POTENTIAL APPLICATION OF GENETIC ALGORITHMS IN THE WATER INDUSTRY

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Executive Summary

Background and motivation

The past decade marks the development of computational capacity that far exceeds the capacity of the "instructor" to define options to be evaluated when optimisation has to be achieved.

The Government's objective to provide "water for all" made it essential that the limited capital has to be employed to provide the maximum benefit. The optimal decision in terms of expansion, addition or rehabilitation of water supply systems has to review the conflicting demands and select a cost effective and efficient solution.

Within the context of water supply, there are numerous variables that can influence the selection and hence the final cost of system improvements.

These variables include:

- The high variance in rainfall and runoff,
- the availability of alternative water supply,
- the demand pattern variability,
- the operational ability of the system,
- the maintenance requirements,
- the running cost-especially power cost and
- the affordability and willingness to pay for services.

The determination of the optimal selection of system components requires techniques that can be employed to assist the decision-maker in finding the appropriate solution within the environment of all the possible solutions (Solution space).

Genetic Algorithms (GAs) have been developed (Holland (1975)) to assist in searching through complex solution spaces for the optimum solution. GAs have been applied as search techniques for various engineering problems such as, structural design optimisation, water distribution network evaluation, pump scheduling, hydrological runoff predictions and resource utilisation, this technique has however not been generally used in South Africa.

The application of the research findings will have a considerable advantage in determining the optimum solutions for the sizing and location of components in water supply system and hence reduce the cost of operation, maintenance and capital expenditure, while decreasing the production cost of water supply. This report will be used as an educational introduction for Genetic Algorithms.

Objectives of this project

The aim of this study was to evaluate the application of genetic algorithms in the optimisation of different components of water supply projects, viz:

- pump selection and scheduling
- optimal pipeline diameter selection
- valves and surge alleviating devices selection
- management of water supply projects
- alterations and extensions required in the upgrading of the capacity of water supply infrastructure.

Methodology

The aim of the study was to investigate the procedures of Genetic Algorithms and determine their application in water supply systems. The literature study was undertaken to evaluate available material on this subject, which is reflected in this report.

The knowledge and understanding of GAs, obtained from this study, was to provide the motivation for further development and application of GA's.

Results

Based on the literature that has been reviewed it can be stated categorically that :

- GAs are not used to its full optimal potential in the optimisation in the water industry of South Africa.
- Potential applications of the technique within the South African context are:
    - Hydrology and water resources assessment,
    - Network optimisation,
    - Optimisation of rehabilitation, extension and upgrading of distribution networks during the planning and design phase,
    - Operation and maintenance scheduling
- A minimum amount of teaching on GAs has been included in the curriculum of civil engineering,
- Feedback from Rand Water reflected the need for the development of software utility programs that can be used in practice and stimulate the further exploration of this technique,
- The pipeline diameter optimisation program that has been developed under this study demonstrated the use of GA's and has been well accepted in practice.

Recommendation

The results of this study reflect the value of GAs and the potential utilisation of GAs in the water industry. It is therefore recommended that:

- A course be presented on the use of GAs in the water industry. World renowned leaders in this field must be invited to participate in such a course in South Africa
- Procedures for the implementation of the technique in:

- Network optimisation,
- Water resources assessment and
- Operational scheduling,

needs to be defined.

- The software that has been developed should be improved and used to transfer knowledge and educate students in the use of GAs.

It is recommended that the following aspects should be researched in a follow-up study:

- A course be presented on the use of GAs in the water industry. World-renowned leaders in this field must be invited to participate in such a course in South Africa.
- Opportunities for the inclusion of this technique in the graduate program should be promoted.
- Procedures for the implementation of the technique in:
  - Network optimisation,
  - Water resources assessment and
  - Operational scheduling,

  needs to be conceptually defined and developed for implementation.
- The software that has been developed should be extended and distributed by the WRC with the objective to enhance the use and transfer of knowledge regarding the value of GAs in the water sector
- Application of GA to optimise the operating rules between reservoirs.
- Conceptual development of coding and "fitness" functions.

Further research that should be considered is as follows:

The potential applications of GAs to Water Resources analysis and management to improve the calibration of the rainfall-runoff (WRSM90) and Water Quality models as well as automating the optimisation of operating rules of water resource systems. Considering the potential benefits of applying GAs in these two areas, it is clear that the optimisation of the operating rules of systems would yield the largest benefits. An automated optimisation tool would reduce the time required by the model user and has the potential benefit of reducing pumping costs, which could amount to millions of rands in savings. Optimising the sizes of proposed infrastructure components in combination with optimising the operating rules could also have significant benefits.

