A SIMPLE OPERATING MODEL OF THE VAN DER KLOOF RESERVOIR USING ANN STREAMFLOW FORECASTS

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A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements of the degree of Master of Science in Engineering

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DECLARATION

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

Signed

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MENARD MUGUMO

…………………. day of ………………………………….….. year ……….………

Dedicated to my children

Einstein, Rachel and Viola

May the good Lord bless you and grow you into seasoned professionals of your choice

ABSTRACT

The operation of Van der Kloof Dam on the Orange River was investigated with an artificial neural network and a spreadsheet model. The objective was to simulate inflow into the dam and optimize reservoir operation for optimum power generation.

The advantage of artificial neural networks lies in their ability to simulate both linear and non-linear systems and the modeller does not need knowledge of the physical processes driving the system hydrology. The current operation of the Orange River was reviewed and literature review was conducted for reservoir operation and artificial neural networks. The hydrology of the Orange River (1977 – 2008), the water requirements and hydropower plant layout were investigated. A 1-month ahead streamflow model was then developed to predict inflow into Van der Kloof Dam over an operating period of 12 months. The resulting simulation was satisfactory, proving the power of artificial neural networks.

The inflows were used to optimize reservoir operation by maximizing hydropower and minimizing water supply deficits. The software used to build the network, NeuroSolutions, however did not have an algorithm for optimizing reservoir operation. The embedded genetic algorithm was only available for optimizing network training. As a result, the operation of the reservoir was optimized on Excel which was found satisfactory for the one reservoir system investigated. Potential areas for further research include seasonal models and annual forecasting models with robust monthly disaggregation.

ACKNOWLEDGEMENTS

In conducting this research I approached a number of people for the valuable information that was needed in shaping the project, developing and running the model. I owe gratitude to all these people who were willing to assist at various stages of data collection. The study would not have succeeded without their assistance.

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I also acknowledge the support I received from my employer, Department of Water Affairs (DWA), represented by Solly Mabuda who was the Director: Options Analysis at the time of study. He allowed reasonable access to most of the resources that were crucial for conducting the study. I was given permission to use library resources, the telephone, fax machine, e-mail, computing and internet facility, printing, photocopying and generous supply of stationary for both the draft and final copies. Through the cooperation of other directorates of the DWA, I was able to access all the information relating to current system operation.

I was introduced to Jane Mogaswa by Celiwe Ntuli, a deputy chief systems analyst with the Sub-directorate System Operation. Jane Mogaswa, a hydrologist with the Directorate: Hydrological Services of the DWA, supplied most of the hydrological data that was needed for the model and pointed to useful sources in the DWA for additional information. The information she provided included rainfall, stream flow, evaporation, dam storage and release records for Van der Kloof Dam. She introduced me to Helena Fourie, a GIS technician with the DWA who supplied the catchment maps of the Orange River which helped to describe the system more clearly.

Robert Bruce Kydd of Eskom introduced me to his colleague, Tinus Keyser, who supplied information on the operation of the Van der Kloof hydropower plant. I am grateful to both of them.

Finally but not least, my wife Sofia and children Einstein, Rachel and Viola were the pillar of my success. They gave the much needed moral support, love and cooperation at a time I was unable to give them the full attention they deserved. Balancing the demands of study, work and family was challenging but with their support I was able to enjoy the research.

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CHAPTER 1

DEFINING THE PROBLEM

1.1 BACKGROUND

The purpose of reservoir operation is to supply a multiplicity of water users including the competing demands of urban, mining, irrigation, hydropower and ecological requirements in the most efficient and sustainable manner. This is especially important because water is a scarce resource that should be managed efficiently for economic growth and social development. This water resource management philosophy is especially relevant to the dry regions of the world such as South Africa.

Water use can be broadly categorized into water supply, hydropower and ecological flows. In addition to these uses, water resource managers also need to manage system losses through river transmission and regulation losses. Regulation losses arise from both ill-timed releases and the inevitable operating losses. The water supply category is made up of urban, strategic industrial, mining and irrigation uses. The urban use can be broken down further into domestic, municipal, commercial and industrial uses. In South Africa, strategic industries such as Eskom and Sasol are so critical to the proper functioning of the economy that they receive special priority. The efficient allocation of water to these user categories is the essence of reservoir operation. These categorises are outlined below for ease of reference.

- Water supply
  - ✓ Urban water (domestic, municipal, commercial and industrial)
  - ✓ Strategic industries

- ✓ Mining
- ✓ Irrigation
- Hydropower
- Ecological flows

1.2 PROBLEM STATEMENT

There is an ever increasing competition for the scarce water resources among water use sectors. Jenkins and Lund (2000) note that the problem is compounded by the relative absence of new cheap water sources; calling for efficient policies of reservoir operation. This argument is supported by Labadie (2004) when he notes that water resource managers should focus their effort on improving the operational effectiveness and efficiency of existing reservoir systems in order to maximise benefits and reschedule costly augmentation schemes further into the future.

Recent studies on the Orange River system have revealed huge water losses in the order of 270 million cubic metres per annum (DWAF, 2005 (b)) largely due to inefficient management of the system. Subsequently, a study was commissioned to investigate operating rules to save water and allocate the savings to productive use in the economy (DWAF, 2010). The current study is aimed at building upon the ongoing efforts to improve efficiency of allocation.

Simulation and optimization models provide effective means of modelling complex water resource systems. The traditional approach for short-term prediction of flow in reservoir operation has been to use autoregressive stochastic models. The South African Water Resource Planning Model (WRPM) (DWAF, 2005 (a)), for example, is a complex software developed to simulate stochastic streamflow, compute the system yield and optimize the annual operation of the system. The complexity of the WRPM limits its application and hence the need for searching for simpler models capable of carrying out the same task. The WRPM is not user friendly and has a structure that requires detailed knowledge of the variables, parameters and their interrelationships. Neural networks proposed for use in this study however do not require knowledge of the relationships of variables as they use their power of connectivity to build this knowledge during training (Kisi, 2004). In recent years, the capability of artificial neural networks in simulating streamflow and optimizing reservoir operation has attracted considerable research interest and results so far have been very promising (Jain et al., 1999).

1.3 IMPORTANCE OF STUDY

Artificial neural networks are relatively simple but powerful platforms for modelling reservoir operation. This modelling technique has not been fully embraced yet for water resource system analysis in South Africa. Its application on Van der Kloof Dam is expected to bring new insights.

Van der Kloof Dam lies on the Orange River and is one of South Africa's only two hydropower plants. The other hydropower plant is at the upstream Gariep Dam. An effective reservoir operating system of the two plants is crucial for reliable power supply to the economy. Van der Kloof is the downstream of the two power plants and was selected for this study because it functions as the final valve on the system in supplying downstream requirements up to the ocean.

1.4 RESEARCH OBJECTIVES

The objective of the study was to investigate the applicability of an artificial neural network and a spreadsheet model to the optimization of hydropower generation at Van der Kloof Dam and to minimize water shortages. This was to be achieved by streamflow forecasting with an artificial neural network and optimization of reservoir operation using an Excel spreadsheet.

The complex WRPM is currently used for optimizing reservoir operation using streamflow generated by the Pitman model.

1.5 DELIMITATION OF STUDY

An artificial neural network was built to predict streamflow into the Van der Kloof Dam. The streamflow generated by the simulation was then used to investigate hydropower generation and water supply downstream of the dam.

In terms of the geographical setting, the Upper Orange River system generated the streamflow and the Lower Orange River basin was the supply area down to the Atlantic Ocean. The Van der Kloof Dam itself was the storage node of the system receiving streamflow from upstream and rainfall over the dam basin, losing water to evaporation from the dam basin, and releasing water for generating hydropower and supplying downstream requirements. Figure 1.1 is a map of the Orange River and Figure 1.2 a map of the Upper Orange River, both showing the study area.

The Orange River rises in the Drakensberg Mountains of Lesotho at an altitude of 3 300 metres above sea level. It flows in a westerly direction, discharging into the Atlantic Ocean some 2 200 km away. The river system drains over 1 million km^2 of catchment area, of which 600 000 km^2 lie in South Africa and the rest is shared between Lesotho, Namibia and Botswana. The last 600 km of the river form the border between South Africa and Namibia. The catchment generates a mean annual runoff of 11 300 x 10^6 m^3.

The Upper Orange Subsystem stretches down to the confluence with the Vaal River. The Lower Orange Subsystem begins at the Orange-Vaal confluence and drains down to the Atlantic Ocean. The Orange River is managed as a system comprising all the tributaries and water infrastructure such as dams, gauging

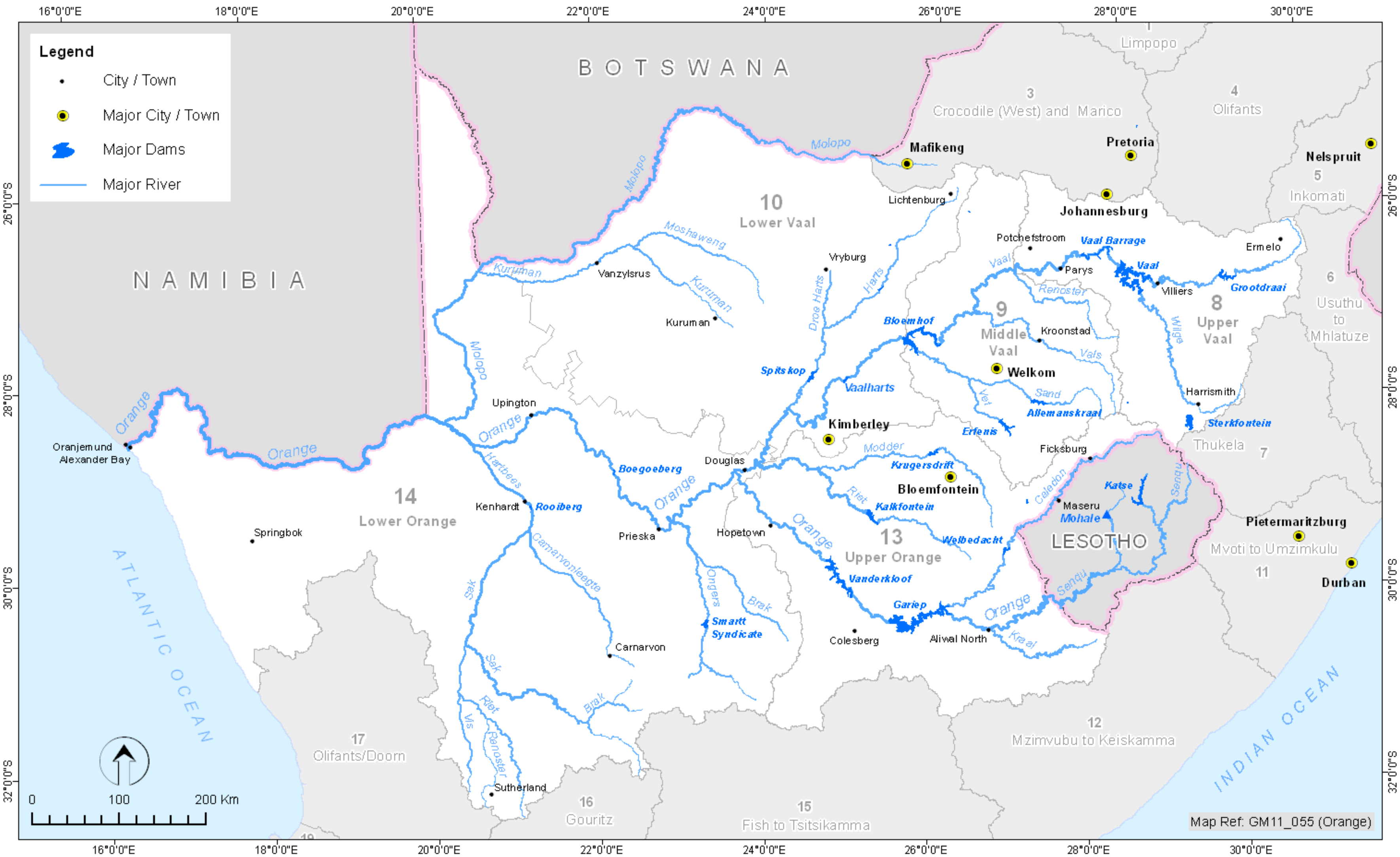


Figure 1.1: Orange River Catchment

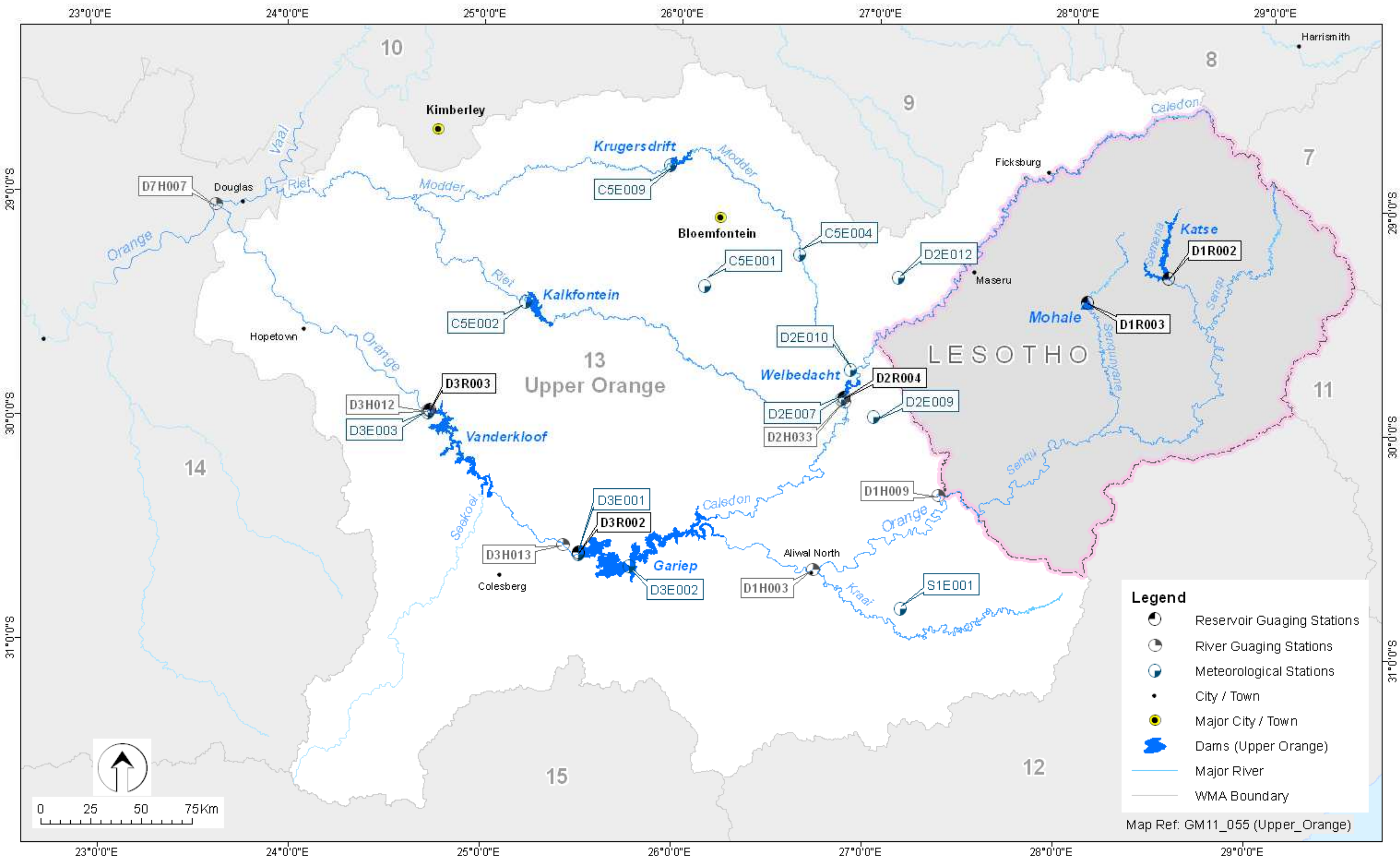


Figure 1.2: Upper Orange River Catchment

weirs, and transfer schemes. The main tributaries are the Kraai River, Stomberg River, Caledon River, Great Brak River and Seekoei River upstream of the Van der Kloof Dam and the Vaal River, Ongers River, Hartbees River and Fish River (from Namibia) downstream of Van der Kloof Dam. Besides pick-up weirs, there is no yield dam downstream of Van der Kloof Dam and all the Lower Orange River demands are supplied from Van der Kloof Dam via the Ramah Canal, Marksdrift Diversion to Douglas Weir, Orange Riet Canal and the river channel itself.

Currently, the Vaal River is managed as a separate system in order to give prominence to this strategic river system supplying the Gauteng Region, the economic hub of South Africa. Another reason is the sheer complexity of the system which makes it difficult to manage if combined with the Orange River system. The minimal regulation losses that spill into the Orange River at the confluence are ignored as insignificant.

Since the Upper Orange River generates the inflow into the dam, only the hydrology of the Upper Orange River was investigated but the water demands occur in the Lower Orange River system. A total of 780 million m^3 per annum (24.7 m^3/s) was transferred from Katse and Mohale Dams in Lesotho to the Vaal River in the 2008/09 operating period. This transfer was not analysed in the current study because it did not form part of the Van der Kloof Dam demands and for reasons elaborated in section 5.1.3.

CHAPTER 2

CURRENT SYSTEM OPERATION

2.1 INTRODUCTION

Research on the current practice of operating the Orange River system was needed to guide the possible application of artificial neural networks in operating the Van der Kloof Dam subsystem.

The operation of a river system is the means by which the water allocation policy for the system is enforced. River system operation is the regulation of reservoir storage in a system to reconcile supply and demand with the minimum risk of failure. An efficient operating policy supplies water at the desired risk level, with minimum system losses. The Orange River system supplies water to urban (domestic, municipal, commercial and industrial), strategic industries, mining, irrigation and hydropower sectors and the Reserve. The Reserve includes domestic use by riparian rural communities and ecological flows. A full description of the river system is given in Chapter 1 in which Figure 1.1 shows a map of the entire Orange River catchment and Figure 1.2 the Upper Orange River catchment.

Different categories of water use are supplied at desired risk levels governed by the economic value of water use and social needs for water. The National Water Act (Act No. 36 of 1998), Part 3 gives priority to the Reserve which supplies ecological requirements and basic human needs riparian to the river. To determine the Reserve, the different reaches of the river system are classified according to resource quality objectives.

2.2 STOCHASTIC STREAMFLOW MODEL

The Orange River operation currently uses stochastic streamflow models of the autoregressive type (ARMA models) to obtain ensembles of probable inflows in the short-term future up to 36 months. These models generate synthetic streamflow which preserves the statistical properties of a historical sequence. The annual synthetic flows are disaggregated into monthly flows using monthly distributions of a single representative historical year. According to Van Rooyen and McKenzie (2004), the auto regressive moving average time series model (ARMA (ϕ,θ)) is defined as:

$$X(t) - \phi 1\ X(t-1) - \phi 2\ X(t-2) = a(t) - \theta 1\ a(t-1) - \theta 2\ a(t-2) \qquad (2.1)$$

Where:

- X1, X2, … Xn is a stationary sequence of centred (zero mean) normal variates
- a(t) is a sequence of independent random variables with a normal distribution having a mean of zero and constant variance (white noise)
- $\phi 1$ and $\phi 2$ are auto-regressive model parameters
- $\theta 1$ and $\theta 2$ are moving average model parameters

The Stochastic Model of South Africa (STOMSA) (Van Rooyen and McKenzie, 2004) is currently used to generate streamflow. STOMSA generates normally distributed flows that preserve statistical properties such as the mean (μ), variance (σ^2), and first order correlation coefficient (ρ) of the naturalised historical flow sequence. A marginal distribution is selected to normalize annual flows and an ARMA (ϕ,θ) time series model is selected to efficiently reproduce the serial correlation and compute normalised residual annual flows. The cross correlation structure of the normalised residual annual flows at multiple sites is determined using singular value decomposition (Van Rooyen and McKenzie, 2004).

Multi-site synthetic sequences are generated by a reverse of the above process. Details of the process of generating synthetic sequences are fully explained in DWA (2007) and were not repeated here.

2.3 RESERVOIR OPERATING ANALYSIS

2.3.1 System Operating Analysis

The hydrology and water requirements of the system define the input space for the Water Resource Planning Model (WRPM) (DWAF, 2007) used to compute optimum operating policy. As new developments take place and land use is modified, the system hydrology is updated. The WRPM analyses the system of reservoirs and water demands under a given hydrology to determine both the short-term and long-term system yield. Long-term yield is a system feature used to determine the timing for system augmentation.

Short-term yield analysis is carried out over 36 months to determine the behaviour of the system made up of Katse and Mohale Dams in Lesotho, Welbedacht, Gariep and Van der kloof Dams in South Africa. The operating analysis involves investigating storage control curves, system water demands and storage trajectory over the critical period, defined as 36 months. Critical period is the time over which reservoir storage, subject to streamflow and demand patterns, reduces from full to empty. Below dead storage, the reservoir is regarded as failed and water restrictions are imposed to avoid emptying the reservoir completely, to guarantee some level of supply. The monthly release schedule that does not result in an empty reservoir is adopted as the operating policy. The monthly release schedule is however only computed for the dams in South Africa for which the Department of Water Affairs has jurisdiction. Abstractions from upstream dams had no impact on Vanderkloof Dam storage behaviour because artificial neural networks are data based which only depend on the training pattern. An elaborate discussion of this subject is covered in section 5.1.3.

On 1 May of every year, the Water Resource Yield Model (WRYM) is run to investigate short-term yield-reliability curves with starting storages of 10%, 20%, 40%, 60%, 80% and 100% of capacity. The decision date for reservoir operation in South Africa is 1 May when reservoir operating analysis is undertaken to decide how the reservoir should be operated in the coming year. The resulting yield is applied to the system water requirements over a period of 36 months for short-term planning or over 12 months for annual operating analysis. If the storage drops to dead storage over the operating period, the system is regarded as having failed because it will not meet the demands for a period of time until the reservoirs have recovered. Whenever the storage drops below some pre-determined level, water restrictions are introduced immediately to prolong the supply until the system has recovered and so avoid severe water shortages.

The WRYM computes both short-term and long-term stochastic yields of the system. Historical data of rainfall, water abstraction and land use are used as input in the Pitman model that simulates the catchment rainfall-runoff relationship which is calibrated with historical streamflow. The rainfall-runoff model is then used to generate naturalised streamflow by setting the historical land and water use data to zero. Naturalised streamflow feeds into a stochastic streamflow generator (STOMSA) to yield synthetic stochastic streamflow. The stochastic streamflow from STOMSA then feeds into the WRYM to compute the yield of the system. Figure 2.1 is a schematic layout of the computation process involved.

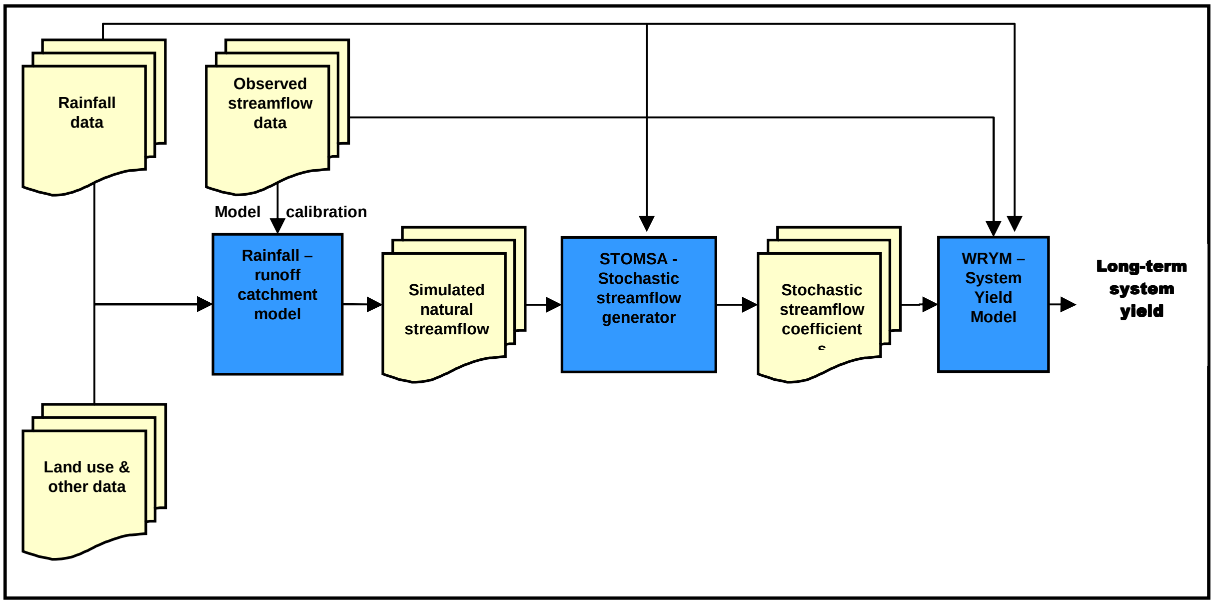


Figure 2.1: Water Resource Yield Model (DWAF, 2007)

The short-term stochastic firm yields at different assurance levels for the Gariep-Vanderkloof subsystem are presented in Table 2.1. It can be observed that short-term yield is low for low starting storages and the yield diminishes with decreasing risk level.

Table 2.1: Gariep-Vanderkloof Short-term Stochastic Yield (DWA, 2010)

STARTING STORAGE	**SHORT-TERM STOCHASTIC FIRM YIELD (million m^3)**				
	1:10 years	**1:20 years**	**1:50 years**	**1:100 years**	**1:200 years**
100%	4956	4449	3927	3652	3406
80%	4753	4304	3768	3449	3188
60%	4536	4057	3550	3144	2956
40%	4058	3507	2971	2666	2478
20%	3058	2580	2203	2000	1782
10%	2275	1840	1594	1478	1203

2.3.2 Reservoir Operating Rules

Operating rules are developed with the WRPM using yield obtained from the WRYM. The WRPM model is an ensemble of four modules; the stochastic streamflow generator, water resource allocation algorithm, network simulation algorithm and the salinity module (Figure 2.2). Details about the operation of the WRPM can be obtained from DWA (2007).

