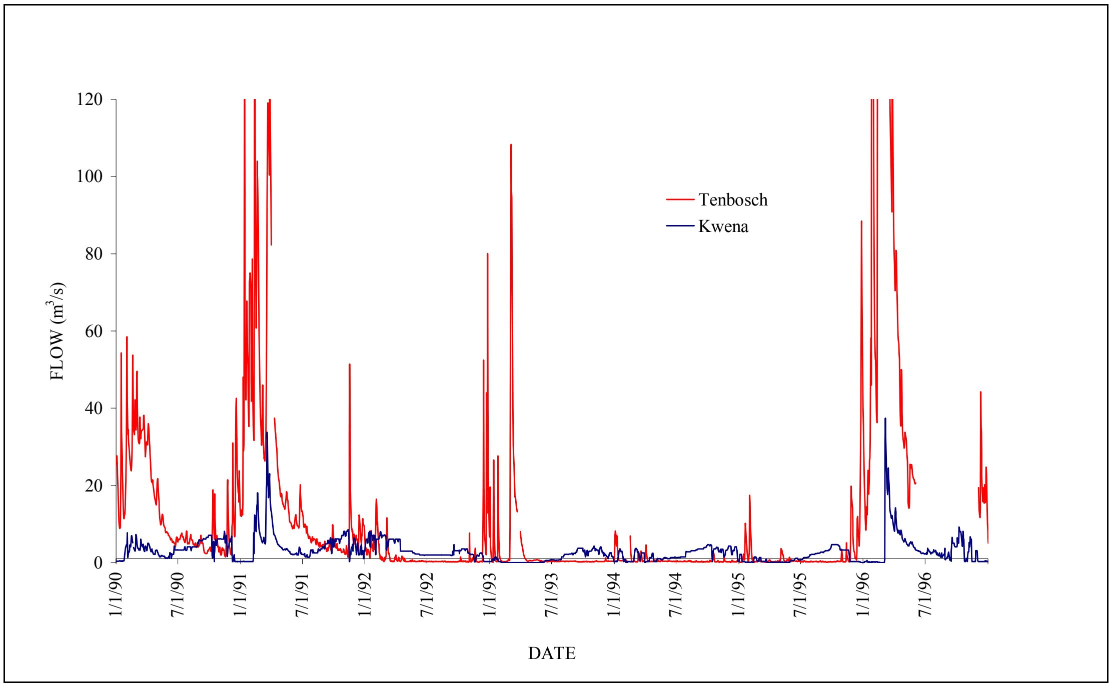

Figure 4-4: Flows at Tenbosch and Kwena dam releases (from 1990-1996)

Based on the foregoing, the analysis considered only times of low flows. An arbitrary threshold flow value of 4m^3/s at Tenbosch was selected. The rationale behind this selection was such that the flows are not too high but at the same time their selection should be that they allowed for a good number of data sets to be used for training the network. Further more, the value of 4m^3/s is reasonably higher than the 0.9 m^3/s requirement. All the flows less than this value within the period from 1985 to 1996 were used for analysis. A spreadsheet was set up in Excel that returned only values of flow less than the threshold of 4.0m^3/s. However, in some cases values just over this value were also considered and included in the analysis to avoid short discontinuities of the series. The result of this exercise was a flow time series consisting of 1956 data sets as shown in Figure 4.5. As can be seen from the graph, this is a complex discontinuous time series. The first one third of the series is reasonably less variable and in most cases meets the cross boundary requirement of 0.9 m^3/s whereas the last two thirds contains very low flow values and in most cases below the flow requirement. It is at times like these that the Kwena dam becomes very important as some water has to be released from the dam to augment the low river flow.

In view of the foregoing, it was then decided to divide the data sets in the following manner: of the 1956, 1272 data points which represent 65% were selected for training; 392 data points accounting for 20% were used for cross-validation whereas the remaining 15% were used for testing (Figure 4.6). Although the $4m^3/s$ threshold was used, there were a few missing points in both the cross validation and testing series which for practical purposes were taken as a continuous series. The selection of these percentages of the data points in this manner was so that all the extreme points (high and low values) especially for training are covered. A training data that has only high values tends to drive the simulation towards high values and performs badly on low values whereas the one with very low values tends to drive the simulation towards very low values and performs badly on high values (Savikumar *et al*., 2002)

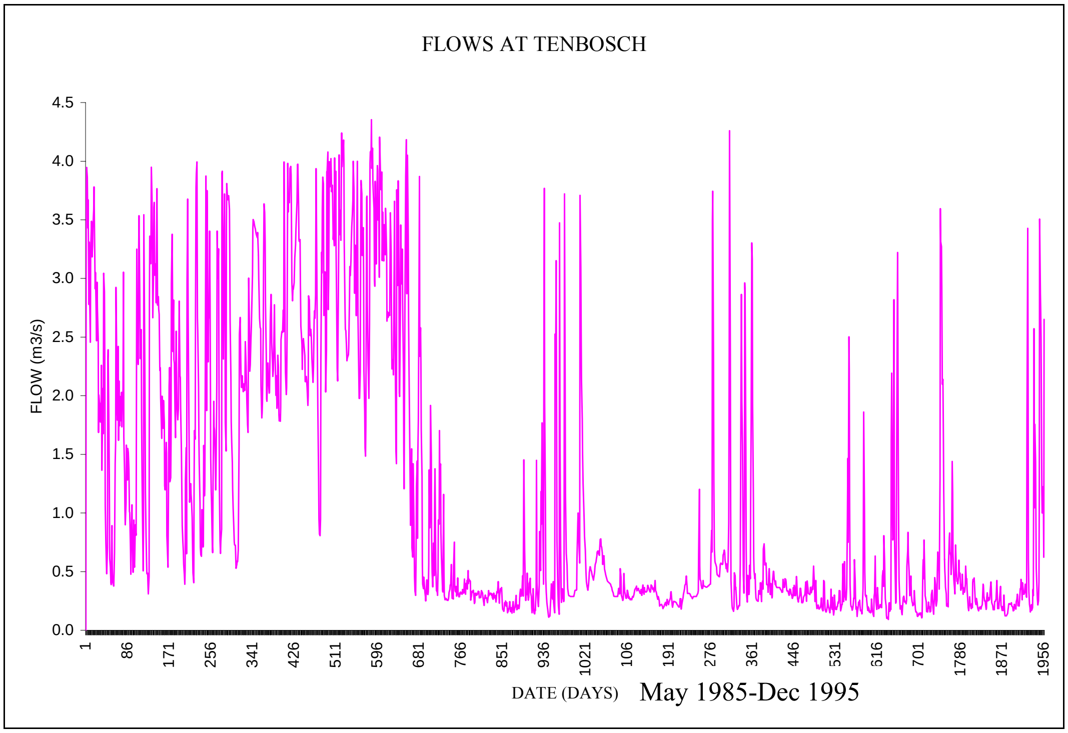

Figure 4.5 Time series flow at Tenbosch for dry periods

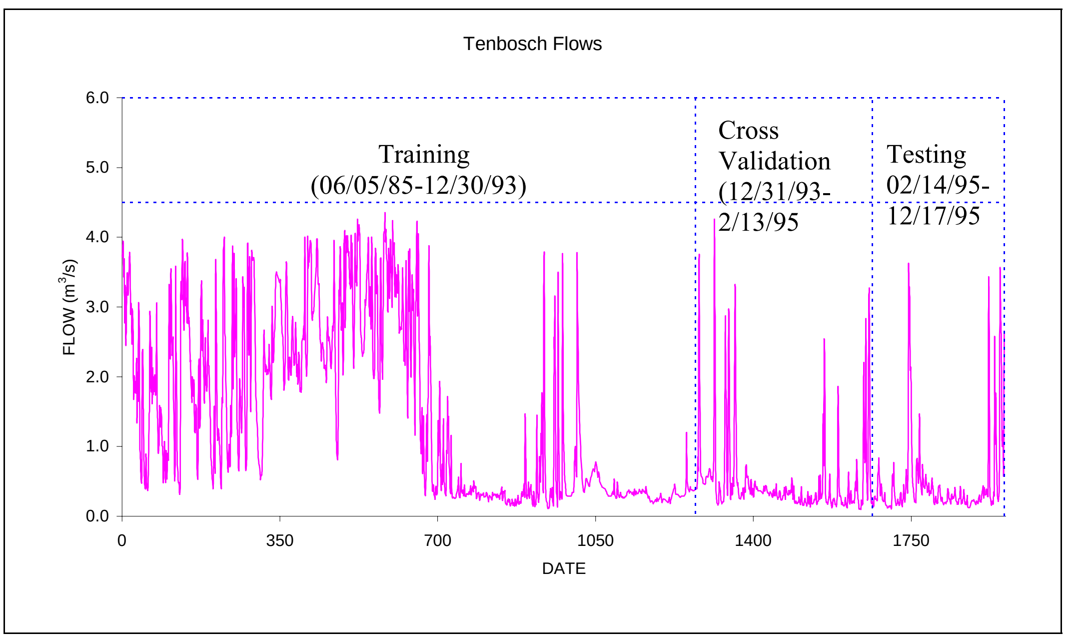

Figure 4.6: Flow time series indicating sections used for ANN training and testing

