A Simple Operating Model of the Van der Kloof Reservoir using ANN Stream Flow Forecasts

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Abstract

Because of the scarcity of water, reservoirs should be operated to supply a multiplicity of water uses such as the competing demands of urban, mining, irrigation, hydropower and ecological requirements in the most efficient and sustainable manner. A water resource management philosophy such as this is especially important for the dry regions of the world such as South Africa.

The operation of Van der Kloof Reservoir situated on the Orange River in South Africa was investigated with an artificial neural network and a spreadsheet model. The objective of the investigation was to simulate reservoir inflow and optimize the operation of the reservoir for maximum power generation.

The operation of the river system with existing modelling tools and the literature on reservoir operation and artificial neural networks (ANN) were reviewed in order to understand the system better and to juxtapose the weaknesses and strengths of the different modelling utilities. The stream flow, rainfall and evaporation records spanning the period 1977 to 2008, the system water requirements and the installed hydropower capacity were all investigated.
A one-month ahead stream flow model was then developed to predict inflow into the Van der Kloof Reservoir over an operating period of twelve (12) months. The ANN was found to forecast streamflows reasonably well although the streamflow record for training the ANN was short. Forecasting performance improved as the prediction offset was reduced.

The inflows simulated by the ANN were used to iteratively obtain reservoir operating rules that maximized hydropower and minimized water supply deficits in the system.

Although the model was able to forecast monthly stream flow adequately at a single site, further research is needed with multi-site systems where a number of reservoirs are managed as a system. Other potential areas for further research include one-step seasonal and annual forecasting models equipped with disaggregation algorithms to determine monthly inflows.

Key Words: Artificial neural networks, hydrology, network training, optimize, simulation, stream flow, water resource system, Van der Kloof reservoir.

Background

Because of the scarcity of water, reservoirs should ideally be operated to supply a multiplicity of competing demands 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 is particularly true for South Africa and other dry regions of the world.

Water use can be broadly classified into water supply, hydropower and ecological flows. In addition to these uses, water resource managers also need to manage system losses which occur through river transmission and regulation losses. In South Africa, strategic industries such as Eskom which generates hydropower and Sasol which manufactures oil are so critical to the efficient functioning of the economy that they receive high priority in water allocation. Efficient allocation of water to all users in a river system is the essence of reservoir operation.

There is an ever increasing competition for the scarce water resources among water users. 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) who notes that water resource managers should focus their effort at improving the operational efficiency of existing reservoir systems in order to maximise benefits and delay costly augmentation schemes further into the future.

Simulation and optimization models offer effective means of managing complex water resource systems. Traditionally, autoregressive stochastic models have been used to predict stream flow used in the operation of reservoirs. The Water Resource Planning Model (WRPM) (DWAF, 2005 (a)), for example, is a complex model that is used to simulate stochastic stream flow, compute system yield and optimize the operation of reservoir systems. The complexity of the WRPM is a major setback and hence the need to search for simpler models. To operate the WRPM one requires detailed knowledge of the variables, parameters and their relationships. Artificial Neural networks (ANN), on the other hand, do not require knowledge of the relationships of variables as they depend on their power of connectivity to build this knowledge during training (Kisi, 2004). As a result, the capability of artificial neural networks in simulating stream flow and optimizing reservoir operation has attracted considerable research interest and results so far have been very promising (Jain et al., 1999).

Study Area

The Orange River (Figure 1) rises in the Drakensberg Mountains in Lesotho at an altitude of 3 300 metres above sea level. From there, it flows in a westerly direction and eventually discharges into the Atlantic Ocean some 2 200 km away. The river system drains a catchment area of over 1 million km^2, of which 600 000 km^2 lie in South Africa and the rest is shared between Lesotho, Namibia and Botswana. The mean annual runoff of the river system is 11 300 x 10^6 m^3. The current study only used the hydrology of the Upper Orange River because this where the stream flow impounding into Van der Kloof is generated. Figure 1 is a map of the Upper Orange River.

Van der Kloof Dam was built on the Orange River to generate hydropower, supply irrigation requirements, domestic and industrial requirements as well as to supply the water needs of mining towns in the Lower Orange River basin. Inflow into Van der Kloof Reservoir is generated in the Upper Orange River while releases from the reservoir supply downstream water requirements all the way to the Atlantic Ocean. Besides pick-up weirs, there is no yield dam downstream of Van der Kloof Dam and so all downstream requirements are regulated at the dam.

Current System Operation

The Orange River system supplies water to urban, industrial, mining, irrigation and hydropower requirements in addition to ecological water requirements. The Reserve comprises water allocated to ecological requirements and basic human needs riparian to the river system. In order to determine the Reserve, the entire river is divided into a number of reaches classified according to resource quality objectives.

Currently, the Stochastic Model of South Africa (STOMSA) (Van Rooyen and McKenzie, 2004) is used to generate stream flow ensembles required by the WRPM to develop short-term operation rules. 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 preserve serial correlation and determine 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).

System Operating Analysis

Hydrology and water requirements make up the input space in the Water Resource Planning Model (WRPM) (DWAF, 2007) that is used for operating analysis. Hydrology is updated regularly to account for new developments and land use changes in the catchment. The Pitman model, a rainfall-runoff model, is used to generate naturalised stream flow which in turn is used as input in STOMSA to generate synthetic stochastic stream flow. The WRPM calculates short-term and long-term stochastic yield.