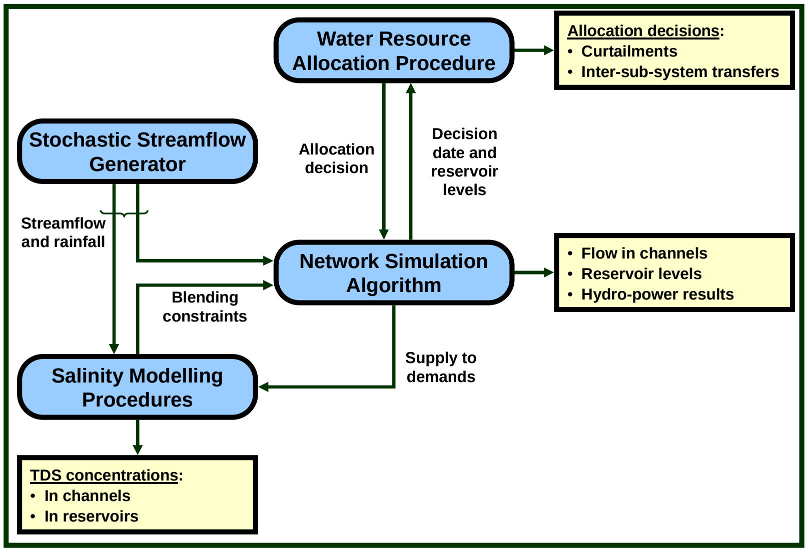


Figure 2.2: Schematic Layout of WRPM (DWAF, 2007)

Reservoir storage control curves define the level of storage at which the supply should be curtailed to comply with system constraints. They are selected to optimise the release and guarantee the desired risk level. The selection of storage control curves is a first step in formulating reservoir operating rules. Figure 2.3 shows the storage control curve adopted in the 2008/09 annual operating analysis to minimize spillage losses. The flood control curve sags during the rain season from about December to April due to the higher risk of spilling in that period.

The operating rule requires all releases to be channelled through the turbines to maximize hydropower. The flood storage control curve is used to minimize non-generating spillage and to create flood attenuation storage. When storage rises above the flood storage control curve, the turbines are allowed to run at full capacity until storage falls below the curve. Storage is allowed to be drawn down to the minimum operating level because the penstock inlet level is slightly above the minimum operating level and power generation could cease for only short periods. To limit the frequency of power disruption, additional support comes from Gariep Dam when Van der Kloof storage is just above the penstock inlet level. The benefit of allowing the storage to be drawn down to the minimum operating level is to supply consumptive users according to stipulated curtailment criteria except in drought periods. The irrigation canal outlet at 1147.78 m, slightly lower than the penstock inlet at 1150.80 m, defines the minimum operating rule. The low level storage of 810 million m^3 is bound between the irrigation canal outlet and the river outlet at 1128.45 m. At present, the low level storage is only accessible to users supplied from river releases. The irrigation canal has no direct access to the storage.

Hydropower generation at Van der Kloof Dam is driven by releases channelled through the turbines. To optimize hydropower, all the releases for both hydropower and water supply are channelled through the turbines. After release, it takes 30 days for the water to reach the Atlantic Ocean. Due to the long distance, two thirds (67%) of the demand is released in the previous month to allow enough travel time before the bottom of the system runs dry.

In the 2008/09 operating analysis, an allocation of 100 million m^3 was reserved for discretionary releases by the Department of Water Affairs (DWA), in addition to the scheduled releases. This allocation gave the DWA a free hand to supply unforeseen water shortages in the system during the year. In the same period, Eskom was allocated an additional 70 million m^3 for discretional use, over and above the scheduled releases, to meet fluctuating energy requirements. However, this additional allocation was not released during June, July and August to comply with ecological flow variability requirements. The discretionary allocations to DWA and Eskom are reviewed every year.

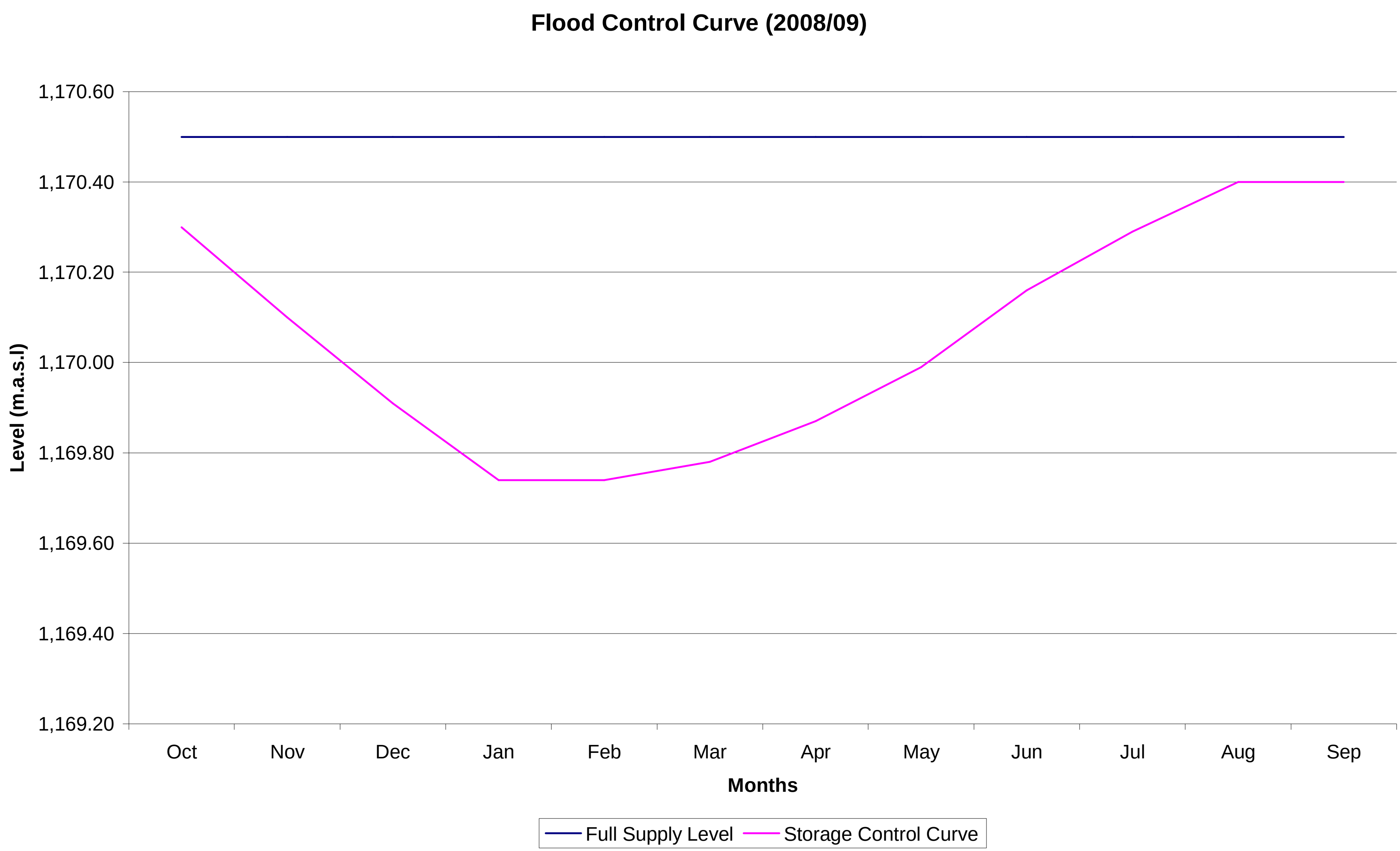


Figure 2.3: Flood Storage Control Curve

2.3.3 System Performance

For short-term planning, an operating analysis is carried out over a period of thirty six (36) months using stochastic streamflow and projected water demands. The annual operating analysis is undertaken to review the system every year. In times of shortage, supply is restricted according to the accepted risk levels to prevent complete failure of the system.

The level of assurance to the various user categories is selected in consultation with key stakeholders. Curtailment levels stipulate the level of restriction to be imposed on each user category in times of shortage. Currently, three curtailment levels are applied on the Orange River system, with level 3 the most severe. The likelihood of level 1 curtailment is 5%, 1% for level 2 and 0.5% for level 3. Table 2.2 gives the priority classification that was adopted in the 2008/09 Orange River system annual operating analysis (DWAF, 2010). The total water allocations to each user category are shown. The total allocation to water supply categories was first allocated to hydropower generation as the operating rule required that all releases be channelled through the turbines to maximize power. Table 2.2 shows that 50% of the irrigation demand was supplied at 95% assurance of supply, 40% demand at 99% assurance and 10% demand at 95.5% assurance. Other user category allocations were similarly distributed to the three assurance levels.

Restrictions are imposed on level 1 category if the curtailment lies anywhere between 0 and 1. A curtailment of 1.0, for instance, means all water allocated to level 1 (95% level of assurance) should be curtailed. A curtailment of 1.5 will curtail all level 1 allocations and 50% of level 2 allocations. A curtailment of 2.5 will curtail all allocations to level 1 and 2 and 50% of level 3 allocations. A severe shortage in the system is represented by a curtailment of 3.0 which implies curtailment to all user categories. There is a 0.5% likelihood (once every 200 years) of this happening. This is an extremely rare event but when it comes it is quite devastating. A shrewd restriction regime in pervious years will likely prevent this from happening.

Table 2.2: Orange River System Priority Classification (DWAF, 2010)

User Category	Priority Classification and Assurance of Supply			
	Total Demand (10^6 m^3)	**Level 1 95.0% (1 in 20 years)**	**Level 2 99.0% (1 in 100 years)**	**Level 3 99.5% (1 in 200 years)**
Hydropower	2394	0%	0%	100%
Urban/Mining	83	20%	30%	50%
Irrigation	1229	50%	40%	10%
Environmental	197	32%	0%	68%
Evapo & Other Losses	885	0%	0%	100%
Curtailment level	0	1	2	3

For the 2008/09 operating analysis, the observed risk of curtailment was 2.5% for level 1 curtailment, 1% for level 2 curtailment and 0.28% for level 3 curtailment compared with the maximum accepted risk of 5%, 1% and 0.5% respectively. This shows that the system was performing well, within the design capacity. The system is under stress if the curtailment criteria are constantly exceeded and this calls for system augmentation.

The level of assurance is a measure of the frequency of water shortages in the system but falls short of specifying the severity of the shortage also known as system vulnerability. A 95% level of assurance, for instance, means shortages are experienced 5% of the time or once every 20 years. System vulnerability is a useful performance criterion because it measures the magnitude or severity of shortage. Water managers tend to prefer a number of small manageable shortages than a single severe shortage. For measuring vulnerability, a severity index is used (Karamouz et al., 2003). The following deficit rate was developed by Hsu (1995) to measure severity of shortage or system vulnerability.

$$DR = \frac{S_T}{D_T} \times 100\% \qquad (2.2)$$

Where DR is deficit rate, S_T is total deficit in a period and D_T is the design water supply for the period. Vulnerability is not currently adopted as a performance criterion in the Orange River system but it holds great potential for improving the management of the system.

2.4 ECOLOGICAL FLOWS

The National Water Act (Act No. 36 of 1998) stipulates the release of the Reserve to supply ecological flow requirements and basic human needs riparian to the river. The determination of the size and temporal variability of the Reserve is therefore a legal requirement.

King and Louw (1998) give a brief description of the building block methodology as applied in South Africa for estimating the Reserve. The building block methodology identifies different components or blocks of the natural flow regime of a river which are ecologically most significant. The methodology results in a recommended flow regime which defines the volume of water and variability required for the maintenance of the natural biota and ecological processes in the river (Hughes et al., 1997). The essential flow components are low flows and small to medium floods. Extreme floods are ignored because they cannot be managed.

Instream flow assessment (IFA) by a panel of specialists at a workshop forms the initial process to define flows required at the selected instream flow requirement (IFR) sites for each month that will sustain the river in a desired future condition. Low flow is derived from the base flow index to sustain riverine ecosystems in drought years and high flow is determined from floods for river channel maintenance.

The results of the IFA process provide general environmental requirements. For instance, the ecological flow requirements of the Orange River system amount to 197.1 million m^3 per annum (DWAF, 2005(b)). Additional methodology is required to define the actual daily patterns of release and how these should be controlled. The IFR model (Hughes et al., 1997) is used to transform the output of the IFA process into release operating rules that meet environmental requirements. Hughes and Ziervogel (1998) give a summary of the IFR model.

The main principle of the building block methodology is that the final modified flow regime should reflect, in some way, the virgin flow regime. A naturalized time series is therefore defined to determine the conditions that would have existed in the river prior to developments and use these conditions to define the patterns of release that should occur. Hughes et al. (1997) recommend the use of an observed flow record from a nearby gauged catchment to define the flow time series. The gauging site could be on the same river or adjacent river as long as the flow time series is naturalized and the runoff response similar to that of the catchment (under natural conditions) upstream of the IFR site in question. The scale problems of the two catchments are circumvented by relating the flows at the two sites through percentage points of flow duration curves. The flow time series is converted into a time series of flow duration percentage points which are then plotted against time, in days, for each month. This is the principle that is used to link patterns of flow variation in a reference time series to release operating rules, regardless of whether the reference time series was taken from the IFR site or a nearby upstream site with a different catchment size. The randomness of catchment streamflow is preserved by applying daily coefficient of variation to the releases.

Duration curve percentage point information is used to define a baseflow status and a flood status for every day of the time series. Duration percentage points represent probability of exceedance for various levels of flow, with low probability of exceedance for high flows and high probability of exceedance for low flows. For convenience, flow status is defined to be high for wet conditions and low for dry conditions. As a result, the percentage point information is inverted (i.e. 100% - % point) to define flow status. The median value of the minimum inverted percentage points for 16 overlapping 15 day periods of the previous month (30 days) defines the baseflow status. The flood status algorithm identifies the highest peak during the next 10 days that falls within the same month as the current day and satisfies the rate-of-rise criterion expressed in Equation 2.3. A future 10 day period is selected because it represents the longest time over which a forecast into the future is likely to be possible with a forecasting time step of 1 day.

$$\text{Flow (i)} - \text{Flow (i-TP)} \geq dQ \times TP \qquad (2.3)$$

Where:
Flow (i) is the flow rate on the day of the possible peak;
Flow (i-TP) is the flow TP days previously;
dQ is the minimum rate of flow rise; and
TP is time to peak.
Figure 2.4 shows a plot of reference flow versus release (or flow status) which illustrates the linear interpolation described in the operating rules specified below. The notations used to define the operating rules are defined as follows:

NLQ = normal low flow for river maintenance determined from reference series
DLQ = drought low flow determined from reference time series
NPP = equivalent reference duration curve percentage point for normal low flow
DPP = equivalent reference duration curve percentage point for drought years
NPP – MPP = equivalent reference duration curve percentage point for upper limit to low flow
QRD = reference flow at percentage DPP (drought rule)
QRN = reference low at percentage NPP (normal or maintenance rule)

QRX = reference flow at percentage point NPP – MPP (upper limit rule)
QR = reference flow at current day

Baseflow Operating Rule 1: If the baseflow status suggests drought flow conditions (≤ 100 – DPP), release is equivalent to low flow IFR for drought years:

$$\text{Release} = DLQ \tag{2.4}$$

Baseflow Operating Rule 2: If baseflow status falls between drought and average flow conditions (> 100 – DPP and ≤ 100 – NPP), release is a linear interpolation between drought and maintenance low flow IFR values (Figure 2.4):

$$\text{Release} = DLQ + (NLQ - DLQ) \times (QR - QRD)/(QRN - QRD) \tag{2.5}$$

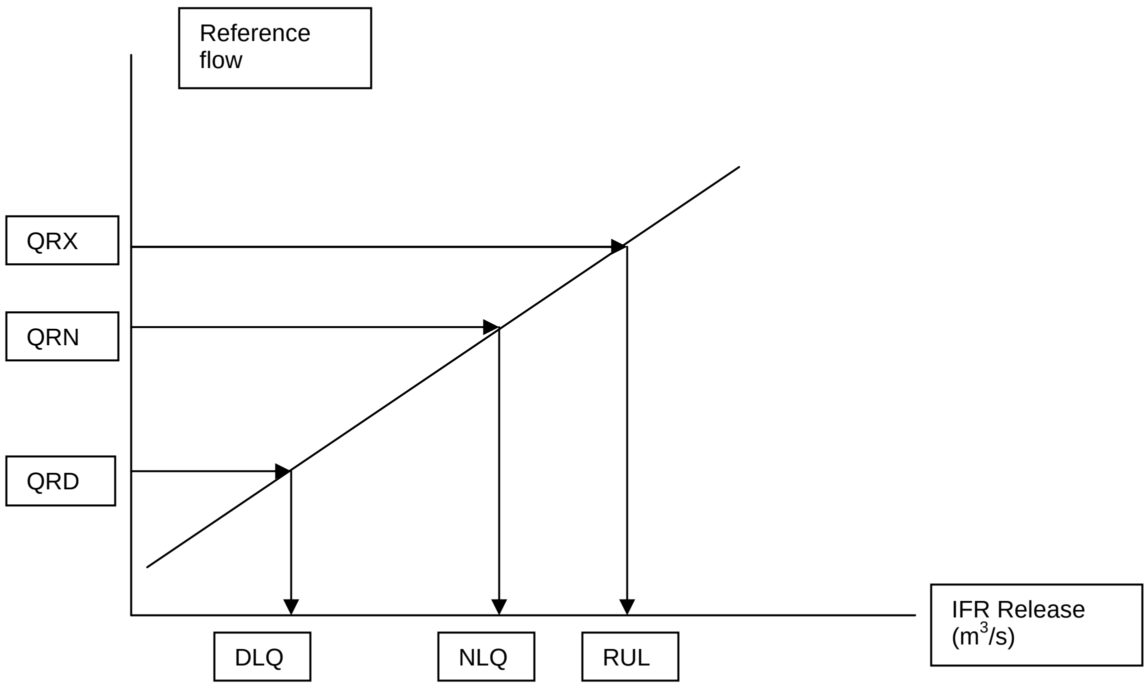
Baseflow Operating Rule 3: If the baseflow status is above average conditions (> 100 – NPP but ≤ 100 – NPP + MPP), release is above the maintenance low flow value:

$$\text{Release} = NLQ \times QRX/QRN \tag{2.6}$$

Baseflow Operating Rule 4: If the baseflow status is above the defined upper limit of low flow conditions (> 100 – NPP + MPP), release is the maximum possible for that month

$$\text{Release} = NLQ \times QRX/QRN \tag{2.7}$$

The flood component of an IFR is expressed in terms of a peak value (NHQ m^3/s) and event duration (D days). In addition, a minimum flood event (DHQ m^3/s) may be specified to ensure that critical floods are released even during drought periods. A critical duration percentage point (HPP) for high flow is defined for each month for comparison with the flood status to determine the size of flood to release in each month. If a flood event has been identified within the



RUL = upper limit rule release. Other symbols carry the same meaning as explained above.
Figure 2.4: Baseflow Operating Rule

reference flow time series, using Equation 2.3, the peak release is calculated as follows:

Flood Operating Rule 1: If the flood status is above the critical high flow condition (≥ 100 – HPP), release is equivalent to the maintenance IFR high flow:

Peak = NHQ (2.8)

Flood Operating Rule 2: If the flood status is between the critical high flow condition and the upper low flow condition (< 100 – HPP but ≥ 100 – NPP + MPP), release is determined from the following linear interpolation:

Peak = NHQ x (status – (100 – NPP) – MPP)/(NPP – MPP – HPP) (2.9)

Flood Operating Rule 3: If the flood status is below the upper low flow condition (< 100 – NPP + MHPP), then no high flow release event occurs in association with the reference flow event.

CHAPTER 3

RESERVOIR OPERATION TECHNIQUES

3.1 INTRODUCTION

There is increasing research interest worldwide for improved techniques for operating reservoirs as water resources become more scarce with an ever rising global population and economic expansion. An efficient reservoir operation will free up more water for critical needs of the economy and society. Labadie (2004) argues that as economies develop attention will eventually shift from dam building to improving the operational efficiency of existing reservoir systems. The marginal cost of water supply increases with the rate of economic development as all the best dam sites are developed first and the only remaining good sites are far away from consumers.

The two main processes of reservoir operation include streamflow prediction and reservoir optimization. Three options are available for operating reservoirs. Historic streamflow could be used to optimize reservoir operation, or streamflow could be simulated and the reservoir optimized manually, or an optimizer could be used to operate the reservoir with simulated streamflow.

In a review of the state-of-the-art of optimization methods Labadie (2004) gives a comprehensive description of the process of reservoir operation. The reservoir optimization problem consists of the objective function to be optimized and system constraints. Optimization models that could be applied to reservoir operation include implicit stochastic (Monte Carlo) and explicit stochastic optimization, linear and stochastic linear programming, network flow optimization, dynamic programming (discrete, differential, stochastic or chance constrained variations), and genetic algorithms. A brief review of the application of some of these methods is presented in sections 3.3.2 to 3.3.4.

3.2 STREAMFLOW FORECASTING

Streamflow is needed in the storage function during reservoir behaviour analysis. Since reservoir operating rules are developed ahead of the operating period, inflow into the reservoir over the operating period is estimated by forecasting. Jain et al. (1999) developed an autoregressive time series (ARMA) model and an artificial neural network (ANN) to forecast reservoir inflow for the Upper Indravati multipurpose project in India. The two models were fitted to monthly inflow data series and one month ahead forecasts, *Flow (t+1)*, were obtained and compared with the historic inflow sequence. The primary objectives of the project were to supply 128 million ha of irrigation and to generate 600 MW of electric power. The ANN performed better with high inflows while low inflows were better modelled with the ARMA model. The release was modelled as a function of storage, inflow and demand using linear and nonlinear regression and ANN. The release was optimized using dynamic programming. The findings of this study demonstrated that the ANN technique is a powerful input-output modelling platform which can be used effectively for reservoir inflow prediction and operation.

Zealand et al. (1999) used an ANN and a conventional forecasting model (Winnipeg Flow Forecasting System (WIFFS)) for short term streamflow forecasting for the Winnipeg River system in northwest Ontario, Canada, with a catchment area of 20 000 km^2. The WIFFS is a stochastic deterministic watershed model for forecasting quarter-monthly reservoir inflows. The lead times modelled were 1-week ahead, *Flow (t+1)*, 2-weeks ahead, 3-weeks ahead and 4-weeks ahead and the present time, *Flow (t)*, one past week, *Flow (t-1)*, two past weeks, three past weeks and four past weeks were used as input. A very close fit was obtained during training (calibration) and the ANN consistently outperformed the WIFFS model during testing (verification) for all the forecasting lead times.

Kisi (2004) developed an ANN and an autoregressive model (AR) to predict mean monthly streamflow. For the ANN, the input data was normalized to fall in the range 0.1 to 0.9. The streamflow Q was standardized by the formula: $Q_s = (Q/1.24Q_{max}) + 0.1$, where Q_s is the standardized flow; and Q_{max} is the maximum flow of the series. The six combinations of input data investigated were (Q_{t-1}), (Q_{t-1}, Q_{t-2}), ……, (Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, Q_{t-5}, Q_{t-6}), where Q_t is the present streamflow in month t. The output layer had one neuron for the present flow Q_t. The ANN with the input nodes Q_{t-1}, Q_{t-2}, Q_{t-3}, and Q_{t-4} produced the best results during testing (validation). The ANN predictions in general were found to be better than the AR predictions. Kisi (2004) concluded that the ANN approach may provide a better model than the AR model for developing input-output simulations and forecasting models that do not require modelling of the internal structure of the watershed.

3.3 RESERVOIR OPERATION

A reasonably good and quasi-optimal operating rule can be derived from a mathematical formulation of the system using simulated results. Simulation in itself however is not an optimization technique, although it can be used effectively for searching out local optima (Loucks and van Beek, 2005). Genetic algorithms are fast gaining popularity for optimizing water resource problems (Mathur and Nikam, 2009), and some artificial neural network software come with genetic algorithms. The common algorithms used for optimizing reservoir operation are presented in section 3.1.

3.3.1 Storage Control Curves

According to Savenije (1995) the active storage in a reservoir is divided into a number of regions or control zones. When storage is in the upper zone, water should be released at full outlet capacity to minimise the likelihood of spillage. In the middle zone, water is released in the most economical manner to satisfy existing demands while in the lower zone, abstraction is restricted to minimise water shortages.

The operating rules for the four storage zones are outlined below (Savenije, 1995). S is the reservoir storage, Q the release, D the demand and L the spillage.

- The Flood Rule Curve (FRC_t) is a hard boundary which should not be crossed. The FRC is only a hard boundary at the time scale used for reservoir simulation (a time step of one month). During day-to-day operation, the FRC can however be crossed temporarily during spilling. Above the FRC, excess water is spilled (L = S – FRC).
  - ✓ If S > FRC, then Q = D + (S – FRC) and S = FRC is used for the next time step

- The Utility Rule Curve (URC_t) is a soft boundary that can be crossed. If the storage drops below the URC the supply (release) is curtailed by a restriction factor, f. There may be more than one URC for multi-purpose reservoirs.
  - ✓ If S < URC, then Q = f*D and Q = f*D is used for the next time step

- The Dead Storage Curve (DSC) is a hard boundary. The storage is never allowed to drop below this level as a result of releases, only due to evaporation and seepage. The dead storage is a reserve to sustain reservoir ecosystems. If the storage drops below the DSC in the simulation, the release is reduced by the shortfall (DSC – S).
  - ✓ If S < DSC, then Q = S + D – DSC and S = DSC is used for the water balance in the next time step

- ✓ If the water balance gives $Q < 0$, then S and Q are adjusted to $S = DSC + Q$ and $Q = 0$

Reservoirs are operated for either normal conditions or for flood mitigation. In their study, Hsu and Cheng (2002) applied three rule curves to divide a typical reservoir into four operating zones throughout the year and applied a network flow programming model to the Tanshui River basin in northern Taiwan. The curves investigated were the upper limit, lower limit, and extreme limit rule curves, similar to the FRC, URC and DSC. The operating policy was based on the storage at the beginning of each time period.

