USE OF DECISION SUPPORT SYSTEMS FOR IMPROVED PLANNING AND OPERATION OF LARGE DAMS ALONG THE VICTORIA NILE

PROPOSAL – SEMINAR

UNIVERSITY OF KWA-ZULU NATAL

Submitted in partial fulfilment of the requirements for the degree of PhD Eng.

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University of KwaZulu Natal
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ABSTRACT

This research proposal considers the regulation of Lake Victoria, Kyoga and Albert in East Africa, from a wider ecological and stakeholder perspective. An accelerated decrease of lake Victoria Levels that can be attributed to a period of drought and excessive release of water to satisfy hydropower demands now poses significant risks to aquatic ecosystems, navigation facilities, and livelihoods of Equatorial Lake communities and other riparian states that depend on the Nile. There is thus an urgent and current need to focus on the improvement of the operational effectiveness and efficiency of existing and planned dams along the Victoria and Kyoga Nile, in Uganda for the benefit of all stakeholders, by conceptualising this system of Equatorial Lakes as multi-facility and multi-purpose reservoirs.

Following a review of approaches, mathematical models and contemporary Decision Support Systems (DDS) for planning reservoir operation and management, a methodology aimed at reaching a compromise regulation policy that satisfies conflicting human needs and ecological requirements is suggested for application. A multi-stage procedure combining multi-objective optimisation and multi-criteria decision analysis techniques will be tested within an integrated decision support framework to foster stakeholder involvement in the decision making process.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLOSSARY OF TERMS</td>
<td>4</td>
</tr>
<tr>
<td>LIST OF ABBREVIATIONS</td>
<td>5</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>6</td>
</tr>
<tr>
<td>1. INTRODUCTION</td>
<td>8</td>
</tr>
<tr>
<td>1.1 Background</td>
<td>8</td>
</tr>
<tr>
<td>1.2 The Case Study</td>
<td>9</td>
</tr>
<tr>
<td>1.3 Rationale for the Study</td>
<td>15</td>
</tr>
<tr>
<td>2. REVIEW OF APPROACHES TO RESERVOIR SYSTEM OPERATIONS</td>
<td>16</td>
</tr>
<tr>
<td>2.1 Heuristic methods of deriving operation rules</td>
<td>19</td>
</tr>
<tr>
<td>2.2 Simulation techniques</td>
<td>20</td>
</tr>
<tr>
<td>2.3 Optimisation/mathematical programming techniques: an overview</td>
<td>20</td>
</tr>
<tr>
<td>2.3.1 Linear and Non Linear Programming</td>
<td>22</td>
</tr>
<tr>
<td>2.3.2 Dynamic Programming (DP) Models</td>
<td>24</td>
</tr>
<tr>
<td>2.4 Optimal Control Theory methods</td>
<td>30</td>
</tr>
<tr>
<td>2.5 Neuro Dynamic Programming and Reinforcement Learning</td>
<td>31</td>
</tr>
<tr>
<td>2.5.1 Solution based on ANNs and approximation of the Bellman Function</td>
<td>31</td>
</tr>
<tr>
<td>2.5.2 Solution based on Q-Learning</td>
<td>34</td>
</tr>
<tr>
<td>2.6 Combinatorial framework approach to derivation of reservoir releases</td>
<td>35</td>
</tr>
<tr>
<td>2.7 Multi-objective and multi-criteria decision analysis of reservoir operation</td>
<td>37</td>
</tr>
<tr>
<td>2.8 Summary</td>
<td>41</td>
</tr>
<tr>
<td>3. SPECIFIC DSS SYSTEMS FOR REGULATION OF LAKE-RIVER SYSTEMS</td>
<td>43</td>
</tr>
<tr>
<td>3.1 Development of a regulation policy for Päijänne-Kyimijoki lake-river system</td>
<td>43</td>
</tr>
<tr>
<td>3.2 Pirkanmaa lake regulation development project</td>
<td>45</td>
</tr>
<tr>
<td>3.3 Lake Verbano project</td>
<td>45</td>
</tr>
<tr>
<td>4. REVIEW OF REVIOUS WORK IN THE CASE STUDY AREA</td>
<td>48</td>
</tr>
<tr>
<td>4.1 HYDROMET Project (1975-1981)</td>
<td>48</td>
</tr>
<tr>
<td>4.2 Lake Water Balance Studies &amp; Water Level Forecasting</td>
<td>49</td>
</tr>
<tr>
<td>4.3 Fisheries, Water Hyacinth and Schistosomiasis Studies</td>
<td>50</td>
</tr>
<tr>
<td>4.4 WRAP Regulation Studies - 1998</td>
<td>51</td>
</tr>
<tr>
<td>4.5 The Nile Decision Support Tool</td>
<td>52</td>
</tr>
<tr>
<td>4.6 Study on Water Management of Lake Victoria</td>
<td>53</td>
</tr>
</tbody>
</table>
5. PROBLEM STATEMENT & RESEARCH OBJECTIVES ............................................................. 53
  5.1 Research problem......................................................................................................... 53
  5.2 Research questions ................................................................................................... 54
  5.3 Research objectives.................................................................................................... 54
  5.4 Research hypothesis................................................................................................. 54
  5.5 Goals of the Case Study .......................................................................................... 54
  5.6 Importance of the case study/problem ..................................................................... 55
  5.7 Limitations of the study and research assumptions.................................................. 55
6. OUTPUTS/EXPECTED CONTRIBUTIONS ........................................................................ 56
  6.1 Deliverables of the project ......................................................................................... 56
  6.2 Contribution of the research results towards scientific knowledge.......................... 56
  6.3 Beneficiaries from the research ................................................................................ 57
7. RESEARCH STRATEGY .................................................................................................. 58
  7.1 Proposed approach..................................................................................................... 58
  7.2 Methodology ............................................................................................................ 58
    7.2.1 Structuring of the problem ................................................................................. 59
    7.2.2 Model identification, customisation and testing ............................................. 61
    7.2.3 DSS application and interactive search for pareto-optimal alternatives........... 62
    7.2.4 Seeking group consensus .............................................................................. 64
  7.3 Software/hardware availability .................................................................................. 65
8. CONCLUSION ................................................................................................................ 65
APPENDIX .......................................................................................................................... 66
REFERENCES ..................................................................................................................... 72

GLOSSARY OF TERMS

Net Basin Supply: Commonly used term in the simulation of lake levels defined as inflow minus net evaporation in the Lake

Separable function: An objective function is separable when it is a sum of terms, each depending on a different decision variable

Markov Process: The elements which comprise a Markov process are a set of states, a set of actions for each state, a set of matrices of transition probabilities (one for each action), and a vector of transition rewards or costs for each state and each action. Reservoir operation can be described in terms of these elements, i.e., states as monthly storage levels, actions as monthly releases from the
reservoir, transition matrices as mass balance equation plus stream flow characteristics, and rewards as benefits from use of water or sale of electricity.

First Order Markov: A stochastic process, in which the probability of being in any particular state in any Process given time period is dependent on the actual state in the preceding time period.

**LIST OF ABBREVIATIONS**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>Agreed Curve</td>
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<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
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<tr>
<td>BDT</td>
<td>Bayesian Decision Theory</td>
</tr>
<tr>
<td>BPA</td>
<td>Back Propagation Algorithm</td>
</tr>
<tr>
<td>BSDP</td>
<td>Bayesian Stochastic Dynamic Programming</td>
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<tr>
<td>CGIAR</td>
<td>Consultative Group on International Agricultural Research</td>
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<tr>
<td>CPWF</td>
<td>Challenge Program on Water for Food</td>
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<tr>
<td>DDDP</td>
<td>Discrete Differential Dynamic Programming</td>
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<tr>
<td>DDP</td>
<td>Differential Dynamic Programming</td>
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<tr>
<td>DM</td>
<td>Decision Maker</td>
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<td>DP</td>
<td>Dynamic Programming</td>
</tr>
<tr>
<td>DSS</td>
<td>Decision Support System</td>
</tr>
<tr>
<td>DSS/M</td>
<td>Decision Support System – Management</td>
</tr>
<tr>
<td>DSS/P</td>
<td>Decision Support System – Planning</td>
</tr>
<tr>
<td>ED</td>
<td>Energy Driven release policy</td>
</tr>
<tr>
<td>ELQGC</td>
<td>Extended linear quadratic Gaussian Control</td>
</tr>
<tr>
<td>ENSO</td>
<td>ELNino-Southern Oscillations</td>
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<tr>
<td>ESKOM</td>
<td>South African electricity supply company</td>
</tr>
<tr>
<td>ESO</td>
<td>Explicit Stochastic Optimisation</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
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<tr>
<td>FSDP</td>
<td>Fuzzy Stochastic Dynamic Programming</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
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<tr>
<td>GRG</td>
<td>Generalized Reduced Gradient Method</td>
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<td>HEP</td>
<td>Hydro Electric Power</td>
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<td>HYDROMET</td>
<td>Hydro-Meteorological survey of the catchments of Lakes Victoria, Kyoga &amp; Albert</td>
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<tr>
<td>IDH</td>
<td>Intermediate Disturbance Hypothesis</td>
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<td>IDP</td>
<td>Incremental Dynamic Programming</td>
</tr>
<tr>
<td>IDPSA</td>
<td>Incremental Dynamic Programming with Successive Approximations</td>
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<tr>
<td>IFR</td>
<td>Instream flow Requirements</td>
</tr>
<tr>
<td>ISMO</td>
<td>Interactive analysis of dynamic water regulation Strategies by Multicriteria Optimization</td>
</tr>
<tr>
<td>ISO</td>
<td>Implicit Stochastic Optimisation</td>
</tr>
<tr>
<td>IWMI</td>
<td>International Water Management Institute</td>
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<tr>
<td>IWRM</td>
<td>Integrated Water Resources Management</td>
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<tr>
<td>LDR</td>
<td>Linear Decision Rule</td>
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<tr>
<td>LP</td>
<td>Linear Programming</td>
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<tr>
<td>LVDST</td>
<td>Lake Victoria Decision Support Tool</td>
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<tr>
<td>LVEEMP</td>
<td>Lake Victoria Environmental Management Project</td>
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<tr>
<td>MCDA</td>
<td>Multi Criteria Decision Analysis</td>
</tr>
<tr>
<td>MW</td>
<td>Mega Watt</td>
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<tr>
<td>NAPE</td>
<td>National Association of Professional Environmentalists</td>
</tr>
<tr>
<td>NDP</td>
<td>Neuro Dynamic Programming</td>
</tr>
</tbody>
</table>
Nile DST  Nile Decision Support Tool
Nile DST  Nile Decision Support Tool
NLP  Non Linear Programming
NSGA  Non dominated Sorting Genetic Algorithm
PIP  Participatory Integrated Planning
RVA  Historical Range of Variation approach
SA  Systems Analyst
SAA  Successive Approximations Algorithm
SDP  Stochastic Dynamic Programming
SLP  Successive Linear Programming
SQP  Successive Quadratic Programming
SSDP  Sampling Stochastic Dynamic Programming
SST  Sea Surface Temperatures
WMO  World Meteorological Organisation
WRAP  Water Resources Assessment Project
WREM  Water Resources Engineering & Management

LIST OF FIGURES

Figure 1: Complex web of interlinked issues and trade-offs that must be considered in planning dam operation (McCartney et al., 2006) .......................................................... 9

Figure 2: Equatorial Lakes Basin (Sutcliffe and Parks, 1999) ............................................. 10

Figure 3: Aerial view of the Nalubaale-Kiira Dam complex .............................................. 11

Figure 4: Map showing existing and planned dams .............................................................. 12

Figure 5: Lake Victoria levels, modelled (1870-1895) & observed (1896-2000) (Tate et al., 2001) 13

Figure 6: Excessive release practices at Kiira-Nalubaale Dams ........................................... 14

Figure 7: Declining water levels in Lake Victoria ................................................................. 14

Figure 8: Rule curve for Itzezi-tezhi Dam on the Kafue River, Zambia (McCartney et al., 2006) 17

Figure 9: Closed loop scheme (Soncini-Sessa et al., 2001) .................................................. 18

Figure 10: Closed loop scheme with feed forward compensation (Soncini-Sessa et al., 2001) ... 18

Figure 11: Problem of Local Optimality (Loucks et al., 1981) ............................................. 23

Figure 12: Relationship among the LP, SLP and NLP models (Barros et al., 2003) ............... 24

Figure 13: Reservoir system optimisation as a sequential decision process in DP (Labadie, 2004) 25

Figure 14: Interactions between a reservoir network, control policy and catchment (De Rigo et al., 2001) ........................................................................................................ 27

Figure 15: A typical feed forward neural network (De Rigo et al., 2001) ................................. 32

Figure 16: The standard reinforcement-learning model (Kaelbling et al., 1997) ..................... 34

Figure 17: Implicit stochastic optimisation (ISO) procedure (Labadie, 2004) ....................... 35

Figure 18: Explicit Stochastic Optimisation (ESO) procedure (Labadie, 2004) ..................... 36

Figure 19: Sketch of compromise solution (Duckstein and Opricovic, 1980) ......................... 38
Figure 20: Illustration of IDH concept (Connell, 1978) ................................................................. 41
Figure 21: Value tree model with five preliminary alternatives (Hämäläinen et al., 1999) .......... 44
Figure 22: Setting of goal points and acceptability levels in ISMO spreadsheet program (Hamalainen & Mantysaari 2001) ........................................................................................................ 44
Figure 23: Stakeholders, sectors and criteria of the Verbano project (Castelleti et al., 2004) .... 46
Figure 24: Phases of the two level decisional process (Soncini-Sessa et al., 2002) ................. 47
Figure 25: Simplified release-elevation rule curve (Huaming and Georgakakos, 2003) ............ 52
Figure 26: LVDST design concept (WREM Inc & Norplan (U) Ltd, 2004) ............................... 53
Figure 27: Stages of the problem structuring process (Marttunen and Hamalainen, 1995) ...... 59
Figure 28: Fuzzy membership function to present the IDH concept applied to ecological flow regimes (Suen and Eheart, 2006) ........................................................................................................ 63
Figure 29: User interface for finding subjects preferred alternatives (Hämäläinen et al., 1999) .... 64
Figure 30: Discrete representation of storage for capacity equal to 16800 and SDN = 8 (Karamouz and Vasiliadis, 1992) ................................................................................................................. 66
Figure 31: Discrete representation of flow (Karamouz and Vasiliadis, 1992) ......................... 68
1. INTRODUCTION

This report constitutes my formal research proposal drafted in fulfillment of the requirements for acceptance to the PhD research degree program of the School of Bioresources Engineering and Environmental Hydrology at the University of KwaZulu-Natal, South Africa. The proposal has been formulated as a case study under the Challenge Program of Water for Food (CPWF) project number 36: Improved planning of large dam operation: using decision support systems to optimize livelihood benefits, safeguard health and protect the environment. The principal objective of this project is to investigate the applicability of linking tools/methods for social appraisal/stakeholder involvement and modern DSS (Decision Support Systems) in the planning and management of dams. Registration formalities for the research program were completed early in April 2006. Funds required for the research activities will be provided by the project. Additional financial support was solicited for and approved by the IWMI PhD Fellowship fund in August 2005.

The proposal is divided into 8 chapters plus references. The introduction consists of a background, a specific description of the study area and the rationale for its selection. Following this introduction, Chapter 2 contains a review of approaches to reservoir operation. Chapter 3 documents applications of specialised decision support systems for regulation of lake-river systems while Chapter 4 contains a review of relevant studies that have been carried out in the case study area. The research problem and objectives are described in Chapter 5 and Chapter 6 contains the outputs, and anticipated contribution to scientific knowledge by this study. The research strategy and methodology is described under Chapter 7 and Chapter 8 is a brief summary and conclusion of the proposal.

1.1 Background

Contemporary management strategies for reservoirs often concentrate on technical solutions that consider only certain parts of the total system. For example, large dams, built to provide urban water and electricity, have extensive impacts on rivers and aquatic ecosystems and, as a consequence of their modification of ecological processes, may deprive those living in rural areas of ecosystem goods and services (Challenge Program on Water for Food, 2001). Failure to take into account the environmental and social costs of dams means that the true value of many of these schemes remains unknown. Where water is extracted on an unsustainable basis, either the quality is degraded or the hydrological regime is modified and as a consequence the natural environment deteriorates and habitats are destroyed and ecological functions lost (Challenge Program on Water for Food, 2001). The wise and sustainable utilization of the water stored in large reservoirs requires consideration of a number of complex and inter-related issues, and poses intricate technical and political problems (Challenge Program on Water for Food, 2001). As such, optimizing reservoir releases must take account of water uses upstream and downstream of the dam, including water supply, agriculture (i.e. irrigation and livestock), fisheries and power generation requirements, as well as the requirements of communities dependent on the natural resources of downstream ecosystems, including the needs of aquatic habitats and possible impacts on human health. These considerations and linkages are summarised in Figure 1.
Figure 1: Complex web of interlinked issues and trade-offs that must be considered in planning dam operation (McCartney et al., 2006)

Following this brief discussion about the range of issues that need to be considered in the planning and management of dams, the management issues to be addressed in the selected case study are discussed in the next section.

1.2 The Case Study

The case study is located along the Victoria Nile River, in the catchments of Lakes Victoria and Kyoga of the Nile Catchment where dams play a significant role in Integrated Water Resource Management (IWRM) and where more dams are planned to be built (Kennedy and Donkin, 1996). The lake-river system that constitutes the case study area is illustrated in Figure 2. The dotted lines represent catchment boundaries.
Lake Victoria, with a surface area of 68,800 km² and an adjoining catchment area of 184,000 km² (Agriculture and Environment Operation Division, E.A.D., Africa Region, 1996) is the largest and most hydrologically dominant lake in the basin. Outflow from Lake Victoria is modified as it flows through Lake Kyoga (surface area = 6,270 km², catchment area = 57,669 km²). Extensive wetlands are a characteristic feature of this lake. Outflows to the Victoria Nile are the result of the balance between direct rainfall on Lake Victoria, tributary inflows, lake evaporation and releases at Owen Falls dam.

Prior to construction of the Owen Falls Dam (now known as Nalubaale), the natural barrier of the Rippon Falls, some 3 km upstream of the dam, controlled the outflow. Following completion of the dam and hydro-electric power station in 1954, outflow was controlled by a combination of releases through turbines and sluices in the dam. By international agreement (Nile Waters Agreement of 1959), the dam has been operated as if natural conditions govern the outflow and the relationship between outflow and lake level being known as the “Agreed Curve”. In the year 2001 an extension to the Owen Falls Dam, (now known as Kiira) was completed at Jinja. The two dams (Nalubaale-Kiira complex) are the principal source of Uganda’s Hydro-Electric Power (HEP) and combined releases through their turbines and sluices now represent outflow to the Victoria Nile River. Figure 3 illustrates the configuration of Kiira (left) and Nalubaale (right) at the outlet of lake Victoria.
The demand for electricity demand in Uganda is increasing at an annual rate of approximately 8.5\% (ref). The installed capacity on Uganda’s power network system is 316 MW, of which only 240 – 260 MW is available depending on how many units are operational at the Kiira and Nalubaale power stations. This implies that currently the generation – demand deficit ranges from 40 – 60 MW which translates directly into the resultant load shedding which is currently being carried out on a daily basis (ref). Additional units (Units 14 and 15) at the Kiira power station have been completed but are yet to be commissioned due to operational difficulties. If these units come on line, they would boost the installed capacity by another 80MW. The demand forecast for future years indicates an increasingly widening gap between the available generation and the system demand (Kennedy and Donkin, 1996). The major hydropower potential sites were identified in the Hydropower Development Master Plan Study (ref) and all the planned new dams are along the Victoria Nile as indicated in Table 1 and Figure 4.