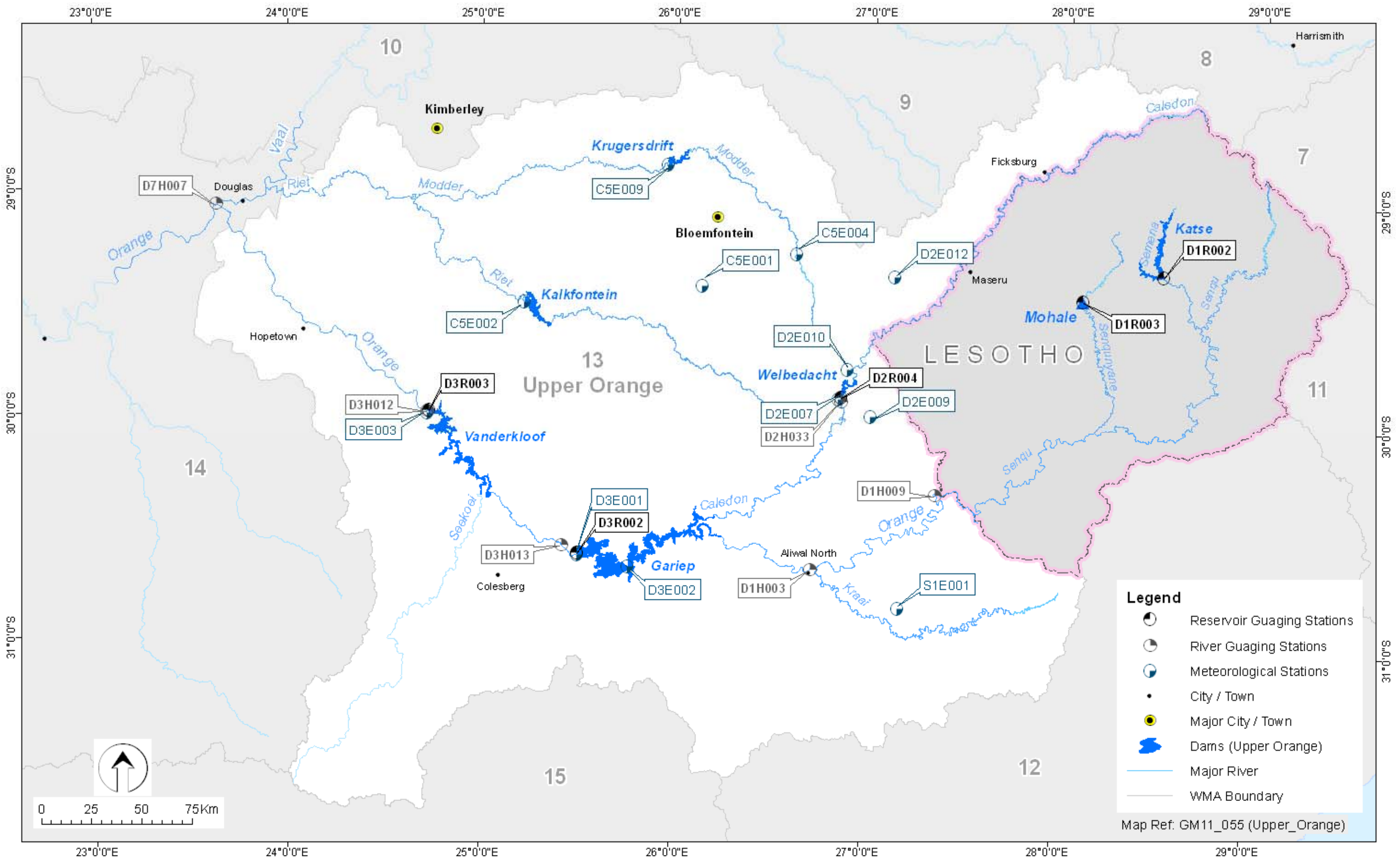

Figure 1 Upper Orange River Catchment

Short-term yield analysis is carried out over the critical period, taken as 36 months, to investigate the behaviour of the reservoir system. If need be, water restrictions are imposed to cushion the severity of the resulting shortage and prevent total loss of supply to essential users.

Operating analysis is undertaken on 1 May assuming reservoir starting storages of 10%, 20%, 40%, 60%, 80% and 100%. The decision date for annual operating rules is 1 May which coincides with the end of the summer rainfall season. The annual operating rule derived from this analysis is then implemented in the next twelve months up to the next annual operating analysis.

Different classes of water use attract different levels of assurance that are decided in consultation with key stakeholders. The allocation to a water use class is spread over a number of assurance levels. For example, 50% of irrigation requirement might be supplied at 95% assurance, 40% of the requirement at 99% assurance and 10% of the requirement at 99.5% assurance depending on the mix of crops grown in a particular area. Citrus, for instance, requires a higher assurance than maize. During a shortage, it may not be possible to achieve these assurances of supply and water restrictions would then be imposed according to stipulated curtailment criteria. A point in time at which curtailment criteria begin to be frequently violated marks the right timing for augmenting the water supply because the existing system is already failing.

To optimize hydropower, releases for both hydropower and downstream water requirements are channelled through the turbines. It takes the water released from the dam about 30 days to reach the river mouth. Due to the long distances involved, two thirds (67%) of water requirements is released the previous month to provide enough travel time to reach demand centres before the users have run dry completely.

Ecological Flows

The National Water Act, 1998 (Act No. 36 of 1998), requires the Reserve to be released to meet ecological flow requirements and basic human needs riparian to the river. King and Louw (1998) offer a brief description of the Building Block Methodology that is used in South Africa to determine the Reserve. Different components of the natural flow regime which are ecologically most significant are identified. And a flow regime defining the quantity and variability of water required for the maintenance of natural biota and ecological processes is prescribed at a workshop of experts (Hughes et al., 1997).

The final modified flow regime should reflect, in some way, the virgin flow regime. A naturalized flow time series is therefore selected to represent conditions that existed in the river prior to developments and to then determine the required release pattern. An observed flow record from a nearby gauged catchment is used to select the naturalized flow time series (Hughes et al., 1997). 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 is similar to that of the catchment being investigated.