CHAPTER 5

5. DEVELOPMENT AND APPLICATION OF ARTIFICIAL NEURAL NETWORK MODEL

5.1 Development of the ANN Model

Tenbosch station is far away on the downstream about 250 km from Kwena Dam. Because of these long distances, if any water released is to reach Tenbosch, it has to be of a considerable quantity. This is so because of losses arising from evaporation, irrigation abstraction and all the other users along the river. The long distance from Kwena to Tenbosch means that releases from the dam reach the station after a few days. In order to carry out a meaningful analysis, a lag time of five days was assumed based on an assumed average streamflow velocity of 0.6m/s. For purposes of model development, the inputs into the ANN for flow at Tenbosch were shifted ahead by five days to account for this time lag.

The development of an ANN model involves the following steps: i) selection of data set for training and testing of the model, ii) identification of the input-output variables, iii) selection of the network architecture, iv) determination of the optimum number of neurons in the hidden layer, v) training of the ANN model and vi) testing of the model using selected performance evaluation statistics. The ANN model developed in this study was a Multilayer Perceptron (MLP) consisting of three layers: an input layer, a hidden layer and an output layer consisting of one output neuron. Several researchers have shown that the hyperbolic tangent activation function produces good performance in terms of convergence and central processing time (e.g. Sahoo and Ray (2006)); hence it was chosen for the hidden layers. However, the output layer was provided with a linear activation function so that the output range was between $-\infty$ and $+\infty$. This avoided the remapping of outputs (de-normalisation). The NeuroSolutions software used in this study automatically scales the data such that the training data lay within the range [-0.9-0.9]. The data is scaled to the range [-1-1] to allow for values beyond the range for which the network was trained. The importance of scaling the data to this range, a process known as normalisation, was to avoid one predictor (input) dominating others since they are of different scale and units and cover different ranges.

After trying out several configurations, the input layer illustrated in Figure 5.1 was eventually chosen. This consisted of the following:

- four daily irrigation water abstraction points at Montrose, Riverside, Karino and Tenbosch river gauge stations
- daily rainfall at Montrose (MR_t), Riverside (RR_t), Karino (KR_t) and Tenbosch (TT_t)
- average daily temperature at two stations; Karino and Nelspruit,
- daily river flow of tributaries of Kaap, Sand, Elands rivers,
- daily releases from Kwena dam,
- the previous day's flow at Tenbosch, and
- average daily rainfall totals for the previous 4 days (MR_{t-1}, MR_{t-2}…) to represent antecedent catchment wetness.

The only neuron in the output layer represented the current flow at Tenbosch, the required ANN model output.

After all the input and output variables were selected, the ANN architecture of the form 32-*N*-1 was further explored for simulating the flows at Tenbosch. The next and most difficult step in the development of the ANN was to determine the 'optimum' number of neurons (*N*) in the hidden layer. These are the neurons that are responsible for mapping the complex relationship among the various input-output variables considered in the development of the ANN.

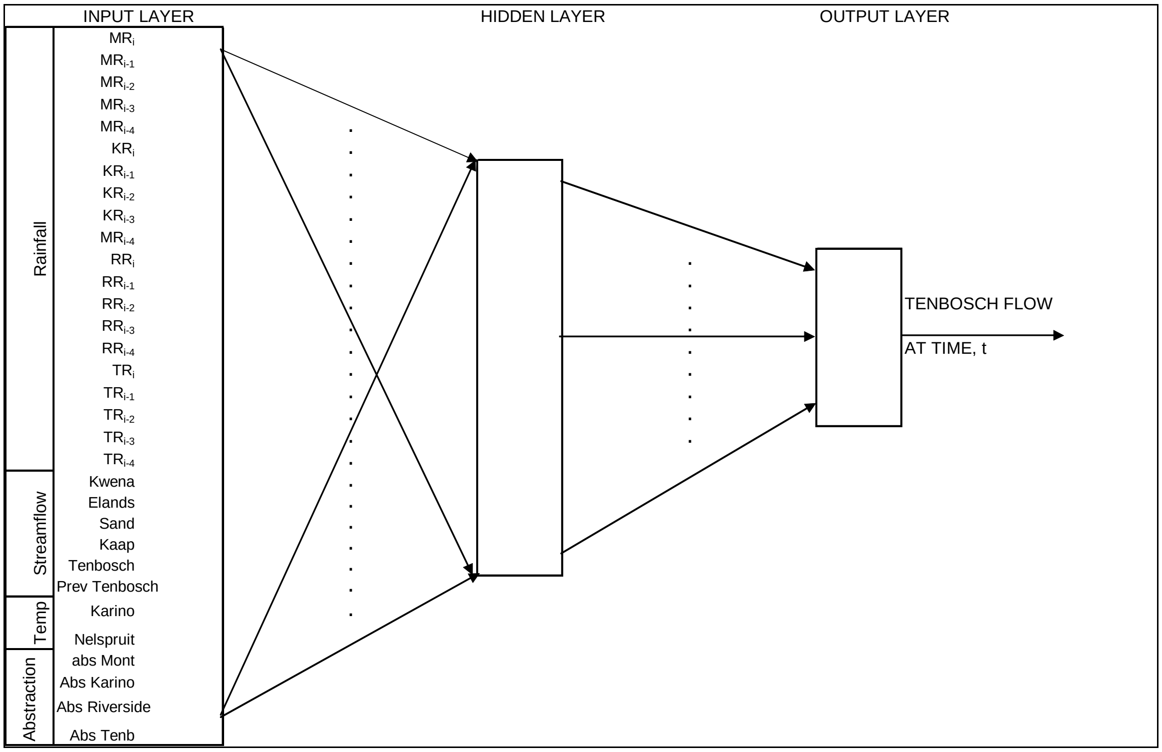

Figure 5.1: Inputs and output of the ANN model

The objective of the training phase in building an ANN is to produce a set of connection weights that causes the outputs of the ANN to match as closely as possible the observed system outputs for every set of training data set. In order to come up with the ‘optimum’ network, the neurons (processing elements) in the hidden layer were varied from 2 to 12. During training, two stopping criteria, the cross-validation and the fixed number of iterations were adopted for this study. The maximum number of fixed iterations (epochs) was set at 1500 and the training continued for a further 100 iterations after reaching a minimum error in the validation set. The optimum network was one which yielded the lowest mean squared error on the training data sets. The training was carried out with a momentum factor of 0.7 and a learning rate of 0.1 in the hidden layer. The network with 8 neurons in the hidden layer was found to be the optimum as it had the lowest mean squared error reached after 1100 iterations. The optimum topology was then represented as 32-**8**-1.