3.3.2 Dynamic Programming

Dynamic programming has been applied successfully to optimize reservoir operation. Raman and Chandramouli (1996) developed four models for a general operating policy for Aliyar Dam in Tamil Nadu, India and compared their performance. The models developed included a stochastic dynamic programming model (SDP), standard operating policy (SOP), multiple linear regression dynamic programming model (DPR) and neural network dynamic programming model (DPN). The objective was to minimize the squared deficit defined as the difference between irrigation demand and the release. The initial storage, reservoir inflow and water demand were the input to the neural network and the release was the output. Twenty (20) years of fortnightly historic data were used to solve the objective function of the four models. The DPN model performed better than the DPR, SDP and SOP models for this reservoir system. They concluded that the neural network performed better because it allowed more complex modelling and developed nonlinear functions with the necessary complexity to learn the system patterns under investigation.

3.3.3 Network Flow Programming

Network flow programming is a special class of linear programming and is the optimizer applied in the WRPM (Basson, et al., 1994). Hsu and Cheng (2002) developed a generalized network flow model to optimize the operation of a river basin in northern Taiwan. A set of nodes and arcs were used to develop the network with reservoir storage and water supply for public and agricultural uses selected as the decision variables. The continuity equations, reservoir operating rule curves, level of water rationing and evaporation loss were the model constraints. The network model was solved with EMMET, an efficient embedded generalized network solver. A well calibrated simulation model was also developed for the system and the results compared. The water shortage computed from the network optimization model was smaller than that computed from the simulation model, proving the power of network flow programming.

Network Flow programming is currently used in the WRPM model for optimizing operation of the Orange River system (Basson et al., 1994). This algorithm lends itself easily to the formulation of a water resource system, represented by the two basic features of network flow programming:

1) representation of the water resource system as a flow network
2) representation of the water resource operating policy by a unique penalty structure

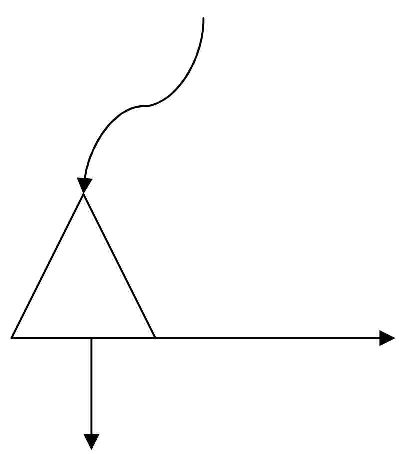


Figure 3.1: Simple Water Resource System

Figure 3.1 shows a simple water resource system with one node (reservoir) and three arcs (inflow, demand and spill). Initial and final reservoir storages are represented by arcs on the system network configuration (Basson et al., 1994).

A water resource problem is defined by a network configuration of arcs and nodes in which the size of flow in an arc is controllable and limited by the lower and upper bounds associated with the arc. Arcs are used to represent all flow paths in the water resource system, such as, rivers, canals, pipelines, diversion flows, flow releases, natural flow, spillage, power flow and reservoir storage. Nodes are used to represent points of interaction between arcs.

The unit cost of flow through an arc determines the size of flow. The optimization problem involves choosing the arc flows, within the arc limits, that will minimize the total cost of flow in the network. The cost of flow takes the form of a penalty charged for releasing water from the different storage zones of the reservoir (Table 3.1). A negative penalty is assigned in cases where flows through certain arcs should be avoided or minimized, such as to minimize spillage. The optimization problem then becomes:

Minimize $Z = \sum_{K} C_k X_k$

Subject to: $\sum_{K \in MOi} X_k - \sum_{K \in MTi} X_k = 0$

$X_k \leq UB_k$

$X_k \geq LB_k$

X_k = flow in arc K

C_k = unit cost of flow in arc K

$k \in M_{Oi}$ = arc K is a member of the set of arcs Originating at node i

$k \in M_{Ti}$ = arc K is a member of the set of arcs Terminating at node i

UB_k = upper bound on flow in arc K

LB_k = lower bound on flow in arc K

Table 3.1: Reservoir Penalty Structure
(Adapted from Basson et al. (1994))

Storage Zone		**Penalty, P_i**
Zone 1	Spillage	- 10 000
Zone 2	Rule curve	10
Zone 3	Intermediate zone	20
Zone 4	Intermediate zone	30
Zone 5	Intermediate zone	200
Zone 6	Dead storage	10 000

3.3.4 Genetic Algorithms

Mathur and Nikam (2009) developed a genetic algorithm (GA) to optimize the operation of the Upper Wardha Dam, a multipurpose reservoir in India, and to derive optimal reservoir operating rules. The fitness function used minimized the squared deviation of monthly irrigation demand and squared deviation in the mass balance equation. The selected decision variables were monthly release and initial storage at the beginning of the month. The reservoir capacity and the bounds of the decision variables provided the constraints for the optimization model. Average annual reservoir inflows were used in the model. The results show that even during low flows, the GA model can satisfy downstream irrigation demand. The conclusion was that the GA model had the capability to perform efficiently in the real world operation of the Upper Wardha Dam.

Wardlaw and Sharif (1999) evaluated the performance of a GA using a four reservoir, deterministic, finite horizon problem. The aim of the study was to provide fundamental guidelines for using GAs in practice. The conclusion was that the most promising genetic algorithm approach for the four reservoir problem comprised real-value coding, tournament selection, uniform crossover and modified uniform mutation. Wardlaw and Sherif (1999) found that real value coding is faster than binary coding and produces better results. The results demonstrated that a genetic algorithm can be used satisfactorily in real-time reservoir operation with stochastically generated inflows. From their analysis, they assert that the genetic algorithm approach is robust, can easily be applied to complex systems and has potential as an alternative to stochastic dynamic programming. For the purpose of using stochastically generated flows with genetic algorithms, Van Vuuren et al. (2005) investigated the development of genetic algorithms linked to the Water Resource Yield Model for determining the optimal operating rule for water resource systems. The recommendation given for further research was to develop a generic inter reservoir optimization model using this modelling platform. Ndiritu (2003) applied a multi-population genetic algorithm to optimise a system of two reservoirs that supplies monthly varying demands and environmental flows in the Elands River catchment in South Africa. The penalty resulting from non-supply of water and low storage states that would inhibit non-consumptive utilisation was minimised. The genetic algorithm obtained reasonable least-penalty solutions for the four cases analysed. In a subsequent research, Ndiritu (2005) applied a behaviour analysis model linked to a genetic algorithm to determine reservoir sizes and monthly operating rules that maximise the yield of the same water supply system subject to multiple reliability constraints of supply and reservoir storage. Yields comparable to the Water Resources Yield Model were obtained and the method has the advantage of automating the derivation of inter-reservoir operating rules. A significant drawback of the simulation-optimisation approach, however, was the long computation times.

3.3.5 Systems Analysis

Reservoir operation involves the analysis of all the interacting components of a river system. According to Hall and Dracup (1970), water resource systems analysis deals with selecting from a large number of feasible options the set of scenarios that will optimize the objectives of the system within the constraints of law, economics, resources, social needs and the forces of nature. It deals with only one phase of the work of the water resources engineer; that of decision making (or scenario analysis) during planning, design or operation. Once the optimal scenarios have been selected, the remaining work of the water resources engineer would involve crystallization of the option, detailed design, construction and the physical operation of the system. The current study only investigated the operational aspects of Van der Kloof reservoir.

A river system is an ensemble of elements driven by the processes of hydrology, land use and water use interacting in a regular, interdependent manner. Systems operation is then concerned with the making of decisions about those aspects of the system which can be controlled, such as water release, in pursuit of system objectives. The principal elements define the system while the less definable elements are regarded as inputs and outputs. The elements of the system, the inputs and outputs and the environment are in constant interaction.

The goal is to modify the controllable inputs so as to maximise the desirable outputs and minimise the undesirable outputs; that is to optimise the system. A merely feasible design is not adequate as it only satisfies the system constraints but does not necessarily optimise the system since optimisation seeks the best of all feasible solutions. The controllable inputs are called decision variables. When each decision variable is assigned a particular value, the resulting set of decisions is called a policy such as reservoir operating policy defined by the release schedule. The condition of the system itself at any time is described by state variables and system parameters. The reservoir storage at any one time is a state variable and the streamflow and evaporation are system parameters which together define the condition of the river system.

CHAPTER 4

ARTIFICIAL NEURAL NETWORKS

4.1 INTRODUCTION

Artificial neural network modelling has drawn tremendous research interest in water resources management in recent years as the technique promises to offer a simple but powerful tool for managing water resource systems. An important feature of artificial neural networks is their ability to handle complex non-linear systems with great ease. Neural networks can be used both to simulate streamflow and optimize the system, a feature which makes them particularly appealing to reservoir operation where streamflow is predicted in the first stage and then applied in the subsequent operation of reservoirs. They are also faster than autoregressive moving average models (Jain et al., 1999).

The following sections present the theory of artificial neural networks and their application to the simulation of reservoir operation.

4.2 ARTIFICIAL NEURAL NETWORK THEORY

4.2.1 Intelligence Systems

An artificial neural network is an intelligent modelling platform with the capability to assimilate complex input-output interactions. The network is built from artificial neurons that process and relay weighted input through a transfer function much the same way the human brain functions. The motivation to develop artificial neural networks arose from the desire to develop an artificial system mimicking the human brain to perform intelligent tasks.

Just like the human brain, a neural network acquires intelligence through learning and stores knowledge within inter-neuron connection strengths known as synaptic weights. The power of neural networks lies in the ability to simulate both linear and non-linear functions and the ability to learn these functions directly from the data being modified.

Loucks and van Beek (2005) describe neural networks as just more complex types of regression or statistical (black-box) model.

4.2.2 Artificial Neural Network Architecture

The most common neural network is the multi-layer perceptron or feed-forward network which only links nodes in adjacent layers also known as columns. This is described as supervised network because it uses a historical output for learning, with the objective of minimising the difference between the simulation and historical data. The goal is to create a model that maps historical input onto historical output accurately so that the model can later be applied to forecast output given a new set of inputs.

The multi-layer perceptron architecture (Figure 4.1) is constructed from three types of layers explained below.

1) Input layer consisting of nodes that receive inputs from the external environment. The nodes do not transform the inputs but just transmit input values to nodes of the adjacent layer known as the first hidden layer,
2) Hidden layer consisting of nodes that receive the weighted inputs from the input layer or previous hidden layer, perform transformations on the values before transmitting the output to the next layer, which can be another hidden layer or the output layer, and
3) Output layer consisting of nodes that receive output from the last hidden layer and transmit the output to the user through a graphical user interface.

The number of hidden layers and nodes in each layer of network are design parameters to be determined during training.

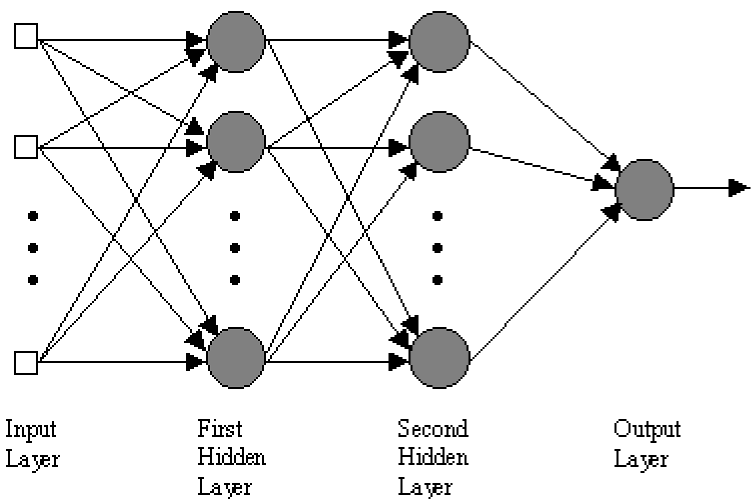


Figure 4.1: Multi-layer Artificial Neural Network

The two main connection topologies which define the flow of data between input, hidden, and output nodes are:

1) Feed-forward networks in which the data flows in one direction from the input layer to the output layer through the hidden layers. Output values solely depend on the current set of inputs. In most networks, the nodes of one layer are fully connected to nodes of the next layer, although this is not a requirement of feed-forward networks
2) Recurrent or feedback networks in which data flows back and forwards. Information from past inputs is fed back and mixed with current inputs through feedback connections. This type of typology is necessary when the solution to the problem depends on both current and past inputs.

The strength of the connection between adjacent nodes is a design parameter of the network. The output values O_j that leave a node j on each of its outgoing links are multiplied by a weight w_j, a measure of the strength of the connection.

The input I_k to each node k of the hidden and output layers is the sum of all weighted inputs w_jO_j from all nodes j reaching the node (Equation 4.1).

$$I_k = \sum_j w_j O_j \tag{4.1}$$

The input I_k is an argument to a linear or non-linear function $f(I_k + \theta_k)$, which converts the input I_k to output O_k. The variable θ_k represents a bias or threshold term that influences the horizontal offset of the function. Although a variety of transformations are possible, the most preferred transformation is the sigmoid function (Equation 4.2)

$$O_k = \frac{1}{1+e^{-(I_k+\theta_k)}} \tag{4.2}$$

4.2.3 Network Building

The procedure adapted from Smith (1993) for neural network building is summarized below. The software used in this study (NeuroSolutions Consultants) performs some of the steps automatically.

1) NeuralExpert utility of NeuroSolutions is used for building the network. This is the recommended utility for beginners although advanced methods are available,
2) The data set is divided into training, cross validation, and testing subsets,
3) The network is trained on the training data set,
4) The training stops periodically to measure the error on the validation data set,
5) A genetic algorithm is used to optimize the weights of the network,
6) Steps 3, 4 and 5 are repeated until the error on the validation data set starts increasing. This is the moment when network over-fitting starts,

7) The weights that resulted in the lowest error during cross validation are saved to define the trained network, and
8) The trained network is tested on out of sample testing data the network has not used previously during training and cross validation. The network is adopted for modelling if it performs satisfactorily, otherwise it will be re-trained and the entire procedure from step 3 repeated. On re-training, the network weights are changed in an iterative process to achieve an optimum network configuration. The weights are a measure of the strength of the connection between adjacent nodes of the network. The number of hidden layers and nodes can also be changed to match the complexity of the problem under investigation.

4.2.4 Network Training

The multi-layer perceptron and other types of neural network use a backpropagation algorithm for learning. The input and output are repeatedly fed into the neural network. With each presentation the output is compared with the desired output from historical time series and an error computed, in a process called supervised learning. The error is then fed back (backpropagated) through the network to adjust the weights (randomly set to begin with) with the goal of minimizing the error and achieving simulation closer and closer to the desired output. The backpropagation algorithm uses the steepest gradient descent procedure to determine the minimum error (Raman and Chandramouli, 1996).

Network training works out the best values of weights of the network. The training is complete when the network performance determined by cross validation is satisfactory. The resulting network weights are saved for later application of the network.

The mean square error (MSE), the mean relative error (MRE) and correlation coefficient (r) are the common performance criteria used to assess the capability of networks and improve the architecture (Jain *et al* (1999) and Raman and Chandramouli (1996)). These criteria are defined in Equations 4.3 to 4.5.

$$\text{MSE} = \frac{1}{N}\sum_{p=1}^{N}\left(T_p - O_p\right)^2 \qquad (4.3)$$

$$\text{MRE} = \frac{1}{N}\sum_{p=1}^{N}\left|\frac{T_p - O_p}{T_p}\right| \times 100 \qquad (4.4)$$

$$r = \frac{\dfrac{\sum_p \left(O_p - \overline{O}\right)\left(T_p - \overline{T}\right)}{N}}{\sqrt{\dfrac{\sum_p \left(T_p - \overline{T}\right)^2}{N}}\sqrt{\dfrac{\sum_p \left(O_p - \overline{O}\right)^2}{N}}} \qquad (4.5)$$

where T_p = target value for the p^{th} pattern; O_p = network output value for the p^{th} pattern; and N = total number of patterns. Effectiveness and convergence of the algorithm depend significantly on the value of the learning rate η. Similarly, a momentum factor α is used to accelerate the convergence. Some software optimize η and α automatically using optimizers such as genetic algorithms.

The architecture of the network is saved after a successful iteration of training. If the architecture is too small, the network may not have sufficient degrees of freedom to learn the system properly. On the other hand, if the network is too large, it may not converge during training and may over-fit the data.

4.2.5 Network Testing

Once a supervised network performs well on training data, it is then tested with a different set of data it has not been trained with. If the network fails to perform satisfactorily on testing, it is retrained until performance is satisfactory. Testing is critical to ensure that the network has indeed learned the general patterns of the system and has not simply memorized a given set of data.

4.2.6 Sensitivity Analysis

As further check on network performance, the effect of each input on network output is determined by sensitivity analysis. This analysis shows the input channels which are critical for performance of the network. From this analysis, it is possible to unclutter the input space by discarding the insignificant input channels. Discarding insignificant inputs simplifies the network and makes it more efficient in terms of training time and data requirements.

Sensitivity analysis investigates the interdependence between the inputs and outputs of a network. Network learning is disabled during sensitivity analysis to avoid affecting the saved network weights. Effectively, the network inputs are varied by small amounts and the corresponding change in the output recorded as a percentage or raw difference. On NeuroSolutions, for instance, the Activation Control prepares input data for sensitivity analysis by temporarily increasing the input by a small value known as dither. The corresponding change in output is a measure of sensitivity.

CHAPTER 5

DATA ACQUISITION AND ANALYSIS

5.1 CATCHMENT HYDROLOGY

5.1.1 Data Acquisition

Hydrological data was needed to simulate streamflow that was used to operate the reservoir. Artificial neural network modelling is a data based technique which requires long records of data to train, validate and test network parameters. The historical monthly streamflow record for the period 1977 to 2008 was available for training the neural network that was subsequently used to predict streamflow. The predicted streamflow and net evaporation, calculated from historical rainfall and evaporation, were used as inputs for operating the reservoir.

The records maintained by the Department of Water Affairs (DWA) were readily available in the form of monthly data. Previous researchers in this field have used monthly data successfully for reservoir inflow prediction and operation (Jain *et al.,* 1999). In addition, monthly series preserve statistical parameters better than annual series on the one hand and on the other hand monthly flow takes less computational memory than daily flow.

The Upper Orange River hydrology was compiled for training the neural network developed to forecast inflow into Van der Kloof Dam. However, besides the demand for hydropower, the demands for water supply that were modelled are all found downstream of the dam. The Hydrological Services Directorate of the DWA provided data on flow, rainfall and evaporation but the water demands were obtained from previous planning studies (DWAF, 2005(b)). Rainfall data provided by the DWA originally came from the South Africa Weather Service

(SAWS). The DWA and the SAWS are the custodians of hydrological and weather data in South Africa and the data was regarded the best that could be found anywhere.

The data collected included monthly streamflow, rainfall, evaporation, water demands, ecological flows and transmission losses. Area-capacity curves and plant capacity and layout were compiled from the DWA and Eskom.

5.1.2 Rainfall and Evaporation

Based on records spanning the period 1920 to 1987 (Station D3E003) (Figure 1.2), the mean annual precipitation at Van der Kloof Dam was found to be 349.8 mm (DWA, 2005(b)). Table 5.1 gives the average net evaporation over the dam basin. Net evaporation was obtained by subtracting rainfall from gross evaporation. Evaporation was not simulated with the ANN network because it had negligible impact on network results while increasing processing time. Historical net evaporation was however used for behaviour analysis in the manual reservoir operation with Excel spreadsheet.

Table 5.1: Net Evaporation

MONTH	NET EVAPORATION (mm)
October	230
November	269
December	313
January	315
February	256
March	191
April	132
May	102
June	81
July	93
August	123
September	176
TOTAL	**2,281**

5.1.3 Streamflow

The streamflow required for training the network model was the inflow into Van der Kloof Dam. For this system, the gauging stations that were selected for streamflow analysis were the station upstream of Van der Kloof Dam (D3H013: Roodepoort), upstream of Gariep Dam (D1H003: Aliwal North) and the station downstream of Welbedacht Dam on the Caledon River (D2H033: Welbedacht) (Figure 1.2). The Caledon River, a major tributary, joins the Orange River just upstream of Gariep Dam and below gauging station D1H003: Aliwal North. The flow into Gariep Dam is the sum of these two stations. The release from Gariep Dam (D3H013: Roodepoort) and the flow generated in the intermediate catchment between Gariep and Van der Kloof Dams add up to the Van der Kloof inflow. The above stations were used by the Hydrological Services of DWA for determining the inflow into the two dams because they each contain long records with very few gaps. Since the two dams are operated as a system, the three stations are also managed as one system. The record length was an important factor in selecting these stations because the neural network requires large amounts of data for training, validation and testing.

Only flow at D3H013: Roodepoort upstream of Van der Kloof Dam was needed to train the neural network because the flow captures the operation of Gariep Dam and very little inflow is generated between the two dams. The monthly hydrograph for D3H013 from October 1977 to February 2008 is presented in Figure 5.1. The longest flow data recorded at this station by the Hydrological Services of the DWA covers the period October 1977 to February 2008. The hydrograph is marked with one extreme event of high flow and this isolated feature presented learning challenges for the neural network.

Although inflow into Van der Kloof Dam was affected by upstream abstractions in Lesotho, the main flow regulation occurs at Gariep Dam which was factored in determining the inflow. For a simple operating model, the effect of upstream abstractions was considered insignificant. On the other hand, upstream abstractions were not considered to have effect on the artificial neural network because this modelling platform is data based and does not depend on whether flow is natural or impacted. If the network is properly trained, it acquires the ability to generalize and handle data it has not seen before. The model will however be impacted if extreme flows outside the training pattern were released from Lesotho. In chapter 8, the study of the operation of dams in Lesotho was recommended for further research with a view to investigating the range of releases from the system. An artificial neural network could then be applied to the entire Upper Orange River system including Lesotho dams. This could be achieved by simulating each reservoir sub-system separately with naturalised streamflow and then linking their operations by cascading abstractions to the downstream reservoir for accounting.

5.1.4 Lower Orange Water Demands

Annual water demands for the major urban and mining centres include Prieska (1.40 million m^3), Upington (26.01 million m^3), Kakamas (1.70 million m^3), Pelladrift (Pofadder, Aggeneys and Pella) (4.48 million m^3), Springbok (Springbok, Kleinsee and Port Nolloth) (4 million m^3), Alexander Bay (2 million m^3), Noordoewer (0.07 million m^3), Rosh Pinah and Skorpion Zinc (14.67 million m^3) and Oranjemund (6.5 million m^3). Pelladrift and Springbok are regional water supply schemes managed by the respective water boards. Annual irrigation requirements include Vanderkloof Canals (195.84 million m^3), Vanderkloof Dam and Riet River (50.42 million m^3), Vanderkloof to Marksdrift (166.07 million m^3), Tierpoort Irrigation Board (6.37 million m^3), Boegoeberg (301.40 million m^3), Upington (233.45 million m^3), Kakamas (173.58 million m^3), Namaqualand (28.76 million m^3), Vioolsdrift (21.54 million m^3), Orange-Fish (11.42 million m^3) and Namibia (40.55 million m^3). Releases to supply all the demands were channelled through turbines to optimize hydropower.

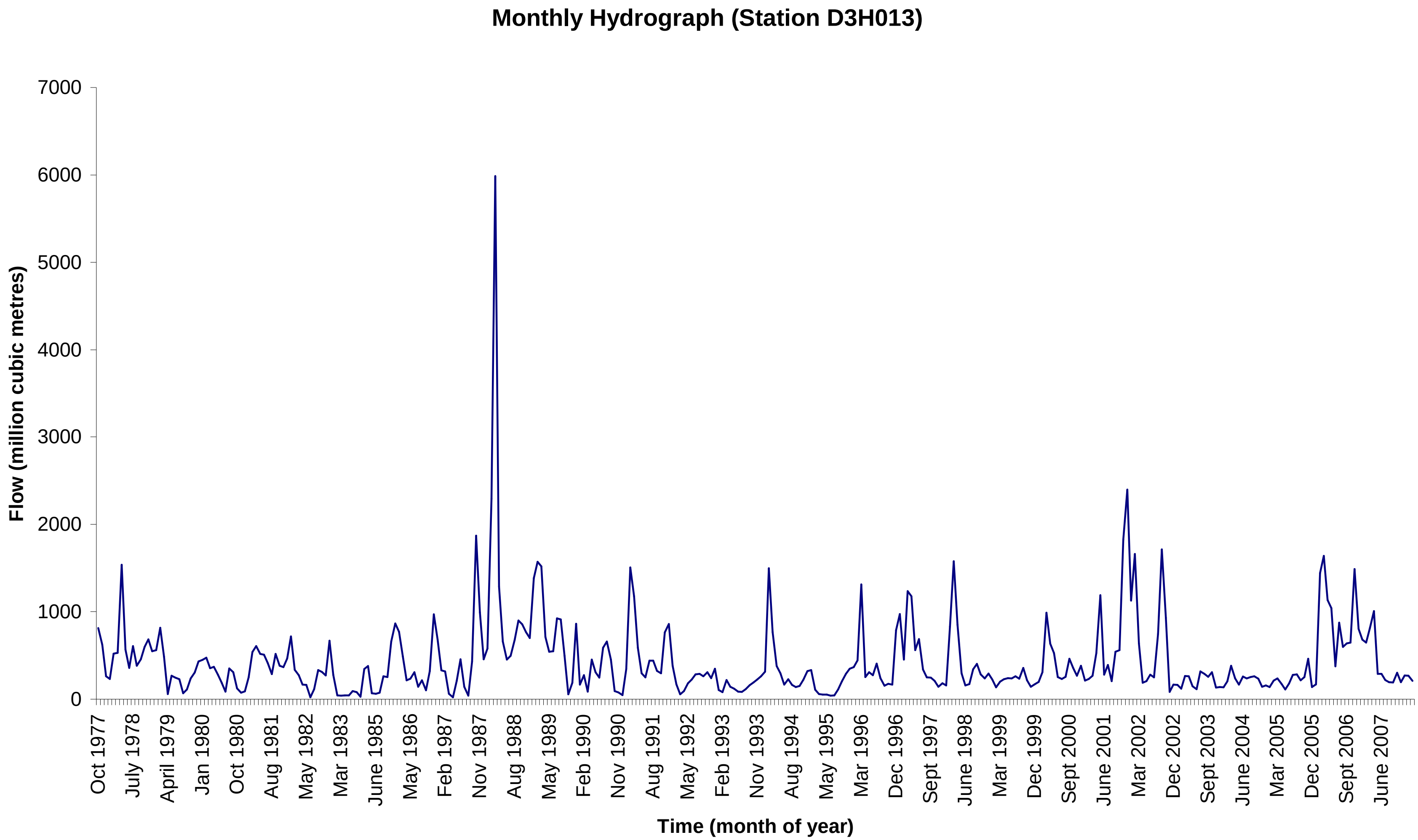


Figure 5.1: Monthly Hydrograph

The water requirements downstream of Van der Kloof Dam were based on the Annual Operating Analysis (DWAF, 2010). The annual water requirements amounted to 2 394 million m^3, broken down into 1 311.89 million m^3 for urban, mining and irrigation demands and 1 082.15 million m^3 for ecological water requirements (Table 5.2). The monthly release pattern produced in the Annual Operating Analysis was applied for disaggregating the annual water requirement into monthly demands needed for reservoir operation. Monthly water demands also included ecological requirements and transmission losses in the river channel. Ecological flows and transmission losses were obtained from the Lower Orange River Management Study (DWAF, 2005(b)).