It is therefore proposed that further research and development be undertaken to apply GAs in the optimisation of the operating rules and sizing of proposed water resource infrastructure. Although the ultimate aim of such an optimisation tool would be to simulate the large integrated systems, it is proposed that the research and development be carried out in incremental steps to first prove the viability of the development.

Following the findings, the research will be extended to include the following:

- Development of a basic software model.
- Testing of parameter values and alternative operators for the GA (mutation percentage, population size, crossover methods etc.).
- Develop a generic inter reservoir optimisation model.

Extending the above model to optimise the operating rules of integrated water resource systems.

- Conceptual development of coding and "fitness" functions. The integration of the GA model with the existing water resource allocation algorithm will be important.
- Development of a basic software model.
- Testing of parameter values and alternative operators for the GA (mutation percentage, population size, crossover methods etc).
- Develop a generic optimisation model.

Accomplishing the above targets the focus needs to shift to incorporate the optimisation of new infrastructure sizing.

This would involve further extending the GA optimisation model to also optimise the sizes of proposed new infrastructure in relation to the operating rules. It would be required to incorporate engineering economic parameters as part of the "fitness" functions to undertake optimisation is this area. The steps required for this phase would be similar to those described for the other two phases.

WRC Project K5/1144

POTENTIAL APPLICATION OF GENETIC ALGORITHMS IN THE WATER INDUSTRY

1. INTRODUCTION

1.1 Background

The focus to provide water for all, has brought about new challenges and responsibilities for the South African Water Supply Industry. One of the big challenges surely is the definition, with full cooperation of the service users, of an acceptable, appropriate and affordable service levels. Furthermore, the lack of sufficient internal capital resources and of slow mobilization of development funds, requires the optimal use of existing infrastructure and where alterations, refurbishment or additions are required, it should be done in a cost effective and efficient way.

Within the context of water supply, there are numerous variables that can influence the selection and hence the final cost of system improvements.

The high variance in rainfall and runoff, availability of alternative water supply, demand pattern variability, operationalability of the system, maintenance requirements, running cost - especially power cost, affordability and willingness to pay for services, all of which will influence the decision as to which section of the water supply scheme should be refurbished, replaced, discarded or expanded.

The past decade was marked with the development of fast computational ability. This has now far exceeded the capacity of the "instructor" in defining which options should be analysed.

Based on the functioning of DNA in nature to produce a gene population with specified characteristics, a mathematical cloning of this process has been defined to produce outcomes with specific characteristics. If the objective outcome however can be defined, be it the minimum cost solution or any other objective, the genetic algorithm process will "calculate" which gene pool will best approach the objective function (Goldberg D E (1989)).

The technique of genetic algorithms has been applied on a number of different real problems and resulted in exciting, but not always straightforward solutions.

In complex water distribution systems for instance, the alternative options when evaluating the extensions to water supply systems become numerous. Genetic algorithms provide procedures for the evaluation of the optimal solutions in the solution space.

Since the South African government has set the objective of supplying safe water to all the citizens, the quest for optimal utilization of the limited capital has been strongly promoted. Techniques like stochastic assessments, linear programming and multi objective analyses have been used to evaluate and optimise different characteristics of water supply schemes. None of these procedures, however, has the ability to apply randomness and hence in principle lack the ability to determine the optimum solution in the solution space, especially when the degree of freedom becomes random and multiple. Genetic algorithms are starting to be recognized as a powerful procedure and its application in water supply warrants investigation.

The challenge to address the backlog in water supply necessitates the use of improved optimisation techniques to reinforce the final selection.

Determination of the system components, required to optimise the solution will have to employ techniques that can assist the decision-maker in finding the optimal solution. Genetic algorithms have been developed as an optimisation search technique. Genetic Algorithms has been developed (Holland J H (1975)) to assist in searching through the solution space to find an optimum solution.

Although the use of Genetic Algorithms have been applied in search techniques for various engineering problems such as, structural design optimisation, water distribution network evaluation, pump scheduling, hydrological runoff predictions and resource utilisation, generally this technique has not been used in South Africa.

1.2 Objective of Research

The aim of this study was to evaluate the application of genetic algorithms in the optimisation of different components of water supply projects.

It was envisaged that the application of the research findings would reflect the advantage of utilising genetic algorithms as an optimisation technique in determining optimum solutions for the sizing and location of components in water supply system. Hence the implementation of these techniques, would lead to the reduction in the capital, operational and maintenance expenditure, leading to a reduction in the production cost of water supply. The results would also be used as an educational tool to introduce the use of Genetic Algorithms the novice.