Artificial Neural Networks

Artificial neural networks use artificial intelligence to model systems and have been used to simulate stream flow. A network is built from artificial neurons that process and transmit weighted input through a transfer function in much the same way the human brain functions. Just like the human brain, a neural network acquires intelligence through learning and stores the knowledge within inter-neuron connection strengths.

Artificial neural networks have the ability to simulate both linear and non-linear functions and they are faster than autoregressive moving average methods (Jain et al., 1999). Because neural networks learn directly from the data being modified they are capable of simulating input-output functions without detailed knowledge of the internal catchment hydrology (Kisi, 2004).

The most common network topology is the multi-layer perceptron or feed-forward network which only links nodes in adjacent layers. It is described as a supervised network because it uses historical output as next level of input so as to minimize the difference between simulated output and input data.

The multi-layer perceptron architecture consists of an input layer that receives inputs from the external environment, a hidden layer that receives weighted inputs from the input layer or previous hidden layer and performs transformations on the values, and an output layer that receives output from the last hidden layer and transmits the output to a graphical user interface.

Orange River Hydrology

The hydrology that was used in the study included monthly stream flow, rainfall, evaporation, water requirements and ecological water requirements. Monthly hydrology was used based on successful previous research on reservoir inflow prediction and operation (Jain *et al.,* 1999).

The stream flow record obtained spanned the period October 1977 to February 2008, with a total of 342 monthly flows. The monthly hydrograph at Van der Kloof Dam (gauging station D3H013) based on this stream flow record is plotted in Figure 2 and the water requirements downstream of Van der Kloof Dam are presented in Table 1.

Table 1: Monthly Water Requirements

MONTH	REQUIREMENTS (10^6 m^3)	% REQUIREMENT	ECOLOGICAL REQUIREMENTS (10^6 m^3)	TOTAL REQUIREMENTS (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**

Model Development

Stream Flow Forecasting

Reservoir operating analysis is undertaken ahead of the operating period to inform the actual operation when the time arrives. This arrangement requires inflow into the reservoir over the operating period to be determined through forecasting. Neural networks are among the many techniques available to forecast reservoir inflows by simulating the reservoir system. For example, Jain et al. (1999) developed an artificial neural network to forecast inflow into the Upper Indravati multipurpose Reservoir in India. For this purpose, a one month ahead forecasting model, *Flow (t+1)*, was constructed. Kisi (2004) also developed a neural network model to predict mean monthly stream flow. The input data included (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 stream flow in month t.

Modelling Process

The model development process (Figure 3) that was followed is summarized below:

i) An annual and monthly forecasting models were initially proposed. The annual model is outlined in paragraphs ii and iii below while the monthly model is described in paragraphs iv and v.