The generating capacity of the Van der Kloof hydropower plant is 240 MW. This is defined by the penstock capacity and generating head. The operating level is 1 150.8 m (1 220.9 x 10^6 m^3 of storage) with a generating head of 79.8 m. The generating head increases as the storage rises. The plant has a maximum discharge capacity of 176 m^3/s at full supply level. The operating policy required all releases to be channelled through the turbines and so the only additional demand to meet hydropower requirements was the excess release over and above water supply requirements.

Table 5.2: Monthly Water Demand

MONTH	DEMAND (10^6 m^3)	DEMAND PATTERN (%)	ENVIRONMENTAL WATER REQUIREMENTS (10^6 m^3)	TOTAL DEMAND (10^6 m^3)
January	51.53	3.9	151.17	202.70
February	49.89	3.8	113.15	163.04
March	56.00	4.3	90.63	146.63
April	82.37	6.3	61.53	143.90
May	122.23	9.3	46.56	168.79
June	148.15	11.3	33.43	181.58
July	146.95	11.2	38.55	185.50
August	173.44	13.2	57.08	230.52
September	166.00	12.7	85.74	251.74
October	124.37	9.5	113.15	237.52
November	112.58	8.6	139.51	252.09
December	78.39	6.0	151.65	230.04
TOTAL	**1,311.90**	**100**	**1,082.15**	**2,394.05**

5.2 RESERVOIR CHARACTERISTICS

Figure 5.2 shows the storage control curves that are used for operating Van der Kloof Dam. The reservoir capacity and outlet layout defined the system constraints during optimization of reservoir operation. The reservoir characteristics are outlined below (DWAF, 2004(a)).

1) The full supply level of the reservoir is 1170.5 m, full supply capacity is 3 187.07 x 10^6 m^3 and dead storage is 1 015.4 x 10^6 m^3.

2) The reduced level of the non overspill crest is 1 180 m and of the bottom of the reservoir is 1 071 m.

3) The Orange-Riet Canal is fed by an outlet at reduced level 1 147.78 m which is the dead storage level. Water is released into the canal when storage falls in zone 1, 2 or 3 (Figure 5.2).

4) The low level storage of 205.48 x 10^6 m^3 is not utilized in order to optimize hydropower. If this storage were used to supply downstream demands, the reservoir could be drawn down to the lowest level of 1 071 m. Releases from the low level storage would however only be accessible direct from the river channel.

5) The maximum drawdown capacity is 5 461 m^3/s designed to draw down the reservoir to empty in 80 days. This drawdown capacity combines the gated spillway (4 993.7 m^3/s), river outlets (176.1 m^3/s) and silt outlets (291.2 m^3/s) for flashing out sediments. The combined outlet capacity for water supply is 391 m^3/s.

6) The ungated spillway has a design discharge capacity of 6 300 m^3/s or 13 393 m^3/s with zero freeboard. The gated spillway has a design capacity of 4 993.7 m^3/s at full supply level or 8 850 m^3/s with zero freeboard.

7) The minimum operating level for hydropower generation is 1 150.8 m and the penstock maximum discharge capacity is 176.1 m^3/s. The combined outlet capacity for water supply and hydropower is 567.1 m^3/s. The minimum net generating head is 54 m, allowing for energy losses in the penstock. Power can only be generated when storage falls above the operating level, that is, above zone 3 (Figure 5.2).

8) The area-capacity curves are presented in Figure 5.3. Both capacity and surface area increase with elevation as defined by site topography. The big surface area at higher elevations gives rise to increased evaporation losses. The generating head also increases with penstock elevation.

VAN DER KLOOF DAM			
Reduced Level (m)	**Zone Volume** (million m^3)	**Capacity** (million m^3)	**LEVEL**
1 170.50		3 187.07	Full Supply Level
ZONE 1 1 153.00	**ZONE 1** **1 802.13**	**ZONE 1** 1 386.47	Normal Operation
ZONE 2 1 150.80	**ZONE 2** **164.37**	**ZONE 2** 1 222.10	Only Eskom
ZONE 3 1 147.78	**ZONE 3** **206.70**	**ZONE 3** 1 015.40	Releases
ZONE 4 1 128.45	**ZONE 4** **809.92**	**ZONE 4** 205.48	Low Level Storage
Low Level Storage 1 071.00	**Low Level Storage** **205.48**	**Low Level Storage** 0.00	Bottom

Figure 5.2: Storage Control Curves (DWAF, 2004(b))

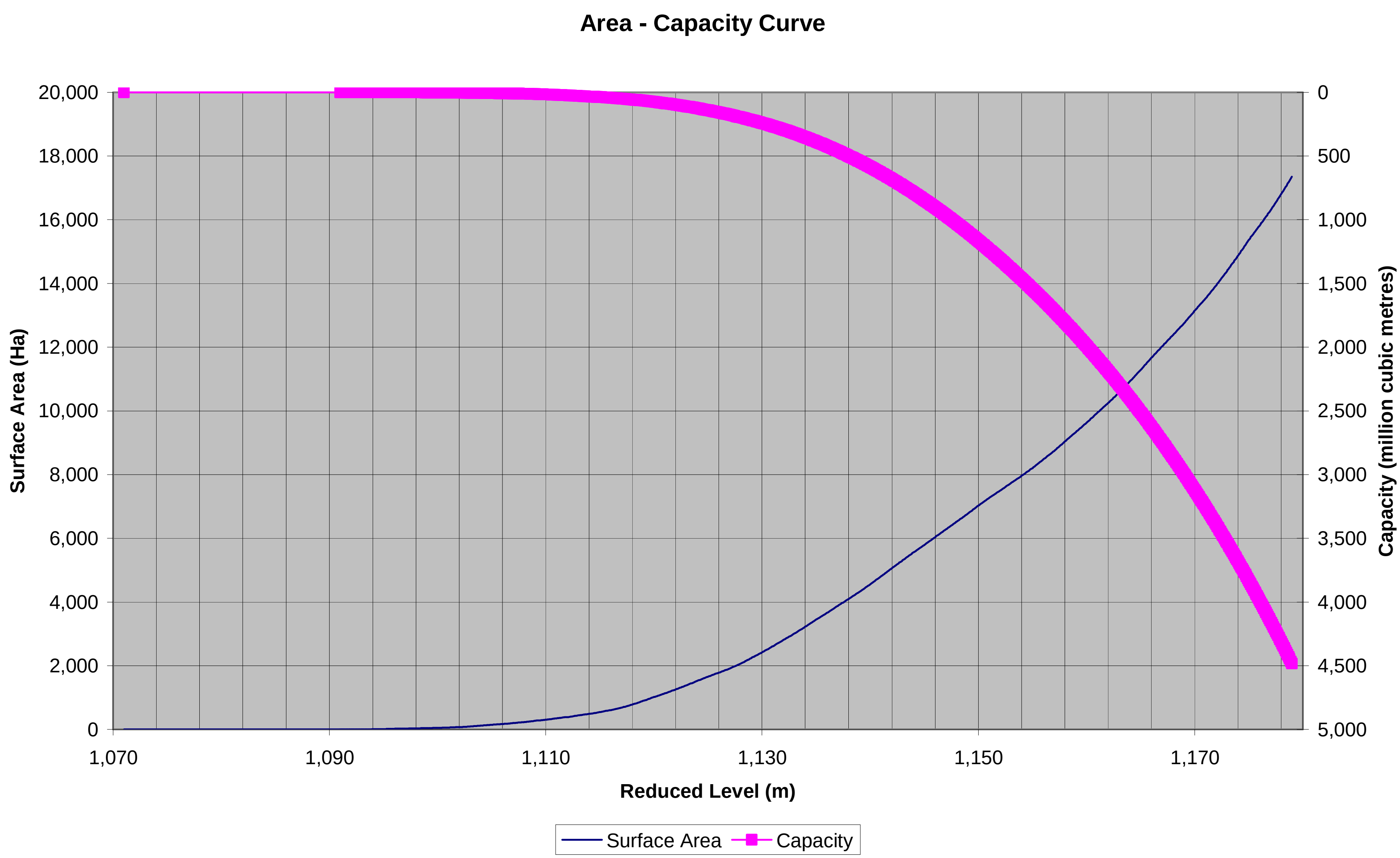


Figure 5.3: Area – Capacity Curve

CHAPTER 6

METHODOLOGY AND MODEL DEVELOPMENT

6.1 RESEARCH METHODOLOGY

A reservoir behaviour analysis was carried out to investigate the reservoir operating policy. Inflow, storage and outflow defined the water balance. The storage function was derived from reservoir storage characteristics while the outflow was defined by water demands, spillage and evaporation lost from downstream releases. Water demands, instead of abstractions, were used in this study because the model was designed to meet the full demands and consequently gauge system performance. If the system failed to supply the full demands, water rationing would be effected. The inflow for operating the reservoir in the next period of twelve months was forecasted with artificial neural network simulation using the historical record. The forecasted inflow did not replicate observed historical patterns because of the stochastic nature of streamflow. Stochasticity of streamflow derives from the random behaviour of the drivers of streamflow generation; namely, rainfall or climate, catchment response and upstream abstractions. The amount and distribution of rainfall received varies from one season to another and the catchment response is influenced by an ever changing land use pattern.

Historical streamflow, rainfall and evaporation data were collected for the ANN simulation and optimization on Excel. Water demands, ecological flows and system losses were obtained together with the layout of the hydropower plant. The artificial neural network was developed with NeuroSolutions Consultants (NeuroDimension, Inc., 2005) to forecast streamflow that was subsequently routed through the reservoir to determine the power generated and the demand supplied and water deficits throughout the operating period. The inflow forecast was based on simulation of 342 flows recorded at station D3H013. The objective of operating the reservoir was to maximize hydropower and minimize water supply shortages.

Several release schedules were simulated and the one that generated the maximum power without emptying the reservoir was adopted as the operating policy. As part of the operating policy, the storage was kept above critical levels to avoid a failure of the system. The system fails if the storage cannot supply the full allocation to all the users.

6.2 MODELLING APPROACH

The modelling approach followed is outlined below.

i) An annual model and monthly forecasting model were selected for investigation. The annual model is outlined in paragraphs ii and iii below while the monthly model is described in paragraphs iv and v. The feasibility of each model was tested as the investigation proceeded with the objective to screen the non-feasible model or to carry the two proposals through the entire modelling process if both proved feasible.

ii) The proposition for the annual model was to predict annual inflow 1 year ahead into Van der Kloof Dam over the operating period. Here the operating period chosen was one year and so it was only necessary to predict one annual flow and to then disaggregate the flow into monthly flows to allow continuous simulation of the reservoir throughout the year. Long-term monthly average flow and mean annual flow (MAR) were to be used to disaggregate the predicted annual flow according to the monthly distribution of low flows, average flows and high flows. The 1-year ahead model that was proposed can be expressed as: Q(t+1) = f(Q(t), Q(t-1), Q(t-2), Q(t-3), Q(t-4)). In year t = 5, for instance, the flow is denoted by Q(5) and model output Q(t+1) is denoted by Q(6).

iii) The function proposed for disaggregating annual flow into monthly flow was: q(t) = (Q(t)/MAR)Q. That is, predicted monthly flow (q(t)) equals mean monthly flow (Q(t)) divided by mean annual flow (MAR) multiplied by predicted annual flow (Q). The mean monthly flow was separately determined for high annual flows, average annual flows and low annual flows. The feasibility of adopting the long-term monthly average flow over the full record was tested with flow distribution pattern analysis of low, average and high flow distributions. This analysis was undertaken with monthly average flows for low, average and high flow conditions. The three average flows referred to the same period of time; that is January through December average flows. Distributions with similar patterns will show flow peaks occurring in the same periods of the year; only the peak magnitudes differ but the variability pattern would be similar. This property was important to permit long-term mean monthly flow to be used to predict monthly flow variation with confidence at all times, in years of low, average or high flow. The flow had to be defined first into low, average and high flows to facilitate flow distribution pattern analysis. The design low flow range of a flow duration curve falls in the 70 to 90 percentile of exceedance range (Pyrce, 2004). The World Meteorological Organization (2008) recommends 90 or 95 percentile for perennial rivers but as low as 30 percentile for arid and semi-arid regions. Scott and Smith (1997) defined low flow as the 75th percentile of exceedance in a study of models to predict reductions in flow resulting from afforestation in South African catchments. The distribution of annual streamflow for the record applied in this study (1977 to 2008) is presented in Figure 6.3. The streamflow was ranked and divided into low, average and high flows. The 70 percentile of exceedance (100% - 30% percentile) was used to define low flow (less or equal to 3 715.84 x 10^6 m^3), the 30 percentile of exceedance to define high flow (higher than 5 396.28 x 10^6 m^3) and the average flow ranged from 70 to 30 percentile of exceedance.

Average flows lie on the central gently sloping section of the curve while low flows lie to the left and high flows to the right. Low flows are plotted in Figure 6.4, average flows in Figure 6.5 and high flows in Figure 6.6. These plots should not be confused with the comparison between observed and simulated flows which is presented in section 7.2. The three curves are distinctly dissimilar, with monthly streamflow peaks for low, average and high flow conditions out of phase. As such, an annual flow forecasting model for this system should analyse long-term monthly average flows separately for low, average and high flow conditions.

iv) The monthly model was developed to predict 1-month ahead flow into Van der Kloof Dam. A prediction length of 1 month was selected to avoid errors involved with long prediction lengths. A recursive prediction process was followed with the 1-month ahead model to predict flow in all the twelve months of the year. The forecasted flow in each month was successively added to the historic flow record (input data set) to allow a forecast for the next month to be made. This process was repeated until flow in month 12 was predicted.

v) The 1-month ahead model that was developed is expressed by the function: $Q(t+1) = f(Q(t), Q(t-1), Q(t-2), Q(t-3), Q(t-4))$. For example, in month $t = 5$, the flow is denoted by $Q(5)$ and model output $Q(t+1)$ is denoted by $Q(6)$ (Figure 6.2).

vi) Actual storage on 1 February 2008 was used as initial storage for reservoir operation with simulated inflow. The flow record was available only up to 1 February 2008 and the storage on 1 May 2008, the standard decision date in the DWA, was not available. Actual storage on 1 February 2008 was the closest estimate because net reservoir drawdown was unlikely to be high since the period from February to April falls within South Africa's runoff season.

vii) The modelling process is schematized in Figures 6.1 and 6.2.

Simulation accuracy depends on the selected simulation time step and length of flow record. The annual model was discontinued because the annual flow record was very short. The flow record obtained for station D3H013 (Van der Kloof Dam) was for a 30 year period (1977 to 2008). Although the record contained 342 monthly flows, only 30 annual flows were available for training, cross validation and testing. The annual flow record was therefore found inadequate for an artificial neural network model.

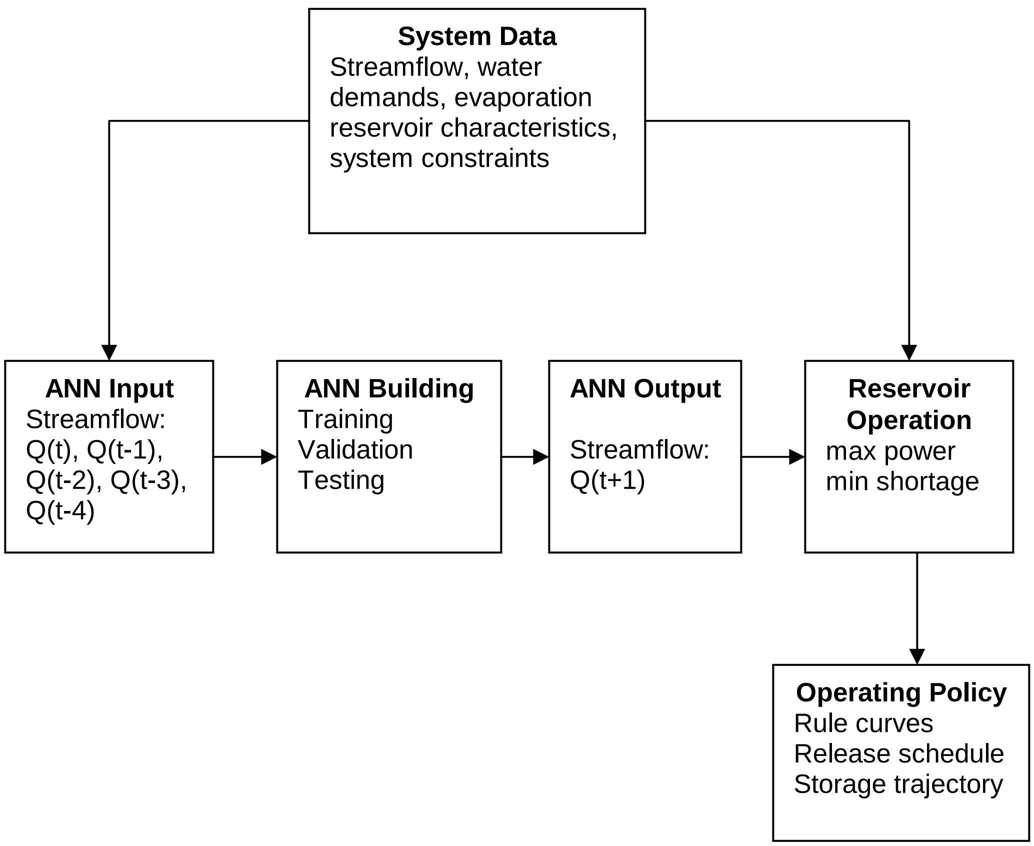


Figure 6.1: Model Flow Chart

Month	1	2	3	4	5	6	• • • • 12
Input Flow	Q(1)	Q(2)	Q(3)	Q(4)	Q(5)	Q(6)	• • • • Q(12)
Forecast Flow					Q(6)		

Figure 6.2: One month ahead flow forecasting

The other model that was abandoned early was a monthly model with a prediction length of 12 months. This model was to produce a complete set of 12 forecasted flows in one run of the model and would not need disaggregation. Its major setback arose from very poor model performance caused by the long prediction length. Based on these findings, the one-month ahead model was found to perform the best.

6.3 ORGANISATION OF DATA

A 1-month ahead model was investigated for predicting reservoir inflow that was needed to optimize release. The input space of the network was populated with the input vector comprising current flow Q(t), flow Q(t-1) in previous month, flow Q(t-2) in previous two months, flow Q(t-3) in previous three months and flow Q(t-4) in previous four months. The model output was the one month ahead streamflow, Q(t+1). For optimizing hydropower, streamflow, net evaporation and water demand data were needed as input while reservoir storage and release defined reservoir operating policy.

The monthly and annual models were selected for investigation because monthly and annual data were available in the Department of Water Affairs and the South African Weather Service. Another advantage with monthly data is that it does not require big computational memory compared to daily data. The monthly time step was further supported by previous research work (Jain *et al.,* 1999) in which monthly inflow, evaporation and irrigation demand were used for reservoir inflow prediction and operation. The annual time step was supported by Mathur and Nikam (2009) who developed a neural network with genetic algorithm for optimization over one year.

The National Water Act (Act No. 36 of 1998) stipulates the release of water for the Reserve to meet ecological requirements and basic human needs riparian to the river. Compliance with the stipulated amount and variability of streamflow over the year is a legal requirement and this was allowed in the monthly demand pattern.

Input data was saved on Excel in the CSV (comma-separated values) format compatible with the column-formatted ASCII used by NeuroSolutions. The historical streamflow was divided into training and cross validation (80%) and testing and production (20%). The most recent records were reserved for model application to predict streamflow over the operating period.

6.4 BUILDING THE NETWORK

6.4.1 Neural Network Software

NeuroSolutions Consultants was selected for this study from a range of six generations of the software; namely, the educator, users, consultants, professionals, developers lite and developers offering increasingly advanced utilities in that order. A hardware key was supplied for installing and operating the software on multiple computers at different times. The software was activated by plugging in the hardware key. Not more than one computer could run the software concurrently.

The choice of software was based on cost and capability. The prominent topologies of the software included the multilayer perceptron, generalized feed-forward network, modular network, probabilistic neural network, general regression neural network, time delay neural network, time-lag neural network, general recurrent network, unlimited inputs and outputs per layer and unlimited hidden layers. Advanced features of NeuroSolutions include macros, sensitivity analysis, genetic optimization and iterative prediction. The genetic optimizer however could only optimize network parameters during training and not the actual reservoir operation. Double precision calculations, extensive probing capabilities and an icon-based graphical user interface were some of the appealing features of NeuroSolutions Consultants.