5.2 Application of the Model

After the model was developed and found satisfactory, it was applied to a real problem situation. In the testing mode of the NeuralExpert, the data that was set aside for testing during training phase was introduced into the model. The objective being to investigate the impact of various release levels from Kwena Dam on the flow at Tenbosch the testing data set was selected for this analysis These data sets were of a typical dry year hence appropriate selection. Several release patterns were tried and their impact on flow at Tenbosch assessed. These patterns included scaling the historical release flows by factors of 1.5 to 4 in steps of 0.5. It was found that as the release was increased from the dam, there was corresponding increase of flow at Tenbosch as expected. Some of the releases obtained by the factoring were too high and unrealistic in comparison with the rest of the releases and this approach was therefore rejected. An attempt to find out how the daily releases from Kwena dam were obtained revealed that there was no strong correlation observed between historical Kwena dam releases and any other variables as shown in Table 5.1. No strong correlations were also found between these releases and rainfall. It was therefore not possible to create operating rule based on any of these variables.

Table 5.1: Correlations between the different stream flows and irrigation abstractions

	IrrMont	*IrrKar*	*IrrRiv*	*IrrTenb*	*Kwena*	*Elands*	*Sand*	*Kaap*	*Tenbosch*
IrrMont	1.0000								
IrrKar	0.3731	1.0000							
IrrRiv	0.2775	0.4483	1.0000						
IrrTenb	0.2324	0.4331	0.4648	1.0000					
Kwena	0.0038	0.0743	0.0741	0.1014	1.0000				
Elands	-0.1539	-0.2062	-0.1695	-0.1796	-0.2148	1.0000			
Sand	-0.1590	-0.2018	-0.1894	-0.2645	-0.0849	0.3371	1.0000		
Kaap	-0.0223	-0.0006	-0.0048	-0.0004	-0.0572	0.1237	0.0339	1.0000	
Tenbosch	-0.0315	0.0163	-0.0042	-0.0083	0.2890	0.2307	0.1206	0.2150	1.0000

The response of Tenbosch flows to releases from the dam were then investigated using four storage scenarios; with the dam starting 100% full, 75% full, 50% full and

25% full and running to the empty condition over a 12 months period at a constant rate of release throughout the year. These gave releases of 5.0, 3.778, 2.50, and 1.26m^3/s respectively. While it is recognised that the release is unlikely to be constant as assumed, there was no justification for trying anything more complex as the irrigation demands were more or less constant throughout the year (e.g. see Figure 5.2 for Tenbosch area abstractions) and the modelling was for the dry or low flow periods. The other assumptions were that the year is dry and there are therefore negligible inflows into the dam during this time of release and all the other variables remain the same. Using the four storage and release scenarios was considered to be reasonably representative of what could be encountered in the actual system.

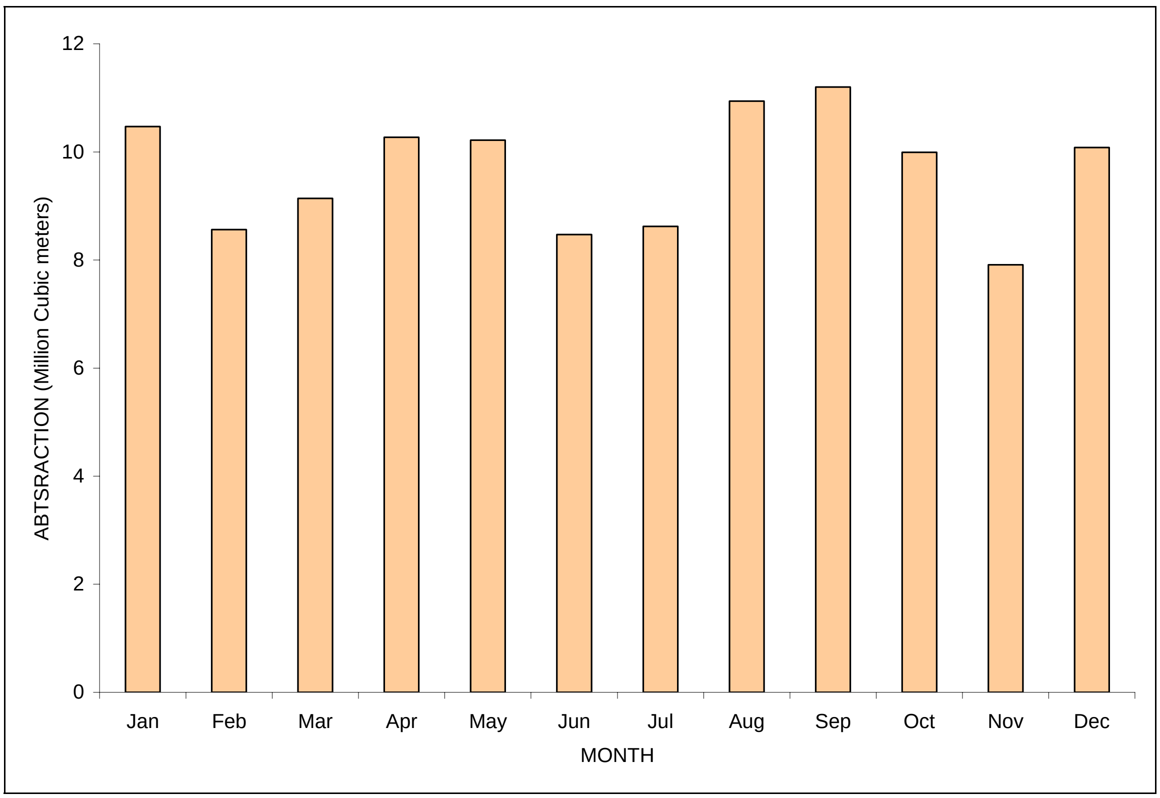

Figure 5.2: Abstractions at Tenbosch for the year 2003/04

Because daily streamflows mostly have high lag 1 autocorrelations, the flow at Tenbosch was found, as expected, to be heavily influenced by the flow of the previous day. Since the Tenbosch outflows were not known for any of the scenarios, it was necessary to use some starting series of the previous day's flows as input. In the absence of any past flows, the historic observed flows were used as the initial input flows and the model run on those inputs. The results so obtained (simulated outputs) were then fed back into the model as inputs in an iterative process until some stopping criteria were met. In this case the coefficient of determination and visual inspection of the way the graphs of the output (Tenbosch flows) in consecutive iterations mapped themselves to each other were used as stopping criteria. This was applied to each of the four storage scenarios. The iteration process for the scenario where the release from the dam was at 75% full is illustrated in Figure 5.3. The graphs converged after four iterations although only the last of the iterations is shown.

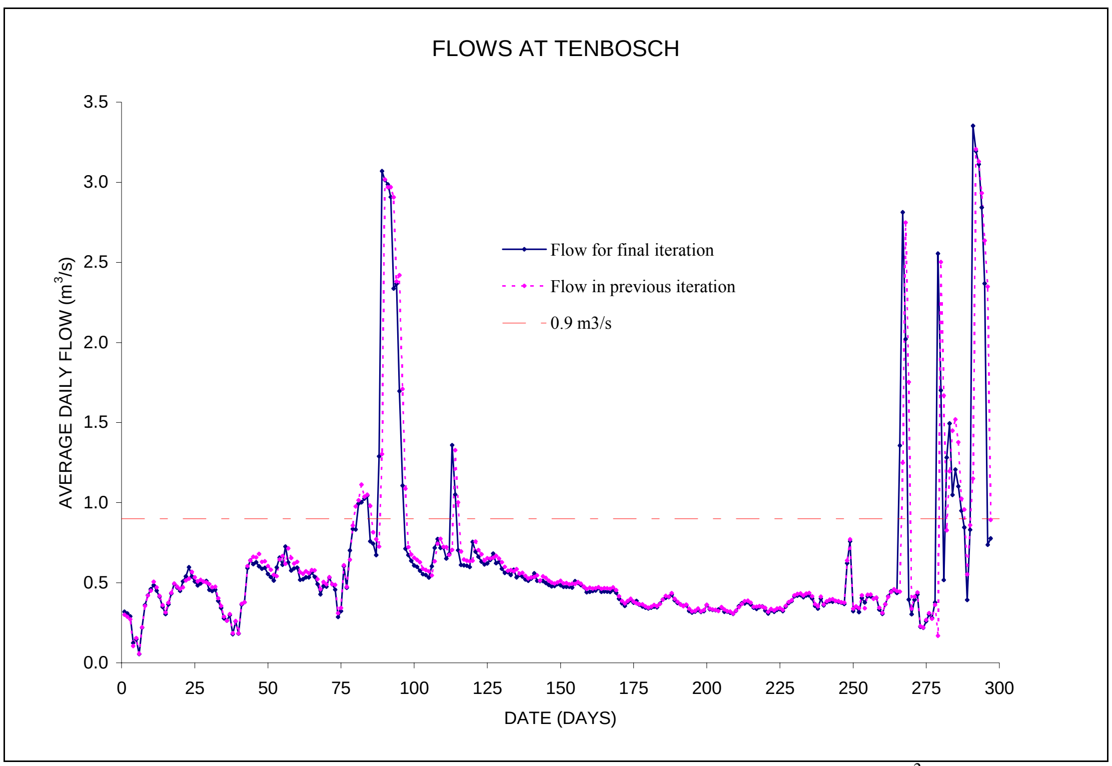

Figure 5.3: Iterative determination of daily flow at Tenbosch with 3.78m^3/s release from Kwena dam

The graph shows a very close fit which means a good model convergence. The same standard of fit was observed for the other three storage scenarios.