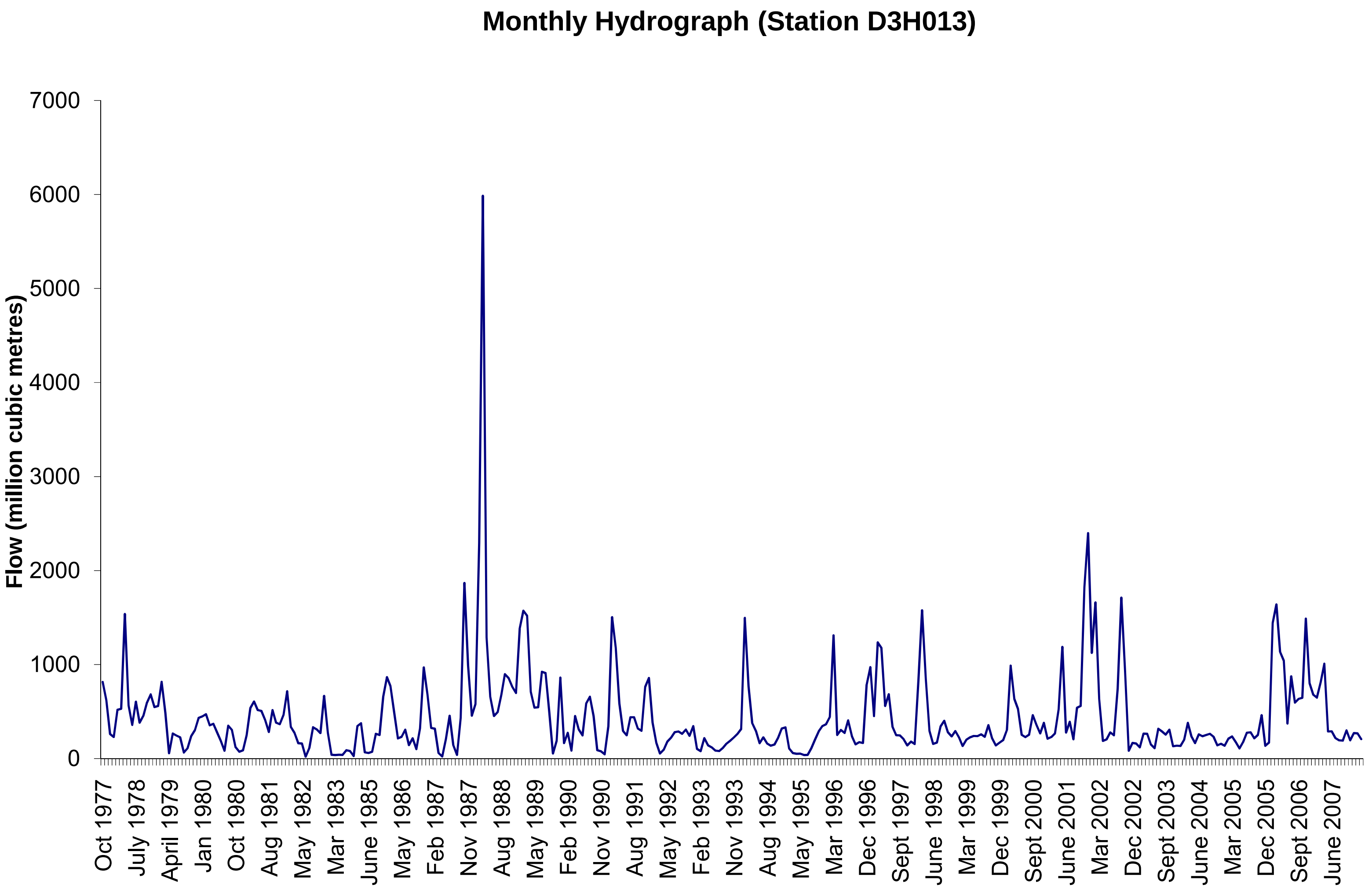

Figure 2: Monthly inflows at Van der Kloof Dam

ii) The annual model involved forecasting annual inflow one year ahead over the operating period. Since the operating period chosen was one year, it was only necessary to predict one annual flow and to then disaggregate the flow into monthly flows to allow continuous operation of the reservoir throughout the year. Long-term monthly average flow and mean annual flow would be used to disaggregate the forecasted annual flow into monthly flows. The one year ahead model was 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 monthly model was constructed to forecast one month ahead flow over the operating period. A prediction length of one month was chosen to avoid big simulation errors produced when long prediction lengths are used. Recursive prediction was used for the one month ahead model to predict flow in all the twelve months of the year. The flow record was extended by adding the recently forecasted stream flow to provide input for forecasting stream flow for the next month. This recursive process was repeated until the twelve flows for the one year operating period had been forecasted. The one month ahead forecasting model was expressed as: Q(t+1) = f(Q(t), Q(t-1), Q(t-2), Q(t-3), Q(t-4)). For month t = 5, for example, the flow is denoted by Q(5) and model output Q(t+1) is denoted by Q(6) (Figure 4).

iv) For initial storage for operating analysis, actual storage on 1 February 2008 was used because storage on the decision date (in this instance, 1 May 2008) was not available. The error was considered negligible because March and April are the last two months of the runoff season in South Africa and stream flow is already tailing off. Any drawdown in that period was likely to be balanced by the receding inflow.

The main determinants of simulation accuracy are length of the time step (prediction length) and length of flow record. The annual model was dropped because the annual flow record was found to be too short, only spanning 30 years from 1977 to 2008. Although the record contained 342 monthly flows, only 30 annual flows were available for training, cross validation and testing.

A one month ahead model was therefore 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 the previous month, flow Q(t-2) in the previous two months, flow Q(t-3) in the previous three months and flow Q(t-4) in the previous four months. The one month ahead stream flow, Q(t+1), was the model output.

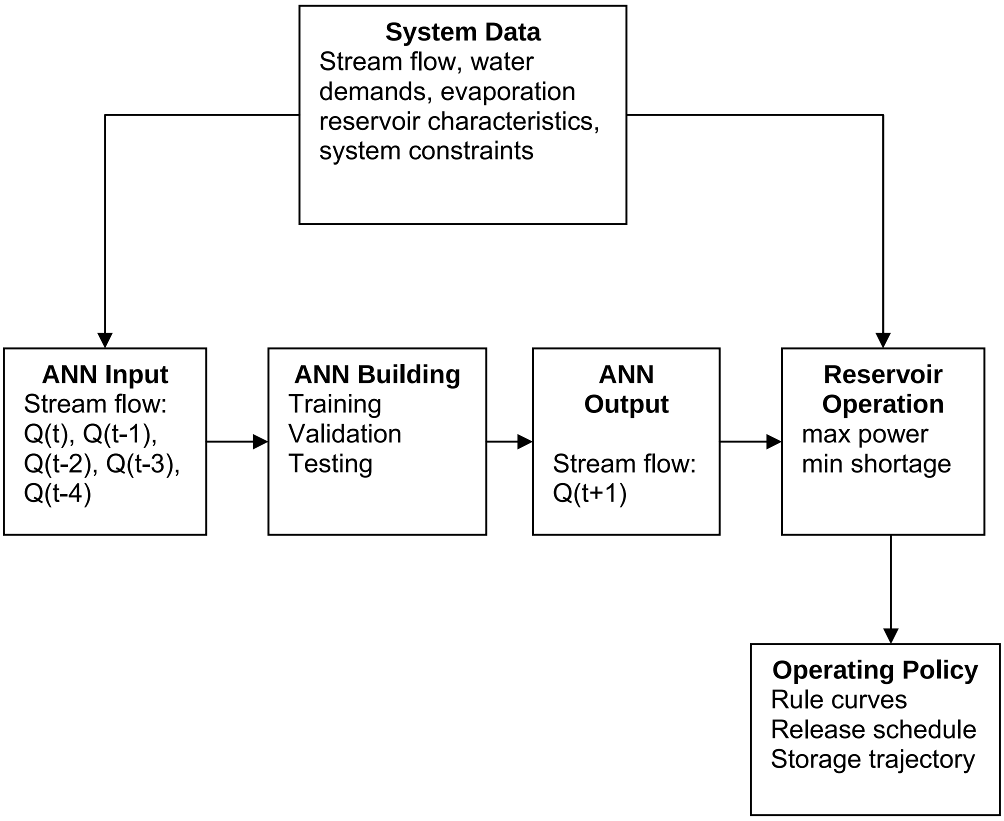

Figure 3: Model Flow Chart

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 4: One month ahead flow forecasting

Objective Function

According to Hall and Dracup (1970), water resource system 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. In the current study the problem was to maximize hydropower and minimize water supply deficits. And the objective function was defined as:

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

Where R_t = penstock release (m^3/s) during time period t; H_t is the average generating head during time period t; N = number of months during operating period; η is the turbine efficiency, ρ is the density of water (kg/m^3) and g is the acceleration due to gravity (m/s^2). The quotient 10^6 was introduced to reduce power to megawatts.