Table 1: Major hydropower potential sites and dams on the Victoria Nile River in Uganda

<table>
<thead>
<tr>
<th>SITE</th>
<th>LOCATION</th>
<th>CURRENT INSTALLED CAPACITY (MW)</th>
<th>MAXIMUM POTENTIAL (MW)</th>
<th>PROPOSED INSTALLED CAPACITY (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nalubaale HEP</td>
<td>Outlet of L. Victoria</td>
<td>180</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Kiira HEP</td>
<td>Outlet of L. Victoria</td>
<td>120</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>Bujagali</td>
<td>Victoria Nile</td>
<td>-</td>
<td>320</td>
<td>250</td>
</tr>
<tr>
<td>Kamdini (Karuma)</td>
<td>Victoria Nile</td>
<td>-</td>
<td>180</td>
<td>150</td>
</tr>
<tr>
<td>Ayago South</td>
<td>Victoria Nile</td>
<td>-</td>
<td>234</td>
<td>N/A</td>
</tr>
<tr>
<td>Ayago North</td>
<td>Victoria Nile</td>
<td>-</td>
<td>304</td>
<td>N/A</td>
</tr>
<tr>
<td>Murchison</td>
<td>Victoria Nile</td>
<td>-</td>
<td>642</td>
<td>N/A</td>
</tr>
</tbody>
</table>
All planned sites for dams along the Victoria Nile are environmentally sensitive and in some cases culturally important. For example, Bujagali, Murchison Falls and Ayago are all within the Murchison Falls National Park. The spectacle at Murchison Falls and Bujagali is classed as outstanding and the landscape is of high quality (Kennedy and Donkin, 1996). Notable in ecological terms are the forest communities of the gorges and the extent of the area of mist flora at Murchison. The crocodile breeding grounds downstream of the falls are of national importance and the avi-fauna are diverse. The site at Kamdini is within the Karuma Game Reserve and Karuma controlled hunting area. The wetlands between around lake Kyoga are very important. All options must cater for environmental flows in the side channels after diversion of water for power consumption.

It is recognised that substantial future consumptive water demand in upstream countries (Kenya, Tanzania, Rwanda and Burundi), and indeed in Uganda itself, will have a significant impact on the flows of the Victoria and Kyoga Nile and the resulting hydropower potential. Most of the potential for irrigation is concentrated around Lake Kyoga and Lake Victoria. The Karamoja area in Northern Uganda frequently experiences droughts and feasibility studies are currently being conducted for the construction of small dams and valley tanks in upstream catchments of Lake Kyoga for provision of
water for irrigation and livestock. If plans for constructing these dams are implemented, they may also have significant impact on the amount of water reaching Lake Kyoga as more water will be used by irrigation and lost to evaporation in upstream impoundments.

The possibility of using Lake Victoria to regulate flows in the Victoria and Kyoga Nile for the benefit of riparian states has been considered on many occasions. Kite (1984) summarises investigations made in the regulation of the Equatorial Lakes. Studies were undertaken in the late 1940s at the time of planning Nalubaale Dam development. A tentative international agreement in 1948 provided for a firm average discharge for power generation at Nalubaale of 505 m$^3$.s$^{-1}$ and this discharge formed the basis for the design of the scheme. Further studies were undertaken in 1958 and 1960 by a technical consultant to the Egyptian Ministry of Irrigation (Bakhiet, 1996) and later, by the Uganda Water Development Department in 1968 (WMO, 1974), the Egyptian Organisation for the Nile Waters in 1972 and as part of the WMO Hydromet Studies in the mid 1970s (WMO, 1974). More recent studies have also considered regulation of Lake Victoria, including the Acres studies of Owen Falls extension (Acres, 1990), the Uganda Water Action Plan and the Water Resources Assessment Project (Mott MacDonald, 1998). In most of the regulation plans developed since 1948 a firm flow at Owen Falls in excess of the 505 m$^3$.s$^{-1}$ discharge has been adopted. A value of 630 m$^3$.s$^{-1}$ has generally been assumed since 1966 for hydropower planning purposes although there is no formal agreement to this effect. Other regulation plans have considered higher target flows up to 750 m$^3$.s$^{-1}$, although without explicitly identifying the level of reliability. However, it is interesting to note that in over 50 years, no progress has been made towards implementing any of the identified plans.

Between 1961 and 1964 lake inflows were extremely high. The lake level rose reaching a maximum in 1964 with a record outflow of over 1600 m$^3$.s$^{-1}$.

![Figure 5: Lake Victoria levels, modelled (1870-1895) & observed (1896-2000) (Tate et al., 2001)](image)

Tate et al. (2001) extended the nomograph of observed water levels of Lake Victoria back to 1870 using a water balance model with similar high water levels in 1878. Lake levels remained relatively high after 1960 and since the natural outflow never dropped below 750 m$^3$.s$^{-1}$, the question of what happens if lake levels do fall was not resolved. The state of affairs was complicated by the design of Kiira based on an average flow of 1200 m$^3$.s$^{-1}$. Kiira dam was commissioned in the year 2001 thereby creating the possibility of drawing in excess of 2000 m$^3$.s$^{-1}$ at the outlet of the lake. The commissioning of Kiira
dam, implied more energy could be generated. However it required passing more water through the turbines than is consistent with the operation of the Agreed Curve. At the time of constructing the hydropower extension, it was generally held that there would be enough water to drive the extra units without causing excessive draw-down of the lake levels. The situation five years after commissioning three units at Kiira is markedly different. There has been a clear accelerated decrease in lake levels that may partly be linked to the extra water above that dictated by the agreed curve that is being let through the new turbines at Kiira power station. Figures 6 and 7 below illustrate the excessive releases between the years 2000-2004.

![Figure 6: Excessive release practices at Kiira-Nalubaale Dams](image)

![Figure 7: Declining water levels in Lake Victoria](image)
A recent study on the Water Management of Lake Victoria utilized the Lake Victoria Decision Support Tool (Huaming and Georgakakos, 2003) and investigated the Energy Demand (ED) driven release policy and the policy of following the Agreed Curve (AC). The results obtained noted that the currently installed power capacity has fallen far behind power demand and that the ED policy which is currently being followed is releasing increasingly higher discharge rates, thus drawing the lake levels closer to unprecedented lows. To meet power demand, an average release rate of 113 MCM.day\(^{-1}\) was applied during the year 2004, a rate 55% higher than the Lake Victoria average net basin supply recorded over past 100 years, with a potential to deplete the lake to a historically unprecedented low level within a year or two. This release rate corresponded to the 79\(^{th}\) percentile of net basin supply frequency distribution, indicating that the present release pattern is unsustainable in the long-term, regardless of recent hydrologic droughts. Lake levels continued to recede in the period running up to February 2006 to 1133.60 metres above mean sea, a state established to be the lowest recorded level in the past 82 years. The lowest historical level recorded in March 1923 was 1133.19 m. Thus Lake Victoria levels are now less than half a metre from the lowest recorded levels attained during a period of relatively severe drought.

If lake levels continue to recede, extensive wetland areas could potentially be lost (i.e. dried up) in addition to many other beneficial functions (e.g. agriculture, fisheries, pollution abatement, harvesting of craft and construction materials). Likewise, landing sites, navigation facilities and shoreline industries and settlements will experience severe interruptions and a range of socio-economic impacts, whose severity cannot be currently fully quantified as a result of the unavailability of a comprehensive high resolution GIS database. Such a database is urgently needed to evaluate the impacted areas in relation to lake draw-down. The study on Water Management of Lake Victoria (WREM Inc. & Norplan (U) Ltd, 2004) confirmed that at the prevailing (2006) lake levels, channel hydraulic capacity cannot support the operation of power generation at Unit 5 at Kiira and Unit 10 at Nalubaale. Hence there is critical need to determine the effective capacity of the Nalubaale-Kiira complex at different lake levels.

The new challenge for Uganda and upstream countries that share Lake Victoria is that energy planning needs to be coordinated with sustainable water management in order to avoid harmful impacts for Uganda as well as the downstream and upstream countries. Significant departures from historical lake levels is bound to impact water uses along the shoreline including navigation, fisheries, wetland uses, human health and environmental sustainability. Conversely establishing tight control of the levels of fluctuation (as a means to protect and support upstream water uses) or transferring significant amounts of water outside the Lake Victoria Basin (as currently considered by Kenya and Tanzania) has crucial impacts on power plant feasibility and commissioning and could cost Uganda billions of shillings (ref).

You must include the rainfall distribution to strengthen your argument

1.3 Rationale for the Study

The reason for selecting this particular problem is that the ED driven policy that has been followed by Uganda since 2003 has proven to be unsustainable in the face of persisting and frequent droughts within the Upper Nile Catchments. It also clear that the Agreed Curve policy is not responsive to the interests of the three East Africa States (Rwanda and Burundi) as it does not address their rights to utilize the water resources of the Nile equitably. There is thus an urgent need current need to re-evaluate operating policies from a wider ecological and stakeholder perspective. Attention must focus on improving operational effectiveness and efficiency of the Nalubaale-Kiira complex and other planned hydropower facilities along the Victoria Nile by considering the systems of Lakes Victoria, Kyoga and Albert and multi-facility reservoirs in a fully integrated manner. Expanding the scope of the working system for more integrated analysis greatly multiplies the potential number of operational policies. The
development of an approach to optimise lake releases for the benefit of all stakeholders is therefore required.

2. REVIEW OF APPROACHES TO RESERVOIR SYSTEM OPERATIONS

The problem of finding operating procedures to optimally plan and manage a reservoir network has challenged analysts since the pioneering work of Rippl (1883). The task has often been formulated as an optimal control problem, and continues to be the subject of extensive research work. The main reason as to why this problem has attracted the attention of many researchers is because it is a scientific area rich in problems and challenges.

The large number of variables involved, the stochastic nature of future inflows, the nonlinearity of dynamics and other uncertainties of water resources systems render their management a difficult but imperative task. Complexity further increases when attempting to combine multiple benefits arising from reservoir system operation (e.g., hydropower, irrigation, etc.) which are frequently competitive or even conflicting, together with the reduction of natural risks (e.g., flood control) and the environmental requirements (Koutsoyiannis et al., 2002). Many times, the management of large hydrosystems, especially when they span on more than one catchment, raises conflicts between authorities or organizations with different interests (e.g. water supply companies, power utilities, farmers organisations and ecologists).

Reservoir operations can be classified as either long-term and short-term operations. Beyond distinguishing according to the time scale, reservoir operation may be further categorized by the number of reservoirs and the objectives to be pursued (single or multiple). In addition to these classifications, deterministic and stochastic planning and operations may be utilised (Huang, 1996). There is also a distinction in the roles inherent to planning and real-time operation of reservoirs. Real-time reservoir operation models often use as input, target parameters established by the planning model (e.g. desired ending storage targets and/or reliability levels). Loaiciga et al. (1987) therefore emphasize that planning and real time models are therefore fundamentally different.

Release schemes i.e. sequences of \( m_1, m_2, m_3, \ldots m_t \) volumes to be released at successive time periods have been proposed to manage reservoir systems. When the release \( u_t = m_t \) the release scheme is termed as an open control scheme in which the decision maker is free to arbitrarily deviate from the scheme every time it is deemed necessary. In their review of mean historical approaches to water reservoir management policies, Soncini Sessa et al. (2001) noted that starting from the end of the 19th century, analysts thought to associate a nominal trajectory \( s_t \) also termed the rule curve or storage guide curve, with the release scheme. The rule curve specifies either reservoir (target) storage volumes or desired (target) releases based on the time of year and the existing storage volume in the reservoir. Figure 8 represents a typical example of such a rule curve for a dam on the Kafue River in Zambia.
The rule curve takes on the form of a trajectory of releases, generally defined by a set of end-of-month target levels or storages. It is of particular use when long-term planning is undertaken in the absence of reliable knowledge of the flows to come and can be computed by a simple simulation. Given the rule curve, on a given day of a given year, the release decision $u_t$ can be defined as that release which allows to the water storage $S_{t+1}$ to get as close as possible to the rule curve. In doing so, Mass (1962) ironically remarked, that the Decision Maker (DM) "spills water when the storage $S_t$ in the reservoir exceeds the quantity specified by the rule curve and hopes for rain when it falls below". DMs have often resorted to empirical methods based on experience and common sense and as a consequence many schemes continue to be operated below their potential. Two control schemes have evolved in the fields of Optimal Control Theory and Operations Research as rational solutions to the DM’s problem. Both are based on a feedback control scheme, illustrated in Figures 9 and 10). The element which closes the feedback loop is a management policy, composed of a sequence of “control laws” in Control Theory terminology and which are also termed “operating procedures” in Hydraulic Engineering terminology.

A “closed loop control scheme” is illustrated in Figure 9, where $I_t$ is the hydro-meteorological information inflow (e.g. rainfall measurements) over the catchment). The resultant inflow volume to a reservoir over a time period $t$ is denoted as $a_t$ while $w_t$ is taken to be the state of the downstream users. Then, figure 9 illustrates a “closed loop control scheme” where the current release decision $u_t$ is computed based on the observed reservoir storage $S_t$. 

Figure 8: Rule curve for Itezhi-tezhi Dam on the Kafue River, Zambia (McCartney et al., 2006)
Adopting the matrix notation from Soncini-Sessa et al. (2001) it follows that:

\[ u_t = m_t(s_t) \]  

where, \( m(.) \) is a succession, generally periodic of T, of monotone non-decreasing functions in \( S_t \) (the control laws). The policy \( \rho \) is therefore defined by the succession \([m_0,(.), m_1,(.) , ..., m_{T-1},(.)] \) of T control laws. The closed loop control scheme can be improved by inserting a feed forward compensation, if the inflow during the present time period (a stochastic quantity) is known in advance. This may not be possible but could be forecasted so that its effects could be anticipated by adopting a control scheme such as shown in Figure 10.

Following this brief introduction to the main methods of reservoir operation and approaches, the thrust of this section will be to compile the body of research relevant to various approaches to reservoir operation. In an effort to organise the literature in a logical and understandable way, they are discussed under broad categories as follows:

- heuristic methods,
- simulation methods,
- optimisation/mathematical programming techniques,
- multi-objective and MCDA techniques, and
- DSS packages and frameworks.
In addition to the peer-reviewed literature, focused literature searches of the “gray literature” and private sector publications, were conducted and are included in the review.

2.1 Heuristic methods of deriving operation rules

Labadie (2004) defines heuristic techniques as methods based on rules of thumb or experience. An example of a rule of thumb rule method of reservoir operation in the case study, is the “Agreed Curve”. The single reservoir regulation rules included in the Nile DST component of the Nile Equatorial Lakes is another example of heuristic rules. Lund and Guzman (1999), review a variety of empirically derived single purpose operating policies for reservoirs in series or in parallel for various uses. A typical example is the “space rule” which seeks to leave more space in reservoirs where greater inflows are expected (Bower et al., 1966). For complex reservoir systems that are to meet multiple objectives and have additional demands or constraints on releases or power production, Oliviera and Loucks (1999), are of the opinion that the general rules of thumb for reservoir operation cannot result in efficient-system-wide operation and propose Genetic Algorithms (GAs) as a practical and robust way of estimating operating policies for such systems.

Methods of deriving reservoir operating rules by GAs (Oliviera and Loucks, 1997), and GA approaches for optimisation of multi-reservoir systems (Esat and Hall, 1994; Fahmy et al., 1994; Wardlaw and Sharif, 1999; Sharif and Wardlaw, 2000) are also classified as heuristic techniques. This is due to their inherent nature of performing optimisation through a process analogous to “the mechanics of natural selection and natural genetics” in the biological sciences. Excellent introductions to GAs are given by Goldberg (1989) and by Michalewicz (1992). Three heuristic processes of reproduction, crossover and mutation are applied probabilistically to discrete decision variables that are coded into binary strings. Rather than generating progressions of single solutions, a GA produces groups or “populations” of solutions whose “offspring” display increasing levels of “fitness”. The power of GAs arises from a simple assumption: the best solutions are more likely to be found in the regions of the solution space containing high proportions of good solutions. These regions can be located by sampling the entire solution space randomly. When a promising region is found, further exploration in that region is carried on, but at the same time the genetic algorithm maintains the search for other solution regions.

Oliviera and Loucks (1997) and Labadie (2004) outline the various attractions and drawbacks of GAs as listed below.

Advantages

- GAs can be directly linked with hydrologic and water quality simulation models without requiring simplifying assumptions in the model or calculation of derivatives.
- Measures of system resilience (i.e., rate of recovery after failure) and vulnerability (i.e., severity of consequences of failure) which are difficult to explicitly include in algorithms are easily incorporated in a GA.
- GAs are robust and have the ability to solve highly non-linear, non convex problems.
- GAs yield good solutions at reasonable computational costs.

Disadvantages

- It is difficult to explicitly account for constraints using GAs.
- GAs tends to be problem specific and must be modified for each new application.
- GAs are unable to clearly identify the best single solution.

As another example of application, GAs were utilised in the WRAP Regulation studies in 1998 for potential real-time regulation of Lake Victoria at Owen Falls Dam. Wardlaw et al. (2005) report that the
objective was to develop a procedure that would permit short-to medium term forecasts, at lead times of 3, 6, 12 and 24 months, of potential reliable power generation that would improve utilisation of high lake levels and plan outage of thermal power plants.

2.2 Simulation techniques

Simulation modelling is a technique used to approximate the behaviour of a system on a computer, representing all the characteristics of the system largely by a mathematical or algebraic description (Yeh, 1985). A simulation model simulates the response of a system for specified inputs, which include decision rules, so that it enables a decision maker to examine the consequences of various scenarios for an existing system or a new system without actually building it.

Many simulation models are customised for particular systems (Emery and Meek, 1960; Hall and Dracup, 1970; Huaming and Georgakakos, 2003) but more recently, the trend has been to develop generic simulation models that can be applied to any basin or reservoir system. These are available as commercial software. The Hydrologic Engineering Centre in the USA, have developed the HEC-3 model (Hydrological Engineering Centre, 1979), for the simulation of reservoir system analysis for conservation) and HEC-5 model (Hydrologic Engineering Centre, 1989), for the simulation of flood and conservation systems. They are flexible enough to include different configurations of reservoirs and channels. HEC-5 has been used as an operational model to calculate flood damage and assess alternative operation plans by Eichert et al. (1975). HEC-5 has continuously been updated (Hydrologic Engineering Centre, 1989) and is to be released as HEC RESSIM to include a Windows-based graphical user interface (Klipsch et al., 2002).

Simulations models assume special significance in the derivation of reservoir operation rules or derivation of reservoir releases because they help define and evaluate predefined rules to ensure that they satisfy various constraints on system operation (Oliveira and Loucks, 1999; Niclow 2002; Labadie 2004). Simulation models can accurately represent system operations and are useful in examining long-term reliability of operating systems but are ill suited, however, to prescribing the best or optimum strategies when flexibility exists in coordinated system operations (Labadie, 2004). Prescriptive optimization models, which are the subject of the next section of this review, have therefore been proposed by various researchers to systematically select optimal solutions, or families of solutions, under agreed upon objectives and constraints.

2.3 Optimisation/mathematical programming techniques: an overview

Mathematical programming techniques have been developed to seek an optimum decision for system operation, which meets all system constraints while maximising or minimizing a defined objective function. Optimisation models usually require assumptions and simplifications on model structure and system constraints for practical implementation, whereas simulation models are more flexible and versatile in simulating the response of the system. Optimization evaluates possible decision alternatives, while simulation is limited to a finite number of input decision alternatives. The two approaches therefore differ markedly.

Studies in the literature on the application of optimisation techniques in reservoir studies is extensively documented in the work of Yakowitz (1982), Yeh (1985), Wurbs (1993) and Labadie (2004). Algorithms and methods surveyed include Linear Programming (LP), Non-Linear Programming (NLP), Dynamic Programming (DP), and other stochastic models. Early applications of these optimization techniques were often focused on the problem of reservoir design rather than operation e.g. Dorfman (1962). To-
date, a diverse array of optimisation methods for operation have been formulated. In all the mathematical optimisation techniques, the problem of reservoir operation is formulated as an optimisation problem where the objective is to maximise or minimise a set of benefits over time, subject to a set of constraints such as explicit upper and lower bounds on storage (for recreation, providing flood control space and assuring minimum levels for dead storage and power plant operation) or limits on releases (to maintain minimum desired downstream flows for water quality control, fish and wild life maintenance as well as protection from downstream flooding). Table 2 contains a summary of currently available optimisation techniques for reservoir operations.