CHAPTER 6

6. RESULTS ANALYSIS AND DISCUSSION

6.1 Results from model development

The results of the statistical performance evaluation measures are shown in Table 6.1

The performance indices in the table are the most commonly used in literature hence they were selected in this study.

Table 6.1: Statistical performance evaluation measures of ANN model

Error indicator	Training Data	Testing Data
Mean Absolute Error (m^3/s)	0.0217	0.0168
Mean Square Error (m^3/s)	1.589	0.103
Root Mean Square Error (m^3/s)	1.261	0.321
Maximum Absolute Error (m^3/s)	4.036	3.705
Minimum Absolute Error (m^3/s)	0.075	0.085
Correlation coefficient	0.9626	0.8574
Coefficient of determination, cd	0.9266	0.7352
Coefficient of efficiency, ce	0.9262	0.7173
Bias (m^3/s)	0.0216	0.0168

From the table it can be seen, as expected, that the ANN model performed better on training data than on testing data. The correlation coefficient which is a commonly used statistic provides information on the strength of linear relationship between the observed and the simulated values. Imrie *et al.,* 2000 suggest that the correlation coefficient of less than 0.7 is problematic else anything more than this is acceptable.

There are no strict rules for the acceptability or rejection of a model. The adequacy of the model for a particular application depends on the application for which the results are intended. However, Table 6.2 gives qualitative guidelines for assessing the adequacy of streamflow estimates as adapted from Chiew and McMahon (1993) based on the coefficient of determination and coefficient of efficiency. Based on these guidelines, the model performance is perfect on training data and acceptable in testing data.

Table 6.2: Qualitative guidelines for assessing the adequacy of streamflow estimates (Adapted from Chiew and McMahon (1993c))

Level of Adequacy	Range of performance coefficients
Perfect	ce ≥ 0.93 or cd ≥ 0.97 or cd ≥ 0.93 and bias ≤ 0.1
Acceptable	ce ≥ 0.80 or cd ≥ 0.90 or cd ≥ 0.77 and bias ≤ 0.1
Generally Satisfactory	ce ≥ 0.60

Figure 6.1 illustrates the relationship between the model simulation and the actual observed data for the training set. The graph shows a very close fit between the two data sets. Figure 6.2 provides a scatter plot together with the 45 degree line, of model simulation versus the observed a data. The error plot of the same is shown in Figure 6.3. Figure 6.4, Figure 6.5 and Figure 6.6 show respectively, observed versus simulated data for testing data, scatter plot of the observed versus simulated and the

error graph for the testing data set. It can be seen also that the maximum error for the training is 1.718m^3/s whereas it is 2.443m^3/s for the testing data set. In general, the model although performing better on training, is still good on testing data. This is a very important aspect of model performance as it shows a good generalisation capability.

The correlation coefficient of the model for the training data is 0.9626 and the coefficient of determination of 0.9266 (Table 6.1). For the training data it can be seen that there is a very high correlation between these values which shows that the model did well especially on training data.