1.3 Methodology

The research will focus on available literature to establish the applicability of genetic algorithm in the optimisation of different components of water supply systems.

Rand Water was closely involved in the study with the objective of establishing procedures for the implementation of genetic algorithms in water supply. Should the benefit of these procedures be proven, programs would be developed in a follow-up study. This would reflect the application of genetic algorithms in the water industry.

The programs would be user friendly and informative in conveying the concept to water supply managers and serve as an educational tool.

Phase 1 of the study will investigate the procedures of Genetic Algorithms and determine their application in water supply systems.

At the outset is was decided that:

- Available material on this subject will be reviewed and a report will be compiled, titled: "POTENTIAL Application of Genetic Algorithms in the Water Industry". The cooperation of Rand Water Board would allow the conceptualisation of the applications of the technique in a real world problem.

- Understanding the procedure and its application in water supply, firm objectives for further development in a follow-up of this study would be identified and described.

2. THE NEED FOR OPTIMISATION IN THE WATER SECTOR

It has been indicated that the challenges in the Water industry in South Africa and the World at large, together with the capital and operational constraints, necessitate the evaluation of technical, economical and environmental parameters to reach an optimal solution.

In the water sector it has been indicated that large savings can be accomplished if optimal solutions are implemented (Walters G A *et al* (1999)) when new systems are designed or when existing systems are refurbished or extended.

The need for the application of optimisation techniques stem from the fact that:

- **Selection of system component** in a water system is dependant on a number of inter-dependant variables for instance: if an optimal diameter has to be determined it is known that by reducing the diameter the capital cost is reduced but the operating cost (pumping) will escalate and the possibility of pipe burst due to surge pressures associated with high flow velocities will increase.

- A number of **uncertainties** exist when the implementation of water infrastructure is considered, such as:
  - what would the influence be of **escalation** on operational and capital replacement cost,
  - how will **natural phenomena** like floods and droughts influence the choice of the system components,
  - how would the **affordability of services** to the consumer influence the design standards and
  - how would **demand variance and increase** influence the selection of the capacity of system components.

Designers are intrigued by the ability to determine the optimum solution and suggested that the following aspects need to be incorporated in optimisation procedures:

- The selection of pipeline for rehabilitation.
- Decision support for the abandoning, renovation or replacements of pipelines.
- Application of genetic algorithms for the phased development of infrastructure for different development horizons.
- Using genetic algorithms for the cost effective development of infrastructure with cognizance of alternative service levels and affordability of service.
- Optimisation of reservoir sizing and pump capacity.

3. AN OVERVIEW OF OPTIMISATION TECHNIQUES

3.1 Traditional optimisation and search methods

The classical literature on algorithmic optimisation identifies three main types of search methods: calculus-based, (greedy) enumerative, and random.

Calculus-based methods subdivide into two main classes: indirect and direct. Indirect methods seek local extrema by solving the usually nonlinear set of equations resulting from setting the gradient of the objective function (the optimal value of which has to be found) to zero. On the other hand, the direct (search) method seeks local optima by hopping on the function and moving in the direction of the local gradient. Both methods are local in scope: the optima they seek are the best in the neighborhood of the current point. Moreover, calculus-based methods depend upon the existence of derivatives. This is a severe shortcoming, for many practical problems have little respect for derivatives and the smoothness it implies. The real world of search is fraught with discontinuities and vast multimodal, noisy search spaces.

The basic idea for (greedy) enumerative schemes is quite straightforward. Within a finite search space, or a discretised infinite search space, the search algorithm starts looking at the values of the objective function at every point of the space, one at a time. These algorithms frequently are horribly inefficient. Many practical search spaces are simply too large to make this method serve any practical end.

Random methods are beginning to play an increasingly important role in computing. It can frequently be shown that by allowing random choices within the execution of an algorithm, one can obtain an answer, with a probability of error, which is practically negligible, after only a very small number of iterations. An example of such an algorithm is the one by Rabin and Miller, which generates prime numbers. This algorithm plays an essential role in the design of cryptographic protocols. It will become clear in the discussion of genetic algorithms, that random choice also plays a central role here. See also the handworked example in section 4.2. However, random search methods, (to be contrasted with general and well-chosen random choices) which search and save the best, are frequently too crude to do better than enumerative methods.