Table 2: Examples of optimisation techniques for reservoir operations

<table>
<thead>
<tr>
<th>Method</th>
<th>Abbreviation</th>
<th>Selected References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic Programming</td>
<td>DP</td>
<td>Hall and Buras (1961), Young (1967), Hall et al. (1968), Meredith (1975), Collins (1977)</td>
</tr>
<tr>
<td>Incremental DP or</td>
<td>IDP</td>
<td>Bernholtz and Graham (1960), Hall et al. (1969), Heidari et al., (1971)</td>
</tr>
<tr>
<td>discrete differential DP</td>
<td>DDP</td>
<td></td>
</tr>
<tr>
<td>Differential DP</td>
<td>Diff DP</td>
<td>Yakowitz (1982)</td>
</tr>
<tr>
<td>IDP with successive approximations</td>
<td>IDPSA</td>
<td>Trott and Yeh (1971,1973)</td>
</tr>
<tr>
<td>Bayesian Stochastic Dynamic Programming</td>
<td>BSDP</td>
<td>Karamouz and Vasiladis (1992)</td>
</tr>
<tr>
<td>Sampling Stochastic Dynamic Programming</td>
<td>SSDP</td>
<td>Kelman et al. (1990)</td>
</tr>
<tr>
<td>Fuzzy Stochastic Dynamic Programming</td>
<td>FSDP</td>
<td>Fontane et al. (1997); Russell and Campbell (1996) and Shrestra et al. (1996)</td>
</tr>
<tr>
<td>Progressive optimality algorithm</td>
<td>NDP</td>
<td>Turgeon (1981a)</td>
</tr>
<tr>
<td>Extended Linear Quadratic Gaussian Control</td>
<td>ELQGC</td>
<td>Geogakakos and Marks (1987), Geogakakos (1989)</td>
</tr>
<tr>
<td>Maximum Principle</td>
<td></td>
<td>Turgeon (1981b)</td>
</tr>
</tbody>
</table>

The summary in Table 2 shows that the literature concerning the use of optimisation tools in planning, design and management of complex water resources systems is extensive. A significant effort in the development of a variety of hydraulic simulation and optimization models for planning, designing, and
managing water resources engineering projects has occurred in the past 30 years (Niclow, 2000). It is also clear from Table 2 that the most widely investigated applied techniques have been LP and DP.

2.3.1 Linear and Non Linear Programming

Application of LP to reservoirs operations has varied from simple straightforward allocation of resources to complex situations of operation and management. Given the limitations of computing power in the early years, optimization was achieved by decomposing reservoir systems in time and space e.g. Meir and Beightler (1967), Roefs and Bodin (1970). These early models were also predominantly deterministic i.e. did not take into account the stochastic nature of inflows but were gradually improved e.g. Loucks (1968), who developed a stochastic LP for a single reservoir subject to random, serially correlated, net flows and highlighted the dimensionality problem associated with this type of model in real situations.

ReVelle et al. (1969) proposed the original Linear Decision Rule (LDR) for reservoir design and/or operation formulated as follows:

\[ R_t = S_{t-1} - b_t \]  

where

- \( R_t \) = release during the time period t;
- \( S_{t-1} \) = storage at the end of time period t-1, and
- \( b_t \) = decision parameter to be determined.

Subsequent modifications to this LDR is reported, inter alia, by Loucks (1970), ReVelle and Kirby (1970), Eisel (1972), LeClerc and Marks (1973), Revelle and Gundelach (1975). These modifications were mainly attempts to incorporate streamflow stochasticity and evaporation losses. Limitations were cited which included issues related to conservative results and mathematical difficulties/convolution problems. LP models have also been deployed to derive LDRs that relate release to storage, inflow and decision parameters in chance constrained programming, which is a model that reflects the probability conditions on constraints. However, chance constrained formulations neither explicitly penalize constrained violations nor provide recourse action to correct realized constraint violations as a penalty. For this reason, Hogan et al. (1981) warn that the practical usefulness of chance-constrained programming as modelling technique is seriously limited. Stedinger (1984), analysed the performance of LDRs for reservoir operation and design and concluded that they have little to offer except their simplicity.

Houck and Cohon (1978) developed a design and management policy for a multipurpose multiple-reservoir system by solving two LP problems sequentially in order to approximate a non-linear formulation. Under the class of LP models, the simplex method and its variants (Nash and Sofer 1996) has been popular. However, although Labadie (2004), lists a number of advantages associated with LP such as ease of problem setup and solutions using readily available, low cost LP solvers, he notes that a major drawback is that these models all require the objective function and constraints to be linear or linearizable.

Hiew et al. (1989) applied a deterministic LP model to an 8-reservoir system in Colorado and utilised multiple regression analysis of the results from the LP model to produce optimal, lag-one storage guide curves. The study was successful because linear models were able to accurately represent the system.
behaviour and strong correlations were obtained from the multiple regression analysis. However, for other systems, such advantages may not be in evidence.

Other extensions of linear programming into binary, integer and mixed integer programming may be available for representing highly non-linear convex terms in the objective function and constraints, as performed by, for example Trezos, (1991) and Needham et al. (2000). However, the authors noted that these approaches are considerably less efficient computationally, would be likely to take excessive computer times when extended to stochastic evaluation or become computationally intractable. Labadie (2004), reports that piecewise linear approximations of nonlinear functions are often used in separable programming applications and solved with various extensions of the simplex method, although problem size can become excessive in some cases. Functions of more than one variable can also be approximated using multi-linear interpolation methods over a multi-dimensional grid. For minimisation problems, Labadie (2004), points out that these functions must be convex; otherwise more time consuming restricted basis entry simplex algorithms must be applied which fail to guarantee convergence to a global optima as, illustrated in Figure 11, where a local peak B is encountered before global peak A.

In contrast to LP and DP, the use of NLP techniques for reservoir system operation has received relatively little attention in the literature. Most applications of NLP have been in the field of hydropower optimisation of systems of several large-scale reservoirs, e.g. Hiew (1987); Grygier and Stedinger (1985), Tejada-Guibert et al. (1990); Arnold et al. (1994) and Barros et al. (2003). NLP algorithms generally considered the most powerful are:

(i) successive (or sequential) Linear Programming (SLP),
(ii) successive (or sequential) Quadratic Programming (SQP) or projected Lagrangian method,
(iii) augmented Lagrangian method [or method of multipliers (MOM)], and
(iv) Generalized Reduced Gradient method (GRG).

All these algorithms require that the objective functions and constraints be differentiable, which may be problematic in some cases. Grygier and Stedinger (1985) and Hiew, (1987), performed a comprehensive comparative evaluation of the above listed NLP algorithms and concluded that SLP was
by far the most efficient in terms of computational speed. All non-linear algorithms require an initial policy, i.e. an initial estimate of the solution in a LP model is usually utilized to derive this initial policy (e.g. average value of the energy production function for each hydropower plant, which is obtained from the long-term operational records) for the SLP model (Barros, 2003). An SLP algorithm is then developed by solving the original non-linear problem via a sequence of localized linear programs so that the final solution is closer to the NLP model solution, as shown in Figure 12.

Figure 12: Relationship among the LP, SLP and NLP models (Barros et al., 2003)

Several linear and non-linear solvers are available for solving LP, SLP, and NLP models. These include MINOS (Murtagh and Saunders 1995), EMNET (McBride, 1985), and interior point methods (Ponnambalaman et al., 1989). A disadvantage of SLP is that “although intuitively appealing and popular because of the availability of efficient linear programming solvers, the method is not guaranteed to converge” (Bazarra et al., 1993). SLP has been applied by Arnold et al. (1994) and Tejada Guibert et al. (1990), who noted that computer execution times increase approximately to the square of the length of the operational period, which does not bode well with applications which have a relatively long time period in a deterministic optimisation mode. In their review of NLP optimisation techniques, Yeh (1985) and Labadie (2004) concluded that NLP had proven to be unpopular due to its demanding computational requirements and its failure to accommodate the stochastic nature of flows.

From the literature surveyed for LP and NLP techniques, it is apparent that their application to reservoir systems optimisation has shown significant limitations or necessitated too many simplifying assumptions. In the next sections, studies which have applied and reformulated DP to overcome the high-dimensional, dynamic, non-linear, non-convex, large scale and stochastic characteristics of reservoir systems that proved to be insurmountable when tackled with LP and NLP methods are reviewed. Solution strategies in the context of DP e.g. Implicit Stochastic Optimisation (ISO), Explicit Stochastic Optimisation (ESO) and real time optimal control with forecasting are explored.

2.3.2 Dynamic Programming (DP) Models

Dynamic programming, (DP) has been one of the most popular techniques in applied to water resources planning and management in general, and reservoir operations in particular (Yakowitz, 1982). Yeh (1985) attributes the success and popularity of DP to its capability to support non-linear and stochastic features that characterize water resources systems and its added advantage of effectively
decomposing highly complex problems with a large number of variables into a series of sub-problems, which are solved recursively over each stage. As originally developed in its general form by Bellman (1957), DP is a procedure for optimising a multi-stage process. This property enables DP to effectively exploit the sequential decision structure of reservoir systems optimisation problems as shown in Figure 13. Release decisions \( r_t \) are made sequentially at different time steps \( t=1,2,\ldots,T \) and stages \( s_t \) where \( T \) is the end of the planning? horizon. Each stage is also associated with a set of reservoir inflows \( q_t \) and stage returns or rewards in the form of benefits from use of water or sale of electricity. These returns are a function of the initial storage (stage), release, final storage at each time period and are denoted by \( f_i(s_i, r_t, s_{t+1}) \) in Figure.

Figure 13: Reservoir system optimisation as a sequential decision process in DP (Labadie, 2004)

DP in reservoir operation can is therefore conceptualised as a Markov process, where the basic concepts are those of “stage” of a system and “state transition” from one stage to another (Howard, 1960). Consider a generalised objective function \( F_t(s_t) \) for deterministic reservoir operation, which represents a cost function representing the maximum return (or minimum cost) accumulated from the current period (stage \( t \) through the final period \( T \)), conditioned on a given storage state vector. Labadie (2004) defined the sequential optimisation process as follows;

\[
F_t(s_t) = \max(\min) \sum_{i=1}^{T} \alpha_i f_i(s_t, r_t) + \alpha_{T+1} g_{T+1}(s_{T+1})
\]

where,

\[
\begin{align*}
  r_t &= \text{n-dimensional set of control or decision variables (i.e., releases from n-interconnected reservoirs) during period } t, \\
  T &= \text{length of the operating horizon (units?)} \\
  s_t &= \text{n-dimensional state vector of storage in each reservoir at the beginning of period } t \\
  f_i(s_t, r_t) &= \text{objective function to be minimised or maximised}
\end{align*}
\]
\[ \phi_{\tau,\ell}(s_{\tau-1}) = \text{final term representing future estimated benefits or costs beyond time horizon } T, \text{ and} \]

\[ \alpha_t = \text{discount factors for determining present values of future benefits or costs.} \]

Optimisation involves calculating an optimal return or “cost-to-go” function - \( F_t(s_t) \) which represents the maximum return (or minimum cost) accumulated from the current period (stage) \( t \) through the final period \( T \), conditioned on a given initial storage vector \( s_t \). A solution is reached via Bellman’s principle of optimality (Bellman, 1957), which states that “no matter what the initial and stage of a Markovian decision process, there exists an optimal policy from that stage and state to the end”.

In discrete form DP, storage is discretized into representative storage zones with a characteristic number of storage levels. Discretization is necessitated by the need to overcome difficulties with functional relationships in the objectives and constraints that may be linear, non-convex or discontinuous. Detailed discussion of various discretisation schemes is documented by Saverenskiy (1940), Moran (1954), Doran (1975), Klemes (1977), Karamouz and Houck (1982) and Kramouz and Vasiladis (1992). An illustration of the schemes, and a procedure for calculating the characteristic storage states is presented in Appendix A.

For all discrete combinations of storage, the function \( F_t(s_t) \) in Equation 3 is optimised recursively over each time period in a (usually) backwards sequence for \( t = T, T-1, \ldots, 1 \), subject to a set of given constraints. Assuming an average of \( m \) discretisation levels for each of \( n \) reservoirs, computational time and storage requirements become proportional to \( m^n \). This problem was named the “curse of dimensionality” by Bellman and it prevented the application of the methodology to real world water systems consisting of more than two or three reservoirs. Various methods of dimensionality reduction were devised involving decomposition into subsystems, coarse grid interpolation, use of iterative procedures e.g. Dynamic Programming with Successive Approximations (DPSA), Incremental DP (IDP) and Discrete Differential DP (DDDP).

The use of IDP for reservoir operation studies was first introduced by Larson (1968), applied by Hall et al. (1969), and systematized and referred to by Heidari et al. (1971) as DDDP. Nopmongcol and Askew (1976) analysed the difference between IDP and DDDP and concluded that DDDP is the generalisation of IDP and the confusion between these two approaches is unfortunate. Sharif and Wardlaw (2000) report that IDP does overcome the dimensionality problem to a large extent, but requires stringent conditions to be satisfied in order to achieve an optimal solution. Labadie (2004) explains that IDP or DDDP are highly sensitive to initial assumed storage trajectories and therefore discretisation intervals must be carefully selected to provide accurate solutions at reasonable computational expense.

Trott and Yeh (1973), and Giles and Wunderlick (1981) have applied the IDPSA technique to problems involving multiple reservoirs. IDPSA require a good initial policy (sequence of states) and whereas, in some cases the convergence of the solution to the global optimum cannot be proved (Yeh, 1985; Mohd Sharif and Wardlaw, 2001), Yakowitz (1983) demonstrated that this state increment DP technique has linear convergence to a global optimum with fine discretisation of state space if the limiting trajectory is an interior point of the admissible policies. He also implied that there is more room for improvement in computer implementation of IDPSA. The methods of IDP, DPSA and DDP have been useful techniques for solving multi-reservoir DP problems in the deterministic case. Attempts to extend these methods to stochastic problems have generally been unsuccessful, mainly since these methods are highly dependent on knowledge of the system state vector \( s_t \).
Various studies have proposed algorithms that incorporate reliability in long-range reservoir operation (e.g., Colorni and Fronza, 1979; Simonovic and Marino, 1980; Marino and Simonovic, 1981). However, Yeh (1985) concluded that although reliability–constrained DP algorithms for reservoir system optimisation are well developed, there are substantial difficulties in developing algorithms that are both truly optimal and computationally tractable for multiple reservoir systems, especially where interdependency between stream flows in each of the reservoirs exists.

The problem of management of a regulated lake/reservoir network which can be represented with a feedback control scheme with feed forward compensation is illustrated in Figure 14.

![Figure 14: Interactions between a reservoir network, control policy and catchment (De Rigo et al., 2001)](image)

Adopting the notation by De Rigo et al. (2001), the control policy, which is the key element of the scheme, returns the volume \( \mu_t \) to be released from the reservoir once the current storage \( s_t \) is known.

When feed-forward compensation is present, the policy also depends upon the vector \( I_t \), which represents the meteorological information and the catchment state. Both these systems are affected by a stochastic disturbance, \( \varepsilon_t \), such as rainfall. The reservoir is represented by the mass conservation equation:

\[
s_{t+1} = s_t + \theta_{m} - r_{t+1}(s_t, \mu_t, a_{t+1})
\]  

(4)

where \( r_{t+1} \) and \( a_{t+1} \) are the actual release and reservoir inflow in the interval \([t, t+1]\) respectively.

In SDP, the meteorological systems and catchment are not modelled. Instead, statistical descriptions of the inflow are utilized in a forecast process instead of a specific inflow sequence to obtain operating policies. The reservoir inflow \( a_{t+1} \) is often represented by simple stochastic autoregressive models of order \( q \) e.g.

\[
a_{t} = \chi_t(a_{t-1}, a_{t-2}, \ldots, a_{t-q}, \varepsilon_t)
\]  

(5)

where \( \varepsilon_t \) is a white Gaussian noise. Here, \( I_t = [a_{t-1}, a_{t-2}, \ldots, a_{t-q}] \). The model of the dynamic system can be represented by a compact vectorial equation:
\[ x_{t+1} = f(x_t, \mu_t, \epsilon_t) \] (6)

where \( x_t \) is the state vector, composed by the state variables in \( s_t \), and \( f \). During the system evolution, the state transition from \( x_t \) to \( x_{t+1} \) can produce an instantaneous cost, which is referred to as "cost-to-go", expressing the lack of fulfillment of management objectives. The objective of the optimal control problem is to determine a policy that will maximise the expected benefits of system operation over a finite or infinite planning horizon. The release and cost-to-go functions derived with SDP depend on the state variable (volume of water in storage in each reservoir) and sometimes other hydrologic state variables (flow during current period, previous flows and seasonal flow forecasts).

Assuming that the system is initially in state \( x_{t_0} \), and denoting the cost-to-go function with \( H^0_{t_0}(x_{t_0}) \): If the optimal cost-to-go would be known for every value of \( x_{t_0} \), the optimal decision \( m_t(x_t) \) at time \( t \) would easily be found by minimising the expected value of the present cost and the discounted optimal cost-to-go:

\[
m_t(x_t) = \arg \min_{u_t} \mathbb{E}_{\epsilon_t} \left[ g_t(x_t,u_t,\epsilon_t) + \alpha H^0_{t+1}(x_{t+1}) \right]
\] (7)

The optimal cost-to-go associated with the present state is therefore given by the following recursive equation:

\[
H^0_t(x_t) = \min_{u_t} \mathbb{E}_{\epsilon_t} \left[ g_t(x_t,u_t,\epsilon_t) + \alpha H^0_{t+1}(x_{t+1}) \right]
\] (8)

Equation 8 is known as the Bellman equation and its solution is the Bellman function (Bellman, 1957). It can be solved using the Successive Approximations Algorithm (SAA), which proceeds backwards in time solving Equation 8 recursively (Bertsekas, 1995). Solution algorithms of the Bellman equation require that the state space be discretized for the sake of computational simplicity (Gablinger and Loucks, 1970), so that the functional equation characterizing the cost-to-go-function can be solved at the state space grid points (Tejada-Guibert et al., 1993). The procedure for discretizing the storage state space that has been outlined under the review on DDP models is also applicable to SDP. The other procedure for representation of reservoir inflows as a discrete random process, as proposed by Karamouz and Vasiliadis (1992), is summarised in Appendix B.

The theory on SDP models has evolved and been improved by many researchers since Howard (1960) first introduced value and policy iteration as procedures for obtaining solutions to a stationary Markov process. White (1963) presented a modified method of successive approximations for Howard’s policy iteration procedure to avoid the computational difficulty in applying policy iteration. Early work by Buras (1963), Butcher (1971), Dudley and Bart (1973), Torabi and Mobasheri (1973) and many other publications derived stationary policies that used the previous periods’ inflow as a hydrologic state variable.

Su and Deininger (1972,1974) generalized White’s method of successive approximations to periodic Markov decision problems and used the approach for optimisation of single reservoir systems. Bras et al. (1983), extended the work of Su and Deininger and developed a steady state stochastic dynamic programming algorithm for reservoir control summarised in Appendix C, by modifying the algorithm...
previously used by Alarcon and Marks (1979). They also suggested a multivariate multi-lag seasonal flow-forecasting model from the work of Curry and Bras (1980) and used it to predict inflows into the High Aswan Dam in Egypt. They used the forecasts with an adaptive control algorithm to introduce real time flow forecasts in reservoir operation. Stedinger et al. (1984) proposed an improvement to the non-stationary adaptive SDP algorithm formulated by Bras et al. (1983) by developing a SDP model which employs the best forecast of the current periods inflow to define a reservoir release policy and to calculate the expected benefits from future operations.

Kelman et al. (1990) expanded the algorithm by Stedinger et al. (1984) to a sampling stochastic dynamic programming (SSDP). Their technique captures the complex temporal and spatial structure of the stream flow process by using a large number of sample stream flow sequences. They regarded sampling SDP as having significant advantages over the traditional SDP approach since it employed selected historical or synthetic flow sequences, thereby allowing actual multi-month persistence of stream flows to be captured in the calculation of expected benefits.

Karamouz (1988, 1990) suggested the use of Bayesian Decision Theory (BDT) in reservoir operation because of its flexibility in being able to incorporate new information in the interpretation of probabilities. He suggested the revision of state transition probabilities in classical SDP in order to capture the uncertainty of the forecast. Karamouz and Vasiliadis (1992) extended the concept of BDT in reservoir operation by proposing Bayesian Stochastic Dynamic Programming (BSDP). BSDP is essentially an extension of a classical SDP model, in the sense that the discrete Markov process of order 1 is assumed to describe the transition of an inflow in season $\tau$ to an inflow in season $\tau + 1$, and that prior transition probabilities are continuously updated to new posterior probabilities using Bayesian analysis which are embedded in the SDP algorithm. Tejada-Guibert et al. (1995) investigated the value of hydrologic information in SDP models and showed that, depending upon the type of objective function, incorporation of hydrologic state variables could improve the performance of models. Kim and Palmer (1997) applied the BSDP model for hydropower generation with a seasonal flow forecast as a secondary choice of hydrologic state variable. In addition to forecast uncertainty, most of the models reported in literature do not consider the demand uncertainty. Vasiliadis and Karamouz (1994) extended the BSDP model to develop a Demand Driven SDP (DDSDP) model which incorporates variable demand for each month.