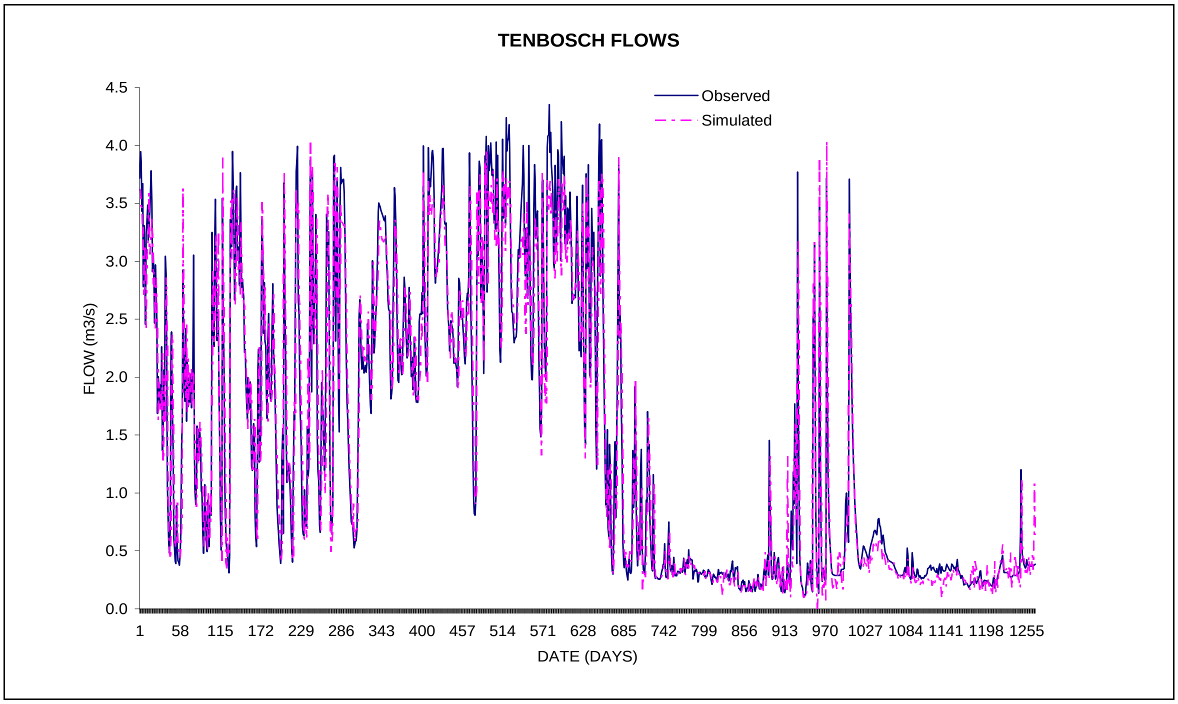

Figure 6.1: Observed flow versus simulated flow for the training data set

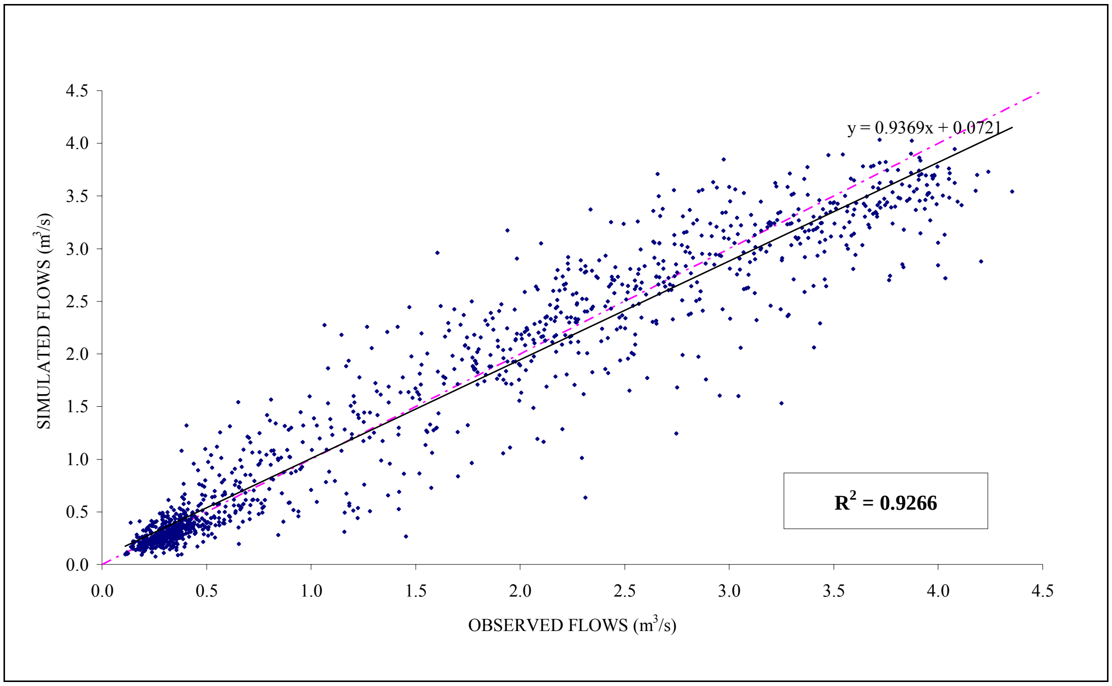

Figure 6.2: Scatter plot of the observed versus the simulated flows for training data set