Hydropower is a function of release through the turbine and generating head:

$$HP(t) = 9810 \bullet k \bullet R(t) \bullet H(t) \bullet \eta \qquad (1)$$

Where HP(t) = power generated in time period t (MW); k = constant for converting monthly release in million m^3/month to m^3/s (0.3858).

System constraints in the optimization problem included:

- Maximum hydropower equals installed capacity (240 MW)
- Continuity equation: S(t+1) = S(t) + Q(t) + P(t) – E(t) – R(t) – SP(t)
  (S(t) = reservoir storage at the beginning of time t; Q(t) = stream flow during time t; P(t) = Precipitation during time t; E(t) = evaporation during time t; R(t) = release through penstock and outlet pipe; and SP(t) = reservoir spill during time t)
- Storage S(t) is bound between lowest and maximum permissible storages which are the dead storage and full supply capacity respectively
- Water deficit rate is defined as: DR(t) = (D(t) – R(t))/ D(t)
  (DR(t) = deficit rate during time period t; and D(t) = water demand including ecological flows during time period t)
- Release is less or equal to combined discharge through penstock and outlet pipe. Outlet pipe capacity is 391 m^3/s and penstock capacity is 176 m^3/s and combined capacity is 567 m^3/s.

Network Building

The stream flow record was divided into 60% for training, 20% for cross validation and 20% for testing. The software manual recommended 20% of data to be allocated to cross validation to provide the required generalization protection during network training. The allocation of 20% to network testing was also the recommended size.

During network training, input and output data were repeatedly fed into the network and with each presentation of data the output was compared with the desired output from the stream flow record and an error was computed in a process called supervised learning. Network training was achieved in 1 000 epochs accompanied with 5 epochs for cross validation all over a period of 10 seconds. A thousand iterations in ten seconds is clear demonstration of the computational power of artificial neural networks. Intermittently, the software stopped 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 a point during cross validation it started to increase. Network training was stopped at this point because it marked the point when the network had started to memorize the training patterns instead of learning the system under investigation.

An embedded genetic algorithm automatically optimized network weights which are a measure of the strength of connections between adjacent nodes. Network weights of the fully trained network were saved and the neural network was later used to forecast reservoir inflow that was needed for operating analysis.

Once the supervised network started to perform satisfactorily on training data, it was then tested with a totally different set of data it had not seen before. The network was repeatedly retrained until it started to perform satisfactorily. Testing provided additional model validation using out of sample testing data which the network had not seen before. This ensured that the network had indeed learned the general patterns of the system and had not simply memorized the given set of data.

After several iterations, a low level of complexity was selected for the relatively simple one reservoir system. According to the manual (NeuroDimension, Inc., 2005), at the present stage of knowledge, establishing the size of a network is more efficiently achieved through experimentation. And experimentation starts with a small network (low complexity), increasing the size until network performance on testing data is satisfactory.

The resulting network constructed for the one month ahead forecasting model is shown in **F**igure 5. The neural network has one input layer with five nodes, one hidden layer with three nodes and one output layer with one node.

Results and Discussion

Figure 6 shows testing results of the artificial neural network constructed to forecast inflow into Van der Kloof Reservoir. The plot shows a very good fit of forecasted stream flow produced with a network with only three layers. This underlines the ability of the ANN for streamflow forecasting as has been found in other studies.

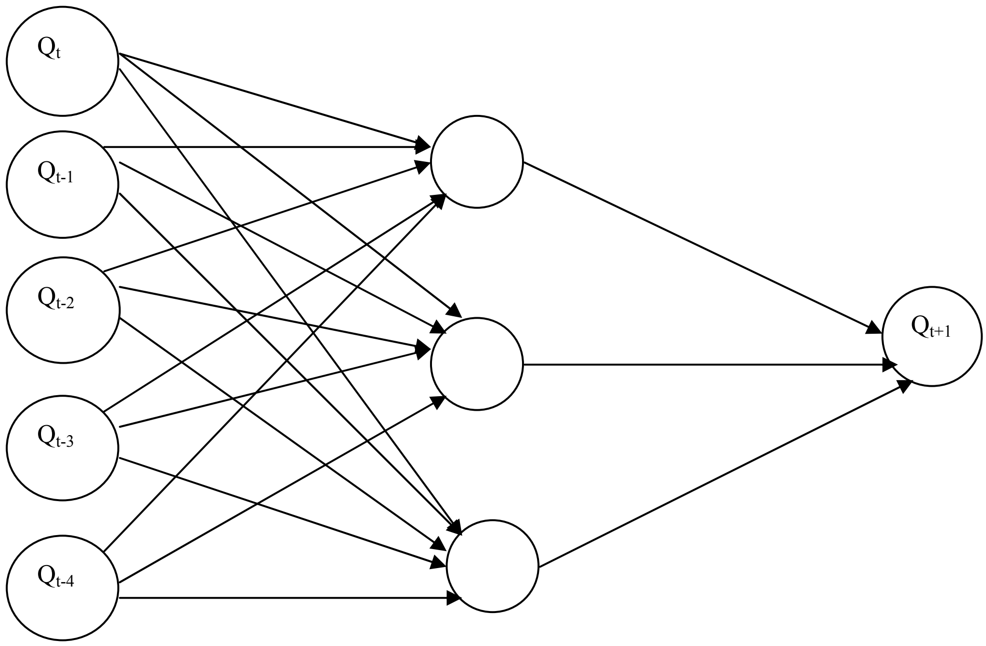

Figure 5: Artificial Neural Network for Van der Kloof Dam streamflow forecasting

Even sharp spikes of high flow were simulated accurately; only the highest spike was underestimated. Small peaks were simulated well because the stream flow record, used to train the network, contained sufficient normal flows. However, extreme flows were not simulated equally well because there were very few extreme flows in the flow record (i.e. a small number of training patterns), so the network did not acquire sufficient intelligence to simulate extreme flows. This demonstrates the limitation of artificial neural networks of requiring sufficiently long data for adequate training.