Besides uncertainty due to the random nature of stochastic variables such as rainfall, stream flow and uncertain demand, other types of uncertainties such as imprecision and vagueness also exist in a reservoir operation model. Fuzzy inference or fuzzy rule based modelling (Zimmerman, 1985), is a framework used to model these types of uncertainties. The theory of fuzzy sets is also capable of tackling the problem of imprecise and non-commensurable objectives in single reservoir operations (Fontane et al., 1997). Russell and Campbell (1996) and Shresta et al. (1996) developed fuzzy rule based models applied to reservoir problems. Fuzzy mathematical programming has also been employed in reservoir operation problems by other researchers e.g. Loganathan and Bhattacharya (1990), Suharyanto and Goulter (1996) and Owen et al. (1997). However, Huang (1996), pointed out that there are limitations with techniques devised in the treatment of non-separable and non-commensurable objectives in solving a multi-objective problem with dynamic programming.

To model the errors associated with discretizing the variables in an SDP model, Mousavi (2000) developed a Fuzzy Stochastic Dynamic Programming (FSDP) model. In the FSDP, a new form of fuzzy Markov chain was defined, and then fuzzy transition probabilities were calculated to determine the expected value of the objective function. Karamouz and Mousavi (2003) expanded the DDSP and FDSP models for operation of the Dez and Karoon reservoirs with real world characteristics in south-western Iran. They presented optimal policies of a complex water resource system in a fuzzy rule based
fashion as a means to incorporate imprecise and subjective information and provide for the participation of operators and decision makers by encoding their experiences and judgements in the definition of the decision variables.

Most of the stochastic SDP models reviewed have been applied in the optimisation of single facility, multi-purpose or multi-facility single purpose reservoir systems. The requirement to discretize the storage and inflow in SDP involves considerable computational difficulties when extended to the multi-reservoir and multi-purpose application. For a multi-reservoir model with $k$ state variables and $N$ discrete levels of each state variable, on line storage requirements for these algorithms are proportional to $N^k$ (Tejada-Guibert et al., 1993). Several models reviewed are also based on the assumption that various natural flows into the systems are not cross-correlated so as to reduce the dimensionality of the SDP problem.

To avoid the unacceptable computational burden associated with the solution of the problem where the correlated inflow assumption has been made and a dense discretization has been adopted, Bellman and Dreyfus (1962), Foufoula-Georgiou and Kitanidis (1988), Foufoula-Giorgiou (1991), Johnson et al. (1993) proposed schemes that at any time step of the dynamic programming algorithm, approximate the cost-to-go function and the operating policy by interpolating polynomials. Another approach is the one proposed by Nardini and Soncini-Sessa (1994). They developed a heuristic control scheme, named Partial Open Loop Feedback Control, based on the substitution of the off-line control problem with a succession of simpler problems, which is effective in presence of a detailed description of the stochastic part of the water system.

Other studies, notably Piccardi and Soncini-Sessa (1991) and Sadecki (2002, 2003) reformulated the standard DP algorithm to exploit the availability of very powerful computers based on innovative architectures (vector and parallel machines) or transputer architecture in the domain of personal computers. Unfortunately, solving such problems, in particular for large dimensions of state and control vectors, can be very time consuming even when parallel systems are implemented (Malinowski and Sadecki, 1990). The supercomputing facilities involved e.g. SUPER NODE 1000 system which is composed of several transputers or processor elements (Sadecki 2002, 2003) are very expensive and require specially written computer codes in a DP algorithm to instruct different processors to execute instruction streams in parallel on different data.

Other approaches for the resolution of the problem of dimensionality within the stochastic context of stochastic programming that are based on Optimal Control Theory, Neuro-Dynamic Programming and Q-learning, are discussed in detail in the next sub sections.

2.4 Optimal Control Theory methods

Modern optimal control theory has its origins with Pontryagin’s maximum principle (Pontryagin et al., 1962), which was originally derived for optimal control of dynamic systems governed by differential equations under control constraints. Several studies have sought to extend the analytic results to linear quadratic problems and thus avoid state space discretization associated with SDP (Wasimi and Kitanidis ,1983; Loaciga and Marino, 1985; Soliman and Cristensen, 1986; Trezos and Yeh, 1987; Georgakakos and Marks, 1987; Georgakakos, 1989; Hooper et al., 1991).

For example, Wasimi and Kitanidis, (1983) modelled the dynamics of a multi-reservoir system by a set of linear differential equations (state space formulation) and employed a quadratic penalty objective function to force the reservoir storages on a pre-specified track. They related reservoir inflows to Gaussian rainfall inputs via a reduced-order state space unit hydrograph model and were able to
formulate a Linear, Quadratic Gaussian (LQG) control problem which they solved analytically. Loaiciga and Marino (1985) presented a parameter estimation and stochastic control scheme using also a state-space, linear –difference equation system model. They represented reservoir inflows by a first order autoregressive model, and their objective was again to optimize a quadratic, penalty-type performance index. Neither model considered release or storage constraints. It is important to note that the algorithms proposed by Wasimi and Kitanidis (1983), Loaiciga and Marino (1985) are stochastically efficient and overcome the curse of dimensionality but are unable to take constraints on storage and releases into account.

Georgakakos and Marks (1987, 1989) proposed the Extended Linear Quadratic Gaussian (ELQG) control, an approach based on the Pontriagyn’s Maximum principle which transcends the dimensionality problem, but requires the cost function to be a quadratic function. It was named ELQG control because it is applicable to LQG problems as well as problems with nonlinear dynamics, control and reliability state constraints, and non-quadratic performance indices. In ELQG control, the system is represented by a set of stochastic differential equations describing the reservoir and river dynamics in state space form. The formulated reservoir operation problem requires finding policies which maximize the expected benefits of a system’s objective while satisfying the remaining objectives at pre-specified reliability levels. ELQG is an open loop feedback control algorithm, is highly complex and initially, it proved more efficient in handling storage rather than release constraints and was limited in application to handling Gaussian independent inflows only. It was modified by Georgakakos (1989) to effectively handle the non-Gaussian disturbances (stochastic structure of inflows) and storage constraints.

### 2.5 Neuro Dynamic Programming and Reinforcement Learning

Two methods, Neuro Dynamic Programming (NDP), and a branch of Reinforcement Learning known as Q-Learning are reviewed in this section. The two methods address specific limitations of SDP outlined briefly below.

- According to Bertsekas and Tsitsiklis (1996), NDP has the advantage of retaining the ability of SDP to deal with highly non-linear problems, while reducing the algorithm complexity by approximation of the Bellman functions via Artificial Neural Networks (ANNs). ANNs are introduced as universal function approximates that are exploited within the framework of a NDP algorithm to approximate the Bellman function, which is solved by the method of SAA.

- The Q-Learning Algorithm (Watkins, 1989; Watkins and Dayan, 1992) is designed to take explicitly into account exogenous information such as average rainfall and other supplemental hydrological information in SDP. This difficulty arises due to the fact that existing hydrological models are far too complex in an optimal control problem to be solved by SDP, mostly because they enlarge the dimension of the state space and aggravate the "curse of dimensionality". Q-Learning is a model-free algorithm of Reinforcement Learning (Kaelbling et al., 1997; Barto and Sutton, 1998) where policies are learnt through trial and error interactions within a dynamic environment.

#### 2.5.1 Solution based on ANNs and approximation of the Bellman Function

An ANN is a nonlinear mathematical structure which is capable of representing complex nonlinear processes that relate the inputs and outputs of any system. A number of studies reported in the literature have discussed the capability of three-layer feed forward ANNs to approximate any
continuous input-output mapping function and its derivatives to any desired degree of accuracy provided, that a sufficient number of hidden units are used (Funahashi, 1989; White, 1990; Hornik et al., 1990; Blum and Li, 1991; Kreinovich, 1991; Gallant and White, 1992; Cardaliaguet and Euvrard, 1992; Takahashi, 1993). A typical three layer feed ANN is shown in Figure 15.

![Figure 15: A typical feed forward neural network (De Rigo et al., 2001)](image)

According to introductory texts on the subject from the work of Dayhoff (1990), Fu (1994) and Haykin (1995), the first layer connects with the input variables and is called the input layer. The last layer connects to the output variables and is called the output layer. Layers in between the input and output layer are called hidden layers and there can be more than one. The processing elements in each layer are called nodes or units. Each of the nodes is connected to the nodes of the neighbouring layers. All connections are “feed forward”; i.e. they allow information transfer only from an earlier layer to the next consecutive layers. Nodes within a layer are not interconnected, and nodes in nonadjacent layers are not connected. Each node receives incoming signals from every node in the previous layer. Associated with each incoming signal is a weight. The weighted sum of incoming signals to a given node is known as the “effective incoming signal”. The effective incoming signal for a particular node is passed through a non-linear activation function, sometimes called a transfer function or threshold function, to produce the output signal for that node. Nordstrom and Svensson (1992) provide a list of different activation functions.

However, Hecht-Nielsen (1990) considers the most commonly used activation function to be the sigmoid function. The two main challenges in the task of identification of an ANN model are specification of the number of nodes in the hidden layer and finding the “optimal” values of connection weights (Hsu et al., 1995). This parameter calibration process is often referred to in all literature as “network training”.

The Back Propagation Algorithm (BPA), as first suggested by Rumelhart et al. (1986) has been adopted by several studies including De Rigo et al. (2001) to train ANNs. Specification of the number of nodes in a network is usually addressed by starting with a large number of hidden nodes and later pruning the network size to remove redundant nodes (Karnin, 1990). However, Hsu et al. (1995) noted that this approach can result in a difficult network training problem of high dimension, with high training time and cost and may not result in the most parsimonious solution. Chang and Abdel Ghaffer (1992) and Masters (1993) favour to instead start with a small number of nodes and gradually increase the network size until modelling accuracy is achieved. Methods to improve the convergence speed (time reduction in training ANNs) of the BPA include modifications based on the use of momentum vectors (Tollenaere, 1990), adaptive back propagation algorithm (Vogel et al., 1988), second-order back propagation algorithm (Battiti, 1992) and conjugate gradient strategies (Charalambous, 1992). In their review of these methods, Hsu et al. (1995) are of the view that these enhancements seem to provide marginal
improvements in training time and do not deal with the problem of sensitivity to initial weights. Other researchers have focused on methods that have the potential to provide improved performance based on their ability to elude local optima. One such strategy that has been tested is the simulated annealing algorithm (Arts and Korst, 1989), however, training time can still be extremely long especially for large networks. Montana and Davis (1989) proposed a Genetic Algorithm combined with BPA and demonstrated improved performance.

Hsu et al. (1995) report on the use of an effective and efficient network training (referred to as LLSSIM) algorithm for training of three-layer feed forward ANNs for modelling the rainfall runoff process. The LLSSIM algorithm uses a partition of the weight space to implement an optimal synthesis of two training strategies. The input-hidden layer weights are estimated using multiple implementation of the simplex non-linear optimisation algorithm (Nelder and Mead, 1965), while the hidden–output layer weights are estimated using optimal linear least squares estimation (Scalero and Tepedelenlioglu, 1992). The algorithm takes advantage of this weight space partition to conduct the non-linear portion of the search in a reduced dimensional space, resulting in an acceleration of the training process. The simplex search algorithm provides improved global search characteristics owing to the use of multiple starts initiated randomly in the search space and its ability not to be trapped by minor local optima. Identification of the structure of the ANN is done using a strategy of progressively adding nodes to the hidden layer until a structure appropriate to the complexity of the problem is achieved.

In their application of a NDP algorithm to some test cases to verify its correct functioning and get some results to understand how to extend it its application to real world cases of reservoir operation, De Rigo et al. (2001) sought to approximate a highly non linear map $H(x)$, such as the Bellman function, where $x$ is a vector, with a feed forward network $\tilde{H}(x, \vartheta)$, where $\vartheta$ is the vector of weights on the arcs connecting the network layers. Once an approximation architecture $\tilde{H}(x, \vartheta)$ of $H(x)$ has been found, the sub-optimal policy $m_t(x_t)$ is given by Bertsekas and Tsitsiklis (1996) as:

$$m_t(x_t) = \arg \min_{\vartheta, u, \varepsilon} E \left[ g_t(x_t, u_t, \varepsilon_t) + \alpha H_{t+1}(x_{t+1}, \vartheta) \right]$$

(9)

It is evident that Equations 8 and 9 are similar. In general, the recursive nature of the Bellman equation is exploited to generate the Bellman functions needed to train their approximations. The detailed procedure and algorithm for the NDP algorithm was derived by Bertsekas and Tsitsiklis (1996) and tested to verify its convergence on a single reservoir by De Rigo et al. (2001). They adopted a hyperbolic tangent as the activation function for a three layer feed forward ANN, which they trained in the BPA with a Levenberg-Marquardt algorithm (Hagan and Menhaj, 1996) and concluded that the results obtained were promising but more work was required to determine the efficient sampling of the discretized state space in order to obtain the most efficient approximation of the Bellman function. Castelleti et al. (2005) extended the work of De Rigo et al. (2001) to a IWRM multi-objective problem in the Paive catchment in Italy which had 3 three reservoirs. They found NDP to be 450% faster than an equivalent SDP. After noting the importance of choosing the right parameters for ANN approximation in an NDP algorithm and the corresponding need to improve efficiency by reducing the training time, Castelleti et al. (2005) propose the SIEVE (Selective Improvement by Evo-lutionary Variance Extinction) technique in order to achieve better performances.
2.5.2 Solution based on Q-Learning

Kaelbling et al. (1997) provides an excellent introduction to the standard reinforcement learning model which they describe as an agent (B) connected to its environment (T) via perception and action as shown in Figure 16.

Figure 16: The standard reinforcement-learning model (Kaelbling et al., 1997)

On each step of interaction the agent receives as input (i) some indication of the current state (s) of the environment and the agent then selects an action (a) to generate as output. The action changes the state of the environment, and the value of this state transition is communicated to the agent through a scalar reinforcement signal (r). The agent’s behaviour (B), should choose actions that tend to increase the long-term sum of values of the reinforcement signal. The model can learn to do this over time by systematic trial and error, guided by a variety of algorithms such as Q-Learning which is the subject of this section.

The agent strives to find a policy (π) by mapping states to actions which maximises a particular long-term measure of reinforcement. Reinforcement learning differs from mathematical optimisation techniques in that, it does not require pre-defined models of state transitions and assumes that the entire state space can be enumerated and stored in memory, an assumption which conventional algorithms such as SDP do not conform. In order to link Q-Learning to Dynamic Programming within the context of reservoir operation and Markov decision processes, the state ‘s’ corresponds to $x_t$ while the actions ‘a’ will be equivalent to $\mu_t$. In Q-learning, the optimal costs-to-go are expressed not only as a function of the state $x_t$ but also of control $\mu_t$ and they constitute the Q-function. In their derivation of the solution of the optimal control problem based on Q-Learning, Castelletti et al. (2001) established the following relationship between the Q-function and the Bellman function.

$$H^*(x) = \min_{u_t} Q^*(x, u_t)$$  \hspace{1cm} (10)

Algorithms for optimal computation of the Q-function are similar to those of the Bellman function and will not be presented here since they are comprehensively documented by Bertsekas and Tsitsiklis (1996) and applied and tested by Castelletti et al. (2001) to regulate Lake Como in Italy. The study demonstrated the extent to which policies generated with the Q-learning were superior in a pareto sense than those obtained by SDP.
2.6 Combinatorial framework approach to derivation of reservoir releases

One of the solution techniques of reservoir optimisation with DP/LP in a deterministic context has been termed as Implicit Stochastic Optimisation (ISO), also referred to as Monte Carlo optimisation, which optimises over a long continuous series of historical or synthetically generated unregulated flow time series, or many shorter equally likely sequences of historical time series. Figure 17 illustrates a framework of generating reservoir operation rules in ISO mode.

![Figure 17: Implicit stochastic optimisation (ISO) procedure (Labadie, 2004)](image)

As shown under figure 17, a deterministic model relies on a specific sequence of inflows (historical, forecasted, or synthetically generated) to determine optimal releases. Multiple Regression Analysis or Artificial Neural Networks (ANNs) techniques are then applied to the optimisation results for purposes of developing seasonal operating rules conditioned on observable information such as current storage levels, inflows during the previous period, and/or forecasted inflows (Young, 1967; Roefs and Bodin, 1970; Bhaskar and Whitlatch, 1980; Karamouz and Houck, 1982). Derived rules are then refined and tested using a simulation model. Labadie (2004) points out that a primary disadvantage of this approach is that optimal operational policies are unique to the assumed hydrologic time series. Karamouz et al. (1992) investigated a multivariate hydrological time series analysis and a deterministic/implicitly stochastic optimisation technique for determining reservoir operating rules for multiple reservoirs. Their approach was to formulate an algorithm with a three-step cycle that begins with an optimisation of reservoir operations for a given set of streamflows. The optimal operations from the solution are then analysed in a regression procedure to obtain a set of operating rules. These rules were evaluated in a simulation model using a different set of data. Based on the simulation results, bounds were placed on operations and the cycle was returned to the optimisation model for refinement.
Raman and Chandramouli (1996) followed a slightly different approach and used an ANN for inferring optimal release rules based on initial storage, inflows and demands. The results of a deterministic DP model (20 years of bimonthly data) served as a training set for the ANN. Chandramouli and Raman (2001) extended this approach to developing operating rules for multi-reservoir systems.

Willis et al. (1984) approached the reservoir operation problem in ISO mode from a slightly different perspective. They proposed a policy that determines probabilistic reservoir release policy by using a Monte Carlo optimisation approach. For a particular stream flow sequence their methodology determines the optimal reservoir release for each time period over the operational horizon by using linear programming. After repeating this procedure for a large number of synthetic flow sequences, an operational policy is determined by utilising the probability mass function of the optimal releases conditioned on observable hydrologic conditions.

In contrast to ISO, Explicit Stochastic Optimisation (ESO) is designed to operate directly on probabilistic descriptions of random stream flow rather than deterministic hydrologic sequences (Figure 18).

Figure 18: Explicit Stochastic Optimisation (ESO) procedure (Labadie, 2004)

Labadie (2004) explains that under ESO, optimisation is performed without the perfect foreknowledge of future events and optimal policies are determined without the need for inferring operating rules from results of optimisation. Raman and Chandramouli (1996) claim that simulation of rules obtained from the trained ANN outperforms rules produced by linear regression analysis as well as optimal feedback laws obtained from ESO using SDP. Karamouz and Houck (1987) compared an ISO model (a dynamic program, regression analysis and a simulation) with a SDP which described stream flows with a lag-one Markov process with a view to test the usefulness of both models in generating reservoir operating rules and evaluate their performance. For their test cases, their findings showed that the ISO
model generated rules that were more effective in the operation of medium to very large reservoirs while SDP generated rules more effective for operation of small reservoirs.

In a state-of-the-art review of optimal operation of multi-reservoir systems, Labadie (2004) further indicates that implicit and explicit stochastic optimisation models can be applied to determining long-range guide curves and policies over weekly, monthly or seasonal time increments. Real-time optimal models are then designed to track these long-term guidelines over shorter time horizons. For example, Loaiciga and Marino (1986) embedded a stochastic daily model for short-term (i.e., 1-month ahead planning horizon) within a monthly model (with a 1-year planning horizon) that had previously been developed by Marino and Loaiciga (1985). Hence the roles inherent to planning and real-time models for reservoir operations are clearly defined. In a planning model (which incorporates seasonal hydrologic data and long-term benefit functions), the schedule of releases (long term planning targets) within a control horizon of typically 1 year, serves as a guideline for resource allocation and management on the part of the responsible management agencies and, as the year progresses, actual realizations of random such as stream-flows as well as unexpected institutional directed actions are taken into account to revise the planning solutions by means of real–time operation models. The ELQG (Georgakakos and Marks, 1987; Georgakakos, 1989) is one example of real-time control of reservoir systems that has been applied under the Nile DST and LVDST tools. This two-level approach, i.e. strategic planning first with later sequential update is widely prevalent in the management of reservoir systems by state and federal agencies in the United States (Loaiciga et al., 1987).

Yang et al. (1995) stressed the importance of hydrological forecasting models in real-time reservoir operation and recommended that forecast and decision making be viewed as a single unit, implying that the linkage between the hydrological forecast model and the operation method should be as strong as possible. Their study presented different operation techniques for real time reservoir regulation on the basis of two hydrologic models and two optimisation methods: the first-order autoregressive (AR) model, the GR3 conceptual rainfall runoff model, the stretched-thread (ST) method and DP.