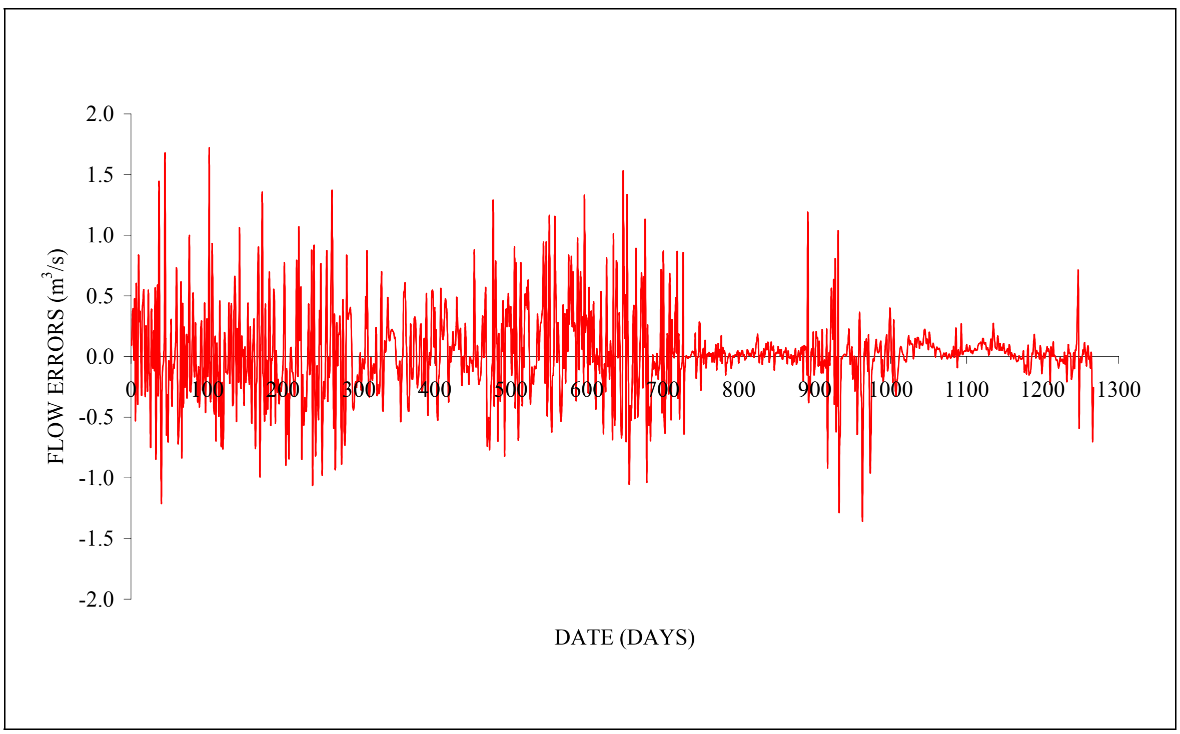

Figure 6.3: Error Plot of training data

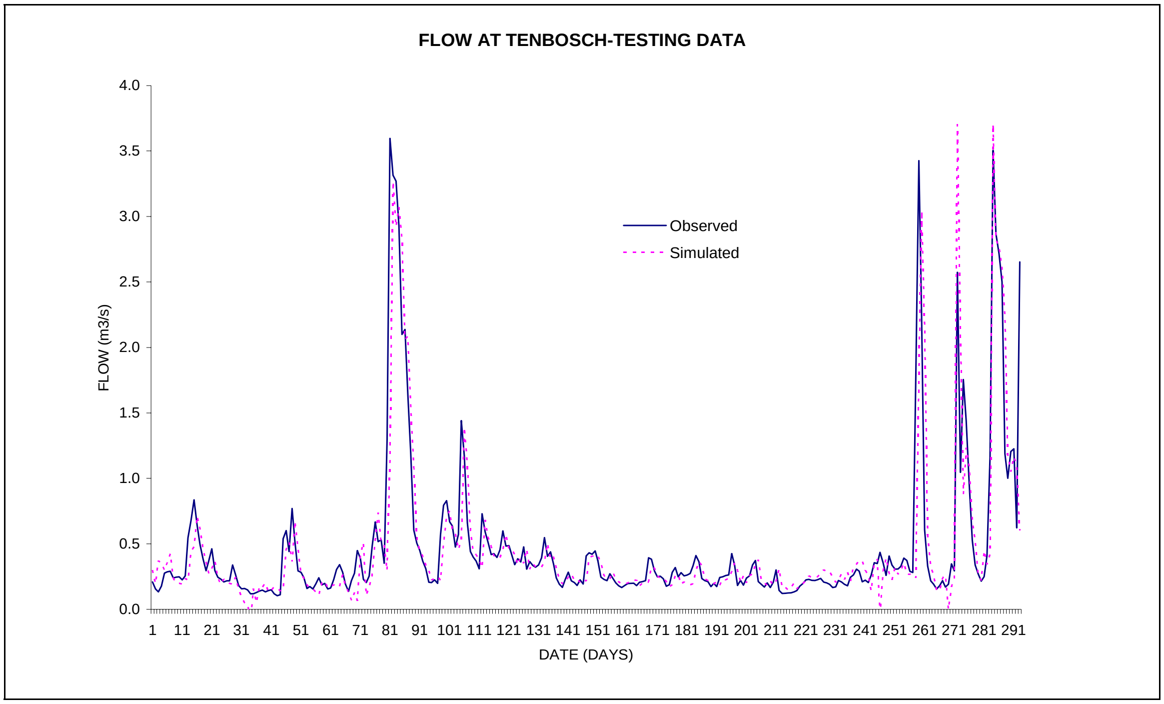

Figure 6.4: Observed and Simulated flows of the testing data sets

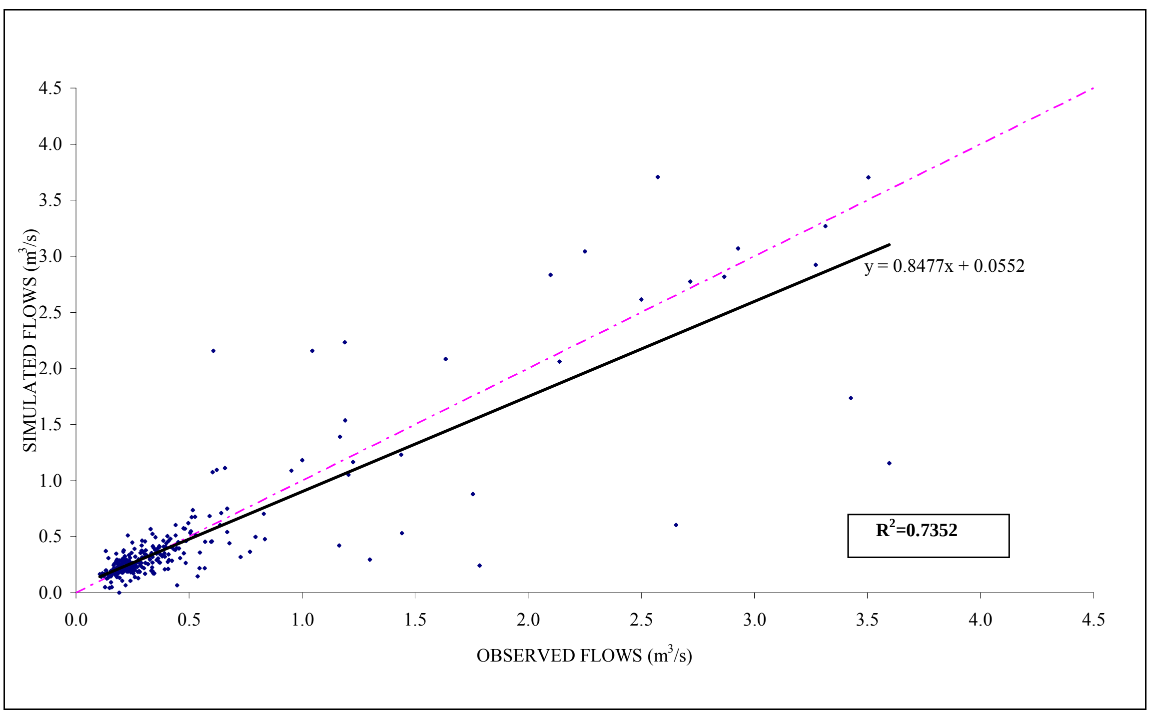

Figure 6.5: Scatter plot of the observed versus the simulated flows for the testing data set

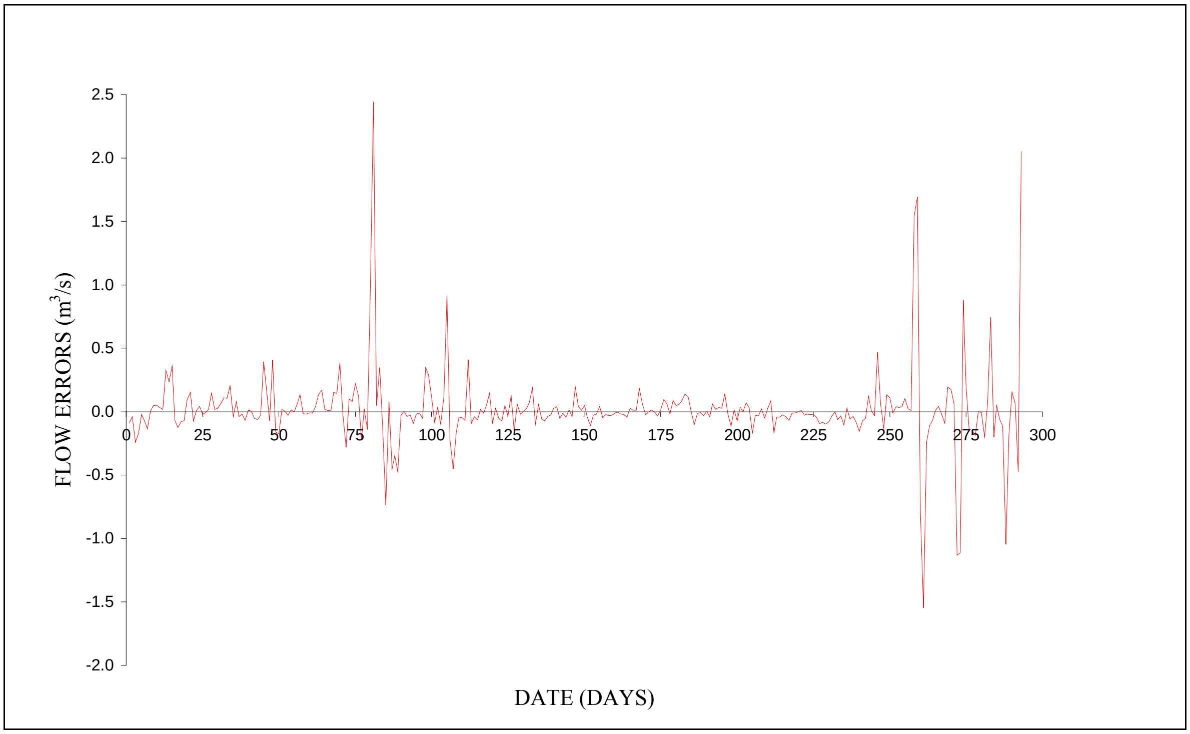

Figure 6.6: Error Plot for testing data

6.2 Results from model application

Figure 6.7 shows flow duration curves for the four release scenarios and the observed flows analysis carried over a period of 12 months using the testing data. Also shown is a line representing the flow of $0.9m^3/s$. From the graph it can be seen that for a release scenario where the dam is 100% full, about 22% of the time the flow is greater than $0.9m^3/s$ which is a great improvement from the 10% from the observed flows. When the dam is 75% full the percentage exceedence of 0.9 m^3/s is 12 %.

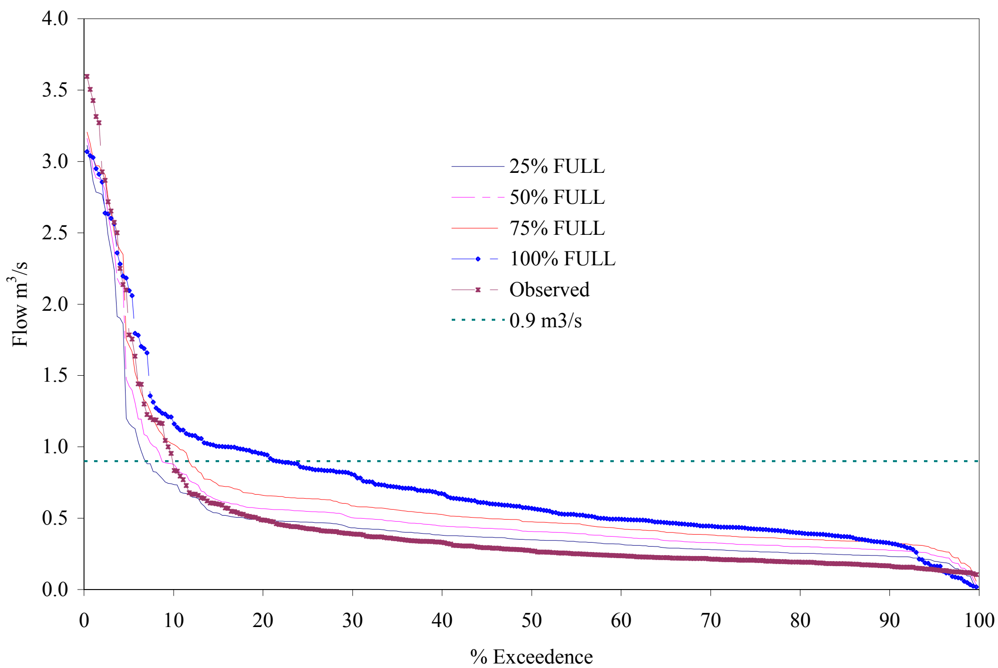

Figure 6.7: Flow-Duration Curves for the Kwena dam release scenarios

Figure 6.8 shows a plot of observed flows with the different scenarios of initial storage and release from Kwena dam. The graph shows that over a period of 12 months to emptiness, if the storage in the dam is higher; there is a higher release and the flow rates at Tenbosch increase accordingly.

It is also evident that there is a remarkable increase towards achieving the flow of $0.9 m^3/s$ only when the dam is initially full and the release is $5 m^3/s$. All the other storage scenarios, although improving on the historic flow, do not increase the flows substantially to reach this flow requirement.