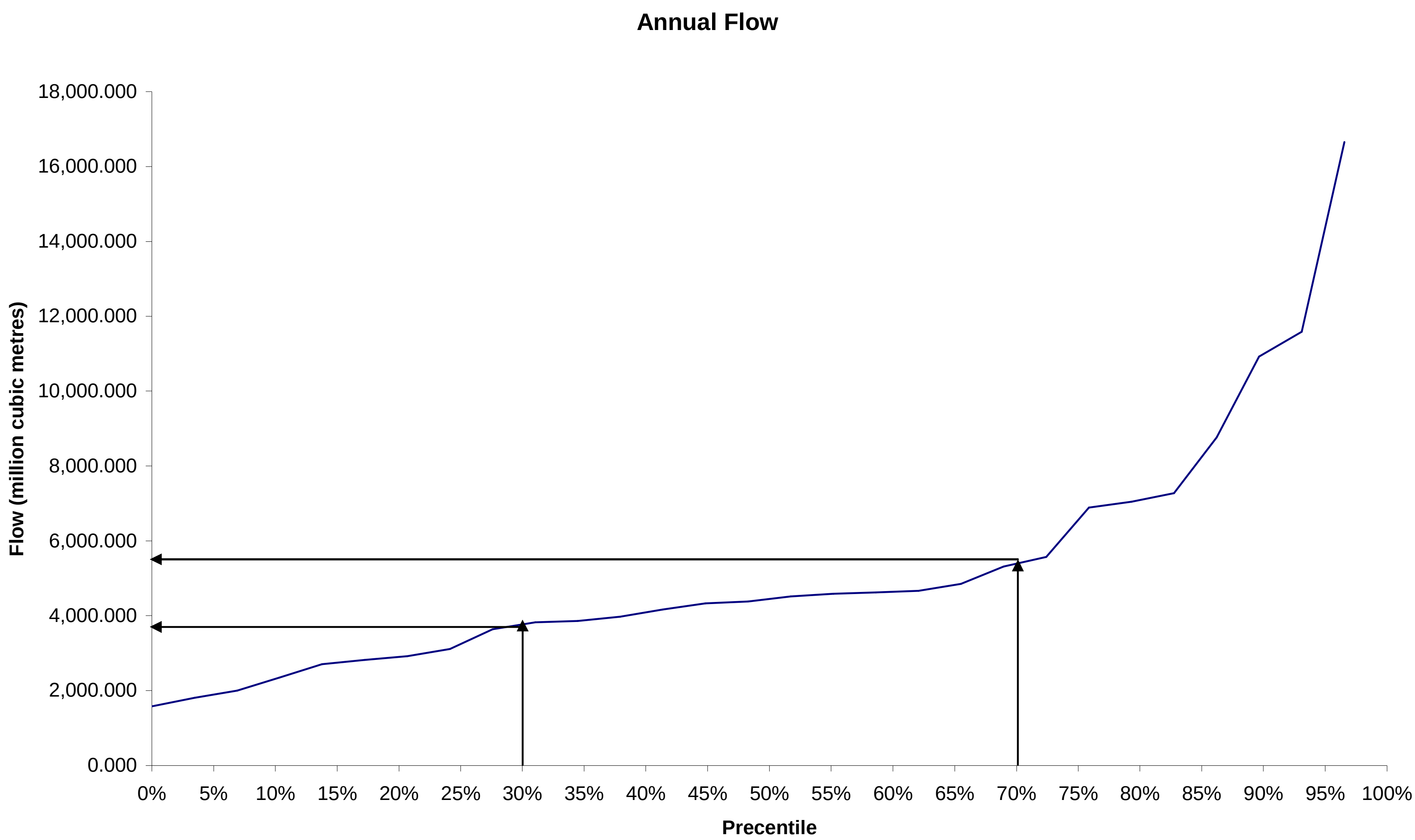


Figure 6.3: Annual flow-duration curve showing 3 flow classes

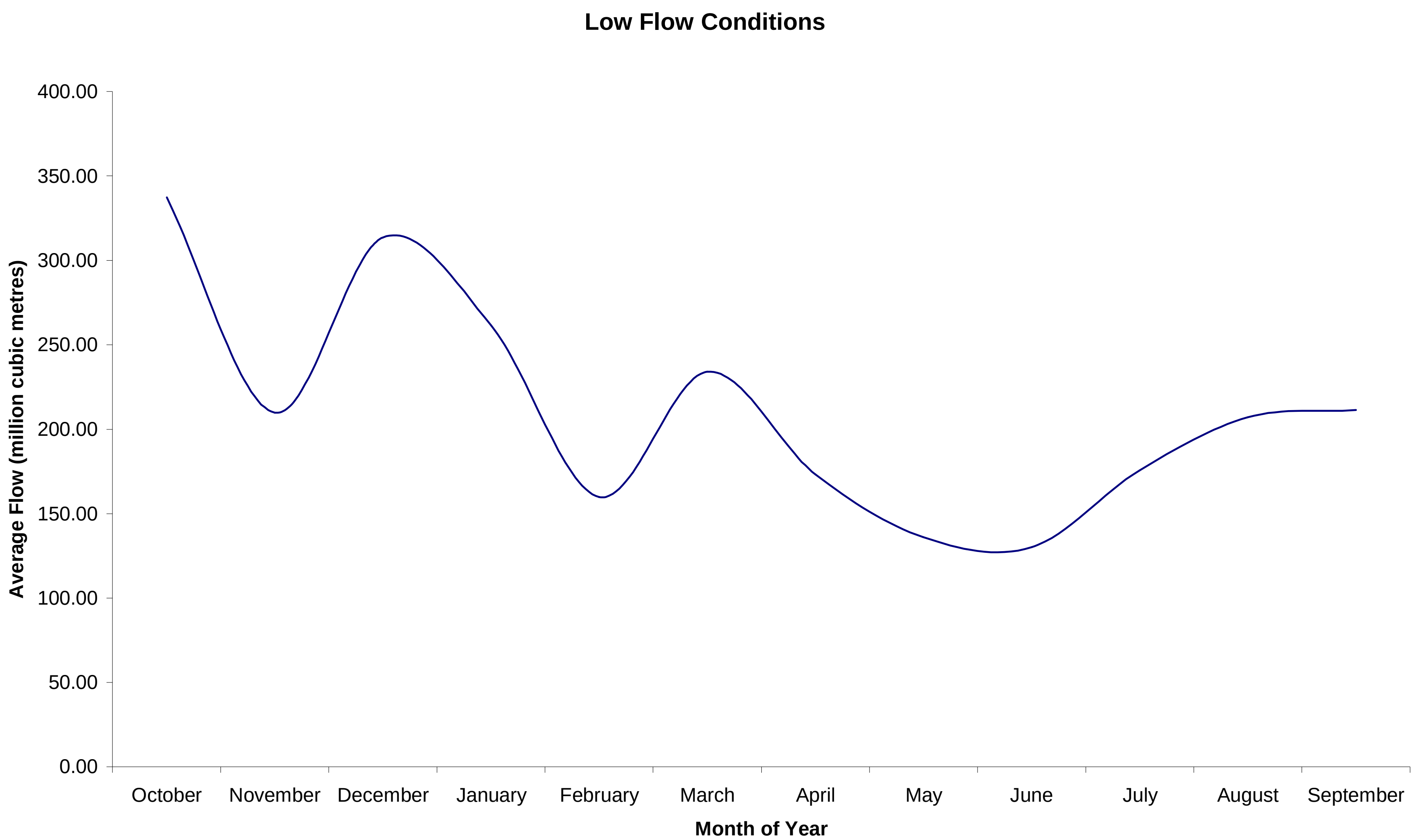


Figure 6.4: Monthly flow distribution of low flow years

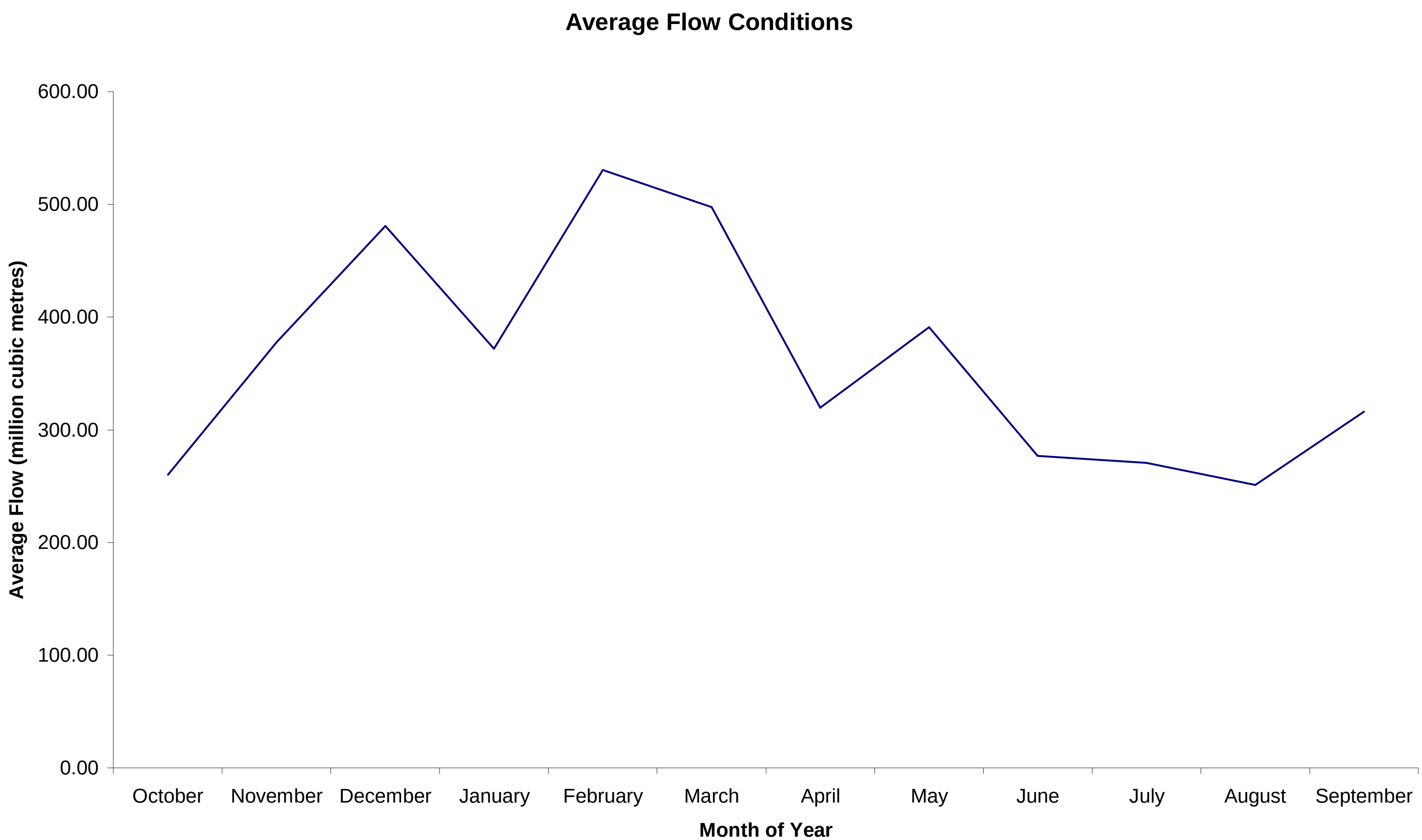


Figure 6.5: Monthly flow distribution of average flow years

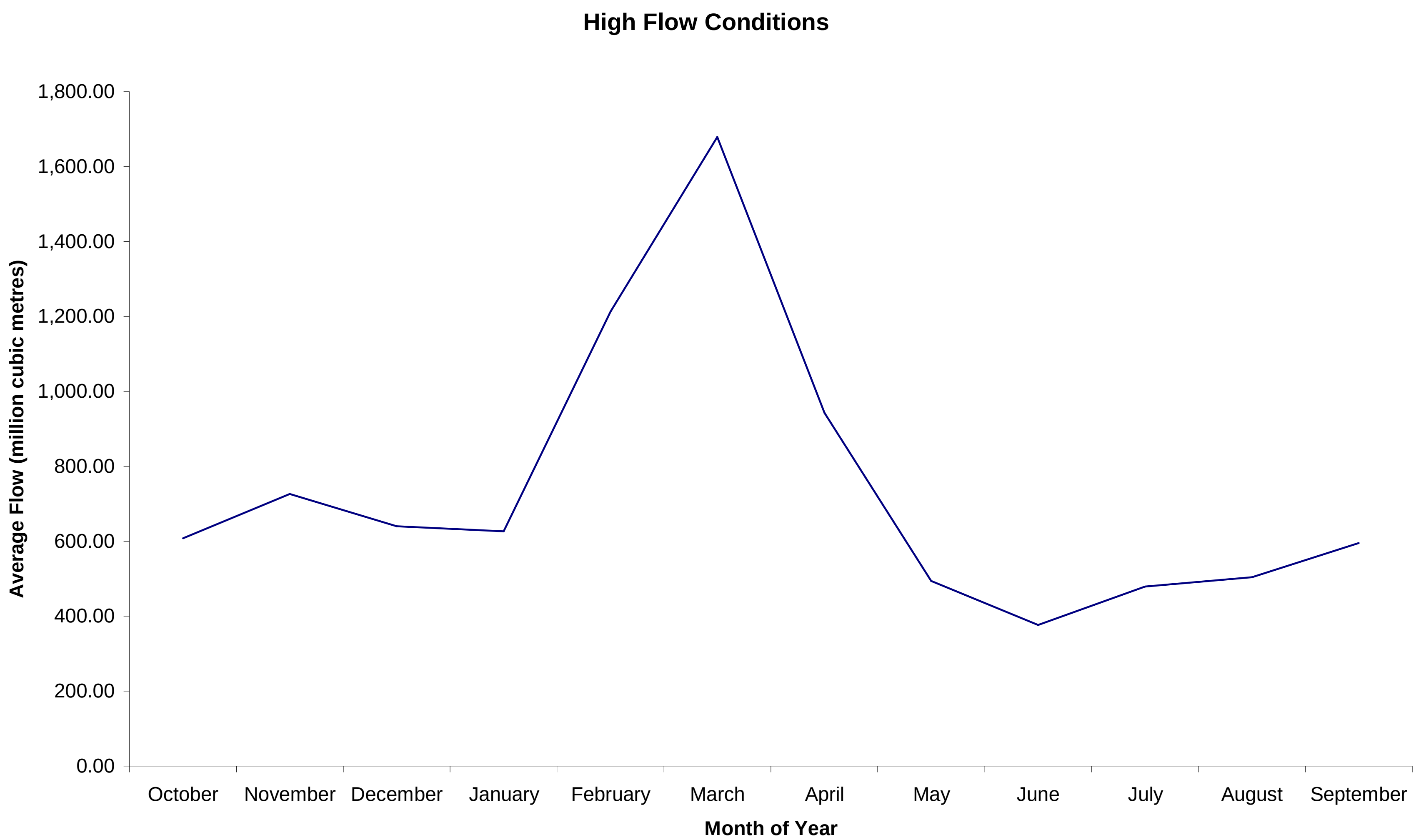


Figure 6.6: Monthly flow distribution of high flow years

During network training, the software learns the system being simulated and saves network parameters of the optimized network configuration. To learn the system, NeuroSolutions Consultants uses one of three learning paradigms; back-propagation, recurrent back-propagation or back-propagation through time.

The software comes with both hard copy and online manuals. However, the biggest hindrance to effective utilization of the software was the shallow manual that failed to provide full guidance on the operation of advanced features. Adequate technical support was unavailable even after purchasing the licence and subscribing for technical support. Comprehensive technical support could only be offered through a consultancy service, which was turned down as unethical for an academic research requiring independent effort. An inordinate amount of time was subsequently spent learning the software with very little technical support. Another weakness of the software was its lack of graphics and print facility. A screenshot had to be created and copied onto MS Word, MS Excel or Paint to print or plot simulation results.

6.4.2 The Network

The network was built with NeuralExpert utility of NeuroSolutions which handled both training and cross validation automatically. The process that was followed in building the network is outlined in section 4.2.3.

Eight steps were followed in building the network with NeuralExpert. The first was to specify the problem type and for this study the problem was defined as a prediction problem for simulating streamflow using historical streamflow data. The second step was to define the Input File from where the network read flow during training, cross validation and testing. A separate Input File was created for forecasting streamflow during model application. For efficient data management, the Input File also carried non input data needed to identify the flow record. So the third step was to tag the input columns of the Input File to link the relevant data for reading during simulation. Step four involving the tagging of symbolic inputs was skipped because the reservoir problem did not require any symbolic data. The Desired File contained output data from network training, testing and production of forecast streamflow. The Desired File was specified in step five to be the same as Input File for ease of data management because all data was then contained in one file. In step six, the columns containing the desired output data were tagged for training, cross validation and testing.

The prediction offset was selected in step seven. This was specified as 0 for the 1-month ahead model. In step eight, the generalization protection was activated to specify the amount of training data that was set aside for cross validation. The normal level of protection of 20% was selected as recommended by the software manual for data set size ranging between 100 and 10 000 rows. In step nine, 20% of the data was set aside for out of sample testing, again as recommended by the manual. A total record length of 342 months of historical streamflow was available. Of this, 80% was allocated for network training and 20% was allocated for testing. The 80% training data was further split into 60% training and 20% cross validation data. Finally, in step 11, network complexity was specified as either low, medium or high. After several iterations, low level complexity was selected for the relatively simple one month ahead flow forecasting. Network complexity depends on the size of the network determined by the number of layers and nodes per layer. The bigger the number of nodes, and so network weights, the more powerful the network. However, as network size continues to increase, there comes a point where network generalisation gets poor. This happens when the network is over-trained and starts to memorize training data. When an over-trained network is later applied to data sets it has not seen before it performs poorly. According to the manual (Dimension, Inc., 2005), at the present stage of knowledge, establishing the size of a network is more efficiently achieved through experimentation. Experimentation starts with a small network (low complexity), increasing the size until performance with the test data is satisfactory. Large networks of medium to high complexity require large amounts of data to adequately train. The manual specifies size of data of 30N as a rule of thumb, where N is the number of input columns.

The neural network developed had three layers comprising the input layer, hidden layer and output layer. Figure 6.1 shows the optimized neural network that was developed for one-month ahead forecasting of inflows into Van der Kloof reservoir system. The structure of the network can be summarized as follows:

i) Input layer had 5 nodes with 5 inputs and 15 outputs feeding into the hidden layer. The input layer had 5 weights with a mean of 0 and range of 0.5. The five inputs consisted of streamflow in the present month (Q(t)), streamflow in the past month (Q(t-1)), streamflow in the past two months (Q(t-2)), streamflow in the past three months (Q(t-3)) and streamflow in the past four months (Q(t-4)). The code generation format used for the input file was the ASCII for training, cross validation and testing.
ii) Hidden layer had 3 nodes with 15 inputs from the input layer and 3 outputs feeding into the output layer. The hidden layer had 45 weights with mean of 0 and range of 0.16.
iii) Output layer had 1 node with 3 inputs from hidden layer and 1 network output, Q(t+1). The output layer had 3 weights with mean of 0 and range of 2.4.

The breadboard for the network developed is shown in Appendix A. The breadboard is a schematic diagram of the network showing the icons that control network operation and showing training results. As can be seen from the breadboard, the training was successful as depicted by the learning curve with both mean squared error for training and cross validation approaching zero. The red line represents the error on training and the blue line represents the error on cross validation. In this instance, the mean squared error for training was 0.0091539 m^6/month and for cross validation was 0.0054610 m^6/month.

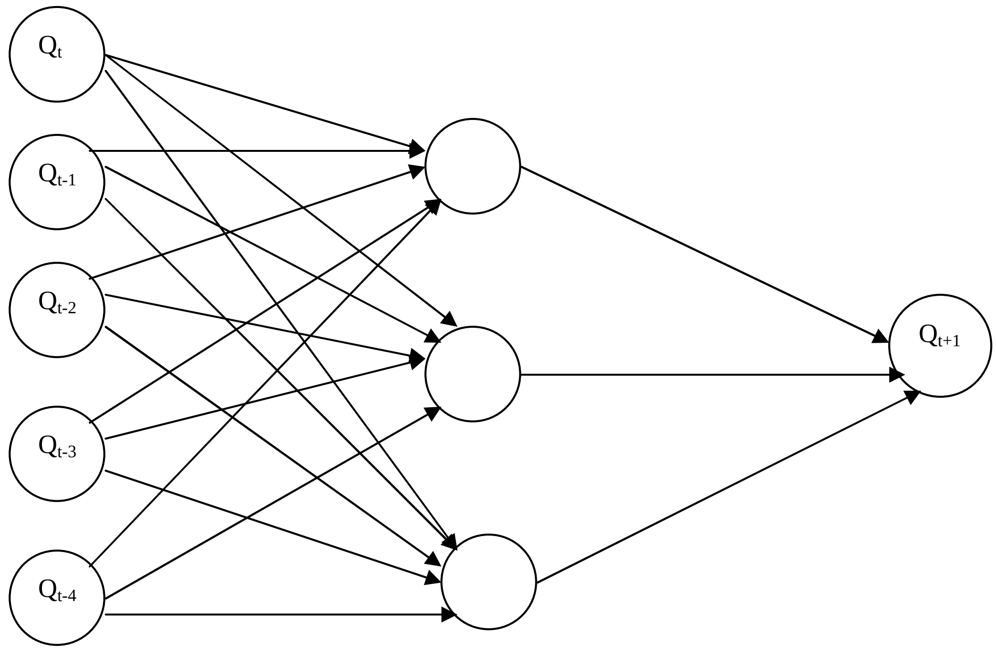


Figure 6.1: Neural Network for Van der Kloof Dam

6.4.3 Network Training

Network building involved training of the network with back-propagation. The network was trained in 1 000 epochs or iterations of training and 5 epochs of cross validation over an average period of 10 seconds, demonstrating the computational power of artificial neural networks. The dither for sensitivity analysis of the network was 0.1; that is, parameter values were changed in steps of 0.1 to test the effect on network performance. Intermittently, the software stopped the training to cross validate the network and avoid overspecialising on training data. The mean squared error from cross validation was saved but the weights were not saved as this was only a validation exercise for the network under training. As the training progressed, the mean squared error kept on decreasing but at one point during cross validation it started to increase. The network training was stopped at this point, when the mean squared error started to increase, as it marked the point when the network had started to memorize the training patterns instead of the system under investigation. At this point the cross validation error was at its minimum and represented the point of best generalization or optimal setting of the network.

For the different training iterations, the level of network complexity was varied from low through medium to high complexity. For each level of complexity, several runs were investigated until the training was satisfactory. The inbuilt genetic algorithm automatically optimized network weights which are a measure of the strength of connections between adjacent nodes. Network performance was evaluated from the mean squared error for training and cross validation as defined by Equation 4.3. After successful training, network weights were saved to define the neural network of the problem under investigation. The neural network was later applied to predict reservoir inflow that was required for operating the reservoir.

6.4.4 Network Testing

Although cross validation data was not used to train the network, it was used to optimize network weights. Strictly speaking, cross validation is not an out of sample test of the network. For a complete out of sample test, the testing data was used to allow unbiased assessment of network performance with new data. The software's Testing Wizard, reading from the testing data file, was used to test the trained network. From a record length of 342 months, 20% of the data was allocated to testing. This allocation of data conformed with the software specification which required 20% of data to be allocated to testing if the record length falls between 100 and 10 000 rows. Network testing provided additional model validation using out of sample testing data the network had not seen before.

Actual, not average, monthly streamflow was used in the model. On testing, the model generated monthly streamflow for the full testing period. On the contrary, an average monthly flow model would generate only 12 flows for the 12 months of the year. Since the training and cross validation data were the same for any proposed model, the same network model was applied recursively to forecast monthly streamflow over an operating period of 12 months.

6.5 OPTIMIZING HYDROPOWER

The purpose of simulating streamflow was to predict reservoir inflow, a system variable required to operate the reservoir. To develop an operating policy, it was necessary to specify the objective function and system constraints that directed the manner the reservoir was operated.

6.5.1 Objective Function

An objective function was developed to measure system performance under a given operating policy. The objective of operating the reservoir was to maximize hydropower and minimize water supply deficit.

Reservoir storage was required to determine the size of release through the penstock and outlet pipe to optimize hydropower. The objective function developed for optimizing hydropower was:

$$\text{Max} \sum_{t}^{N} \frac{\eta \bullet \rho g \bullet R_t \bullet H_t}{10^6} \text{, under system constraints} \qquad (6.1)$$

Where R_t = penstock release (m^3/s) during time period t; H_t is the average effective head during time period t (average water level – tail water level); N = number of months in operating period; η is the turbine efficiency (specified by Eskom), ρ is the density of water (kg/m^3) and g is the acceleration due to gravity (m/s^2). The objective function was divided by 10^6 to convert to MW.

The quantity $\rho g \eta$ or 9 810η was a constant for any given system and could be assumed to be unity (1) without altering the optimization problem. The problem would then reduce to one of maximizing the quantity R_tH_t. However, the full formula was applied to allow a comparison of optimized power and the plant generating capacity.

Hydropower is proportional to the release and operating head.

$$HP(t) = 9810 \bullet k \bullet R(t) \bullet H(t) \bullet \eta \qquad (6.2)$$

$$0 \le h(t) = H(t) - H_p$$

Where HP(t) = energy generated in time period t (MW); k = constant for converting monthly release in million m^3/month to m^3/s (0.3858); other symbols are defined in Equation 6.1.

The cap on hydropower is defined by the installed capacity.

$$HP(t) \le HP_{max} \qquad (6.3)$$

Where; HP_{max} is installed capacity (240 MW for penstock capacity of 176 m^3/s).

6.5.2 System Constraints

The reservoir operating policy should conform to the system layout. Reservoir rule curves were important constraints used to define the bounds of storage fluctuation.

The constraints which defined the system environment and operation can be divided into two groups; namely, those representing the inherent system characteristics which did not change during optimization and others which are loss or penalty functions. The system constraints are discussed below.

1. Mass balance or continuity equation:

$$S(t+1) = S(t) + Q(t) + P(t) - E(t) - R(t) - SP(t) \qquad (6.4)$$

Where S(t) = reservoir storage at the beginning of time t; Q(t) = streamflow during time t; P(t) = Precipitation during time t; E(t) = evaporation during time t; R(t) = water release through penstock and outlet pipe; and SP(t) = reservoir spill during time t.

2. Reservoir area-capacity-reduced level curves:

$$E(t) = e \times f\bullet\ (A(t)) \quad (6.5)$$

$$A(t) = f\bullet\ (H(t))$$

Where e = evaporation rate (mm/month); H(t) = water level in reservoir during time t (m); A = reservoir surface area during time t (m^2); f denotes the relationship between surface area and water level as defined by site topography and shape of reservoir basin. An area-reduced level curve (table) or empirical formula is developed to define the relationship.

3. The storage S(t) can only vary between the maximum and the lowest permissible storage. The reservoir fails if it is drawn down to dead storage.

$$S_d \leq S(t) \leq S_C \quad (6.6)$$

Where S_d = dead storage (million m^3); and S_C = reservoir capacity at non-overspill crest (million m^3).

The storage was not allowed to drop to dead storage as a result of releases, only due to evaporation and seepage, because the dead storage is a reserve to sustain the reservoir ecosystem and the outlet pipe is built above dead storage. The utility rule curve lies between the dead storage and the non-overspill capacity. This curve is a soft boundary that can be crossed and it represents the generating capacity of the power plant. In optimizing hydropower, a penalty is charged for releases drawn from storages below the utility rule curve (see Section 3.3.3).

4. The water deficit rate:

$$DR(t) = (D(t) – R(t))/ D(t) \tag{6.7}$$

Where DR(t) = deficit rate during time period t; and D(t) = water demand during time period t including ecological flows and system losses (million m^3). The limit on deficit rate adopted is 20% as stipulated by the DWA to cushion the frequency and severity of shortages.

5. Release cannot be greater than combined penstock and outlet capacity.

$$0 \leq R(t) \leq Q_{out} + Q_{pen} \tag{6.8}$$

Where Q_{out} = outlet pipe capacity (391 m^3/s); Q_{pen} = penstock capacity (176 m^3/s), giving a combined capacity of 567 m^3/s.

The software manual lacked detail and failed to provide enough guidance on the operation of the embedded genetic algorithm for optimizing hydropower. On closer scrutiny, however, it turned out the genetic algorithm was only available for optimizing network weights during training and had no facility for optimizing reservoir operation. It was therefore decided to limit the application of the neural network to the task of predicting reservoir inflow and then optimize reservoir operation manually on Excel. Although the method was satisfactory for the one reservoir system investigated, it would be ineffective for complex reservoir systems.

An operating period of 12 months was selected, from 1 March 2008 to 28 February 2009. The storage on 1 February 2008 was used as the initial storage for investigating the storage trajectory over the operating period. Simulated streamflow was routed through the reservoir over 12 months and the hydropower optimized on Excel. The area-capacity curve was used to calculate storage at the end of every month. The monthly release schedule that produced maximum power under the system constraints was adopted as the operating policy. The releases were required to supply downstream water demands with a maximum permissible deficit rate of 20%.

CHAPTER 7

RESULTS AND DISCUSSION

7.1 SIMULATION RESULTS

The neural network developed performed well in predicting monthly streamflow as presented in Figure 7.1. The satisfactory performance of the network reinforces the finding of Zealand et al. (1999) that three layered feed-forward networks were sufficient for most applications because of the capability of neural networks to handle complex problems. Figure 7.1 is a plot of desired streamflow versus output streamflow from network testing. Historical streamflow was used as the desired streamflow while the output streamflow was generated by the model. The plot shows very good simulation of streamflow with model output following the desired streamflow very closely. Even the sharp spikes of high flow were closely simulated; only the highest spike was underestimated. The small peaks were better estimated because the historical pattern that was used to train the network contained sufficient low to normal flows. However, simulation of high peaks was not equally good because there were few extreme flows in the training data, so the network did not build sufficient intelligence to simulate extreme flows. As a result, high flows were suppressed by the learning weights of the network. On the other hand, low flows were slightly overestimated due to the effect of the few extreme flows on network weights. This phenomenon shows the limitation of artificial neural networks to simulate extreme flows. The finding supports the work of Shrestha et al. (2005) who cautioned the use of artificial neural networks for extreme flood events. Thirumalaiah and Deo (1998) used artificial neural networks for river stage forecasting and found that although lower water levels were predicted fairly accurately, higher water levels were underestimated. This was thought to be due to a smaller number of training patterns for higher water levels.