### 2.7 Multi-objective and multi-criteria decision analysis of reservoir operation

Development of optimal operating policies for large-scale reservoir systems is often complicated by a multiplicity of conflicting project uses and purposes that ultimately affect different groups of people or interests. The resolution of this problem is often difficult, particularly in the operational phase, in the face of real time stream-flows, demands, constraints and pressures of concerned interest groups. Yeh and Becker (1982) note that the difficulty is compounded when the system managers cannot easily perceive the trade-offs between the several purposes, given the existing and predicted conditions relevant to system operation, nor how such tradeoffs might have to be modified if predictions are updated. Unless legal or contractual priorities have been established, the usual refuge of the system manager is to assign priority to the objective (commonly hydropower) which realises the greatest monetary benefit for the operation while adhering to minimum performance requirements corresponding to other objectives.

Use of classical optimisations techniques, would require that the beneficial and adverse effects of a project be accurately quantified in terms of a single measure of good e.g. $. However, in most water resources projects the beneficial and adverse effects are not all commensurable and, they cannot be readily combined into a single objective, and there is no clear definition of optimality. Tauxe et al. (1979a) therefore made the observation that the application of such classical optimisation techniques that have been reviewed above to a multi-objective objective problem, would be difficult if not impossible.
Solutions to non-commensurable multi-objective problems are classified as either ‘inferior’ or ‘non-inferior’, (Vemuri, 1974; Cohon and Marks, 1973; Haimes et al., 1975). Roughly defined, an inferior solution to a maximisation problem is one that has an objective whose level of attainment is increased without necessitating a decrease in the level of attainment of any other objective. Conversely, a non-inferior solution is one for which no objective’s level of attainment can be increased without another objective’s attainment level decreasing. Figure 19 illustrates the various terminologies associated with multi-objective optimisation. In this case, the problem considered is the maximisation of a two objective function $f_1$ and $f_2$ i.e. $\text{max} (f_1,f_2)$, subject to a constraint set in the decision space that defines the feasible and infeasible regions. The non-inferior solution set is a sub-set of the feasible region and it can alternatively be referred to as the set of non-dominated solutions.

Assuming that the non-inferior points can be generated and trade-offs between objectives calculated, one non-inferior solution cannot be chosen over another without utilising the decision maker's preferences. However, when preferences are known, then one of the non-dominated solutions or non-inferior solutions can be identified as the best compromise solution. Hence when more than one objective is considered, the traditional optimisation techniques cannot directly solve for the optimal solution.

In response to the need for multi-objective analysis, new mathematical techniques have been developed, and others have been modified to handle more than one objective. Cohon and Marks (1975) discuss several methods of generating non-dominated solution sets and their limitations. Of these techniques, the weighting method, the $\epsilon$-constraint method and the surrogate worth trade-off method were favoured. Variations of these techniques and DP have been applied to the problem of reservoir optimisation. Most approaches tend to generate non-dominated solutions for a reservoir where the number of objectives and constraints is small in order to avoid prohibitive dimensionality, (Tauxe et al., 1979b; Georgakakos, 1993). Objectives other than the primary objective are treated as constraints whose levels may be parametrically varied, which necessitate the addition of one state variable for each objective, but the number of decision variables remains the same. By varying the minimum acceptable levels of the secondary objectives a set of trade offs may be generated between all of the objectives. There are however, some limitations of using this approach with dynamic programming. The
mathematical form of the second level objectives (formulated as constraints) must meet specific constraints. First, they need to be separable, and second; each of these objectives must be of the form where each component of the objective at each stage must be defined in terms of its aggregate objective level. This was demonstrated in part by Harboe et al. (1970) in their analysis of the monthly operation of a reservoir in which firm energy, the primary objective was maximised. A second objective, which was treated as the constraint, specified a minimum level of firm water. This formulation permitted solution by dynamic programming because the firm water objective was separable and of the form where each component (required monthly water supply) could be defined in terms of the overall objective level (annual firm water).

Once non-dominated solutions have been generated, there are a variety of search techniques available for converging to the solutions preferred by the decision maker. They include (i) goal programming (ii) compromise programming and (ii) the trade-off development method. Summarised descriptions of each of these methods is to be found in the work of Ko et al. (1992) whose study provides guidance as to which methods are best suited to dealing with the challenging large-scale, non-linear and non dynamic and stochastic characteristics of multi-reservoir systems operations. From their analysis, they concluded that for application to reservoir operation problems, the ε-constraint method of determining non-dominated solutions was superior to the weighting method while “trade off development method“ identified the most preferred solutions by progressive articulation of the preferences of a reservoir operator through interactive involvement in the solution process.

Multi-Criteria Decision Analysis (MCDA) techniques can also be used to identify preferred solutions for alternatives that are difficult to quantify or those that are not commensurable. Flug et al. (2000) describe an objective quantification method, which included inputs from special interest groups, the general public, and concerned individuals as well as professionals for each resource in a trade off analysis by use of a numeric rating and priority-weighting scheme for purposes of quantifying various flow alternatives for Glen Canyon Dam on the Colorado River.

Ko (1989) performed an extensive evaluation of MCDA techniques for ranking non-dominated alternatives for reservoir systems operations. The comparison included evaluation of methods such as ELECTRE I and II (Roy, 1971), the Analytical Hierarchy Process (Saaty, 1980), and discrete compromise programming (Zeleny, 1982). Ko (1989) concluded that the Analytical Hierarchy Process was preferable for reservoir operational problems due to advantages such as of ease of use, explicit evaluation of non-quantifiable criteria and the ability to provide a complete ranking.

Ko et al. (1994) extended the work of Harboe (1986), Ko (1989) and Ko et al. (1992) and with a view to consider multiple quantitative and qualitative reservoir operational objectives with varying degrees of importance in a single framework. Ko et al. (1994) presented a two-stage procedure combining multi-objective optimisation and MCDA techniques for selecting an operation rule for a multi-objective, multiple-reservoir system. In the first stage of the procedure, primary quantitative operational objectives were used to generate non-dominated alternatives via multi-objective optimisation using successive linear programming and the ε-constraint method. In the second stage, primary and secondary operation objectives are combined within MCDA techniques to select the most preferred alternatives from the generated set. Difficult to quantify objectives are handled in MCDA techniques through the use of subjective rating scales.

Problems do exist where various objectives under consideration exist and which need to be traded off between each other in a meaningful or tractable way i.e. the Pareto optimum or simultaneous satisfaction of objectives is impossible and the method of Lexicographic optimisation is required. Rentmeesters et al. (1996) point out the distinction, from a theoretical perspective, between
lexicographic optima and proper Pareto optima and present an adequate theoretical framework to facilitate the automatic solution of such problems in which objective functions are not necessarily linear. Weber et al. (2002) proposed a method of lexicographic optimisation to efficiently manage the water resources of Lake Verbano in Italy in compliance with the different priorities. A primary optimal control problem is formulated for a given set of objectives and an optimal policy is computed. Given the system regulated with this policy, a second set of objectives is chosen and a new control problem is formulated. The process can be iterated, taking into consideration new objectives at every step. Optimal policies are computed using SDP. Volgenant (2002) refer to this procedure as lexicographic thus, extending the meaning of this term, traditionally used in the context of multi-objective problem decomposition.

Despite the abundance of multi-objective optimisation techniques that address water supply objectives with predetermined minimum flow requirements for the ecology and environment as a constraint, Cardwell et al. (1996) report that few previous reservoir operations studies have included both water supply and instream flow objectives implicitly. Instream flow models exist that are capable of addressing conflicts between human demand and environmental releases from a reservoir at the planning stage (see for example Hughes et al., 1997; Hughes and Ziervogel, 1998). In these models that have been widely applied in South Africa, the process of determining Instream Flow Requirements (IFR) is referred to as an Instream Flow Assessment (King and Louw, 1995) and is commonly carried out during a workshop involving a multidisciplinary team of specialists. However, these models must be combined with other models for a more complete set of procedures contributing to sustainable reservoir design and operation that can satisfy human demand and environmental releases. Koel and Sparks (2002) related the historical hydrological patterns of river stages to fish abundance in the Illinois River. They used these relationships as criteria for dam operation based on the historical range of variation (RVA) approach (Richter et al., 1998). The RVA approach provides the range of hydrological criteria that reservoir operations should achieve.

In a similar fashion, Suen and Eheart (2006) propose a holistic, regime-based approach to regulation of rivers, which recognizes that flow magnitude; duration, frequency, timing and predictability must be incorporated into any flow management strategy. In their study, the “ecological flow regime paradigm” is used to establish such comprehensive and complex management targets for operating a reservoir to satisfy a downstream aquatic ecosystem. Their paradigm incorporates the Intermediate Disturbance Hypothesis (IDH), which holds that ecosystems are healthier under disturbances that are neither too small nor too large. According to Townsend et al. (1997) too many disturbances such as floods and droughts in an ecosystem may reduce species richness by excluding taxa that cannot quickly recolonize between disturbances, and only a few disturbances may allow competitive exclusion to occur because some species, which are frequently the most desirable species, are capable colonists but poor competitors. Figure 20 below illustrates the IDH concept.
In the study by Suen and Eheart (2006), both ecosystem and human needs are considered in a multi-objective approach towards optimising reservoir operation for both human and ecosystem considerations with the help of a non-dominated sorting genetic algorithm (NSGA-II) to identify tradeoffs. Deb et al., (2001) and Deb (2002) provide details of the computational architecture of this algorithm.

2.8 Summary

There is a general consensus amongst various reservoir operations researchers that the various reservoir systems analysis techniques and optimisation methods reviewed above, have not been widely adopted by practitioners (Fiering, 1976; Eichert, 1979; Helweg et al., 1982; Yeh, 1985; Oliveira and Loucks, 1997; Simonovic et al., 1989; Simonovic, 1992; Soncini-Sessa et al., 1999; Nicklow, 2000; Labadie, 1997; Labadie, 2004; Salesicz and Nakayama, 2004). A gap still exists between theories and applications particularly in the area of real time reservoir operation. Salesicz and Nakayama (2004) explain that due to the complex nature of water resources management problems, lack of consistent and complete data and uncertainties, the process of finding optimised decisions cannot be limited to the solving of mathematical optimisation techniques or performing complex simulations. This view had earlier been held by Rosenthal (1980) who assessed the status of optimisation models designed to aid in the planning and operation of water resource systems. Four characteristics of reservoir systems that such models should incorporate were identified: multiple reservoirs, multiple time periods, stochastic inflows, and non-separable benefit functions. One hundred existing mathematical models at the time were cited but none of the models were found to handle effectively all characteristics.

Other limitations of some of the approaches to reservoir operation that have been reviewed have been identified and cited by various researchers as follows;

- According to Little (1970), Beard (1973) and Fults and Hancock (1974), a fundamental limitation of mathematical optimisation models is their incompatibility with prevailing behavioural and organisational settings in water resources management. All too often, too little attention has been devoted to building models into the dynamic management, planning, or policy-making process (Walker, 1982; Lara and Sachs, 1978). Management questions, policy objectives, and policy makers frequently change yet the models remain static.
From examination of the past experiences with optimisation models, Adiguzel and Coskunoglu (1984), observed that: (I) models were often constructed in an attempt to drive the underlying and important decisions by prescribing decisions to be implemented rather than making the model serve the decision makers; (II) model builders focussed extensively on refinements to algorithms to alleviate computational complexities at the expense of accommodating flexible and a meaningful man-machine interaction environment.

Many researchers have often prescribed optimisation tools for reservoir operation that emphasize average performance optimisation over long term planning horizons, yet in practice reservoir managers tended to be “risk averse” and prefer to avoid dramatic failures whenever the system approaches critical conditions (Nardini et al., 1992).

Individuals often do not know what questions they want answers for before some exploration and comprehension of the impacts of some of their ideas for plans and policies (Loucks et al., 1985). The outcome of this exploration often leads to new questions and the need for additional exploration.

All optimisation methods are designed to reach an optimal solution as quickly as possible, and the result is that they generate as little information as possible about alternative optimal and nearly optimal solutions. It therefore follows that the use of mathematical models to identify only a single optimal solution results in a loss of potentially very valuable information. Such a modelling approach has tended to limit generation, exploration and synthesis of a wide spectrum of alternatives (Loucks et al., 1985). Multi-objective models have been used to attempt to eliminate from further consideration solutions that were not efficient, i.e. that were inferior with respect to the objectives considered in the models. However, there is increasing realisation that so called inferior solutions may not be inferior at all when considering other objectives.

Labadie and Sullivan (1986), noted that one of the major complaints by reservoir managers was that their experience and understanding of the system was not properly incorporated by systems analysts and computer modelling specialists.

Labadie (2004) attributes the lack of success in the implementation of reservoir system optimisation models is due to the lack of interactive involvement of decision makers during system development, poor linkages with simulation models which operators more readily accept and recommends better packaging of systems as suggested by Goulter (1992).

The large number of simplifications that have to be made in order to make a complex system more tractable from an optimisation point of view are perceived as deceiving by operators who practically refuse to implement proposed solutions (Yeh, 1982). Since the real problem usually cannot be sufficiently represented by a mathematical model, Harrington and Gidley (1985) are of the view that the “the bigger the better” is not necessarily true of mathematical models.

Nicklow (2000) observes that most optimisation models are formulated in a way that does not adequately account for inherent uncertainty that is present in a water resources systems; the variety of optimisation methods that researchers have historically applied leads to confusion regarding which to select for a particular application; and that most applications would require customized program development since, in many cases, generalised software packages are not available.
From this chapter, it can be concluded that there is no simple answer to the question of which models and analyses techniques should be used in a particular modelling application. However, it is evident that certain factors that are unique to the problem to be solved dictate that existing models whose attributes have been widely accepted by practitioners offer a good starting point by way of modification. Consideration of other needs may warrant coding new programs specifically for a particular system or integration of other algorithms to achieve desired results. It is also easy to notice that economic-analysis models that compute benefits and or costs associated with various operating plans are still lacking. The derivation of optimal operating rules dictates that a number of models or approaches are combined e.g. forecasting, optimisation models, ANNs, simulation models and the rules refined in a recursive process as illustrated under Figure 17. The requirement to subject these rules to stakeholder appraisal and evaluation calls for the combination of MCDA techniques with multi-objective optimisation.

The focus of the next chapter is to review collections of interactively linked stakeholder based models with capability of impact exploration, synthesis and evaluation that are often termed decision support or decision aiding systems (Sprague and Carlson, 1982; Soncini Sessa et al., 2001). Particular attention has been given to models that allow interaction of managers, planners, and policy makers possibly coupled to graphical and pictorial input and display devices (Loucks et al., 1985).

3. SPECIFIC DSS SYSTEMS FOR REGULATION OF LAKE-RIVER SYSTEMS

DSS are defined by Booty et al. (2001) as a specific decision information system that integrates a hierarchy of tools (e.g. for real-time monitoring, database, modelling, visualization, management scenario analysis) seamlessly linked to one another in a single system. Several other researchers such as Loucks et al. (1985) and Simonovic (1996) offer slightly varying definitions but essentially emphasize the importance of an built-in capability in a DSS that allows decision makers to combine personal judgment with computer output, in a user–machine interface in order to produce meaningful information for support in a decision making process. Examples of application of such systems in real life situations are summarized in the following sections.;

3.1 Development of a regulation policy for Päijänne-Kyimijoki lake-river system

Hämäläinen et al. (1999) report on the testing of an approach for multi-criteria modelling and support of multi-stakeholder decision making in the development of a new water level management policy for a regulated lake-river system in Finland. Their approach is an example of the Evolutionary Systems Design (Shakun, 1996) for task oriented group processes. This framework involves the modelling of evolving relations between players (negotiators, decision makers, stakeholders), values, operational goals, control decisions, criteria and group preferences. In the first stage of their approach, interest groups consisting of individual stakeholders and their important decision criteria are identified through questionnaires. For further analysis, selected decision criteria are divided into main objectives and a value tree is constructed. Figure 21 shows an example of a value tree where the decision criteria have been divided into two main objectives, i.e. ‘Economic’ and ‘Socio-ecological’. In this illustrative example, there is a shortlist of five prioritised preliminary alternatives denoted by A1, A2, A3, A4 A5 selected such that they represent a wide range of different regulation practices.
Martunen and Hämäläinen (1995) discuss in detail how value tree analysis can be utilized in citizen participation through decision analysis interviews. The decision analytic prioritisations performed by the stakeholders are entered into web pages for the public to see by using a general purpose Multi Attribute Decision Analysis (MADA) web-based tool called web-HIPRE (Hämäläinen and Mustajoki, 1998). During the second stage, a set of pareto optimal alternatives for the regulation policy is generated using a software called ISMO (Hamalainen and Mantysaari 1998a; 1998b; 2001). In this software, the decision variables, which are used to define the regulation policy alternatives, are target water levels at different times of the year as shown in Figure 22.
the planning period. In ISMO, inflow forecast to the system is updated periodically resulting in a series of dynamic rolling horizon goal programming problems that are solved in an EXCEL spreadsheet with a graphical user interface. In order to have meaningful connections between values and criteria decision levels, Hämäläinen et al. (1999) proposed that analytical value functions e.g. an impact model expressing target water levels in terms of annual flood damages, power generation, vegetation loss etc. be constructed to facilitate stakeholders to state their preferences over different regulation policy alternatives. In that way the socio-economic and ecological impacts of selected regulation policies were tested using a simulation model of the river-lake system.

In the next stage, a search for efficient alternatives with the method of improving directions (Ehtamo et al., 1998; 2001) was conducted through another process of stakeholder interaction whereby participants are asked to state preferences over different regulation policy alternatives. The method of seeking group consensus is fostered by role-playing experiments using an interactive web-based computer tool that supports a preference trade-off identification known as WINPRE (Hämäläinen and Helenius, 1998).

3.2 Pirkanmaa lake regulation development project

Marttunen and Suomalainen (2006) document experiences and lessons learnt through a process of reviewing regulation policies for a system of four interconnected lakes and a river course within the watershed of Kokemäenjoki River in Finland. The existing regulation policy for the lakes prior to the review process was designed to minimise flooding around lake-shores and maximise hydropower production during the winter period when tariffs were highest. However, the policy did not find favour with the fisheries sector who argued that sustained lowering of lake levels prior to the onset of floods impacted negatively on aquatic ecosystems and fish stocks.

Pirkanmaa lake regulation project was conceived to quantify the effects of existing regulation practices and identify alternative regulation options through a participatory stakeholder consultative process. An approach for support of multi-stakeholder decision process similar to the one deployed for lake Päijänne was applied together with a new value tree based excel spreadsheet model known as REGAIM. The REGAIM model is constructed to assist stakeholders to define widely acceptable target water levels at different times of the year in series of decision analysis interviews. It is interesting to note that Marttunen and Suomalainen (2006) report that stakeholders encountered significant difficulties when asked to indicate the extent to which deviation from set targets would be tolerated in order to accommodate a different set of conflicting target levels. It appears that limited success was registered under the Pirkanmaa project since consensus building proved to be difficult.

3.3 Lake Verbano project

Lake Verbano is a natural lake located on the Swiss-Italian border. It is used as a multipurpose reservoir where the main management objectives are the satisfaction of downstream water supply for hydropower generation and irrigation control of floods and protection of environment quality. Unilateral approaches to resolution of these conflicting objectives were not acceptable to all stakeholders concerned. The Lake Verbano project was therefore designed with the purpose of comparing different options and to address conflict by a structural modification of the lake outlet and modification of the release regimes. A participatory integrated planning procedure (Castelletti et al. 2004) was applied to support the decision making process according to the requirements of the EU water framework directive and the integrated water resources management paradigm.
Application of the Participatory Integrated Planning process (PIP) in the Lake Verbano project commenced with identification the stakeholders. The stakeholders were asked to agree on the objectives, criteria to be used in evaluation of the alternatives and indicators which are summarised in Figure 23.

Thereafter, models of the system components (catchment, lake, irrigation district, hydropower plants, rivers etc) were identified and aggregated for purposes of computing the value of indicators with respect to a given alternative. The stages of model identification, alternative generation and evaluation take place during the planning stage and are integral to the architecture of a Multi-Objective DSS known as TwoLe (Soncini-Sessa et al., 1999) that was used to support stakeholders involvement in the decision making process. In this two level decision approach, the control level is served by a controller, while the other two levels need two separate DSSs: DSS/M and DSS/P where M stands for management and P for Planning.