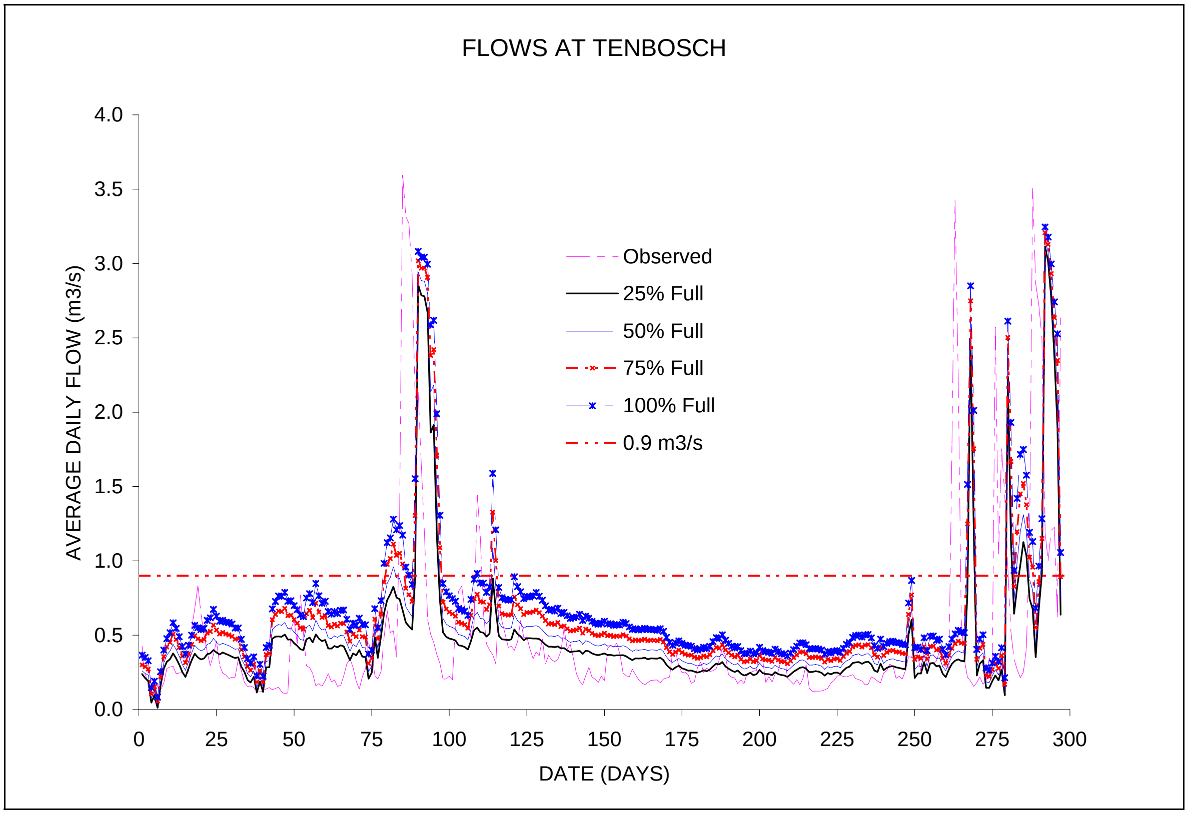

Figure 6.8 Variation of observed flows at Tenbosch with the different scenarios of initial storage and release from Kwena dam.

6.3 Discussion

This discussion looks at both the model development and model application stages. The model worked very well even though it can be improved further. Several factors could have affected the results of this study. These will be discussed in the following section. The training data set as used in this study could be one of the reasons the ANN not performing to the expected levels especially with the testing data. There were some sections of the data that were unrealistic especially with regards to the Kwena dam releases as they remained constant over a long period of time. The other reason could be attributed to lack of sufficient data included in the ANN model to fully represent the whole dynamics of the system both hydrologically and operationally.

6.3.1 Use of Multi-Layer Perceptron (MLP) trained with Back Propagation Algorithm (BPA)

The choice of the training algorithm affects the overall performance of the model. Some researchers, for example, Srinivasulu and Jain, (2005); Hsu *et al*., (1995) have reported that rainfall-runoff models trained using BPA do not perform well in predicting low magnitude flows. They however, do not try to define what constitutes low and high values. Use of some other or a combination of training algorithms could perhaps produce better results. Srinivasulu and Jain, 2005 found that the predictive capability of using the real-coded genetic algorithm (RGA) and the self-organising map (SOM) was superior to those trained using BPA. ANNs have been reported extensively as yielding very good simulation results of streamflow for a number of catchments e.g. Shrestha *et al.,* (2005). ANNs are data-driven and normally use historical data observed over a certain period of time.

6.3.2 Selection of training data sets

ANNs by their nature are data-driven. The more data is available to them, the better the performance. The data sets used in this report could have been inadequate in terms of number for the neural networks to extract meaningful patterns from them since only 1956 data sets were used for a total of 32 inputs. The selection of the training data set in the ANN approach may also contribute significantly to the overall results. Very high values in the training may drive the simulated values towards high values while very low values may drive the results towards the low values. As far as this study is concerned, which focuses on times of low river flows, the selection of training data sets could have played a significant role in influencing the results. This is because the period concerned is a drought period with very low river flows especially in the later part of period of interest. In addition to this, some of the assumptions made could have distorted the end results e.g. the monthly abstractions have been assumed to remain constant over the entire period under investigation. This has not taken into consideration the cropping patterns of the irrigators and the type of crops planted and over what period these have not changed. This is a very difficult task that can only be overcome if the actual abstractions are recorded. There may be days when the irrigators did not irrigate at all but the model has assumed there was irrigation just because the selected threshold rainfall had been exceeded. The model disaggregating monthly abstractions to daily values assumed a catchment wetness threshold of 4mm. This was subjective, but due to time constraints other thresholds and their impacts on the general performance, have not been tried out.

6.3.3 Selection of network topology and architecture

The number of neurons in the hidden layer enhances the performance of the neural network. However, there is no algorithm to use for the determination of the appropriate number of the neurons in this layer and it is therefore achieved by a tedious trial and error process. This could affect the results of the model since it is then based on the level of experience of the modeller. Different modellers doing the modelling will come up with different best topologies. The other factor that could affect the results is the choice of the transfer function adopted. Different transfer functions produce different results.

6.3.4 Practical Application of the model

Although the developed model gives good results, it would need to be thoroughly investigated before it can be used in practical situations by subjecting it to different types of data. However, as it is, it has the advantage that for a single testing run it only takes on average five minutes of running time. This makes it a very attractive tool as it is not too tedious, cumbersome or time consuming.

The Kwena dam becomes significant in the dry season when there are low flows and the minimum flow is not met. However, it was observed that it is difficult to meet this flow requirement based only on the river flow.

CHAPTER 7

7. CONCLUSIONS AND RECOMMENDATIONS

The importance of proper water management cannot be overemphasised. With increasing demands on limited water resources, it is essential that the available limited water resources be carefully planned, managed and efficiently operated to meet the present and future water needs. To accomplish this, water managers need some form of tool to use to achieve the objective. This research has shown that Artificial Neural Networks have a great potential of being used as a decision support tool because of their advantages alluded to in this report and the successful development of an ANN model for the Crocodile River. The ability to simulate river flows quickly and accurately is of crucial importance in water resources management operations. Hydrodynamic models provide a good physical basis for this purpose. However, their river geometric data requirements which may not be available in many locations, makes their use as a decision support tool especially in real time, unsuitable. This study has developed and demonstrated an ANN model that can be very helpful as it can give a good estimate of the next day's flow at Tenbosch given the present day's flow, the measured rainfalls, temperatures, abstraction rates and releases from Kwena dam. As such, the model indicates that with further refinement, the ANN can be used to guide operators as to how much to release based on the storage status of the reservoir and measurements of the hydrometric variables. The developed ANN model relates the important components of the system: release from Kwena, irrigation abstractions, current and previous rainfalls and flow at Tenbosch reasonably well. It can therefore be tried out in place of a more complex data intensive and time consuming simulation model in optimisation studies of the system. Caution, however, would need to be taken and more thorough studies and testing required before this as the ANN is a black box model. Furthermore, the model developed here was for the low flow periods only and a modelling of the high flows would need to be developed and integrated to a low flow one for effective system optimization.

A point worth-noting, however, is that it is very difficult to meet the water flow requirements of $0.9m^3/s$ at least on a daily basis at Tenbosch especially during times of drought where there are very low flows. If there is no water in the hydrologic system there is very little that can be done to meet the requirement without emptying the Kwena Dam in the shortest time; a situation no water manager would like to experience. The model developed quantifies the relationship between the releases at Kwena to the flows obtained at Tenbosch and can therefore be used to help operate the system optimally within the inadequacies of the system.