The one-month ahead ANN model was applied to forecast inflow into Van der Kloof Dam for the period March 2008 to February 2009 for the purpose of developing an operating rule. The forecasted streamflow is presented in Table 7.1 and Figure 7.2. According to model formulation (see section 6.2), the smooth variability of forecasted flow was influenced by the nature of flow received in the previous five months which were used as model inputs. Because forecasting was performed progressively, there was a tendency for the variability to reduce as the prediction proceeded. However, a plot of the historical flows in the previous twelve months (Figure 7.3) reveals flow variability of the same order as for the forecasted flow (Figure 7.2). The two plots show similar variability in historical flow over the past five months, October 2007 to February 2008, and forecasted flow.

Table 7.1: Forecasted Reservoir Inflow

DATE	**FLOW (10^6 x m^3)**
Mar 2008	304.082
April 2008	369.597
May 2008	425.430
June 2008	437.687
July 2008	429.876
Aug 2008	443.163
Sept 2008	453.006
Oct 2008	457.399
Nov 2008	452.159
Dec 2008	445.180
Jan 2009	443.997
Feb 2009	444.481

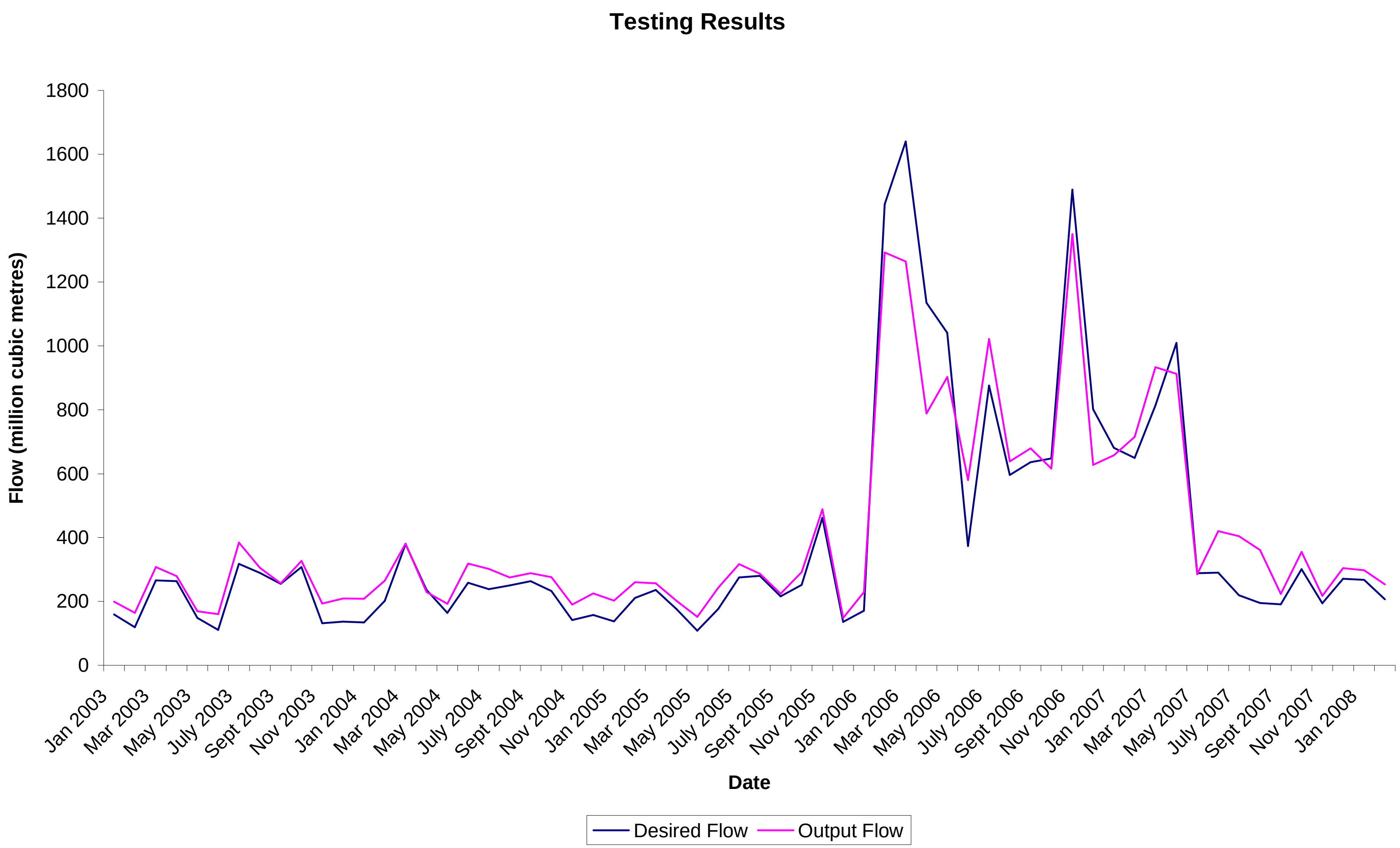


Figure 7.1: Testing Results

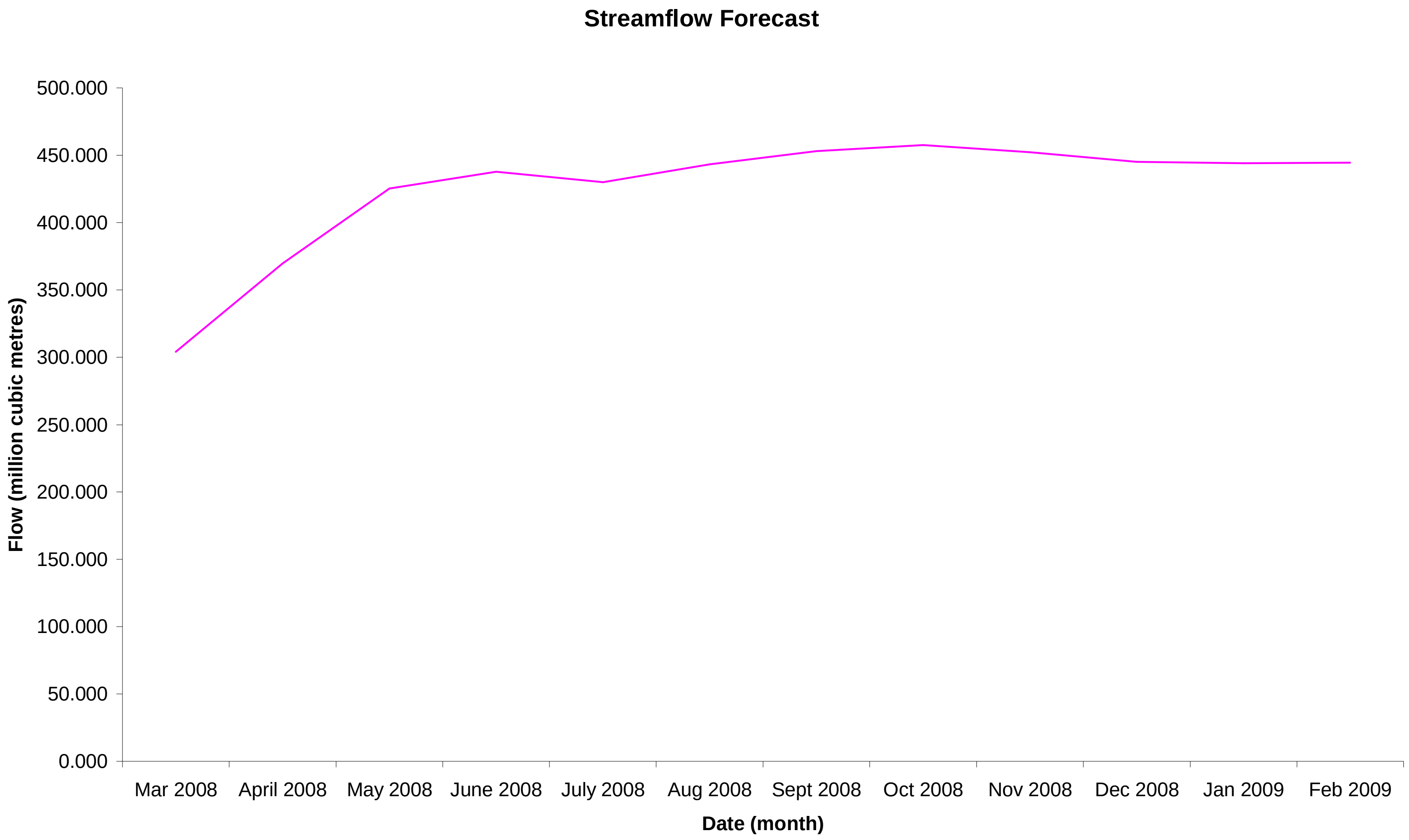


Figure 7.2: Streamflow Forecast

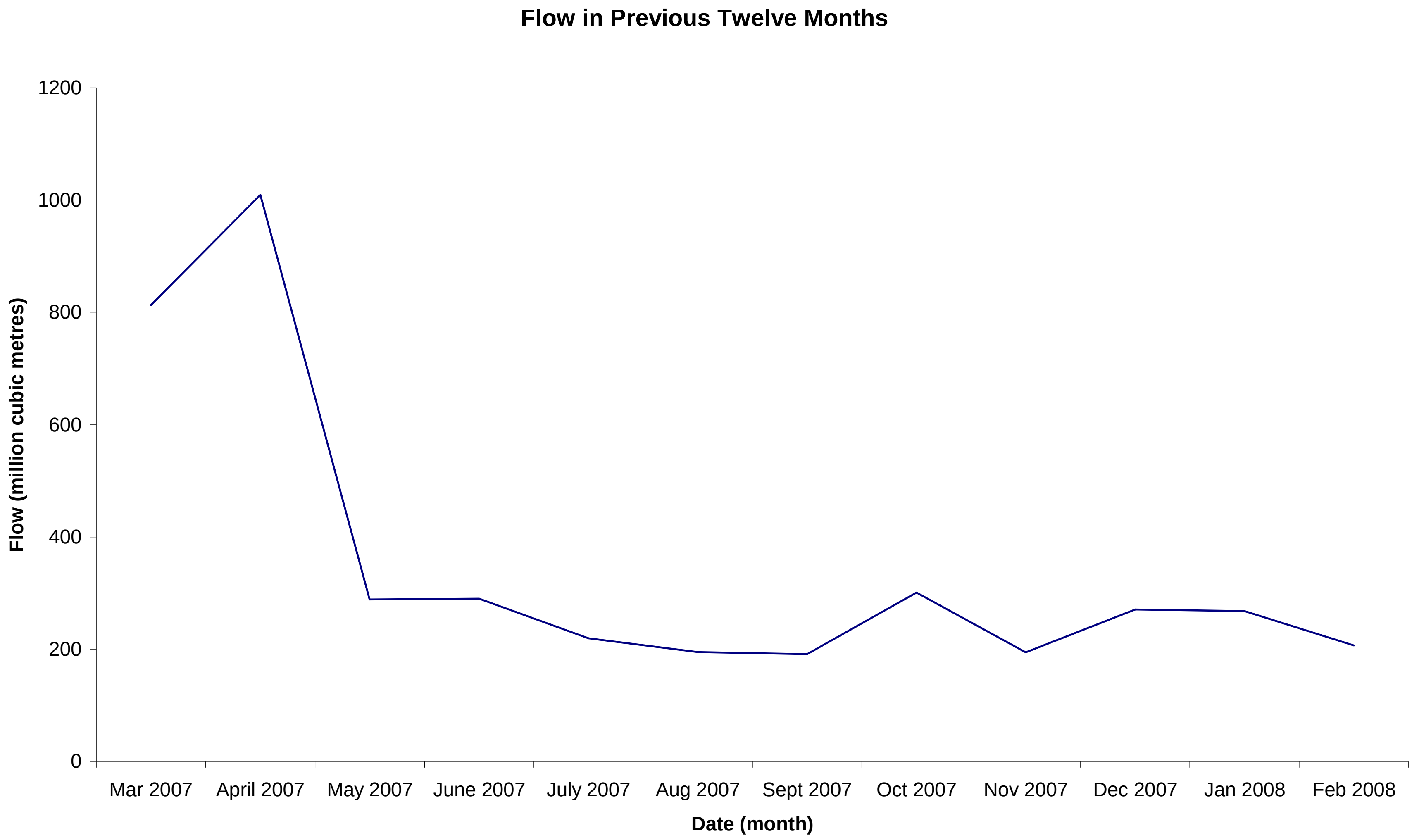


Figure 7.3: Flow in Previous Twelve Months

7.2 RESERVOIR OPERATING POLICY

The operation of the reservoir was to be optimized by maximizing hydropower. To do this, all releases for both power generation and water supply were channelled through the turbines.

7.2.1 Release and Hydropower

Optimization of hydropower was undertaken manually on Excel (see Appendix C for the optimized result). The streamflows given in Appendix C are the forecasts obtained with the ANN model as explained in Section 7.1. Hydropower generated at different levels of release during the period 1 March 2008 to 28 February 2009 is given in Table 7.2. The fluctuation of the reservoir storage height over the year for an optimum release of 127 m^3/s is presented in Table 7.3. The storage height remained above the power generating head of 79.8 m throughout the year. In addition to optimizing hydropower, the release was required to supply at least 80% of downstream demands according to the standard DWA practice of reservoir operation. November recorded the highest water requirement of 252 million cubic metres per month (97.3 m^3/s).

A release of 97.3 m^3/s generated 151.2 MW which was lower than the generating capacity of 240 MW. The release was varied, starting with a peak water requirement of 252 million m^3 for November until maximum power was achieved. Equation 6.1 was used to compute hydropower. Maximum power of about 210 MW was generated with a release of 330 million cubic metres per month (127 m^3/s); enough to supply 1.31 times the water requirements. This level of release was adopted as the operating rule throughout the year because it optimized power. The release of 127 m^3/s was considered realistic as it falls within the normal operating range. In the 2008/09 operating period, releases ranged from 33.6 m^3/s to 150.8 m^3/s with 89% starting storage. The penstock has enough capacity (176 m^3/s maximum) to pass the optimum release. Penstock discharge capacity varies from full supply level (1 170.5 m) to minimum operating level for hydropower generation (1 150.80 m). The study assumed 84% starting storage. For full storage condition at the start of the operation, optimum release will be higher. The hydropower generated with the release channelled through the turbines is plotted in Figure 7.4 using information presented in Table 7.2. Monthly release is plotted because the time step used both in simulation and optimisation was one month. However, for the optimal release to be useful to the dam operator, the release had to be converted to cubic metres per second.

Table 7.2: Hydropower Generation

RELEASE (Million m^3)	**RELEASE (m^3/s)**	**HYDROPOWER (MW)**	**LEVEL OF SUPPLY (R/D) %**
252	97.3	151.2	100.0
300	115.7	203.9	119.0
325	125.4	206.5	128.9
330	127.3	206.9	130.9
346	133.5	206.4	137.3
350	135.0	206.1	138.8
380	146.6	201.2	150.7
410	158.2	191.6	162.6
434	167.4	179.5	172.2

The level of supply in Column 4 of Table 7.2 was calculated from Equation 7.1.

$$LS = 1 - DR, \text{ or}$$
$$LS = R/D \qquad (7.1)$$

Where LS is level of supply, DR is deficit rate defined by Equation 6.7, D is water demand and R is the release also equal to supply. Since LS ignores spillage, it underestimates level of supply. However, in the operating analysis conducted for this research, no spillage was recorded.

Table 7.3: Storage Height Fluctuation

(For release of 127 m^3/s)

DATE	**STORAGE HEIGHT (m)**
March 2008	95.4
April 2008	94.6
May 2008	94.1
June 2008	94.0
July 2008	94.2
August 2008	94.4
September 2008	94.7
October 2008	95.1
November 2008	95.7
December 2008	96.4
January 2009	97.2
February 2009	98.1

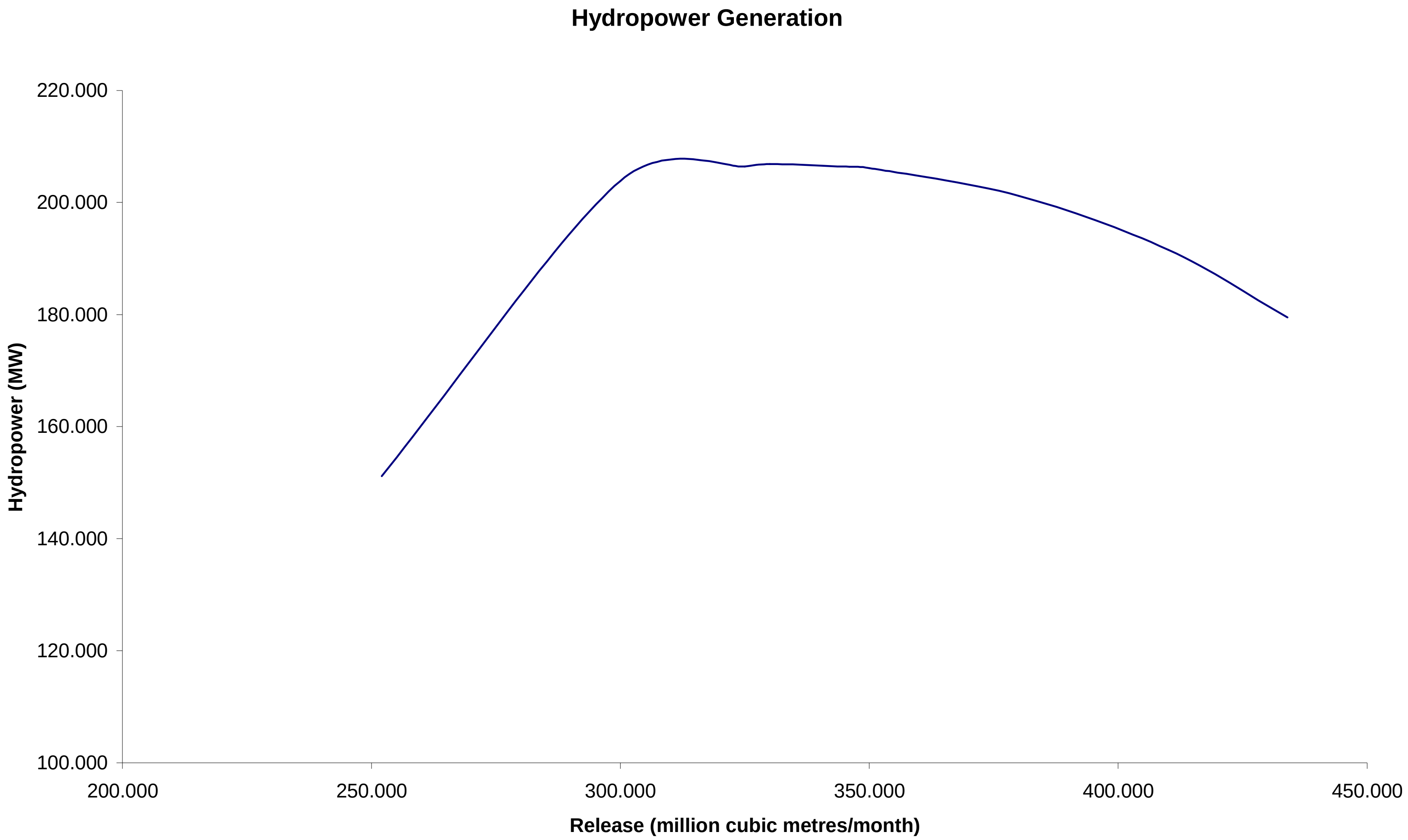


Figure 7.4: Hydropower Generation

7.2.2 System Performance

Depending on performance of a water resource system, water restrictions may become necessary as a short-term measure to evade a complete failure of the system or system augmentation may be required if the design capacity has become inadequate. The deficit threshold for the system was set at 20% of demand according to standard practice of the Department of Water Affairs for water restrictions. A prolonged deficit of 20% or worse is an indicator of inadequate design capacity to supply the full demand, alerting water managers of the need to augment the system.

A release of 127 m^3/s provided water supply amounting to 131% of the demand or an excess of 31%. The excess 31% was not a waste because it was channelled through the turbines to generate power. On the other hand, a smaller release could have wasted water through spillage. The deficit rate was zero in all the months of the operating period and there was no need for water rationing. The end storage on 1 February 2009, end of operating period, was 94% full. Figure 7.5 shows the storage trajectory resulting from this operating policy. FSC denotes full supply capacity.

The supply situation could however shift if a longer operating period, say 36 months, was adopted depending on forecasted streamflow over the extended period. The starting storage is another critical factor affecting reservoir behaviour in the short to medium term (12 to 60 months). In this study, the actual storage on 1 February 2008 was used as initial storage. A lower starting storage, for instance, would result in a smaller release to avoid the reservoir running dry.

The system yield was sufficient to supply the full demand and there was no immediate need to augment the system.

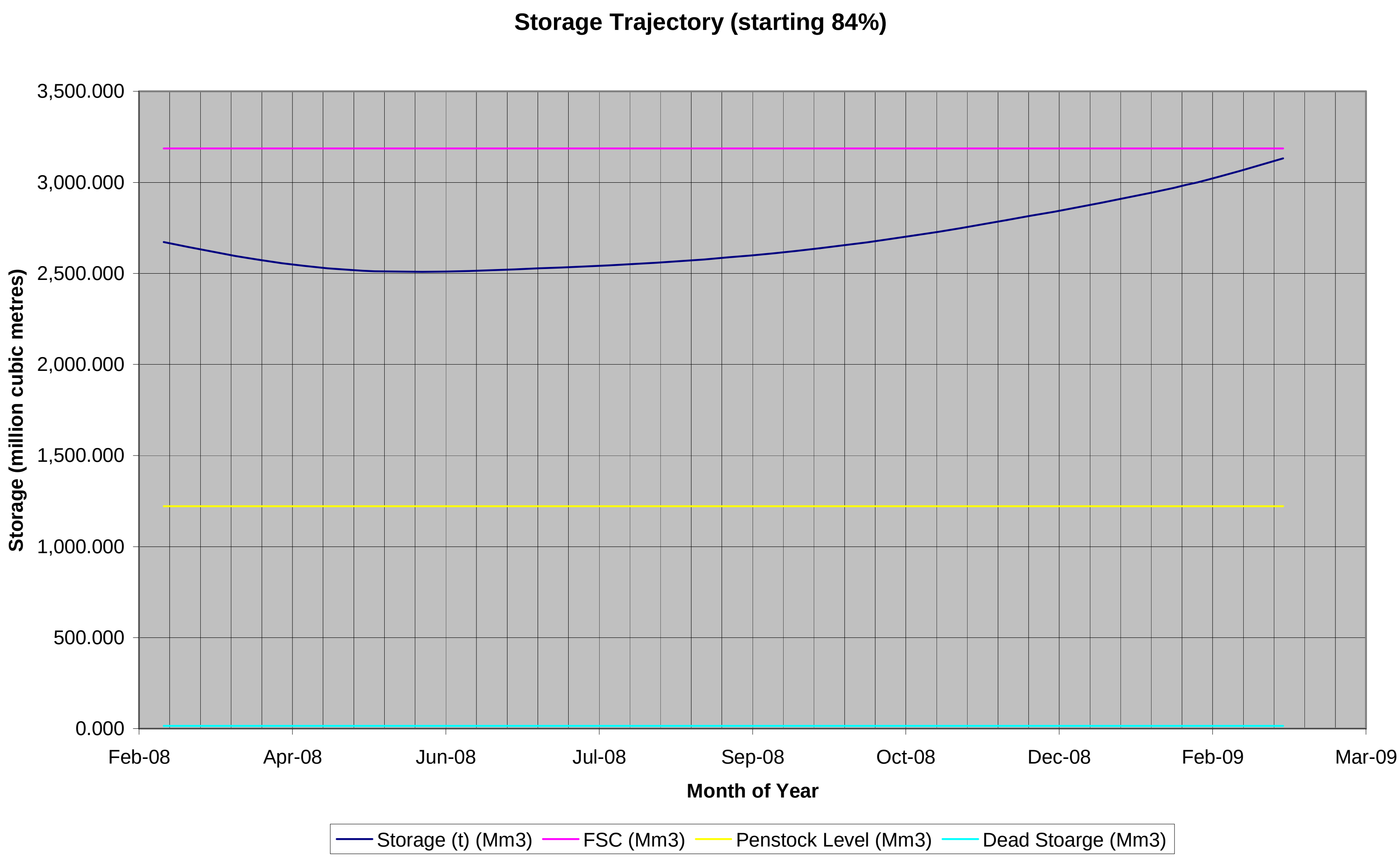


Figure 7.5: Storage Trajectory

7.2.3 Reservoir Operating Policy

The aim of the research was to demonstrate how a simple reservoir operating policy could be obtained using ANN forecasting and water balance on a spreadsheet. The Van der Kloof reservoir was operated to maximize hydropower and limit water restrictions according to standard practice. The simple operating rule for Van der Kloof Dam based on the analysis carried out in this research is as follows:

1) Release 127 m^3/s through the turbines throughout the year to optimize hydropower and supply downstream water demand. This level of release generates optimum power of 210 MW and supplies the full downstream demand. The generating capacity of 240 MW cannot be achieved with the predicted inflow and a starting storage of 84% full. A variable release throughout the year would require a more advanced model than developed here.
2) Depending on starting storage and forecasted inflow, vary the release from 97.3 m^3/s to 127 m^3/s in order to maximize power and supply the full downstream demand of 252 million m^3 per month. Keep the selected release uniform throughout the year for the reason explained in paragraph (1).
3) Release 77.8 m^3/s (80% of demand) if the storage is too low to avoid the reservoir running empty. A curtailment of 20% will reduce the release to 80% of demand. As the storage continues to drop, more severe curtailments would become necessary as determined by the water managers of the system. The analysis to determine when to start curtailing fell outside the scope of the current research.
4) The general procedure involves running the ANN model to forecast reservoir inflow. The resulting inflows are then applied to a water balance on Excel spreadsheet to determine power generated. The release producing maximum power, subject to a 20% water deficit ceiling, is selected.