This separation of roles in TwoLe is designed to endear it to structures of water agencies where policies are designed at planning level, and decisions taken at the management level; thus allowing the decision makers to have an active part in planning the policies embedded in the DSS. The planning Module DSS/P deals with the choice of alternatives and its outputs are planning decisions, management policies and models. All of them constitute inputs to the management module DSS/M. The interaction among the Systems Analyst (SA), the Decision Maker (DM) and stakeholders takes place in the DSS/P at the planning level and in the DSS/M at the management level. This scheme is illustrated in Figure 24.
The algorithms used in the planning level are described in Aufiero and SonciniSessa (1995, a,b,c), Guariso et al. (1984), Nardini et al. (1992), Orlorvski et al. (1983 and 1984) and Piccardi and Soncini-Sessa (1991). These algorithms are constructed around a central theme of "set-valued" management policies that are intended to play a central role in the process of assisting stakeholders to generate a diverse range of alternatives. A set–valued policy refers to that set of releases associated with the same performance. The approach is motivated by the min-max approach to operation of reservoirs (Orlorvski et al., 1983, 1984), where the focus is avoiding substantial failures of the system during severe hydrological episodes (risk-averse attitude). Nardini et al. (1992) extended the work of Orlorvski et al. (1984) by integrating risk aversion and average performance in reservoir control. According to this methodology, a risk aversion problem is formulated whose solution is not unique, but rather a whole set of policies, all equivalent from the point of view of the risk aversion objectives. Then a stochastic average-performance reservoir control problem is solved, to select from the set previously obtained the best policy from the point of view the average-performance objectives. This property is particularly important since it introduces flexibility at this stage of the decision making process.

In order to evaluate the alternatives, stakeholders having the same concerns and priorities are grouped in one sector which is associated to an index. These indices are used in the successive phases to compare the alternatives. The best compromise alternative may be obtained by allowing the stakeholders to express their preferences by means of weights or a negotiation process between DMs. In the case of Lake Verbano, which is a trans-national case, there are two decision makers i.e. the governments of Switzerland and Italy. To facilitate the negotiation process, the set of alternatives are skimmed by to identifying a set of compromise alternatives, each one preferred by a group of stakeholders and possibly refused by others. Negotiation processes were established that attempted to reach the widest ranging consensus. To support alternative comparison and negotiation, Weber et al. (2002) describe a lexicographic optimisation process where the SA carries out a series of successive multi-objective optimisations after identification of set valued policies. A primary control problem is formulated for series of given objectives (e.g. flood protection and minimisation of water of the deficit of water supply for irrigation) and an optimal policy is computed. Given the system regulated with this policy then a second sect of objectives is obtained (e.g. optimisation of hydropower production) and a new control problem is formulated and solved: a new policy is obtained. The process can be iterated, taking into consideration new objectives at each stage. Pareto boundary projections obtained for both the primary and secondary optimisation problems were used to illustrate how the set of admissible control values shrink during the iterated application of lexicographic optimisations. When the first set of
alternatives is explored to find a new alternative that improves the utilities of the unsatisfied stakeholders without lowering too much, the utilities of the favourable ones, then iteratively, a compromise alternative can be reached.

TwoLe provides a set of identification tools, a wide choice of policy design optimisers and a number of simulators. The latter includes deterministic, Markovian and Monte Carlo simulators, while optimisers are based on different algorithms such as SDP. Its architecture allows a rapid prototyping of various modelling situations both at planning and at management level via a friendly user interface (Soncin-Sessa et al., 1999). The DM can use the DSS/M to produce forecasts, compute the daily release decision and simulate the effects of a release decision in the short run.

4. REVIEW OF REVIOUS WORK IN THE CASE STUDY AREA

There are a number of focused studies that have made significant contributions to application of some of the above approaches in the chosen case study area (i.e. the Victoria Nile). Others have enriched the body of scientific knowledge on the hydro-meteorological, biological and fresh water ecosystem of Lake Victoria, Kyoga and Albert and hold promise for utilisation in emerging decision frameworks. These are reviewed separately.

4.1 HYDROMET Project (1975-1981)

The Hydro-meteorological Survey of the catchments of Lakes Victoria, Kyoga and Albert, referred to as HYDROMET, was a co-operative venture between the eight riparian countries of the Nile Basin (Burundi, Egypt, Kenya, Rwanda, Sudan, Uganda, Tanzania and Zaire) with Ethiopia as an observer with the assistance of the World Meteorological Organisation as the Executing Agency for the United Nations Development Programme (UNDP).

Under the HYDROMET project, attempts were made to determine the character of the fluctuation in the levels of Lake Victoria. These studies showed seasonal oscillation with a maximum in May–June and a minimum in October to November. Long-term fluctuations of water level also are known to occur. Prior to 1927, Lake Victoria had a 10 or 11 year cycle of water level maxima (Bargman et al., 1965). There have been no studies to confirm these cycles after 1927.

The HYDROMET project (reference?) produced the following outputs:

- Establishment of hydro-meteorological instrumentation networks within the catchment.
- Topographic and hydrographical surveys of the lakes as well as aerial photography and ground survey of critical shore-lines.
- The computer processing of hydrological and meteorological data.
- The development of a mathematical model of the lakes and rivers of the upper Nile Basin.
- Hydrological studies of selected river basins.
- The evaluation of various alternative patterns of lake regulation, singly and as a system.

Of particular importance and significance was the development of the upper Nile Catchment model, (Nemec and Kite, 1979), consisting of fifty computer programs written in FORTRAN. The WMO (1982) outlines the objectives in regulating Lake Victoria as follows:
to maximise power output at Owen Falls dam,
- to maximise power potential in the Kyoga Nile,
- to meet foreseeable water resource requirements of riparian countries of the Upper Nile Basin, and
- to minimise the impact on riparian people.

Kite (1984) identified and evaluated a number of historic operational plans and also developed a series of improved plans. Bakhiet (1996) provides a review of both historic and more recent plans. Most plans involve setting discharge criteria within different zones in Lake Victoria. Regulation plans proposed during the project lacked economic and environmental data but a set of computer programs were written so that economic information could be included when the necessary data became available. Water use studies were performed and demands in all major towns and catchments were estimated. The development of a water quality and environmental model was also initiated. It was conceived to consist of ten sub-models, each individually calibrated, for the different processes involved. The major sub-models were algae growth, fisheries, nutrient, moss balance, coloform count, pesticide and bilharzias components. This model was scheduled to be completed by the end of 1981 and was to form a major portion of an enlarged hydrological model of the Upper Nile Basin.

Unfortunately, when the project ended in 1982, much of what had been achieved was not consolidated and further work was disrupted by civil strife and instability in the region. Most of the hydro-meteorological network was vandalised. Numerous publications, data and software were poorly archived and consequently misplaced or lost during the period. However, some principal recommendations made by this project, and which are still relevant and of interest in the context of this study, are as follows (ref):

- Comprehensive studies should be taken to evaluate correct specific water demands and consumptions for urban and rural populations, for industry and for irrigation, taking into account regional conditions and standards.

- Regulations plans that were proposed should be considered for application or developed further e.g. to include studies of economic and environmental aspects.

- Consideration be given to modification of the mathematical model to incorporate optimisation routines.

Prior to detailed consideration of the regulation studies under HYDROMET, the potential for utilisation of Lake Albert as a reservoir had been considered over many years (see Hurst and Phillips, 1938) on the basis that the relatively steep shores made it more suitable than lake Victoria for intra-year storage to control the supply of water to Egypt. The effect of flooding around Lake Albert was studied in 1956 to assist Uganda in possible negotiations (Sutcliffe et al., 1957) and also as one component of control for the Nile under the HYDROMET Project (WMO, 1982). Although construction of the High Aswan Dam has since satisfied Egypt’s storage requirements, it may be useful to reconsider this option, but in a manner that reconciles the need for Uganda to optimize the hydroelectric potential of the Nile below Lake Victoria by storage, and present requirements of those inhabitants of the southern Sudan to avoid disturbance of the pattern of seasonal flooding.

### 4.2 Lake Water Balance Studies & Water Level Forecasting

Interest in Lake Victoria’s water balance can be traced back to the study by Brookes (1923). Since then, numerous subsequent works have evaluated and successively and updated the lake’s water balance.
Initially, researches found it difficult to explain the sharp rise in the level of Lake Victoria between 1961-1962, as shown in Figure 5, until Piper et al. (1986) were able to explain the rise through rainfall and resulting tributary inflows. Sene & Plinston (1994) investigated trends in levels of Lake Victoria and outflows in more recent years and concluded that the levels remained relatively high from the early 1960s to the early 1990s as a result of sustained increase in rainfall on the lake. Although tributary inflow is small compared with direct rainfall on the lake surface, its greater variability is important in the fluctuations of the basin supply (Piper et al., 1986). Lake rainfall is almost balanced by evaporation. Annual means of these are 1780 and 1537 mm, respectively, (Nicholson et al. 2000), compared to 338 and 524 mm for inflow and discharge (Sutcliffe 1988).

The net effect of Lake Kyoga on the Nile flows was studied by Sutcliffe and Parks (1999), who performed a regresional analysis between monthly inflows and outflows. They determined an optimum equation linking inflow and outflow of lake Kyoga for the period 1940-1977 and noted a delay of river outflow due to lake storage of approximately one month. Their findings supported the hypothesis of Hurst and Phillips (1938) that Lake Kyoga system is responsible for net losses in dry years and for net gains in wetter years. This has been attributed (Institute of Hydrology, 1984) to the evaporation from Lake Kyoga exceeding direct rainfall and local runoff during relatively dry periods while local runoff increases during wetter periods and together with lake rainfall exceeds lake evaporation which remains relatively constant from year to year. Comparisons of the predicted and measured end of month levels for Lake Kyoga and Albert for the period 1951-1960 & 1966-1975 are illustrated by Sutcliffe and Parks (1999). These figures have however, not been updated since then.

Within the context of regulation of lake Victoria levels, the confirmation by previous water balance studies that fluctuations of lake Victoria levels are driven predominantly by rainfall is significant and motivated Nicholson et al. (2000) who derived a water balance model for Lake Victoria that simulates end-of-year lake level changes using only rainfall on the lake as input. The similarity of calculated and measured lake levels (correlation of 0.98) demonstrated the model was robust. Yin and Nicholson (2002) refined the model to estimate end-of-year lake level as follows;

\[ H_i = 0.857 H_{i-1} + 1.135 P_i - 270 \]  

Where \( H_i \) and \( H_{i-1} \) are the end-of-year lake levels in the current and prior year respectively and \( P_i \) is annual over lake rainfall. This equation has potential for numerous applications in the regulation of Lake Victoria. First, it is a lake level predictor model. With any annual rainfall information obtained from other sources, the end-of-year lake level is easily calculated. Second, knowledge of end-of-year level can be utilised in the setting of storage targets for long-planning for allocation of water for different purposes. Other interesting approaches for fore-casting lake levels that hold promise for investigation have been developed else where within the Great Lakes in America (Cohn and Robinson, 1976) and the Aswan High Dam (Eltahir, 1996; Wang and Eltahir, 1999). The methods involve spectral analysis of water levels and use of El-Nino Southern Oscillation ENSO data to improve forecasting ability respectively.

### 4.3 Fisheries, Water Hyacinth and Schistosomiasis Studies

Welcomme (1969, 1970) studied the effects of abnormally high water levels between 1961 and 1966 on the ecology of fish around the Napoleon Gulf in Lake Victoria. He noted that the increase in levels,
produced changes around the shoreline of the lake, creating new habitats in the form of lagoons. Such lagoons were cut off from the main lake by differing widths of floating vegetation and were colonized by fewer fish species, which also showed a tendency to stunt. The population changes associated with isolation were attributed to the floating mats of vegetation that caused de-oxygenated conditions underneath, thus acting as a form of biological filter. Welcomme (1969) reported that the rise in water level was accompanied by short-term increases in catch per unit effort for endemic Oreochromis Esculentus (formerly Tilapia esculenta). Marten and Guluka, (1976) noted that fish catches of most species show two peaks a year and that there is good correlation of catch time-series with rainfall and lake levels.

Water Hyacinth is also another threat to lake Victoria Fisheries. It can cause the death of fish and other water organisms largely by depleting oxygen in the water when the plant dies and rots in large quantities. Seeds of the weed can lie dormant for years, buried under water. When the water level falls and the seeds are exposed, they are ready to shoot. Most of seeds will grow once the water level begins to rise as they are supplied with the necessary moisture. The Daily Monitor (12/06/2006) reported a resurgence of the weed following the recently declining water levels.

The weed provides an ideal habitat for bilharzia carrying snails and malaria carrying mosquitoes. The vectors anchor onto the plants and they are protected from waves. Many investigators have shown that Shistosomiasis is prevalent along the shores of Lake Victoria, Albert and Kyoga (e.g. Nelson, 1958; Ongom and Bradley, 1972; Bukenya and Abongomera, 1985; etc.) and noted that an effective control scheme could be delineated only when sufficient information regarding the dynamics and distribution of transmission, and in particular the influence of Lake Victoria, became available. Magendantz (1972) recorded the distribution and bionics of certain snail hosts located along Lake Victoria shoreline and their role in their transmission of Schistosoma mansoni. McCullough and Magendantz (1974) correlated prevalence and other factors to determine the relative importance of Lake Victoria in the transmission of Schistosoma mansoni and proved unequivocably that the lake can play a dominant role in the transmission of future infections. Kabateraine et al. (2004) established a clear relationship between distance to lake shore and prevalence of Schistosoma mansoni, a with prevalence < 15% at distances greater than 5 km.

4.4 WRAP Regulation Studies - 1998

Prior to completion of the Owen Falls extension, a DANIDA funded Water Resources Assessment Project (WRAP) under the Ministry of Water Lands and Environment of Uganda, commissioned a study to explore the regulation possibilities of Lake Victoria as a means to fully realise the potential benefits of the new dam.

Under the WRAP study, a simulation model was developed through which the impacts of alternative regulation rules on hydropower production can be assessed. The model represents Lake Victoria, Lake Kyoga and Lake Albert, and includes provision for the calculation of hydropower production at Owen Falls and at other potential sites downstream at Bujagali, Kalagala, Murchison Falls, Kamdini and Ayago. The model is driven by historical net basin supplies to each of the three lakes, and may be run using historical data from 1899 and 1997 (Mott MacDonald, 1998; Wardlaw et al., 2005). Outputs from the model include time series of simulated levels and discharges from each of the three lakes, and time series of potential power production at each hydropower installation. The time step of the model is monthly. The impact of any other consumptive uses of water and constraints on environmental flow on forecasted hydropower production is not explicitly taken into account in the simulations.
4.5 The Nile Decision Support Tool

The Nile Decision Support Tool (Nile DST) was developed as part of the Nile Basin Water Resources Project (GCP/INT/752/ITA) in collaboration with the Nile focal point institutions in the 10 countries of the Nile Basin (Huaming and Georgakakos, 2003). The purpose of the model is to assess the benefits and tradeoffs associated with various basin wide water development and management options. The Nile DST includes six main components: database, river simulation and management, agricultural planning, hydrologic modelling, remote sensing, and interface for the user. Detailed descriptions of each component are available in separate technical reports and manuals published by the FAO (Georgakakos, 2004).

The Nile-DST river simulation and management model component of equatorial lakes sub-basin is particularly relevant for this study since it is capable of simulating the flow of water through the various system nodes, reaches, and reservoirs. In it, two types of single reservoir regulation rules are included:

- Simple static rules e.g. releases are governed by the "Agreed Curve" for Lake Victoria and the natural unregulated outflow-lake level relationships for Lakes Kyoga and Albert.

- Simplified release-elevation rule curve, as illustrated under Figure 25. The rule divides the reservoir elevation into three zones: Zone 1, Zone 2 and Zone 3. If the elevation is in Zone 2, the release equals a constant \( Q_0 \); if the elevation is in Zone 1, the release decreases linearly slides to a minimum value; and if the elevation is in Zone 3, the release linearly increases to a maximum value. The boundaries of the zones, the constant value \( Q_0 \), and the minimum and the maximum values are all user specifiable.

![Figure 25: Simplified release-elevation rule curve (Huaming and Georgakakos, 2003)](image)

- Simple coordination built upon the single release rule but aimed at keeping the reservoirs fluctuating uniformly

Obviously, these rules do not offer system wide (multi-reservoir) coordination in short or real-time reservoir operation within the Equatorial Lakes Basin as the overriding objective was to simulate rules that are easier to implement while avoiding computationally intractable formulations.
4.6 Study on Water Management of Lake Victoria

The Lake Victoria Water Management Study was executed under a the Power IV - World Bank & NORAD funded project whose main objective was to improve power supply to meet demand by supporting least cost investments in Uganda (WREM Inc & Norplan Ltd, 2004). The Lake Victoria Decision Support Tool (LVDST) was one of the major outputs of the study. Figure 26 illustrates the LVDST design concept.

![LVDST design concept](image)

The LVDST (WREM Inc & Norplan (U) Ltd, 2004) includes four modelling layers, three of which pertain to operational planning and management of the Hydropower facilities at Kiira and Nalubaale and a fourth to assessment. The turbine load dispatching model identifies the most efficient turbine operation that meets a certain power target. The short/mid range model considers the integrated operation of power plants over a horizon of one month while the long range planning model prescribes the release targets to be utilized by the first two models and derives the benefits accruing to power and assess impact on the Sudd wetlands in Sudan on Energy Driven (ED) release policies or Agreed Curve (AC) policies.

5. PROBLEM STATEMENT & RESEARCH OBJECTIVES

5.1 Research problem

The research problem is to optimise releases from Lake Victoria to satisfy water uses and stakeholder interests upstream and downstream of the Nalubalea-Kiira Complex, including water supply, navigation, agriculture, fisheries and power generation requirements, as well as the requirements of communities dependent on the natural resources of downstream ecosystems, the needs of aquatic habitats and possible health impacts. Consideration of such wide-ranging demands and linkages has up to now not been considered in a holistic manner or within a unified decision support framework in the study area.
The problem essentially comprises the definition of monthly releases, hydroelectric generations and end of planning period storage levels for a three-lake system in series that can be harnessed for several purposes. There also exists a reservoir operator’s problem of detecting differences between present situations and goals and acting to eliminate such differences. The research will therefore deliver a set of improved real-time forecasting, planning and real-time reservoir operation models, that will be selected, customised and adapted for application with the objective of assisting stakeholders to reach compromise regulation policies.

5.2 Research questions

The three key questions that will be addressed by the research are:

- Which decision support systems are most appropriate for planning and managing large multi-dam operation along the Victoria and Kyoga Nile?

- How can such decision support systems be applied, adapted or developed to most effectively ensure successful participation and to assess the costs and benefits to all stakeholders?

- What are the optimum operating rules or regulation policies for Lake Victoria as defined by such decision support systems? How effectively can this research address issues related to adoption and acceptance of defined operating rules or regulation policies by practitioners.

5.3 Research objectives

The case study has two specific objectives:

- To utilize and further develop the existing DSS capability developed by various initiatives in the upper Nile and contribute to the development of an optimised release policy for Lake Victoria that takes into account all energy development and water management alternatives in a sustainable manner.

- To demonstrate and assess the applicability of innovative methodologies and tools to improve engagement and participation of stakeholders and decision makers at every stage of the decision process in the management of reservoir systems along the Victoria Nile and illustrate how the negotiation-facilitating tool can be used to arrive at the best win-win solution by identifying the optimum set of compromise alternatives.

5.4 Research hypothesis

The basic premise of the proposed case study is that traditional methods for planning dam operation which tend to maximise hydropower production in Uganda are inadequate and not sustainable. The principal research hypothesis of this proposal is:

"Contemporary decision support systems can play an important role in improving the operation of large dams along the Victoria Nile, minimizing negative impacts, improving livelihoods and public health, and sharing the development benefits."

5.5 Goals of the Case Study
The main goal of the case study is to optimize the productivity and equitable use of water stored in Lake Victoria and Lake Kyoga by generating and applying knowledge on how to manage trade-offs and promote synergies between different options for use, in a way that optimizes hydropower production, food security and water productivity especially for shoreline and riverine communities to ensure environmental sustainability while minimizing negative health and socio-economic impacts.

By acquiring, synthesizing and communicating knowledge about the benefits of using modern DSS in planning dam operations along the Victoria Nile, this case study will contribute to the specific research objectives of the CGIAR Challenge Program on Water & Food, Theme 4: “Integrated Water Basin Management Systems. This case study is also in line with the Mission Statement and research objectives of IWMI.