Figure 7 shows the forecasted flows over the twelve month operating period. The variability of forecasted flows is low but this corresponds reasonably well with the low variability of the historic inflows of the previous year that were used as inputs to the ANN. These historic inflows are shown in Figure 8 and apart from March and April, the flows in the rest of the months are reasonably close.. Because forecasting was performed recursively, there was also a tendency for variability to reduce as forecasting progressed.

Following the iterative optimization of the dam to maximize hydropower production, Figure 9 was obtained. This Figure gives an optimal release of 330 million m^3 per month (127 m^3/s) all channelled through the turbines.

With 84% storage at the start of the operating period, a constant release of 127 m^3/s throughout the year generated optimum power of 210 MW compared to installed capacity of 240 MW. A release of 127 m^3/s is able to supply 131% of the water requirements, resulting in an excess of 31%. The excess 31%, however, does not go to waste because it was channelled through the turbines to maximize power generation. Thus the deficit rate was zero in all the months during the operating period and there was no need for rationing water supply.

Conclusions and Recommendations.

For further research, the capability of artificial neural networks to simulate multi-site systems could be investigated. This would involve selecting a system of three or more reservoirs with both parallel and series connections. The stream flow forecasting methodology developed for the one reservoir system could then be modified to accommodate the expanded system.

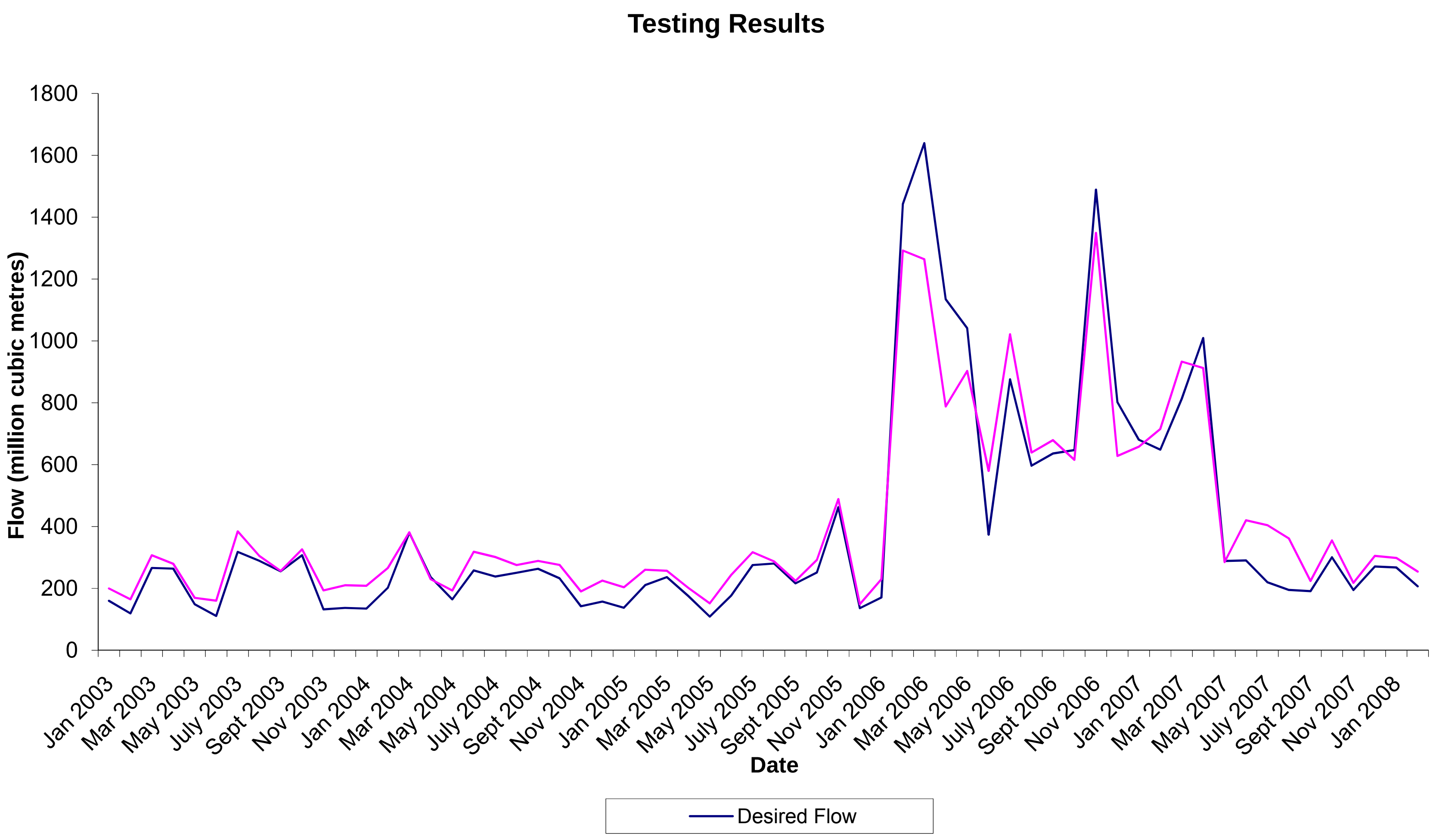

Figure 6: Testing Results

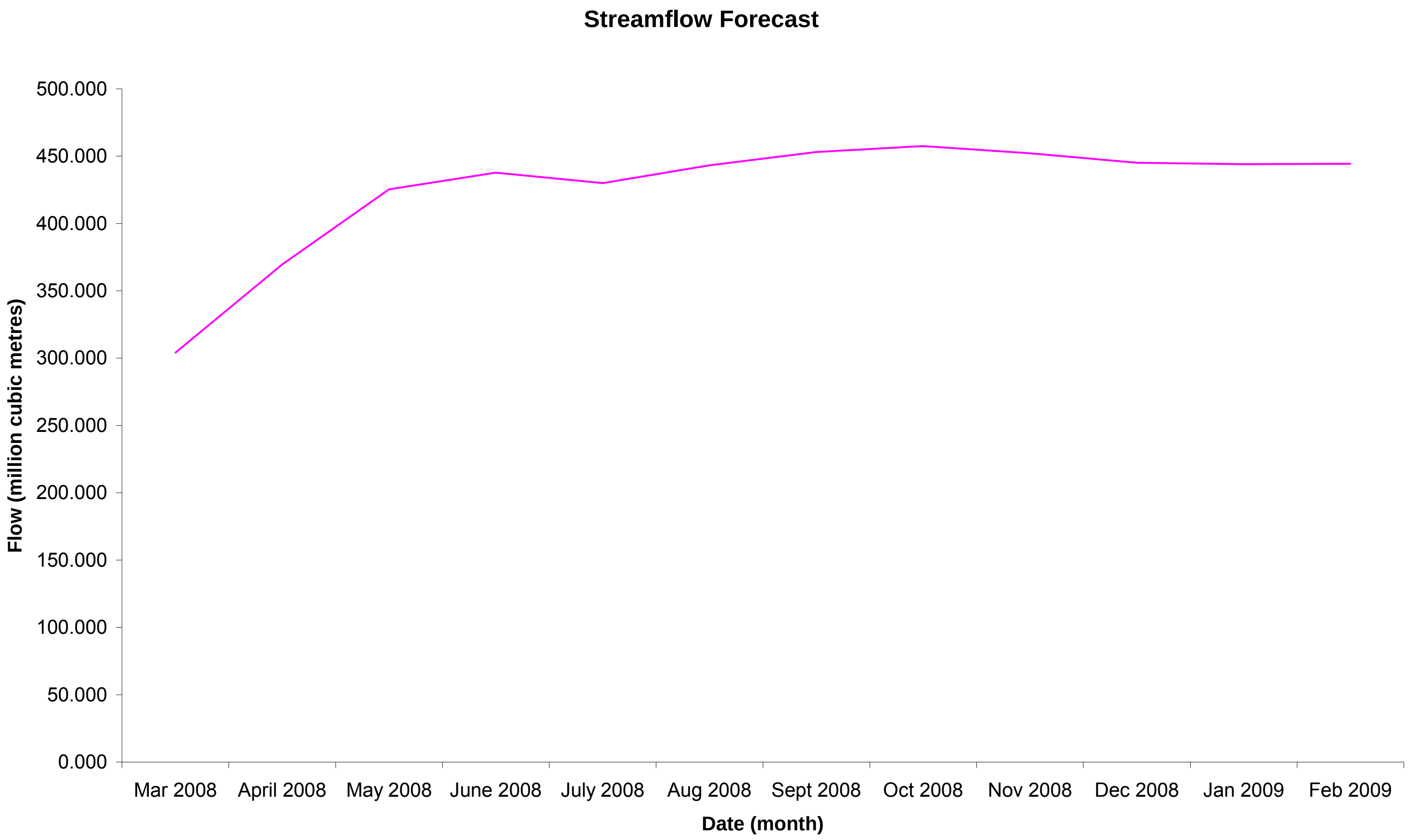

Figure 7: Stream flow Forecast

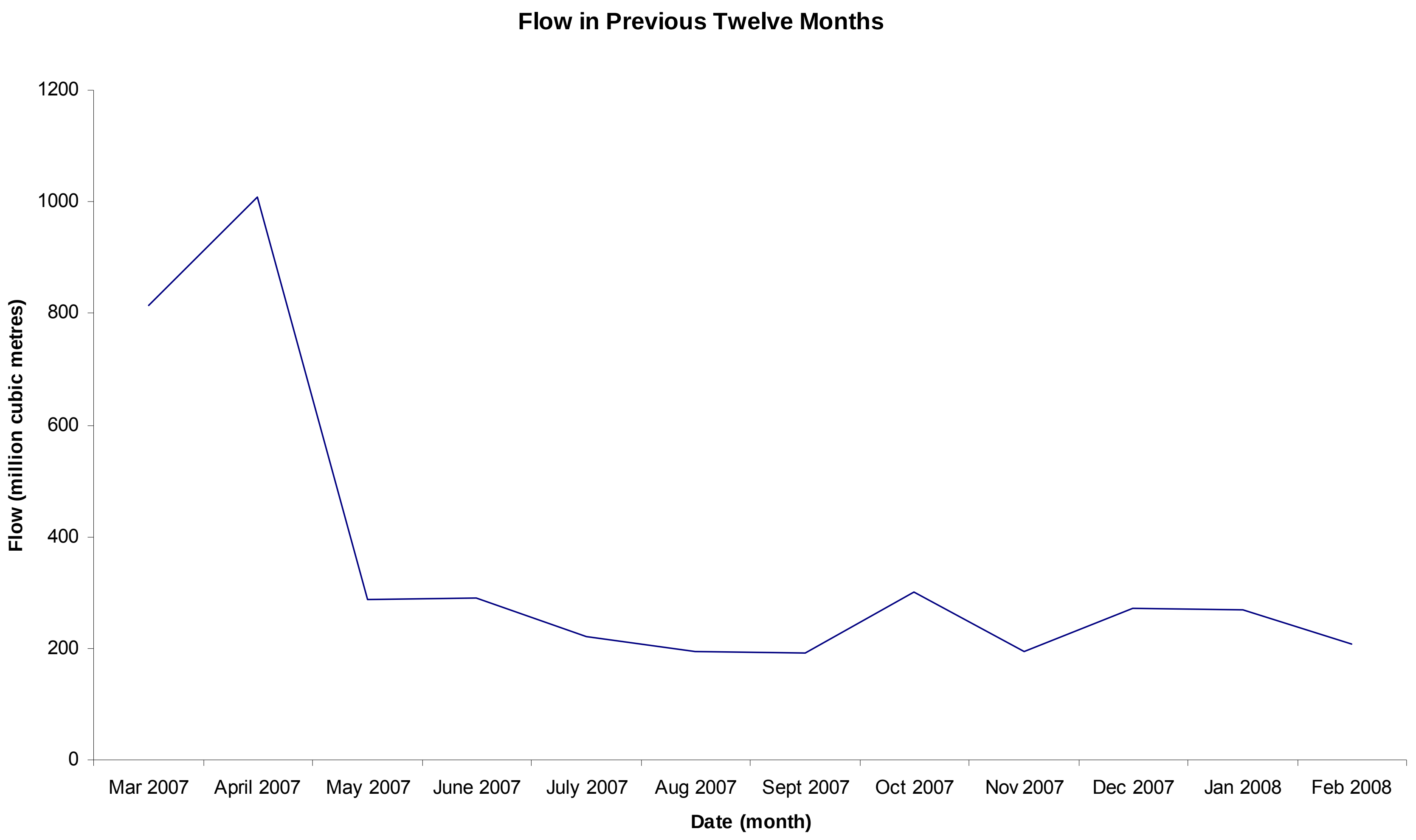

Figure 8: Flow in Previous Twelve Months

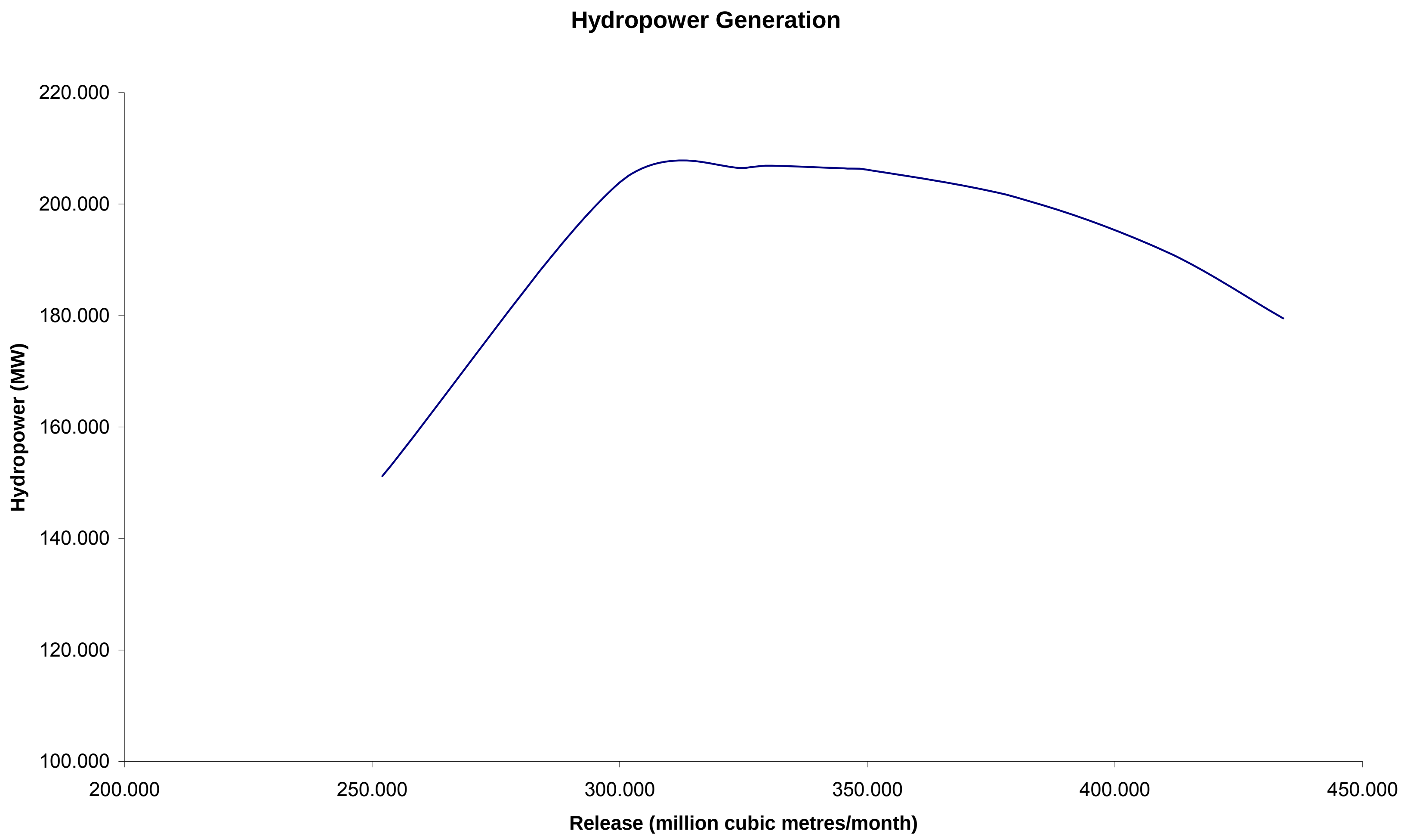

Figure 9: Hydropower Optimization

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