Although manual optimization on Excel worked satisfactorily for the one reservoir system that was investigated, it is unlikely to be effective for more complex systems.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

8.1 CONCLUSIONS

The model that was developed demonstrated the capability of artificial neural networks to forecast monthly streamflow for reservoir operation. A long uninterrupted record is needed for adequate training of a neural network. The investigation also showed that the prediction capability of neural networks is largely dependent on the size of the prediction offset selected. The further into the future the prediction is, the less accurate the model becomes. Consequently, a one-month ahead model was developed to predict streamflow a month ahead.

Although the artificial neural network developed was able to adequately forecast monthly streamflow at one site, more research will be needed with multi-site systems where a number of reservoirs are managed as a system. Another important observation was the need for good software, preferably recommended by specialist researchers in the field. The software should be reliable, possess an optimizing algorithm for reservoir operation and possess features to manipulate results such as Excel for analysis, graphics for plotting and a print facility.

A three layer ANN network was developed with an input layer, one hidden layer and one output layer. The input layer has five nodes, the hidden layer three nodes and the output layer one node. The fact that this simple network could satisfactorily simulate reservoir inflow demonstrates the power of artificial neural networks for simulation problems. Large networks would only be required for complex reservoir systems.

With a starting storage of 84% full, a constant release of 127 m^3/s throughout the year generated optimum power of 210 MW against a generating capacity of 240 MW. This release is 1.31 times (31% more than) the downstream water demands. The excess of 31% of demand was not wasted as all the releases were channelled through the turbines to generate power.

8.2 RECOMMENDATIONS

The following recommendations suggest areas for further research to improve the utility of neural networks to predict streamflow and to optimize reservoir operation.

1) NeuroSolutions software had the capability to forecast streamflow but had its weaknesses. What lacked was an algorithm for optimizing reservoir operation and features to manipulate results such as Excel, graphics and a print facility. A more versatile optimizing algorithm is needed not only to optimize network training but also to optimize reservoir operation. The software should be supported by a comprehensive yet simple user manual and technical support service (not consultancy service). A thorough market survey should be undertaken in consultation with specialist researchers in the field before purchasing software because the quality of software selected has a strong bearing on performance of the network. It is further recommended to select software dedicated to water resource management and not general purpose software. Lastly, software developers who also offer consultancy services should be avoided if possible because they tend to promote the consultancy business at the expense of technical support.
2) Dynamic programming should be investigated for a one reservoir system instead of the low confidence Excel spreadsheet used in the current study. Although dynamic programming suffers from the curse of dimensionality, it is likely to perform satisfactorily with stand alone dams. Preferably, the

ANN software should be supplied with dynamic programming as an add-on.

3) It is recommended to investigate the annual model further. This should be developed as a 1-year ahead model involving disaggregation of the predicted annual flow. More research effort in this direction should concentrate on developing effective flow disaggregation techniques. For an annual model however a much longer flow record will be needed. For instance, for a continuous 30 year record, a monthly model has 360 flows to simulate while an annual model only has 30 flows. The NeuroSolutions manual recommends a minimum record length of 30N, where N is the number of input columns, for proper network training. Limiting the number of input columns to four, the minimum record length would be 120 flows if the record is continuous with no gaps. Allowing for 4% gaps, minimum record length could be set at 125 flows (125 years) for an annual model. If the flow record is short, an ANN could be developed to extend the record using Function Approximation as a first step and then simulate in a second stage. The annual model will avoid the error of recursive prediction associated with the monthly model.

4) A monthly model could be developed for each month of the year. For example, the model for January would be based on streamflow sequence for January extracted from the population. This model will require a long record since only one flow for the month is picked in every year. It requires the same amount of data as an annual model. Similarly, models would be developed for the remaining eleven months of the year. In all, 12 independent models are developed. The advantages with these models are that they avoid the recursive error as each month has its own separate independent model and they do not need disaggregation because they already predict monthly flows.

5) Instead of an annual model, another possibility is to develop a seasonal model with summer and winter as the simulation periods. Both 1-season and 2-season ahead models could be investigated. The year would be

divided into two seasons and each season properly defined. For South Africa, summer flow is received between October and April and winter flow between May and September. As with the annual model, a disaggregation model will be needed for operating the reservoir. The advantage with a seasonal model is that the disaggregation model is more accurate than for an annual model.

6) The capability of artificial neural networks to simulate multi-site systems could be investigated. This involves selecting a system of three or four reservoirs with both parallel and series combinations. The streamflow forecasting methodology developed for the one reservoir system could then be modified to accommodate the expanded system. This could be achieved by simulating each reservoir sub-system separately with naturalised streamflow and then linking their operations by cascading abstractions to the downstream reservoir for accounting. Streamflow forecasts would then be applied to an Excel spreadsheet to develop a simple operating policy for the expanded system. A consolidated spreadsheet would make it possible to manage the system as one. Since the current study was inconclusive as to whether the simple methodology developed would be effective on complex systems or not, the proposed research could shed more light in that direction. This methodology could be applied to the entire Upper Orange River system to investigate the impact of upstream abstractions in Lesotho. This would require accompanying investigation into the operation of dams in Lesotho to determine the range of releases from Lesotho.

REFERENCES

Basson M S, Allen R B, Pegram G G S and Van Rooyen J A. (1994) Probabilistic Management of Water Resource and Hydropower Systems. Water Resources Publications, Colorado, USA

Department of Water Affairs. (2010) Orange River System Annual Operating Analysis (2008/09)

Department of Water Affairs and Forestry. (2004(a)) Van der Kloof Dam: Third Dam Safety Inspection Report

Department of Water Affairs and Forestry. (2004(b)) Bridging Study into the Utilisation of the Low Level Storage at Van der Kloof Dam. BKS (Pty) Ltd

Department of Water Affairs and Forestry. (2005 (a)) Water Resources Yield Model: Procedural Manual

Department of Water Affairs and Forestry. (2005 (b)) Lower Orange River Management Study: Hydrology, Water Quality and System Analysis, Volume B

Department of Water Affairs and Forestry. (2007) Assessment of Stochastic Methodologies used in South African Water Resources Planning Analyses

Hall, W A and Dracup, J A. (1970) Water Resources Systems Engineering. McGraw-Hill, New York

Hsu, S K. (1995) Shortage Indices for Water Resources Planning in Taiwan, Journal of Water Resources Planning and Management, Volume 121, No. 2, pp. 119 – 125

Hsu, N S and Cheng, K W. (2002) Network Flow Optimization Model for Basin-Scale Water Supply Planning, Journal of Water Resources Planning and Management, Vol. 128, No. 2, pp. 102 – 112

Hughes, D A, O'Keeffel, J, Smakhtin, V and King, J. (1997) Development of an operating rule model to simulate time series of reservoir releases for instream flow requirements, Water SA 23, No. 1, pp. 21 – 30

Hughes, D A and Ziervogel, G. (1998) The inclusion of operating rules in a daily reservoir simulation model to determine ecological reserve releases for river maintenance, Water SA 24, No. 1, pp. 293 – 302

Jain, S K, Das, A and Srivastava, D K. (1999) Application of ANN for Reservoir Inflow Prediction and Operation, Journal of Water Resources Planning and Management, Vol. 125, No. 5, pp. 263 – 271

Jenkins, M W and Lund, J R. (2000) Simulation Techniques for Design of Water-Resource Systems. Macmillan, London

Karamouz, M, Szidarovszky, F and Zahraie, B. (2003) Water Resources Systems Analysis. Lewis Publishers, New York

King, J M and Louw, D. (1998) Instream flow assessments for regulated rivers in South Africa using the Building Block Methodology, Journal of Aquatic Ecosystem Health, Vol. 1, No. 2, pp. 109 – 124

Kisi, O. (2004) River Flow Modelling Using Artificial Neural Networks, Journal of Hydrologic Engineering (ASCE), Vol. 9, No. 1, pp. 60 – 63

Kumar, D N, Raju, K S and Ashok, B. (2006) Optimal Reservoir Operation for Irrigation Multiple Crops Using Genetic Algorithms, Journal of Water Resources Planning and Management, Vol. 132, No. 2, pp. 123 – 129

Labadie, J W. (2004) Optimal Operation of Multireservoir Systems: State-of-the-Art Review, Journal of Water Resources Planning and Management, Vol. 130, No. 2, pp. 93 – 111

Loucks, D P and van Beek, E. (2005) Water Resources Systems Planning and Management: An Introduction to Methods, Models and Applications. UNESCO Publishing, Italy

Mathur, Y P and Nikam, S J. (2009) Optimal Reservoir Operation Policies Using Genetic Algorithms. International Journal of Engineering and Technology, Vol. 1, No. 2, pp. 184 – 187

Ndiritu J G. (2003) Reservoir System Optimisation Using a Penalty Approach and a Multi-population Genetic Algorithm, Water SA, Vol. 29, No. 3, pp. 273 – 280.

Ndiritu J G. (2005) Maximising Water Supply System Yield Subject to Multiple Reliability Constraints via Simulation-optimisation, Water SA, Vol. 31, No. 4, pp. 423 – 434.

NeuroDimension, Inc. (2005) NeuroSolutions: Getting Started Manual, Version 5

Pyrce, R. (2004) Hydrological Low Flow Indices and their Uses. Water Science Centre, Trent University, Canada

Raman, H and Chandramouli, V. (1996) Deriving a General Operating Policy for Reservoirs Using Neural Network, Journal of Water Resources Planning and Management, Volume 122, No. 5, pp. 342 – 347

Republic of South Africa. (1998) National Water Act: Act No. 36 of 1998

Savenije, H H G. (1995) Water Resources Management Concepts and Tools – Lecture Notes. Delft University, the Netherlands

Scott, D F and Smith R E. (1997) Preliminary Empirical Models to Predict Reductions in Total and Low Flows Resulting from Afforestation, Water SA, Vol. 23, No. 2, pp. 135 – 140

Shrestha, R R, Theobald, S and Nestmann, F. (2005), Simulation of Flood Flow in a River System using Artificial Neural Networks, Hydrology and Earth Systems, Vol. 9, No. 4, pp. 313 – 321

Smith, M. (1993) Neural Networks for Statistical Modelling. Van Nostrand Reinhold, New York

Thirumalaiah, K and Deo, M C. (1998) River Stage Forecasting using Artificial Neural Networks, Journal of Hydrological Engineering, Vol. 3, No. 26, pp. 26 – 31

Van Rooyen, P G and McKenzie, R S. (2004) Monthly Multi-Site Stochastic Streamflow Generation Model. Water Research Commission, Report No. K5 909/1/04

Van Vuuren, S J, Van Rooyen, P G, Van Zyl J E and Van Dijk, M. (2005) Application and Conceptual Development of Genetic Algorithms for Optimization in the Water Industry. Water Research Commission, Report No. 1388/05

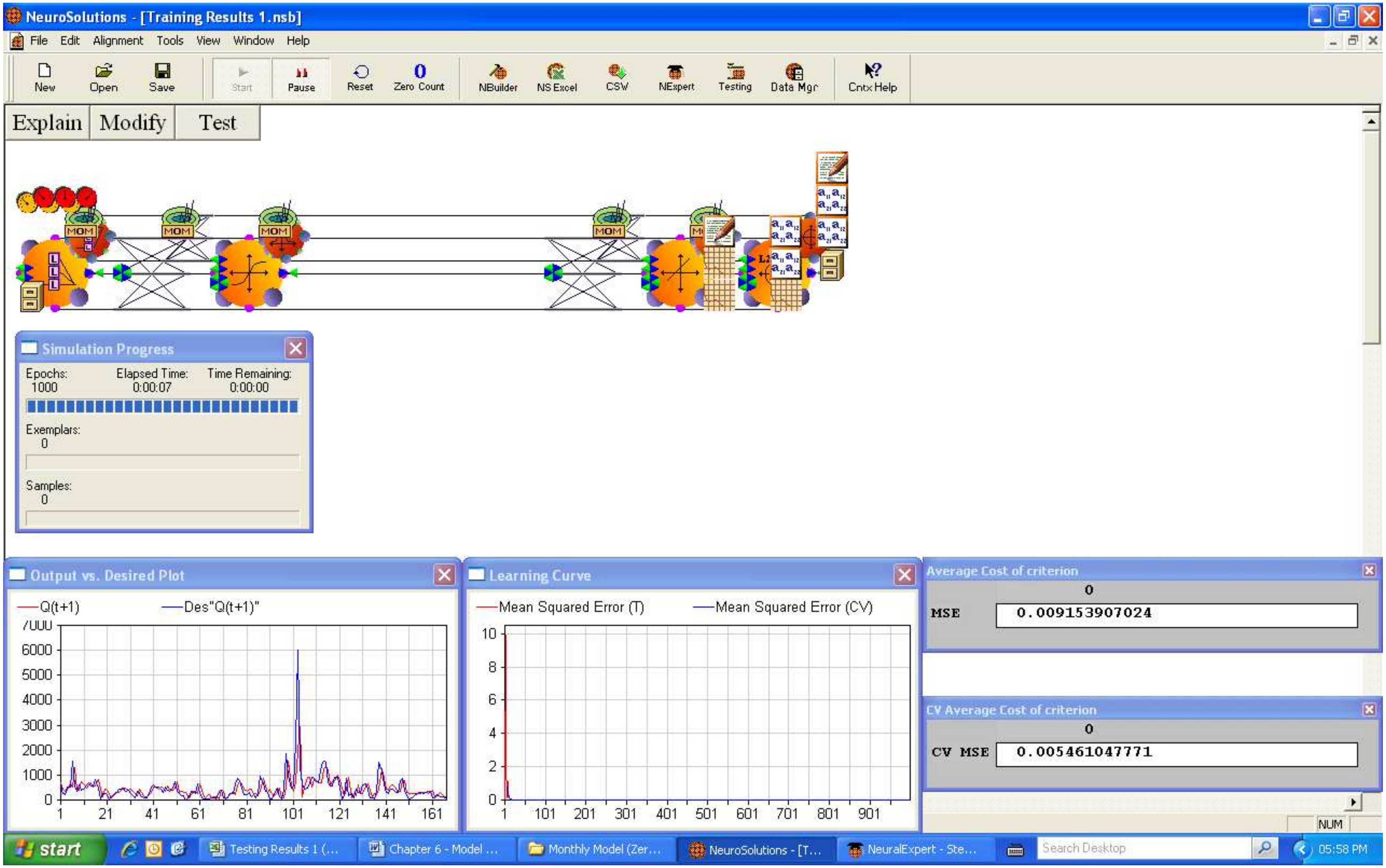
Wardlaw, R and Shariff, M. (1999) Evaluation of Genetic Algorithms for Optimal Reservoir System Operation, Journal of Water Resources Planning and Management, Vol. 125, No. 1, pp. 25 – 33

World Meteorological Organization. (2008) Manual on Low-flow Estimation and Prediction. Operational Hydrology Report No. 50

Zealand, C M, Burn, D H and Simonovic, S P. (1999) Short Term Streamflow Forecasting Using Artificial Neural Networks. Journal of Hydrology (Elsevier), 214, pp. 32 – 48

APPENDIX A: TRAINING RESULTS

(Chart of network training result)



APPENDIX B: MONTHLY WATER REQUIREMENTS

(DWAF, 2005(b))

Environmental Requirements and System Losses

Reach	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec	Annual
Marsdrift	7.83	5.86	4.69	3.18	2.41	1.73	2.00	2.95	4.44	5.86	7.22	7.85	**56.0**
Prieska	10.92	8.17	6.54	4.44	3.36	2.41	2.78	4.12	6.19	8.17	10.08	10.95	**78.1**
Boegoeberg	6.75	5.05	4.05	2.75	2.08	1.49	1.72	2.55	3.83	5.05	6.23	6.77	**48.3**
Gifkloof	11.84	8.86	7.10	4.82	3.65	2.62	3.02	4.47	6.72	8.86	10.93	11.88	**84.8**
Neusberg	6.44	4.82	3.86	2.62	1.98	1.42	1.64	2.43	3.65	4.82	5.94	6.46	**46.1**
20^0 N	5.18	3.88	3.11	2.11	1.60	1.15	1.32	1.96	2.94	3.88	4.78	5.20	**37.1**
Pella	9.08	6.80	5.44	3.70	2.80	2.01	2.32	3.43	5.15	6.80	8.38	9.11	**65.0**
Vioolsdrift	11.02	8.25	6.61	4.49	3.39	2.44	2.81	4.16	6.25	8.25	10.17	11.06	**78.9**
Fish River	7.57	5.67	4.54	3.08	2.33	1.67	1.93	2.86	4.29	5.67	6.99	7.60	**54.2**
BrandKaros	5.69	4.26	3.41	2.32	1.75	1.26	1.45	2.15	3.23	4.26	5.25	5.71	**40.7**
River Mouth	3.60	2.69	2.16	1.46	1.11	0.80	0.92	1.36	2.04	2.69	3.32	3.61	**25.8**
Total Evap	**85.92**	**64.31**	**51.51**	**34.97**	**26.46**	**19.00**	**21.91**	**32.44**	**48.73**	**64.31**	**79.29**	**86.20**	**615.1**
% of Total	13.97%	10.46%	8.37%	5.69%	4.30%	3.09%	3.56%	5.27%	7.92%	10.46%	12.89%	14.02%	100.00%
System Losses	37.72	28.23	22.61	15.35	11.62	8.34	9.62	14.24	21.39	28.23	34.81	37.84	270.00
EWR	27.53	20.61	16.51	11.21	8.48	6.09	7.02	10.40	15.62	20.61	25.41	27.62	197.10
EWR + Losses	**151.17**	**113.15**	**90.63**	**61.53**	**46.56**	**33.43**	**38.55**	**57.08**	**85.74**	**113.15**	**139.51**	**151.66**	**1,082.15**

EWR + Evaporation + System Losses = 615.05 270 197.10 **1,082.15**

Source: Lower Orange River Management Study (2005)

SECTORIAL WATER DEMANDS

URBAN DEMANDS	Million m^3
Vanderkloof (RSA)	63.34
Vanderkloof (Namibia)	20.00
Total Urban Demands	**83.34**

IRRIGATION DEMANDS	Million m^3
Vanderkloof (RSA)	1,188.55
Vanderkloof (Namibia)	40.00
Total Irrigation Demands	**1,228.55**
Total Urban and Irrigation	**1,311.89**
EWR and Losses	1,082.15
TOTAL DEMAND	**2,394.04**

	(%)	**(Mm^3)**	**(Mm^3)**	**(Mm^3)**
January	3.9%	51.53	151.17	202.70
February	3.8%	49.89	113.15	163.04
March	4.3%	56.00	90.63	146.63
April	6.3%	82.37	61.53	143.90
May	9.3%	122.23	46.56	168.79
June	11.3%	148.15	33.43	181.58
July	11.2%	146.95	38.55	185.50
August	13.2%	173.44	57.08	230.52
September	12.7%	166.00	85.74	251.74
October	9.5%	124.37	113.15	237.52
November	8.6%	112.58	139.51	252.09
December	6.0%	78.39	151.65	230.04
TOTAL	**100%**	**1,311.89**	**1082.15**	**2,394.04**

% Demand pattern from Orange River Annual Operating Analysis (2008/09)

APPENDIX C: HYDROPOWER OPTIMIZATION

Van der Kloof Storage Trajectory **TRIAL 4**

Starting storage = 2 672.94 x 10^6 m^3 (84% full)

FSL = 1 170.50 m, FSC = 3 187.07 x 10^6 m^3
NOC = 1 179 m, NOC Capacity = 4 483.26 x 10^6 m^3
Generating Capacity = 1 150.8 m (Head = 79.8 m)
Full Supply Area = 13 340.20 Ha
Lowest Outlet = 1 109.80 m, Dead Storage = 15.775 x 10^6 m^3
Dam Height = 108 m

Maximum demand = 252.1 Mm^3 (97.26 m^3/s)
Water rationing = 80% of demand
Penstock + outlet = 825 m^3/s
Penstock capacity = 434 m^3/s
Turbine efficiency = 90%
Installed capacity = 240 MW

$S_{t+1} = S_t + Q_t + P_t – E_t – SP_t – R_t$

Date	Storage (t+1) (Mm^3)	Storage (t) (Mm^3)	Head (t) (m)	Streamflow (t) (Mm^3)	Net Evap (t) (Mm^3)	Spillage (t) (Mm^3)	Release (t) (Mm^3)	Release (t) (m^3/s)	Hydropower (t) (MW)
Mar 2008	2,574.574	2,672.940	95.4	304.082	22.556909	0.000	330.00	123.21	16.970
April 2008	2,518.985	2,574.574	94.6	369.597	15.195840	0.000	330.00	127.31	16.636
May 2008	2,510.783	2,518.985	94.1	425.430	11.549215	0.000	330.00	123.21	15.556
June 2008	2,528.104	2,510.783	94.0	437.687	9.140931	0.000	330.00	123.21	15.447
July 2008	2,551.165	2,528.104	94.2	429.876	10.565172	0.000	330.00	127.31	16.187
Aug 2008	2,587.706	2,551.165	94.4	443.163	14.066292	0.000	330.00	123.21	15.882
Sept 2008	2,639.237	2,587.706	94.7	453.006	20.328035	0.000	330.00	127.31	16.749
Oct 2008	2,708.677	2,639.237	95.1	457.399	26.912185	0.000	330.00	123.21	16.643
Nov 2008	2,793.993	2,708.677	95.7	452.159	32.063482	0.000	330.00	123.21	17.296
Dec 2008	2,889.647	2,793.993	96.4	445.180	38.094698	0.000	330.00	136.41	19.992
Jan 2009	2,999.612	2,889.647	97.2	443.997	39.236180	0.000	330.00	123.21	18.928
Feb 2009	3,131.863	2,999.612	98.1	444.481	32.728090	0.000	330.00	127.31	20.570
								TOTAL	**206.855**

APPENDIX D: STREAMFLOW, RAINFALL, EVAPORATION AND STORAGE

Source: Directorate Hydrological Services of the Department of Water Affairs

Historical Record

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
1977/10/01	2,474.72	10,994.86	20.658	188	2.996	27	815.687
1977/11/01	2,756.79	11,897.94	29.764	250	4.658	39	621.349
1977/12/01	2,487.51	11,034.56	29.735	269	4.244	38	260.430
1978/01/01	2,386.12	10,723.28	27.632	258	13.925	130	230.866
1978/02/01	2,352.99	10,623.27	24.154	227	2.936	28	519.003
1978/03/01	2,436.55	10,877.13	25.774	237	10.180	94	530.298
1978/04/01	2,688.54	11,674.43	14.427	124	7.620	65	1,538.320
1978/05/01	3,327.53	13,829.05	13.944	101	0.000	0	566.226
1978/06/01	3,156.94	13,248.85	10.704	81	0.000	0	358.419
1978/07/01	3,164.16	13,273.50	12.009	90	0.450	3	606.621
1978/08/01	2,979.07	12,642.62	13.887	110	0.837	7	382.258
1978/09/01	2,798.30	12,035.23	15.330	127	5.877	49	455.342
1978/10/01	2,657.13	11,572.56	22.883	198	0.742	6	597.337
1978/11/01	2,589.98	11,357.07	34.818	307	1.044	9	683.673
1978/12/01	2,704.29	11,725.75	31.777	271	2.850	24	547.615
1979/01/01	2,710.50	11,746.03	36.326	309	1.713	15	559.086
1979/02/01	2,546.78	11,220.15	26.647	237	7.718	69	817.351
1979/03/01	2,757.91	11,901.63	30.614	257	0.836	7	485.721
1979/04/01	2,793.66	12,019.84	19.921	166	3.302	27	57.960
1979/05/01	2,641.11	11,520.87	11.900	103	5.242	46	266.963
1979/06/01	2,651.21	11,553.44	10.058	87	0.059	1	245.559
1979/07/01	2,669.58	11,612.86	9.335	80	2.051	18	226.866
1979/08/01	2,657.59	11,574.05	12.279	106	2.650	23	64.367
1979/09/01	2,592.58	11,365.36	18.102	159	0.116	1	109.644
1979/10/01	2,499.97	11,073.36	23.401	211	3.383	31	238.720
1979/11/01	2,461.21	10,953.06	25.000	228	6.584	60	303.902
1979/12/01	2,491.40	11,046.66	39.259	355	0.000	0	432.708
1980/01/01	2,594.61	11,371.83	39.155	344	0.886	8	449.590
1980/02/01	2,595.37	11,374.25	26.905	237	3.094	27	472.076
1980/03/01	2,666.89	11,604.15	20.750	179	6.237	54	353.818
1980/04/01	2,699.04	11,708.62	20.817	178	1.627	14	369.722
1980/05/01	2,821.71	12,113.07	16.389	135	0.000	0	278.701
1980/06/01	2,894.92	12,358.21	10.823	88	0.097	1	188.346
1980/07/01	2,752.43	11,883.58	11.917	100	0.390	3	83.702
1980/08/01	2,539.00	11,195.64	13.228	118	3.354	30	349.969
1980/09/01	2,591.67	11,362.46	18.133	160	2.923	26	306.592
1980/10/01	2,646.70	11,538.89	29.236	253	0.000	0	121.838
1980/11/01	2,469.49	10,978.66	23.452	214	9.467	86	72.764
1980/12/01	2,343.86	10,595.85	30.328	286	4.519	43	87.377
1981/01/01	2,138.18	9,993.83	29.623	296	5.499	55	248.869