It is anticipated that better decision-making will bring more equitable distribution of benefits and that optimised use and allocation of water resources to competing water demands in the lakes Victoria & Kyoga and conservation of environmental functions will help alleviate poverty. By reducing inter-community and stakeholder tensions, the direct beneficiaries will be both people with lake-dependent livelihoods and people with downstream river-dependent livelihoods. The goals of this case study will be achieved by applying and assessing appropriate technologies and methods for integrated planning and management of water resource systems that have matured considerably over the past decades and simulating the operation of the next hydropower facilities.

5.6 Importance of the case study/problem

Lakes Victoria, Kyoga and Albert contain an estimated 3200 km$^3$ of fresh water (Kite, 1984). Lake Victoria catchment supports a population of 25 million people at income ranges in the range of US $ 90-270 per capita p.a. and although it is not possible to put a single estimate to the global value of the lake in sustaining the regional economies of Uganda, Kenya and Tanzania, over exploitation of the water resources and resulting deterioration can possibly result in an annual loss of productivity of the order of US$ 150 million (LVEMP, 1996).

The Nalubaale-Kiira complex is the principal source of power in Uganda. The cascade development program of dams proposed along the Victoria Nile presents operational challenges related to the need to regulate the lake for sustained benefits to both downstream and lakeside communities. By setting out to improve operational effectiveness and efficiency of the Nalubaale-Kiira complex and other planned hydropower facilities along the Victoria Nile through a process of conceptualising the systems of Lakes Victoria, Kyoga and Albert as multi-facility reservoirs, the study will contribute significantly towards enhancing livelihood benefits and protection of the environment.

5.7 Limitations of the study and research assumptions

A study of this magnitude ought to be supported by a number of ecological and socio-economic models to support meaningful decision-making. It will surely be difficult to model all aspects of ecosystem behaviour and response to altered lake levels and flow regimes and finally integrate it in an appropriate DSS. It order to overcome these limitations, expert judgement of a spectrum of practitioners, scientists and stakeholders will by captured through fuzzy set theory. It will be assumed that the stakeholders have a clear image of a good solution their minds and that during a supported decision-making exercise, compromise solutions can easily be reached. It will also be assumed that selected models to support the decision making exercise are sufficiently representative of what is actually a very complex system of water resources and are credible and acceptable to practitioners.
One of the limitations is that leave from absence from my workplace shall be granted for a maximum of only 4-months each year. A flexible program is therefore required to support completion.

6. OUTPUTS/EXPECTED CONTRIBUTIONS

The key outputs from this case study will be;

- PhD thesis
- Improved knowledge on the use of state-of-the-art DSS to assist in better planning of reservoir and dam operation. More specifically research findings are expected to demonstrate how:
  - Quantitative, qualitative, commensurable and non-commensurable objectives can rationalised in a comprehensive decision-making framework, that enables aspects of a system to be linked in a consistent manner.
  - To improve understanding of the consequences of different options for reservoir operation in terms of food security, energy production, health and ecological objectives.
  - To facilitate stakeholder participation in the decision-making process, with an emphasis on weak social and economic groups.
- Contribute towards the complex process of formulating an alternative release policy and negotiation strategy for Uganda Government within the frame-work of the Nile Basin Initiative.

6.1 Deliverables of the project

- Adapted and customised operational decision support tools for the case study
- Operational curves and their impacts on ecosystem and human needs objectives
- Documented experiences and lessons learnt in the use of such tools in a multi-stakeholder process of interaction whereby participants are asked to state preferences over different operational or regulation polices and alternatives.
- Possibly a set of consensus derived operating rules and policies for Lakes Victoria, Kyoga and Albert to be considered for political debate.

6.2 Contribution of the research results towards scientific knowledge

The literature reviewed for this study has demonstrated that formulations of linear quadratic stochastic control problems with linear constraints and quadratic benefit functions have successfully been applied to yield optimal operating policies for similar larger systems of reservoirs and hydropower plants. In such formulations it has been assumed that benefit functions are strictly concave or convex. Linear-quadratic control algorithms do not require discretization of the state and control spaces and therefore do not suffer from the curse of dimensionality generally associated with other dynamic programming techniques. However, the stochastic dynamic programming approach has the advantage of accommodating a wider range of possible benefit functions, state equations, inequality constraints, statistical descriptions of future inflow and preservation of system generality (McLaughlin and Velasco, 1990). Whereas it has often proven to be difficult to obtain a solution when these generalities are fully
exploited for multiple reservoirs, functional approximation of Bellman functions with Artificial Neural Networks offers exciting possibilities to reduce computer time in deriving solutions.

It is envisaged that the approach to the research problem shall be a search for optimal operating rules within in a framework of conflicting objectives/stake holder preferences, some of which are expected to be non-commensurable. In order to increase the resolution of the discretisation to enhance adherence of the model to the real world and to consider more controls and states to describe a complex system of lakes, it may happen that the time required to compute a policy becomes excessively long.

The set of adapted and customised models that will be developed for this study are expected to contribute towards scientific knowledge by generating data on the theoretical performance of NDP techniques to a real world-case study of a system of large lakes. In their preliminary work on a similar problem, De Rigo et al. (2001) and Castelletti et al. (2005) have reported promising results and scope for more research on the efficient sampling of the discretised search space in order to obtain the most efficient approximation of the Bellman function. The study shall offer insight into methods of choosing the right ANN networks, the number of neurons and if multiple layers are required, the distribution of neurons in each layer.

The basis of a good reservoir-operation system is to view forecast and decision making as a whole unit (Yang et al., 1995). One of the undertakings under this study is to set up a forecast model for the Equatorial Lakes water levels to support decision making in reservoir operation. Application of Spectral analysis techniques to Equatorial water level fluctuations will reveal the presence of prominent frequent components that can be isolated and described with respect to their amplitudes and phases. Because these fluctuations are natural phenomena that have recurred throughout the recorded history and are expected to continue in the future, they can be extrapolated and combined to provide a forecast which predicts future stages of high and low levels (Cohn and Robinson, 1976) from the position and amplitude of component frequencies. If this output is achieved, this is another area of potential contribution to the body of scientific knowledge of Equatorial Lake Levels that can be utilized within the context of risk-averse reservoir optimisation. The work of Eltahir (1996, 1999), who established a relationship between the mean annual flow of the Nile at Aswan and the index of Elnino-Southern Oscillations (ENSO) given the Sea Surface Temperatures (SST) conditions in the Pacific Ocean is potentially applicable to the Equatorial Lakes. If spectral analysis presents evidence of a 3-6 month lag time period between ENSO phenomena and Equatorial Lake Net Basin Supply series then a suitable forecasting algorithm can be formulated for use in operational decision-making.

6.3 Beneficiaries from the research

The beneficiaries of this research can be categorised as;

- Local environmental pressure groups such as National Association of Professional Environmentalists (NAPE)
- Stakeholder groups such as shoreline populations, operators of navigation facilities such as piers and landing sites, white water rafting companies, Hydropower producing companies such as ESKOM and the fisheries industry.
- Government regulating agencies such as Water Resources Management Department at Entebbe and Ministry of Energy-Uganda
- Lake Victoria Development Program of the East African Community secretariat and the Lake Victoria Basin Commission
7. RESEARCH STRATEGY

7.1 Proposed approach

The survey of contemporary DSS and approaches to reservoir operation in Chapter 4 of this proposal suggests a common framework of an appropriate decision-making framework that consists of four main stages;

1) Structuring the problem
   - identification of interest groups
   - definition of objectives and selection of decision criteria
   - identifying operational, measurable attributes
   - criteria for use in evaluation of alternatives

2) Model identification

3) Interactive search of Pareto optimal alternatives

4) Seeking group consensus

The activities will be broadly divided into six phases:

Month 1-8: Completion and defense of this research proposal. This phase has been ongoing and will be completed before the end of November 2006.

Months 9-12: Participatory problem structuring

Months 13-30: Model identification and customisation and testing

Months 31-34: DSS application and interactive search for pareto-optimal alternatives

Months 34-37: Seeking group consensus

Months 38-45: Consolidation and write-up of study findings

Between month 9 and 12, decision analysis interviews will be held to clarify different stakeholder opinions, confirm and agree upon management objectives and range of management interventions. During months 13 to 30, a Multi-Objective DSS for management of reservoir systems will be adapted, customised and tested for application to the case study. Months 31-37 have been set aside for testing and refinement of approaches suggested for stakeholder consultation and modification through experience gained. The last phase (months 38-45) of the program will comprise synthesis and consolidation of research findings. The principal activities will be the write up of the PhD Thesis and at least two papers to be published in scientific journals.

7.2 Methodology

The detailed methodology is described along the four main stages of the research approach as follows;
7.2.1 Structuring of the problem

The main activities under problem structuring shall be the decision analysis interview process which involves stakeholder seminars and computer aided decision analysis interviews. A sequential illustration of what needs to be done is illustrated in Figure 27.

![Diagram of problem structuring process]

Figure 27: Stages of the problem structuring process (Marttunen and Hamalainen, 1995)

The primary aim will be to promote understanding of the problem by value structuring. The issue of stakeholder involvement and eliciting public values will be approached by organising seminars or role-playing experiments where decision analytic problem solving will take place. Stakeholder representatives will be selected carefully to ensure they advocate for a wide range of different opinions. They could also be grouped according to similarity of interest or commonality of sectors they represent. Individual interactive computer supported interviews will be based upon prioritisations in a value setting without explicitly modelling the uncertainties about consequences of the flow alternatives. The prioritisation process will be initiated by inspecting pre-assigned rating of alternatives. The computer program HIPRE 3+ will be used for value tree analysis and presentation of results in graphical form.
Flow alternatives that could be presented for elicitation of stakeholder responses would include, but are not be limited to the following:

a) maintaining current historical dam operations (AC policy),
b) fully utilize existing hydropower plants (ED policy),
c) releases designed to minimise costs of a combined Hydro-thermal system, and
d) releases in accordance to historical regulation plans (Kite, 1984; Bakhiet, 1996).

Typical assignment of impact response or rating value for every objective together with indicators and indexes for a shoreline dweller stake holder representative may resemble Table 3.

Table 3: Typical indicators and indexes of a lake coastline population (Soncini-Sessa et al., 2000)

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Description</th>
<th>Unit</th>
<th>Estimator</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings</td>
<td>Highest peak level</td>
<td>m</td>
<td>( \max_i (h_i) )</td>
<td>0.378</td>
</tr>
<tr>
<td></td>
<td>Mean annual flooded surface</td>
<td>km²/dy</td>
<td>( \frac{1}{N} \sum_i s (h_i) )</td>
<td>0.622</td>
</tr>
<tr>
<td>Shoreline Walls</td>
<td>Low level fluctuations</td>
<td>-</td>
<td>( \sigma (h_i; h_i &lt; 0.8 \text{ m}) )</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>Mean annual number of low level days</td>
<td>d/y</td>
<td>( \frac{1}{N} \sum_i l_i \text{ where } l_i = 1 \text{ if } h_i &lt; 0.3 \text{ m, } l_i = 0 \text{ else} )</td>
<td>0.300</td>
</tr>
<tr>
<td>Navigation</td>
<td>Minimum level</td>
<td>m</td>
<td>( \min_i (h_i) )</td>
<td>0.100</td>
</tr>
<tr>
<td></td>
<td>Mean annual lake level deficit</td>
<td>m/y</td>
<td>( \frac{1}{N} \sum_i (0.3 - h_i) )</td>
<td>0.600</td>
</tr>
<tr>
<td>Tourism</td>
<td>Mean annual number of days with lake level not in the tourism range (t.r.)</td>
<td>d/y</td>
<td>( \frac{1}{N} \sum_i T_i \text{ where } T_i = 1 \text{ if } h_i \leq t.r. ), ( T_i = 0 \text{ else} )</td>
<td>1.000</td>
</tr>
<tr>
<td>Other Activities</td>
<td>Mean annual flooded surface</td>
<td>d/y</td>
<td>( \frac{1}{N} \sum_i s (h_i) )</td>
<td>0.233</td>
</tr>
<tr>
<td></td>
<td>Mean annual number of flood days</td>
<td>d/y</td>
<td>( \frac{1}{N} \sum_i f_i \text{ where } f_i = 1 \text{ if } h_i &gt; 2.0 \text{ m} ), ( f_i = 0 \text{ else} )</td>
<td>0.767</td>
</tr>
<tr>
<td>Environment</td>
<td>Correlation index between the levels in the controlled and in the natural lake</td>
<td>-</td>
<td>( \tau (h_i, h'_i) )</td>
<td>1.000</td>
</tr>
</tbody>
</table>

\( h_i \) = lake level in day \( i \), \( s(h_i) \) = lake surface at level \( h_i \); \( N \) = number of years, \( \sigma \) = standard deviation, \( \tau \) = correlation of \( x \) and \( y \); \( h_i' \) = lake level in natural regime.

These need to be generated for each flow alternative and for every stakeholder grouping. The rating is generally expected to produce a matrix of non-commensurate values that include a mix of qualitative statements and/or numeric values in a variety of units. To overcome the non-commensurate mix of units used in ratings, one standard quantitative rating scale may be adopted.
7.2.2 Model identification, customisation and testing

To model the effects induced by a given alternative and to support choice of efficient alternatives at later stages, a set of models is required. Selection of applicable models will be influenced by observations documented under Section 2.9 of this proposal. The most appropriate model conforming to the adopted decision making framework is TwoLe (Figure 24). However, the forecasting component and the real-time operating module for this model need to be developed further before it can be considered suitable for application to this case study. Furthermore, for purposes of generating operating rules, TwoLe must be complimented with a more suitable simulation tool such as NILE DST. Even then, the combination of TwoLe and NILE DST is not sufficient to simulate the operation of the next hydropower facilities given a known operating policy. The LVDST and the tools developed under WRAP Lake Victoria regulation studies are better equipped to provide such information. One of the key questions to be tackled at this stage will be how to most efficiently link predictive models together. The issue to resolve here is compatibility of software tools. It will be of interest to establish whether models have been written in an object oriented language so as to diminish concerns about integration.

There is no reported case of application and testing of TwoLe to a system of multiple reservoirs. This is due to the fact that the core algorithms constituting the planning level of the DSS reported in the studies by Aufiero and Soncini-Sessa, (1995, a,b,c); Guariso et al. (1984); Nardini et al. (1992); Orlovski et al. (1983 and 1984) and Piccardi and Soncinî-Sessa (1991) were formulated to find operating policies with two management goals (water supply and flood control) as the consideration of other objectives within a framework of multi-purpose reservoirs would pose considerable difficulties in computational efficiency. However, recent studies by De Rigo et al., (2001) and Castelletti et al., (2005) that demonstrated a superior efficiency of NDP over NDP to the solution of an IWRM multi-objective problem in the Paive catchment in Italy which had 3 three reservoirs hold promise to investigate the viability of application of TwoLe to the Equatorial Lakes case study. However, it is not clear as to whether these improvements to the core algorithms, are incorporated into Twole. If it is not the case then it is envisaged that the modification, adaptation to the requirements of the case study and integration of these NDP techniques will be a major task.

TwoLe is designed to generate “set-valued” management policies (releases associated with the same performance) that are intended to play a central role in the process of assisting stakeholders to generate a diverse range of alternatives utilizes lexicographic optimisation to find a new alternatives that improve the utilities of the unsatisfied stakeholders without lowering too much the utilities of the favourable ones, in an iterative fashion to assist stakeholders reach a compromise. Whereas these attributes make it an attractive option of choice for a stakeholder based DSS tool, the need to preserve and sustain ecosystem integrity, underlines the importance of combining it with other models in order to have a more complete set of tools to support sustainable reservoir operation to balance human needs and environmental releases. For this reason, the non-dominated sorting genetic algorithm (Suen and Eheart, 2006) will be considered as an option to complement TwoLe for purposes of finding a Pareto set of operating rules that provide decision makers with the optimal-trade off between human needs and ecological flow regime maintenance.

Forecasting serves two purposes in TwoLe. Long range forecasts (lead time longer than the hydrological response timescale) provide real, synthetic or hypothetical sequences of inflows, which the reservoir manager considers suitable for testing the reliability of any operating rule at planning level while medium range forecasts (lead time shorter than the hydrological response timescale) assist in the utilisation of resources in an efficient way in the short and medium term at the management level in accordance to directives issued at planning level. Approaches to formulating long-term and medium-term forecasts will be different.
Algorithms to perform spectral decomposition and digital filtering of historical Equatorial Lake levels to permit isolation and description of low-frequency periodicities and tentative prediction of water levels will be formulated. Monthly measurements of the lake stages will be decomposed into series of component sinusoids that can be characterised by wavelength, amplitude and phase components (Jenkins and Watts, 1968). According to Cohon and Robinson (1976), High amplitude components reflect periodic variations in lake levels while low amplitude components are more representative of noise and contribute mainly to minor variations in the frequency spectrum. Wavelength of components denote the repeat time of events while phase reflects repeat time of specific years when peaks and troughs actually occur. Evidence of high amplitude frequency components that normally suggest naturally cyclic events in the lakes (Bargman et al., 1965) will be confirmed, extrapolated and projected to possibly predict forthcoming fluctuations in Equatorial Lake Levels.

Eltahir (1996), reported results from analysis of data sets describing the sea surface temperature of the Pacific Ocean and the flow of water in the Nile at Aswan. The analysis suggested that 25% of the annual variability in annual flow is associated with El Nino-Southern Oscillation (ENSO) phenomena. Motivated by successful ENSO predictions with a lead time of several months or longer (Zebiak and Cane, 1987), Wang and Eltahir (1999) extended the study by Eltahir (1996) and established by method of cross spectral analysis that ENSO precedes the Nile flow by about 3-5 months. Similar analysis will be performed for time series of to establish whether such time lags are also evident between ENSO and Lake Victoria NBS time-series. Wang and Eltahir (1999) developed algorithms for dealing with the forecasting probability of the Nile Flood using three sources of information (ENSO, rainfall, and prior river flow). The viability of adapting and customising these algorithms to predict Lake NBS using ENSO data, rainfall over the lake and prior observed NBS (based on observed change in storage and releases) will be investigated. Wang and Eltahir (1999), report that this methodology is appropriate for long term forecasts where lead times are longer than the hydrological time scale response.

In medium forecasts, ENSO information does not play a dominant role. Information of rainfall and tributary inflow are more likely to produce large improvement to forecasting quality. Suitable stream flow forecasting procedures based on periodically stationary Markov processes are readily available and widely reported in the work of Curry and Bras (1980), Buchanan and Bras (1981) and Bras et al., (1983) and for purposes of brevity, details of algorithm development will not be expounded. In general, they in the form of multivariate autoregressive (AR) stream flow techniques that take into account cross correlations between different stream-flow stations and permit the introduction of multi-lags in the AR process. The AR parameters can be estimated by maximum likelihood and the AR process can be utilized for recursive stream flow forecasting. This particular approach is more suited for forecasting releases for Hydropower stations along the Victoria Nile.

7.2.3 DSS application and interactive search for pareto-optimal alternatives

The DSS/P in Twole will be utilized to derive alternative schemes of reservoir controls/operating policies. Alternative schemes are defined in accordance to the range of objectives of the stakeholders. These may include maximisation of hydropower use, historical regulation plans or desirable strategies such as the integration of risk aversion to avoid dramatic failures due to floods and droughts and average performance optimisation to yield the best long-term average performance. As an example of application, a risk aversion (min-max) problem may be formulated, whose solution is not unique, but rather a whole set of policies, all equivalent from the point of view of the risk-aversion objectives. This means that, given the system state, a whole range of releases is permitted. This range of permitted releases is referred to as the “min-max range”. The theory, formulation and solution algorithms for a
min-max two-objective problem was first developed by Orlovski et al. (1983,1984). Results of application are illustrated by Guariso et al. (1984) and Soncini-Sessa et al. (1990). The approach can be briefly described as optimisation of the worst performance of a reservoir system corresponding to several one year inflow sequences defined by a reservoir manager as representative of critical sequences of hydrological conditions experienced in the past or generated synthetically. Efficient solutions suggested by the min-max approach can be visualized in terms of classical storage allocation zones whose min-max range at time t depends on the reservoir inflow $a_t$ (in flow volume in the interval $(t, t+1)$). The formulation of the risk-averse problem is deterministic and $a_t$ is assumed to be a known quantity. Thereafter, average performance two-objective optimisation problems can be formulated in accordance to defined stakeholder interests or management objectives and solved, with the constraint that sought policies belong to the set previously selected. The solution of the two-objective problems can be reduced to the solution of several one-objective optimal control problems by means of the weighting method or constraints (Cohon and Marks, 1975).