In conclusion, no study is complete in itself and there is always scope and room for improvement. This study just lays a foundation on which further research can be built. To the author's knowledge no work on application of ANNs to river simulation has been undertaken in South Africa and this study should give enough motivation and impetus towards directing research in this direction. The findings of this study are therefore preliminary in nature and would need to be refined further before they can be used in a real life situation.

7.1 Recommendations for data collection

Although it was never an objective of this research to asses the practicality of the Inco Maputo agreement, it is worth-noting that as it is not very specific about the $0.9m^3/s$ flow requirement from the Crocodile River. It does not state over what time period this flow is to be sustained as it is not possible to satisfy this condition during times of severe drought. If this condition were to be met every day of the year, then the Kwena dam would likely dry up in a short time as the tributaries cannot guarantee a daily flow that would meet this condition. The best option then would be to base the flow into Mozambique on the naturalised flows in the Crocodile River at Tenbosch. The current flow needs to be shared between the two countries. The author is aware of the Tripartite Interim Agreement between the countries of the Republic of South Africa, Republic of Mozambique and the Kingdom of Swaziland of 2002 for Cooperation on the Protection and Sustainable Utilisation of the Water Resources of the Inkomati and Maputo Water Courses. However, this agreement is too general and does not direct itself specifically to the situation at Tenbosch and Komatipoort (border with Mozambique).

It is very clear that the Crocodile River catchment is a catchment under stress. This can be attested by the fact that currently, its water demands far outweigh its firm yield. This, coupled with its obligation to the international agreement with Mozambique, makes it imperative for all water managers, to have a proper and up-to-date readily available data. Difficult as it is to monitor irrigation abstractions especially if illegal abstractions happen, every effort needs to be put in place to overcome this problem. This is borne out of the fact that during data collection for this study, the author was in some cases referred to some independent irrigators for data who were not willing to share their data as the DWAF did not have their data. It is however gratifying that there is currently a multimillion Rand project to try and do this task.

The importance of the international agreement calls for a thorough water management and auditing; therefore there needs to be a clear understanding of the catchment water use. If the ANN models were to be adopted and implemented for catchment water management, there is need to equip the rivers with telemetric equipment to capture all hydrologic variables and events. It would be desirable if this equipment could operate at real or almost real time.

7.2 Recommendations for Model Improvement

The model presented in this study only lays a foundation for further and thorough research on the applicability of the ANNs to both modelling the rainfall-runoff process and operation of the Crocodile system and incorporating it into a decision support tool for catchment water management. The model could be investigated further using other training algorithms and different topologies to assess the most suitable. There is new literature e.g. Dawson *et al*., 2006 that suggests that ANNs trained with the common error backpropagation tend to under estimate low flows. This therefore calls for a trial of some other error functions other than the one used in this research.

The neurosolution used for this study was operated at the USER version level which has some limitations. Upgrading to the more powerful Consultant or Professional versions would provide a lot of options on operation of the model and possibly better results.

CHAPTER 8

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APPENDIX A

Model for disaggregating monthly abstractions

Known: Total monthly abstraction, T_m

Daily rainfalls, r_i; *i* is the i^{th} day of the month

Required: Daily irrigation abstractions

Concept: If the catchment wetness on a given day R_i exceeds a threshold R_T, then no abstractions happen as the farms are adequately wet. If catchment is dry, then the maximum abstraction, *ave*, is made on that day.

If the catchment wetness is between the dry state and the threshold, then the abstraction is directly proportional to the deficit R_T-R_i. The Figure illustrates the model.

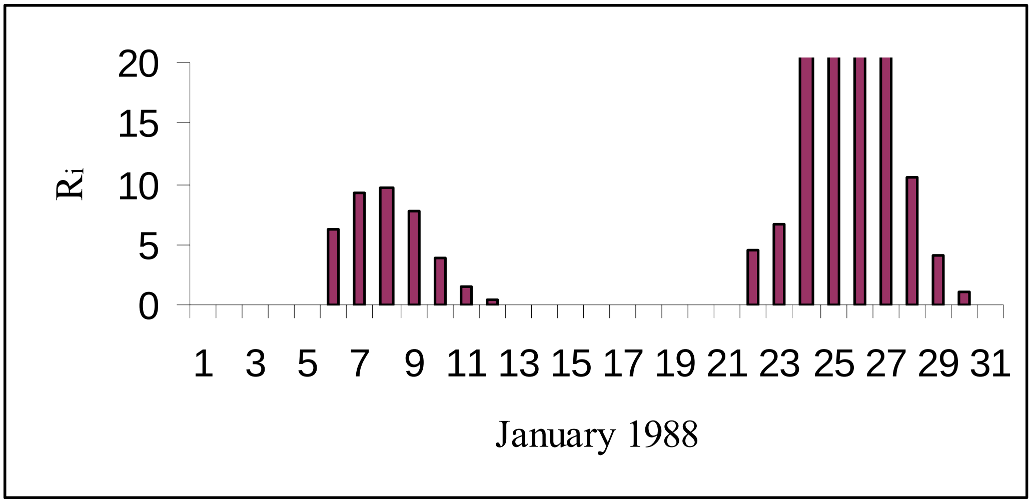

Figure A1: Modelled catchment wetness

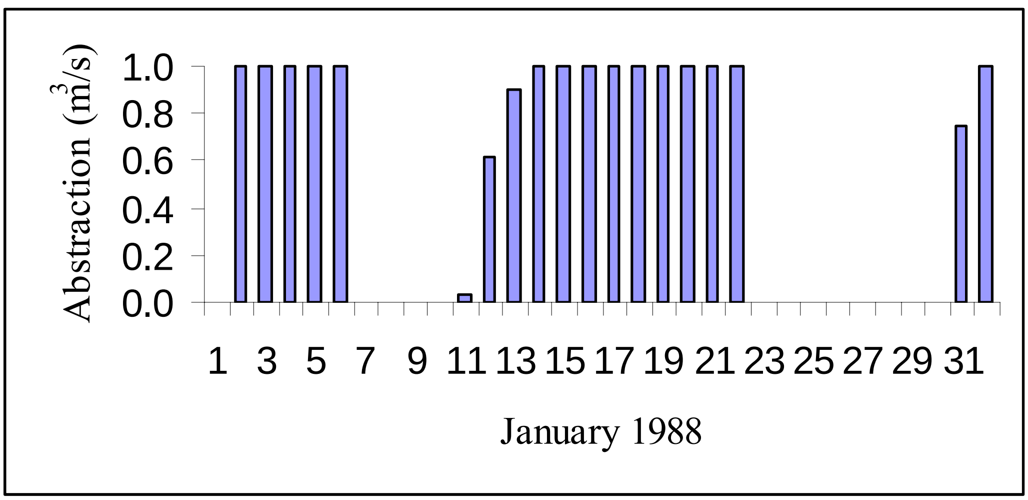

Figure A2: Modelled abstractions for January 1988

The total abstraction for the month = $\sum_{i=1}^{nr}\left(\frac{R_T - R_i}{R_T}\right)ave$ $\quad 0 < R_i < R_T$

$+ \, nd{*}ave$ $\quad R_i = 0$

$+0$ $\quad R_i >= R_T$

where: *nr* is the number of days when $0 < R_i < R_T$

nd is the number of days when $R_i = 0$

The total abstraction has to equal T_m

Therefore $\sum_{i=1}^{nr}\left(\frac{R_T - R_i}{R_T}\right)ave + nr * ave = T_M$

Therefore $ave = \dfrac{T_m}{\sum_{i=1}^{nr}\left(\frac{R_T - R_i}{R_T}\right) + nr}$

Knowing *ave*, the actual abstraction for each day can be computed. The catchment wetness was obtained as a weighted sum of the rainfall in the current and the previous three days according to:

$R_i = r_i + 0.75r_{i-1} + 0.5r_{i-2} + 0.25r_{i-3}$

where r_i is the rainfall in the i^{th} day.