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
1981/02/01	2,009.64	9,630.58	19.039	198	12.244	127	538.298
1981/03/01	2,295.40	10,451.36	20.243	194	5.544	53	607.417
1981/04/01	2,636.29	11,505.35	19.085	166	0.986	9	516.320
1981/05/01	2,852.07	12,214.43	13.517	111	2.202	18	507.581
1981/06/01	2,976.64	12,634.38	9.467	75	0.914	7	411.527
1981/08/01	2,889.24	12,339.11	12.808	104	11.628	94	283.044
1981/09/01	2,773.66	11,953.62	18.591	156	0.000	0	515.495
1981/10/01	2,809.01	12,070.81	22.835	189	2.686	22	381.926
1981/11/01	2,684.85	11,662.43	30.796	264	3.442	30	365.990
1981/12/01	2,620.09	11,453.31	31.460	275	8.508	74	463.355
1982/01/01	2,642.91	11,526.67	38.761	336	0.526	5	716.352
1982/02/01	2,791.15	12,011.52	29.677	247	4.237	35	336.329
1982/03/01	2,680.28	11,647.58	24.665	212	2.937	25	273.046
1982/04/01	2,467.20	10,971.58	11.865	108	5.737	52	163.970
1982/05/01	2,256.18	10,335.66	12.338	119	0.000	0	161.248
1982/06/01	2,115.80	9,929.97	7.764	78	1.695	17	20.863
1982/07/01	1,912.59	9,360.84	7.654	82	3.816	41	113.153
1982/08/01	1,862.96	9,223.79	11.975	130	0.122	1	333.907
1982/09/01	2,040.69	9,717.60	17.116	176	0.317	3	311.032
1982/11/01	2,043.96	9,726.79	24.948	256	3.181	33	271.614
1982/12/01	2,098.37	9,880.43	34.312	347	0.979	10	667.476
1983/01/01	2,490.77	11,044.70	39.780	360	0.807	7	276.132
1983/02/01	2,511.82	11,110.36	32.307	291	0.034	0	41.616
1983/03/01	2,302.40	10,472.12	23.380	223	1.970	19	38.110
1983/04/01	2,088.16	9,851.48	17.350	176	0.326	3	40.874
1983/05/01	2,008.55	9,627.54	10.576	110	1.181	12	40.075
1983/07/01	1,888.97	9,295.56	7.630	82	1.870	20	88.947
1983/08/01	1,855.25	9,202.53	10.441	113	0.000	0	80.066
1983/09/01	1,779.00	8,992.38	13.941	155	0.857	10	27.093
1983/10/01	1,662.94	8,671.02	18.723	216	0.668	8	345.254
1983/11/01	1,642.02	8,612.61	19.146	222	5.084	59	376.122
1985/05/01	1,973.12	9,528.73	11.774	124	0.000	0	67.022
1985/06/01	1,880.82	9,273.06	8.138	88	0.027	0	60.037
1985/07/01	1,798.53	9,046.22	8.297	92	0.000	0	72.935
1985/10/01	1,508.18	8,232.63	16.413	199	5.653	69	263.413
1985/11/01	1,557.40	8,373.89	19.145	229	1.161	14	250.423
1985/12/01	1,588.64	8,462.56	21.664	256	5.458	64	658.433
1986/01/01	2,022.24	9,665.85	29.174	302	3.050	32	866.808
1986/02/01	2,521.31	11,140.07	28.221	253	1.824	16	771.156
1986/03/01	2,631.23	11,489.07	25.574	223	1.540	13	490.346
1986/04/01	2,786.83	11,997.20	18.230	152	4.978	41	214.861
1986/05/01	2,795.78	12,026.87	14.306	119	0.000	0	231.354
1986/06/01	2,816.98	12,097.32	9.412	78	1.669	14	307.880
1986/07/01	2,902.37	12,383.29	9.902	80	0.050	0	142.959
1986/08/01	2,827.94	12,133.84	11.850	98	1.350	11	215.843
1986/09/01	2,808.35	12,068.61	16.996	141	0.000	0	101.403
1986/10/01	2,645.19	11,534.02	20.121	174	3.648	32	320.280
1986/11/01	2,597.61	11,381.40	25.776	226	2.153	19	970.001

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
1986/12/01	2,862.52	12,249.42	39.609	323	0.000	0	682.576
1987/01/01	2,771.77	11,947.37	37.316	312	0.000	0	327.337
1987/02/01	2,534.36	11,181.04	23.360	209	10.054	90	317.591
1987/03/01	2,575.16	11,309.95	22.848	202	1.607	14	60.540
1987/04/01	2,376.99	10,695.64	14.600	137	1.115	10	22.691
1987/05/01	2,174.62	10,098.44	11.761	116	0.494	5	208.232
1987/06/01	2,180.32	10,114.86	7.893	78	0.504	5	455.577
1987/07/01	2,448.50	10,913.87	8.483	78	3.176	29	143.435
1987/08/01	2,389.18	10,732.56	11.739	109	0.701	7	39.251
1987/09/01	2,261.55	10,351.44	12.096	117	9.326	90	432.782
1987/10/01	2,415.78	10,813.53	21.914	203	3.324	31	1,868.554
1987/11/01	2,875.83	12,294.06	30.909	251	7.594	62	991.251
1987/12/01	3,048.57	12,879.01	36.030	280	2.786	22	456.279
1988/01/01	2,797.31	12,031.95	41.514	345	0.498	4	579.728
1988/02/01	2,840.29	12,175.05	18.517	152	27.036	222	2,293.750
1988/03/01	3,696.09	15,035.10	21.857	145	11.080	74	5,987.260
1988/04/01	3,357.43	13,929.91	13.798	99	14.200	102	1,288.300
1988/05/01	3,151.67	13,230.86	10.656	81	2.668	20	658.845
1988/06/01	2,901.11	12,379.05	7.484	60	1.225	10	452.808
1988/07/01	2,697.56	11,703.80	8.696	74	0.179	2	495.232
1988/08/01	2,616.70	11,442.44	12.536	110	0.000	0	678.974
1988/09/01	2,518.28	11,130.58	14.570	131	5.503	49	899.012
1988/10/01	2,540.39	11,200.02	19.592	175	6.897	62	856.587
1988/11/01	2,489.57	11,040.97	23.340	211	2.066	19	764.186
1988/12/01	2,320.58	10,526.22	23.218	221	19.056	181	698.571
1989/01/01	2,371.38	10,678.68	23.503	220	12.092	113	1,382.100
1988/02/01	2,645.91	11,536.34	18.346	159	15.768	137	1,572.619
1989/03/01	2,661.45	11,586.53	21.358	184	3.960	34	1,518.700
1989/04/01	2,291.40	10,439.51	11.768	113	2.798	27	710.493
1988/05/01	2,321.78	10,529.80	10.309	98	0.000	0	541.641
1989/06/01	2,417.10	10,817.56	8.415	78	0.112	1	546.723
1989/07/01	2,570.24	11,294.34	9.033	80	0.139	1	924.349
1989/08/01	2,631.47	11,489.85	13.353	116	0.355	3	911.091
1989/09/01	2,617.23	11,444.14	16.783	147	1.542	13	495.022
1989/10/01	2,552.52	11,238.27	23.596	210	0.000	0	53.833
1989/11/01	2,210.43	10,202.05	22.246	218	3.220	32	189.432
1989/12/01	1,969.50	9,518.65	28.082	295	1.097	12	862.114
1990/01/01	2,004.66	9,616.66	28.173	293	1.457	15	165.237
1990/02/01	1,791.29	9,026.26	19.062	211	3.125	35	273.869
1990/03/01	1,726.30	8,846.88	17.680	200	5.111	58	84.290
1990/04/01	1,456.98	8,083.26	9.070	112	5.777	71	453.140
1990/05/01	1,605.17	8,509.20	8.660	102	0.000	0	308.830
1990/06/01	1,703.16	8,782.80	6.082	69	2.888	33	246.802
1990/07/01	1,746.11	8,901.63	6.578	74	0.737	8	587.765
1990/08/01	2,102.86	9,893.18	12.022	122	0.586	6	658.194
1990/09/01	2,326.74	10,544.60	16.313	155	0.416	4	451.332
1990/10/01	2,250.96	10,320.34	23.154	224	0.504	5	88.940
1990/11/01	2,001.24	9,607.11	24.617	256	0.397	4	77.078

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
1990/12/01	1,736.71	8,875.66	22.781	257	2.721	31	45.078
1991/01/01	1,467.92	8,115.41	17.861	220	13.577	167	345.086
1991/02/01	1,512.01	8,243.70	21.521	261	3.653	44	1,505.430
1991/03/01	2,466.84	10,970.47	19.346	176	12.233	112	1,176.730
1991/04/01	2,641.65	11,522.61	18.565	161	0.120	1	587.806
1991/05/01	2,746.86	11,865.24	13.976	118	0.036	0	294.671
1991/06/01	2,750.80	11,878.21	9.090	77	3.480	29	248.212
1991/07/01	2,516.09	11,123.72	9.103	82	0.089	1	439.791
1991/08/01	2,551.49	11,235.01	11.955	106	0.000	0	440.211
1991/09/01	2,697.14	11,702.43	15.497	132	3.608	31	321.211
1991/10/01	2,676.51	11,635.34	17.676	152	19.893	171	296.420
1991/11/01	2,586.49	11,345.96	24.594	217	0.563	5	761.872
1991/12/01	2,440.67	10,889.78	28.030	257	3.993	37	858.748
1992/01/01	2,540.96	11,201.81	36.295	324	0.172	2	384.016
1992/02/01	2,321.34	10,528.49	28.093	267	0.097	1	170.014
1992/03/01	1,948.92	9,461.48	21.392	226	4.087	43	54.980
1992/04/01	1,649.17	8,632.60	12.492	145	0.460	5	93.513
1992/05/01	1,430.04	8,003.50	8.755	109	0.000	0	181.411
1992/06/01	1,334.67	7,713.35	5.881	76	0.076	1	223.656
1992/07/01	1,315.75	7,654.14	6.065	79	0.166	2	281.549
1992/08/01	1,318.49	7,662.75	7.903	103	2.184	29	288.791
1992/09/01	1,343.36	7,740.35	12.443	161	0.000	0	263.406
1992/10/01	1,301.42	7,608.88	14.842	195	4.298	56	309.437
1992/11/01	1,300.48	7,605.90	17.498	230	1.129	15	241.539
1992/12/01	1,273.35	7,519.16	24.359	324	0.157	2	346.051
1993/01/01	1,356.23	7,780.12	24.724	318	0.471	6	104.438
1993/02/01	1,133.59	7,047.88	12.702	180	4.980	71	79.384
1993/03/01	995.28	6,531.42	12.373	189	1.907	29	217.932
1993/04/01	1,012.73	6,599.82	8.247	125	0.743	11	142.115
1993/05/01	998.96	6,545.93	6.655	102	0.454	7	120.181
1993/06/01	1,013.54	6,602.97	4.865	74	0.449	7	85.630
1993/07/01	1,011.18	6,593.78	5.264	80	0.600	9	80.892
1993/08/01	1,000.95	6,553.76	7.013	107	0.388	6	113.301
1993/09/01	998.56	6,544.36	11.300	173	0.000	0	158.565
1993/10/01	998.56	6,544.36	12.324	188	6.228	95	189.980
1993/11/01	1,012.89	6,600.44	14.131	214	1.498	23	224.391
1993/12/01	1,008.32	6,582.63	17.624	268	4.147	63	263.679
1994/01/01	1,016.80	6,615.62	14.564	220	4.356	66	315.223
1994/02/01	1,070.05	6,817.65	15.170	223	6.919	101	1,497.250
1994/03/01	2,348.18	10,608.81	21.828	206	7.078	67	768.693
1994/04/01	2,854.71	12,223.27	20.410	167	1.448	12	377.040
1994/05/01	2,989.69	12,678.67	15.705	124	0.000	0	294.047
1994/06/01	2,943.61	12,522.49	8.783	70	0.000	0	164.269
1994/07/01	2,553.89	11,242.59	8.755	78	0.563	5	226.771
1994/08/01	2,478.20	11,005.65	12.681	115	0.000	0	162.223
1994/09/01	2,410.14	10,796.32	18.365	170	0.000	0	137.625
1994/10/01	2,274.51	10,389.60	22.455	216	0.000	0	149.477
1994/11/01	2,113.39	9,923.11	23.649	238	3.350	34	221.776

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
1994/12/01	2,054.29	9,755.84	32.125	329	0.000	0	320.884
1995/01/01	2,073.81	9,810.90	27.797	283	2.842	29	331.804
1995/02/01	2,096.69	9,875.66	27.385	277	0.354	4	106.842
1995/03/01	1,942.67	9,444.14	17.477	185	8.245	87	58.208
1995/04/01	1,780.43	8,996.33	12.876	143	0.072	1	50.798
1995/05/01	1,671.35	8,694.44	8.054	93	2.543	29	52.679
1995/06/01	1,608.36	8,518.18	6.352	75	0.201	2	37.736
1995/07/01	1,550.76	8,354.95	6.515	78	0.000	0	40.499
1995/09/01	1,352.75	7,769.39	11.575	149	1.033	13	109.034
1995/10/01	1,264.24	7,489.72	14.945	200	0.435	6	203.509
1995/11/01	1,222.00	7,351.04	17.324	236	3.646	50	290.042
1995/12/01	1,275.27	7,525.34	16.664	221	4.137	55	346.439
1996/01/01	1,410.37	7,944.70	20.187	254	1.256	16	366.545
1996/02/01	1,544.04	8,335.75	18.302	220	7.619	91	443.024
1996/03/01	1,824.70	9,118.33	21.130	232	0.000	0	1,310.880
1996/04/01	2,680.56	11,648.49	15.990	137	2.441	21	250.880
1996/05/01	2,708.75	11,740.31	11.905	101	0.024	0	305.451
1996/06/01	2,811.40	12,078.76	10.629	88	0.000	0	272.204
1996/07/01	2,893.55	12,353.61	10.473	85	5.166	42	406.946
1996/08/01	3,086.26	13,007.55	13.521	104	0.851	7	239.632
1996/09/01	3,150.33	13,226.29	18.648	141	0.000	0	152.529
1996/10/01	3,067.10	12,942.19	23.254	180	0.000	0	175.015
1996/11/01	1,931.58	9,413.40	24.886	264	7.663	81	165.915
1996/12/01	2,779.00	11,971.28	30.973	259	12.616	105	786.893
1997/01/01	3,130.11	13,157.25	29.165	222	8.001	61	973.047
1997/02/01	3,134.23	13,171.31	33.405	254	5.466	41	451.932
1997/03/01	2,911.27	12,413.28	19.228	155	15.118	122	1,236.248
1997/04/01	3,271.10	13,637.84	16.590	122	2.150	16	1,177.184
1997/05/01	3,183.66	13,340.05	12.303	92	5.240	39	559.516
1997/06/01	3,072.19	12,959.55	8.790	68	2.986	23	684.984
1997/07/01	3,026.96	12,805.40	10.353	81	0.579	5	337.862
1997/08/01	3,030.91	12,818.85	14.442	113	0.000	0	249.542
1997/09/01	3,079.23	12,983.56	20.927	161	0.000	0	246.875
1997/10/01	3,062.15	12,925.30	22.669	175	4.457	34	207.980
1997/11/01	2,972.01	12,618.67	31.286	248	0.188	1	140.502
1997/12/01	2,792.14	12,014.80	32.094	267	0.706	6	180.414
1998/01/01	2,630.21	11,485.80	29.056	253	5.655	49	155.540
1998/02/01	2,445.41	10,904.36	23.587	216	4.642	43	827.800
1998/03/01	2,851.47	12,212.43	24.130	198	9.923	81	1,578.285
1998/04/01	3,278.82	13,664.05	19.524	143	1.808	13	849.868
1998/05/01	3,028.95	12,812.18	14.629	114	0.902	7	295.672
1998/06/01	3,049.51	12,882.21	11.909	92	0.000	0	157.003
1998/07/01	3,037.47	12,841.19	10.798	84	0.141	1	171.061
1998/08/01	2,993.98	12,693.24	13.146	104	0.551	4	342.699
1998/09/01	2,851.69	12,213.16	18.012	147	1.143	9	402.473
1998/10/01	2,839.34	12,171.88	24.892	205	0.457	4	280.304
1998/11/01	2,809.76	12,073.30	28.121	233	10.255	85	236.116
1998/12/01	2,749.65	11,874.42	32.132	271	4.524	38	292.508

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
1999/01/01	2,737.68	11,835.07	30.388	257	1.787	15	224.158
1999/02/01	2,643.86	11,529.73	30.692	266	0.114	1	134.762
1999/03/01	2,478.36	11,006.15	26.109	237	1.262	11	199.428
1999/04/01	2,375.29	10,690.50	19.348	181	1.331	12	225.808
1999/05/01	2,386.41	10,724.16	9.153	85	5.572	52	240.911
1999/06/01	2,484.66	11,025.71	9.081	82	0.000	0	238.719
1999/07/01	2,576.34	11,313.69	9.600	85	0.235	2	258.603
1999/08/01	2,678.71	11,642.48	13.090	112	0.000	0	232.531
1999/09/01	2,664.96	11,597.90	17.360	150	0.242	2	355.398
1999/10/01	2,760.05	11,908.69	21.688	182	1.444	12	216.362
1999/11/01	2,662.24	11,589.09	30.735	265	0.227	2	140.420
1999/12/01	2,484.88	11,026.39	22.905	208	15.611	142	168.877
2000/01/01	2,354.02	10,626.36	21.178	199	5.190	49	196.346
2000/02/01	2,254.37	10,330.35	21.510	208	6.008	58	305.355
2000/03/01	2,298.02	10,459.12	17.414	166	11.923	114	989.172
2000/04/01	2,887.77	12,334.17	13.152	107	19.302	156	635.149
2000/05/01	2,846.27	12,195.04	11.329	93	0.000	0	528.669
2000/06/01	2,949.28	12,541.67	9.337	74	0.951	8	252.333
2000/07/01	2,954.60	12,559.68	10.186	81	0.000	0	229.444
2000/08/01	2,932.71	12,485.64	14.951	120	0.000	0	253.151
2000/09/01	2,994.50	12,695.01	16.527	130	12.504	98	462.808
2000/10/01	3,151.47	13,230.18	23.430	177	0.705	5	358.330
2000/11/01	2,980.05	12,645.95	24.702	195	6.973	55	267.830
2000/12/01	2,910.31	12,410.04	33.558	270	4.095	33	380.991
2001/01/01	2,853.33	12,218.65	31.848	261	1.898	16	211.558
2001/02/01	2,619.44	11,451.22	24.915	218	0.000	0	228.909
2001/03/01	2,565.15	11,278.21	22.786	202	5.434	48	268.669
2001/04/01	2,568.23	11,287.97	11.228	99	8.738	77	524.423
2001/05/01	2,863.74	12,253.51	10.668	87	3.201	26	1,189.500
2001/06/01	3,066.90	12,941.50	8.827	68	2.149	17	277.676
2001/07/01	3,014.30	12,762.32	9.166	72	0.402	3	391.588
2001/08/01	3,128.16	13,150.59	12.674	96	0.000	0	205.941
2001/09/01	3,120.11	13,123.10	14.450	110	8.471	65	541.304
2001/10/01	3,109.77	13,087.80	22.861	175	3.865	30	561.014
2001/11/01	3,079.31	12,983.84	22.605	174	16.365	126	1,823.810
2001/12/01	3,411.79	14,112.29	30.520	216	11.917	84	2,398.440
2002/01/01	3,284.29	13,682.62	30.494	223	5.578	41	1,124.890
2002/02/01	3,189.96	13,361.55	29.490	221	2.888	22	1,661.910
2002/03/01	3,189.07	13,358.51	23.689	177	3.143	24	636.016
2002/04/01	2,942.69	12,519.37	21.306	170	0.000	0	188.885
2002/05/01	2,798.30	12,035.23	13.883	115	3.384	28	204.713
2002/06/01	2,872.34	12,282.35	10.593	86	3.835	31	279.344
2002/07/01	3,048.05	12,877.24	8.844	69	0.000	0	247.626
2002/08/01	3,108.41	13,083.16	12.397	95	13.978	107	745.885
2002/09/01	3,173.35	13,304.87	17.643	133	4.257	32	1,712.450
2002/10/01	3,186.23	13,348.82	25.406	190	0.000	0	930.024
2002/11/01	3,106.52	13,076.70	25.695	196	0.000	0	82.997
2002/12/01	2,773.53	11,953.19	26.199	219	8.482	71	166.553

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
2003/01/01	2,623.49	11,464.21	30.010	262	0.755	7	159.948
2003/02/01	2,415.08	10,811.39	22.307	206	4.589	42	119.238
2003/03/01	2,243.85	10,299.51	21.766	211	4.974	48	266.057
2003/04/01	2,217.58	10,222.84	13.250	130	2.344	23	263.647
2003/05/01	2,309.22	10,492.39	10.709	102	3.893	37	148.623
2003/06/01	2,292.67	10,443.27	9.359	90	0.000	0	110.935
2003/07/01	2,281.65	10,410.67	9.788	94	0.000	0	318.214
2003/08/01	2,421.21	10,830.12	11.572	107	1.061	10	289.483
2003/09/01	2,535.85	11,185.73	15.252	136	0.434	4	255.236
2003/10/01	2,547.60	11,222.74	23.137	206	2.174	19	307.396
2003/11/01	2,458.63	10,945.10	20.942	191	4.820	44	132.004
2003/12/01	2,265.13	10,361.97	24.834	240	0.000	0	136.965
2004/01/01	2,067.15	9,792.09	20.908	214	6.023	62	134.924
2004/02/01	1,884.16	9,282.28	20.505	221	7.235	78	201.720
2004/03/01	1,819.70	9,104.55	15.017	165	10.693	117	379.875
2004/04/01	1,967.10	9,511.98	12.341	130	10.487	110	235.912
2004/05/01	2,059.91	9,771.68	13.101	134	0.000	0	164.836
2004/06/01	2,109.63	9,912.41	8.329	84	0.498	5	258.097
2004/07/01	2,269.14	10,373.77	8.245	79	0.152	1	238.340
2004/08/01	2,374.72	10,688.77	10.455	98	0.000	0	250.362
2004/09/01	2,457.52	10,941.67	16.535	151	7.477	68	263.414
2004/10/01	2,485.61	11,028.66	19.691	179	6.468	59	232.455
2004/11/01	2,414.35	10,809.16	24.160	224	0.961	9	141.902
2004/12/01	2,236.89	10,279.15	24.736	241	4.068	40	157.135
2005/01/01	2,050.95	9,746.45	23.343	240	2.757	28	137.527
2005/02/01	1,840.04	9,160.60	18.501	202	4.942	54	211.173
2005/03/01	1,794.64	9,035.50	16.656	184	4.860	54	236.575
2005/04/01	1,797.25	9,042.69	11.255	124	0.461	5	175.622
2005/05/01	1,822.45	9,112.13	11.292	124	2.658	29	108.737
2005/06/01	1,834.05	9,144.09	8.676	95	2.497	27	176.898
2005/07/01	1,923.54	9,391.14	8.336	89	0.000	0	275.544
2005/08/01	2,062.26	9,778.30	10.798	110	0.615	6	280.282
2005/09/01	2,171.11	10,088.33	13.022	129	0.000	0	215.995
2005/10/01	2,181.88	10,119.38	18.599	184	1.504	15	251.803
2005/11/01	2,099.64	9,884.03	23.028	233	2.503	25	462.313
2005/12/01	2,244.13	10,300.33	30.357	295	0.000	0	135.869
2006/01/01	2,023.87	9,670.41	18.341	190	9.450	98	170.584
2006/02/01	1,864.54	9,228.14	13.915	151	8.134	88	1,442.960
2006/03/01	2,441.53	10,892.42	20.508	188	6.223	57	1,639.550
2006/04/01	3,239.45	13,530.22	18.397	136	13.631	101	1,134.900
2006/05/01	3,275.53	13,652.89	10.043	74	5.677	42	1,041.190
2006/06/01	3,125.24	13,140.62	9.266	71	2.306	18	373.534
2006/07/01	3,035.67	12,835.06	7.118	55	0.780	6	876.024
2006/08/01	3,084.56	13,001.75	11.970	92	10.927	84	596.429
2006/09/01	3,098.98	13,050.96	16.332	125	0.000	0	636.105
2006/10/01	3,029.59	12,814.36	21.562	168	2.183	17	647.266
2006/11/01	3,001.71	12,719.51	28.548	224	0.923	7	1,489.190
2006/12/01	3,156.21	13,246.36	33.850	256	4.409	33	802.237

Date	Storage (Mm^3)	S. Area (Ha)	Evap (Mm^3)	Evap (mm)	Rain (Mm^3)	Rain (mm)	Flow (Mm^3)
2007/01/01	2,929.17	12,473.68	32.817	263	1.620	13	680.687
2007/02/01	2,682.01	11,653.20	30.374	261	0.327	3	648.728
2007/03/01	2,564.92	11,277.48	23.688	210	4.355	39	812.979
2007/04/01	2,495.17	11,058.40	14.918	135	5.565	50	1,009.430
2007/05/01	2,610.48	11,422.52	13.148	115	0.238	2	288.673
2007/06/01	2,781.23	11,978.66	7.811	65	1.900	16	290.077
2007/07/01	2,969.10	12,608.81	9.908	79	0.130	1	219.551
2007/08/01	3,045.99	12,870.22	14.037	109	0.585	5	194.842
2007/09/01	3,070.52	12,953.85	18.998	147	1.410	11	191.046
2007/10/01	2,997.57	12,705.44	21.924	173	4.453	35	300.829
2007/11/01	2,972.71	12,621.05	24.416	193	1.978	16	194.353
2007/12/01	2,830.55	12,142.54	27.174	224	10.011	82	270.823
2008/01/01	2,755.88	11,894.94	22.755	191	1.849	16	267.919
2008/02/01	2,672.94	11,623.75	22.515	194	10.841	93	206.849

The mean annual run-off is 5 613.58 x 10^6 m^3 and the monthly average streamflow is:

- October 398.96 x 10^6 m^3
- November 431.83 x 10^6 m^3
- December 478.47 x 10^6 m^3
- January 416.77 x 10^6 m^3
- February 627.48 x 10^6 m^3
- March 794.99 x 10^6 m^3
- April 474.99 x 10^6 m^3
- May 339.87 x 10^6 m^3
- June 265.21 x 10^6 m^3
- July 304.51 x 10^6 m^3
- August 328.97 x 10^6 m^3
- September 376.08 x 10^6 m^3