Each of these one-objective problems can be solved as an average cost optimisation problem and after discretisation, the problem can be solved by means of SAA based on DP (White, 1963; Bertsekas, 1976; Nardini et al., 1998). The DP solution technique associated with this approach strongly limits the complexity of the reservoir inflow models. Computational efficiency is also likely to be adversely affected by the number of reservoirs in the study therefore Bellman functions in the DP formulation will be approximated a suitable ANN and a solution by NDP will be sought.

DSS/P in TwoLe allows the Systems Analyst scope for experimenting with other approaches in reservoir management such as those not confined to a min-max constraint and others that allow the use of sophisticated inflow models. These options will be utilized to consider the maintenance of ecological flow regimes as one of the management objectives in the case study. An optimisation problem will be formulated to determine a release rule to maintain managed flow regimes as similar as possible to the flow regimes least affected by human influence and still provide reliable amounts of water for human needs (domestic, agricultural and power needs). Application of the non-dominated sorting genetic algorithm (NSGA-II) proposed by Suen and Eheart (2006) will be investigated as a complimentary tool to TwoLe so as to find the Pareto set of target effective storages which can determine trade-off between human needs water shortages and ecological regime maintenance. Historical data for the case study area will be considered as a reference set for a minimally disturbed system and ideal levels of variation will be ascertained. Fuzzy set theory (Zimmermann, 1985), will be applied to a set of selected eco-hydrological indicators as a means of representing the degree of disturbance levels. Each indicator will be assigned membership values of a fuzzy number ranging between zero and 1 as illustrated under figure 28 below.

![Fuzzy membership function to present the IDH concept applied to ecological flow regimes (Suen and Eheart, 2006)](image)

Figure 28: Fuzzy membership function to present the IDH concept applied to ecological flow regimes (Suen and Eheart, 2006)
The fuzzy number possesses a Gaussian shape membership function used for a scaling process according to equation 12 below where \( \mu \) is the membership value of the ecohydrological indicator. The \( m \) and \( \sigma^2 \) are the mean and variance of the historical indicator values, respectively as extracted from stream flow gauge stations.

\[
\mu(x) = e^{-\frac{(x-m)^2}{2\sigma^2}}
\]  

(12)

For each ecohydrological indicator, membership values of the intermediate ranges are shown as closer to 1, while lower or higher hydrologic variations are assigned lower membership values. As a guideline, eco-hydrological indicators proposed by Suen et al. (2004) may be adapted or modified to facilitate their use for the case study. These indicators are dry-season 10-day minimum, wet season 3-day maximum, number of high flow events and mean duration of low flow events. Maximising the membership values of the indicators then becomes the surrogate objective for maintenance of aquatic ecosystems. A suitable GA will be used to find the optimal solution for ecosystem and human need separately. A pareto front similar to Figure 19 with a number of non-dominated solutions for considered objective functions will be presented and explained to stakeholders for preference selection.

Alternative operation policies will be associated with costs or implications and presented to stakeholders with the aid of suitable computer software. The interface proposed by Hämäläinen et al., (1999), will be adopted to find stakeholders’ preferred alternatives in a “jointly improving direction”, by seeking answers from a set of pairwise comparison questions iteratively as illustrated in Figure 29.

![Figure 29: User interface for finding subjects preferred alternatives (Hämäläinen et al., 1999)](image)

7.2.4 Seeking group consensus

Previous stages of the decision support framework have included structuring and identifying the problem and scanning of alternatives to identify the efficient ones. At this third and last stage, a set of well studied and carefully selected efficient alternatives will be examined further by the stakeholders. The objective will be to reach consensus about the alternative defining the action to be taken, in our case the future regulation practice. Lexicographic optimisation (Weber et al., 2002) and interactive decision aiding techniques (Salo, 1995), will be applied in this group decision task. Parallel sessions of specific stakeholder groups will be set up where each group may be represented by one subject. Subjects will be asked to prioritise presented alternatives and decision criteria within a commonly agreed Value Tree model (see Figure 21). The web-based model web-HIPRE which can be run in the
world wide web will be utilized for this task. Pairwise preference statements made by the subjects will be combined in a preference programming model according to the methodology proposed by Hämäläinen et al., (1999). For example, under the element “Economic” in the Value Tree illustrated in Figure 21, one subject may state that “Fishing” is five times as important as “Tourism”, another may weight these two criteria equally while all others may indicate that “Fishing” is three times as important as “Tourism”. These individual preference statements will be combined into an interval group preference model with the HIPRE 3+ Group Link software (Hämäläinen and Kettunen, 1994). The next step will be to evaluate the group interval preference model with the subjects. The model helps to guide discussion into conflicting issues. Using an interactive computer tool consensus will be reached searched by adjusting interval preference statements by proposing preference tradeoffs. This can be supported by WINPRE software (Hämäläinen and Helenius, 1998), which shows interactively how changes in preference intervals affect the weights of alternatives. If a dominant alternative can be found by this process, then it is a very strong consensus.

7.3 Software/hardware availability

Software required for the group decision interaction and negotiation processes has already been obtained from the Systems Analysis laboratory of the Helsinki University of Technology. Formal permission to apply the Nile DST and LVDST for the study will be sought from FAO. The status of availability of Twole software and conditions of application for academic purposes has not yet been resolved. The research budget for this study allows for the procurement of a high processor speed computer with provision for large external storage devices and Landsat images.

8. CONCLUSION

An accelerated decrease of lake Victoria Levels that has been attributed to a period of drought and excessive release of water to satisfy hydropower demands poses significant risks to aquatic ecosystems, navigation facilities, and livelihoods of Equatorial Lake communities and other riparian states that depend on the Nile. There is thus an urgent and current need to focus on the improvement of the operational effectiveness and efficiency of existing and planned dams along the Victoria and Kyoga Nile, in Uganda for the benefit of all stakeholders, by conceptualising this system of Equatorial Lakes as multi-facility and multi-purpose reservoirs. The regulation of Lakes Victoria, Kyoga and Albert is therefore considered as a case study problem to be tackled from a wider stakeholder and ecological perspective, to test a research hypothesis for this proposal that states that “contemporary decision support systems can play an important role in improving the operation of large dams along the Victoria Nile, minimising negative impacts, improving likelihoods and public health and sharing the development benefits”.

From a review of approaches, mathematical models and contemporary DSS for planning reservoir operation and management, it is concluded that there is no simple answer to the question of which models and analyses techniques to be used to test the research hypothesis. However, certain factors that are unique to the problem to be solved e.g. high state dimensionality of a system of interconnected lakes impact of stochastic inflows, inherent system non-linearities and non-convexities, the dynamic multi-stage structure of reservoir operation dictate that at least two optimisation models (SDP, NSGA-II), different approaches to reservoir operation (risk averse, average performance optimisation, maintainance of ecological flow regimes) are combined together with non-linear mathematical structures (NDP and ANNs), simulation models (Nile DST, LVDST) to define suitable operating rules or flow management alternatives. The requirement to subject these rules to stakeholder appraisal and
evaluation had led to a proposed methodology and four-stage procedure that integrates multi-objective optimisation models and multi-criteria decision analysis techniques to enable the systems analyst to take into account evolving relationships between the decision makers, regulators and stakeholder values. It is hoped that application of this methodology to the study area will contribute towards the complex process of formulating alternative release policies for the Equatorial Lakes for the benefit of all Nile Basin Countries.

**APPENDIX**

A. Discrete Representation of Storage

In a scheme that has been widely used by many researchers, the number of zones Z is equal to SDN (Z = SDN) and the storage increment is $\Delta S = \text{CAP}/\text{SDN}$ (Figure 30).

![Figure 30: Discrete representation of storage for capacity equal to 16800 and SDN = 8 (Karamouz and Vasiliadis, 1992)](image)

For each state $k$, at time $t$, the characteristic storage sets can be calculated as

$$S^c_t(k) = \frac{\Delta S}{2} + (k-1)\Delta S = \frac{2k-1}{2} \Delta S \quad \forall \ k \in [1, \ldots, \text{SDN}],$$

(13)
In this scheme, the zero and full storage levels are not included as separate characteristic storage values. As an improvement to this scheme, two other approaches are available in the literature, one by Saverenskiy (1940) and the other by Moran (1954). In Saverenskiy’s scheme, each of the Z zones is regarded as a class interval, and the corresponding storage state is defined as centre point of this interval. In addition, empty and full reservoirs are defined as separate states with zero class intervals. As a result \( Z = SDN-2 \) and the storage increment is \( \Delta S = \frac{CAP}{(SDN - 2)} \), with characteristic storage values calculated as

\[
S_t^c(k) = S_0^c + \frac{(k-2)\Delta S}{2} \quad \forall k \in [2, \ldots, SDN - 1],
\]

with \( S_t^c(1) = 0.0 \) and \( S_t^c(SDN) = CAP, \forall t \in [1, \ldots, T] \).

In Moran’s scheme, the characteristic storage values are defined on the boundaries between the zones, so \( Z = SDN-1 \), \( \Delta S = \frac{CAP}{(SDN - 1)} \), and with storage states calculated as

\[
S_t^c(k) = (k-1)\Delta S \quad \forall k \in [1, \ldots, SDN]
\]

It may seem that the difference between the last two schemes is unimportant, but it has been shown by Doran (1975) that SDP algorithms using Saverenskiy’s scheme converge to the steady state solution faster those based on Moran’s. The value of SDN is a very important factor, and it has been shown by Klemes (1977) that if the representation of the storage is too coarse, the accuracy of a discreet approximation to represent the continuum of the storage will be lost. Karamouz and Houck (1982) showed that for a reservoir of up to 170% of the mean annual flow, 20 storage values could be adequate. They also suggested that for reservoirs of 20-100% of the mean annual flow; little or no improvement can be gained using a higher number of characteristic storages.

B. Procedure for calculation of characteristic flows for each interval in a flow discretisation scheme

A flow discretization scheme that has been used by many researchers e.g. Karamouz and Houck (1982), consists of diving the entire flow range \( \Delta F \), from \( Q_{min} \) to \( Q_{max} \) into DN class intervals with constant flow increment \( \Delta F = \frac{\Delta F}{DN} \). In this scheme, the characteristic flow \( F^c(i) \) for each class interval is defined as the mean of the lower and upper bounds of the corresponding class interval. This value will represent all the flows in that class interval. Karamouz and Vasiliadis (1992) noted that any changes in the values of the upper and lower bounds of the class intervals result in a completely different value. To overcome these shortcomings, they tried an improved approach where each class interval is divided into a number of intervals which are called class subintervals, and a probability distribution of inflows occurring in each class interval is defined, using frequency analysis for each class subinterval. The characteristic flow for each interval is then defined as the expected value of flows in that interval. Karamouz and Vasiliadis (1992), then found that the mean mean and variance of the characteristic flows could turn out to be very different from those of the original series and that some intervals might have a small number of data, which could result to a poor estimation of transition probabilities from these intervals to others. Karamouz and Vasiliadis (1992) therefore proposed another method where the intervals are equiprobable, by adjusting the width of each class interval (figure31), and the variance of data within each class interval is kept small by increasing the number of class intervals.
The procedure for calculating $F^c(i)$ is summarised as follows; Let

- $N(i)$ be the number of data in the $i$th class interval
- $n(i,j)$ be the number of data in the $i$th and the $j$th sub interval (where $n(i,j) < N(i)$)

$f^c(i,j)$ is the average of the lower and upper bound of the $j$th sub interval

**Equations:**

- $F_{\min} = FR(1) = fr(1,1)$
- $F_{\max} = FR(DN+1) = fr(DN,dn+1)$
- $N(i) = \text{INT} \left( \frac{N}{DN} \right)$ (constant)
- Note: $FR(i)$ is the $[N(i) x (i-1) + 1]$th flow, after sorting
- $dn(i) = \text{INT} \left( 1 + 3.3 \times \log (N(i)) \right)$ (constant)
- $df(i) = \frac{FR(i+1) - FR(i)}{dn(i)}$
- $fr(i,j) = df(i) \times (j-1) + F(i)$
- $f^c(i,j) = \frac{fr(i,j) + fr(i,j+1)}{2}$
- $F^c(i) = \sum_{all j} \left[ \frac{n(i,j)}{N(i)} \times f^c(i,j) \right]$
- all $i$ in $[1,...,DN]$
- all $j$ in $[1,...,dn(i)]$
SI (i) is the number of class intervals the ith class interval is divided

Then the characteristic value for each class interval is calculated using the following formula:

\[ F^c(i) = \sum_{j=1}^{N(i)} \left( \frac{n(i,j)}{N(i)} \right) f^c(i,j) \quad \forall i \in [1, \ldots, DN], \]

\[ n(i,j) \in [1, \ldots, N(i)], N(i) \in [1, \ldots, N] \]

An alternative expression to (10) is

\[ F^c(i) = \sum_{j=1}^{N(i)} \left( \frac{x(i,j)}{N(i)} \right) \quad \forall i \in [1, \ldots, DN], N(i) \in [1, \ldots, N] \]

where \( x(i,j) \) is the jth flow in the ith class interval. Karamouz and Vasiliadis (1992) explain that this method of selecting characteristic flows results in better transition matrices. Furthermore, the characteristic flows preserve the mean and variance of the original time series, as well long as the number of class intervals is sufficiently large.

B. A Steady State Stochastic Dynamic Programming Algorithm

Following the notation used by Bras et al. (1983), consider the following:

- \( T \) number of time periods per cycle
- \( t \) number of time periods remaining in a cycle (\( t = 1, \ldots, T \));
- \( m \) integer number of full cycles remaining until the end of the planning horizon;
- \( n \) number of time periods remaining until the end of the planning horizon.

Here, one cycle pertains to a year, and each time period corresponds to one month (i.e., \( T = 12 \); \( t = 1 \) for December, \( t = 12 \) for January). The relationship \( n = mT + t \) holds. This implies that for a given value of \( T \), the value of \( n \) uniquely determines the value of \( t \) (for example, when \( T = 12 \), \( m = 0, 1, 2, \ldots \), and \( n = 1, 13, 25, \ldots \), respectively, \( t = 1 \)). The state variables are defined as follows:

- \( S_i^t \) storage state variable representing reservoir volume at the beginning of the month time interval \( t \). This storage may take on \( M \) discrete values \( i = 1, \ldots, M \);
- \( Q_{j+1}^t \) inflow state variable representing flow into the reservoir during the time period \( n+1 \) (or \( t +1 \)). This inflow may take on \( N \) discrete values \( j = 1, \ldots, N \);
- \( S_i \) ith discrete value of storage, \( i = 1, \ldots, M \)
  \[ S_1 > S_2 > \ldots > S_M \];
- \( Q_j \) jth discrete value of inflow \( j = 1, \ldots, N \)
  \[ Q_1 > Q_2 > \ldots > Q_N \]

Inflow transition probabilities are defined:
$P_{nk}^*$ is the probability of occurrence of inflow k during time period n, given that in that in Period n+1 inflow j was realised.

The definition of $Q_n$ and $P_n$ as a function of the cycle $m (n=mT+t)$ implies that the stochastic description of the inflow process for each month can vary from year to year. Assuming a periodic stationary markov process the following conditions are assumed to hold:

$$\mathbb{E}[Q_{n+1}^m] = \mathbb{E}[Q_{n}^j] \quad \forall j,m,t \quad (18)$$

$$\mathbb{E}[P_{n+1}^m] = \mathbb{E}[P_{n}^j] \quad \forall j,k,m,t \quad (19)$$

By using conditions (18) and (19), the remaining definitions are given as follows:

$$R^*(S_i^k, Q_{j+1}^*)$$ optimal release decision for month t, when the storage state is $S_i^k$, the inflow is $Q_{j+1}^*$, and $n(=mT+t)$ periods remain until the end of the planning horizon;

$$L_i(S_i^k, Q_R^k)$$ losses from reservoir during month t, when the initial storage is $S_i^k$, the inflow during the month is $Q_R^k$, and the release is $R$;

$$g_n(S_i^k, Q_R^k)$$ costs incurred during time period n(=mT+t), when the initial storage is $S_i^k$, the inflow during the month is $Q_R^k$, and the release is $R$;

$r$ monthly rate of discount ($r=0$ for the undiscounted case);

$\beta$ $1/(1+r)$

$S_{\text{max}}$ maximum reservoir storage;

$S_{\text{min}}$ minimum reservoir storage;

$f^{**}(S_i^k, Q_{j+1}^*)$ minimum expected cost from the present period to the end of the planning horizon ($mT+t$ periods to go), provided that in month t the system is in states $(S_i^k, Q_{j+1}^*)$

Bras and Curry (1983) explain that for a given definition of $g_*(\cdot)$, the system will be stationary (in a periodic manner) if the following conditions holds:

$$g_{m,t,l,k}(S_i^k, Q_R^k) = g_t(S_i^k, Q_R^k) \quad \forall m,t,l,k \quad (20)$$

By assuming that conditions (1), (2) and (3) hold an optimal steady state release policy can now be derived from the solution procedure to follow.
The conservation of mass equation is applied:

\[ S_{t-1}^i = S_t^i + Q_k^i - R - L \ (S_t^i, Q_k^i, R) \]  (21)

The algorithm uses a backward induction solution scheme, computing \( f^n(\ ) \) for \( n \geq 1 \) from the recursive relation:

\[
f^n(S_t^i, Q_{t+1}^j) = \min_{j} \left\{ P_j \left( g_i(S_t^i, Q_k^i, R) + \beta f^{n-1}(S_{t-1}^i, Q_k^i) \right) \right\}^{T = 1, \ldots, 12}
\]
\[
t + 1 = 1; \quad \text{if } t = 12
\]
\[
t - 1 = 12; \quad \text{if } t = 1
\]

where

\[ R = S_t^i - S_{t-1}^i + Q_k^i - R - L \ (S_t^i, Q_k^i, R) \]  (23)

Should \( S_{t-1}^i \) be greater than \( S_{\text{max}} \), it is then made equal to \( S_{\text{max}} \) and used in (6). If the storage \( S_{t-1}^i \) falls below the minimum storage, it is again made equal to that \( S_{\text{min}} \) before using it to compute releases in (6). Su and Deininger (1972) show that arbitrary values can be assigned to boundary conditions \( f^0(\ ) \) and are here taken as:

\[
f^0(S_t^i, Q_{t+1}^j) = 0 \quad \forall \ i,j
\]  (24)

For example, in their application of a similar model to the operation of the High Aswan Dam (HAD), Oven-Thompson et al. (1982) assumed that at some future horizon point the HAD and other thermal power plants will not be usable anymore; the expected operating costs from that point on will be zero. There model then takes successive steps back in time from that point, searching for an optimum release decision that will minimize costs from that point to the end of the horizon.

Su and Deininger (1972) also show how the recursive computations, using (5), converge upon an optimal reservoir release policy for both the undiscounted and discounted case. In particular, assuming that (1), (2), and (3) hold, two important results proved by Su and Deininger (1972) are as follows:

1. In the undiscounted case, for arbitrary values of \( f^0(\ ) \),

\[
\lim_{m \to \infty} f^{(m+1)t+i}(S_t^i, Q_{t+1}^j) - f^{mt+i}(S_t^i, Q_{t+1}^j) = c \quad \forall \ i,j,t
\]  (25)

where \( c \) is the minimum expected annual cost of operating the system over an infinite time horizon.

2. In the undiscounted case, for arbitrary values of \( f^0(\ ) \),

\[
\lim_{m \to \infty} f^{mt+i}(S_t^i, Q_{t+1}^j) = f^*(S_t^i, Q_{t+1}^j) \quad \forall \ i,j,t
\]  (26)

where \( f^*(S_t^i, Q_{t+1}^j) \) is interpreted as the unique minimum expected cost of operating the system over an infinite time horizon, starting in state \( (S_t^i, Q_{t+1}^j) \) for time period \( t \).
For the undiscounted case, Su and Deininger show that upper and lower bounds on c monotonically converge. When the bounds on c are sufficiently tight (as defined by the user), the final cycle (m') of computed releases, $R^{m'-1}(S_i^t, Q_j^{t+1})$, is the optimal reservoir control policy.

For the discounted case, upper and lower bounds on c monotonically converge to $f^{t+1}(S_i^t, Q_j^{t+1})$ for all i,j, and t, but convergence criteria must be applied separately to each state $(S_i^t, Q_j^{t+1})$. Thus when the bounds are sufficiently tight for each state, the control policy will again be last cycle of optimal releases, $R^{m'-1}(S_i^t, Q_j^{t+1})$.

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84


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