It is, however, possible that, in some cases, a great deal of ingenuity might lead to an effective (and provably correct) solution of an optimization problem, which exploits an underlying structure in order to avoid an extensive search over all the possibilities. In combinatorial optimization methods, there is an extensive literature on the design and analysis of exact and efficient algorithms. The identification of underlying structures, which are algorithmically relevant, and the limitations of exact algorithms for solving combinatorial optimization problems are currently of considerable research interest. For an introduction to this topic, the reader can consult Cook et al (1998).

Recent research has shown that, in geometric search problems, very efficient search algorithms can be designed which are based on "ordering principles": these ordering principles include entropy, pseudo-randomness, empirical statistics, game theory and combinatorial designs of a low discrepancy. A thorough discussion of these techniques, together with the underlying theory, appears in Matousek (1999). It is also possible to use parallelised computations to speed up the search process. In general, the technology for exploiting parallelism is still lacking although quantum computation might become a practical reality in the near future, providing the possibility of exploiting parellelism.

Designed to search irregular, poorly understood spaces, genetic algorithms are general purpose algorithms developed by Holland (1975) with precursors suggested by Bledsoe (1961) and others. Holland's hopes were to develop powerful, broadly applicable techniques, to provide a means of attack on problems which had turned out to be resistant to other known optimization methods. Inspired by the example of population genetics, genetic search is population based, and proceeds over a number of generations. The Darwinian criterion "survival of the fittest" provides evolutionary pressure for populations to develop increasingly fit individuals.

Fixed length binary strings are typically the members (genes) of the population. They contribute to the gene pool in proportion to their relative fitness (determined by the objective function). There, they are mutated and recombined by crossover (or crisscrossing). Mutations correspond to flipping the bits of an individual with some small probability (the mutation rate). The simplest implementation of crossover selects two "parents" from the population pool and, after choosing the same random position within each string, exchanges their tails. Crisscrossing is typically performed with some probability (the crisscrossing rate) and parents are otherwise cloned. The resulting "offspring" form the subsequent population. In the following few sections a detailed exposition of a genetic algorithm is given. This will be followed by a mathematical analysis of how the performance of the algorithm is affected by the parameter settings for population size, crossover rate and mutation rate. The role that the encodings of the search plays in genetic algorithms will also be considered.

3.2 The genetic algorithm

3.2.1 Introduction

Let D be a (discrete) domain and $g : D \rightarrow \mathrm{R}$ a mapping, which associates with each $d \in D$ a real number $g(d)$. In this context, the real number $g(d)$ may be called the *fitness level* of d. In the discussion that follows, D will always be a finite set. The problem is to find a method that effectively (i.e. algorithmically) and efficiently (i.e. in real time) approximates the external value

$$\max_{d \in D} g(d).$$

3.2.2 Encoding in genetic algorithms

A crucially important aspect of genetic algorithms is to find a suitable encoding for the elements of D. The efficiency and correctness of the algorithm of the algorithm can be very sensitive to the way in which the encoding is designed. This matter will be returned to at a later stage. For the moment it is assumed that this aspect has been dealt with. The encoding can be modeled by a function

$$e : \{0,1\}^{\ell} \longrightarrow D.$$

The number e will be referred to as an *encoding function*. In most cases e will be one-to-one on a large part of $\{0,1\}^{\ell}$ and it will be surjective, i.e., for every $d \in D$ there is some $x \in \{0,1\}^{\ell}$

such that $e(x) = d$. The elements of $\{0,1\}^\ell$ can be thought of as binary words of length ℓ. In the sequel, a typical element of $\{0,1\}^\ell$ will be denoted by

$$x_1 \ldots x_\ell ,$$

where, of course, each x_i *is either 0 or 1.*

If $e(x) = d$, *where* $x \in \{0,1\}^\ell$ and $d \in D$, then x is called a *code* for d. The composition $f := ge$ is called the encoding function:

$$e : \{0,1\}^\ell \to D$$

and the fitness level function function:

$$g : D \to \mathbf{R}$$

the *objective function*. Thus $f(x) = g(e(x))$ for all binary words x of length ℓ. The problem now boils down to maximizing the objective function. The aim is to effectively and efficiently approximate

$$\max_{x \in \{0,1\}^\ell} f(x).$$

3.2.3 The initial population

An interesting feature of genetic algorithms is that entire populations of some fixed size are processed. This size n, say, is the designer's choice and depends on the problem under investigation.

The first step of the algorithm is to randomly select n elements from $\{0,1\}^\ell$ by means of $n \times \ell$ fair coin tosses by means of a random process. This will be the so-called initial population. This population is thus selected with a probability, which equals

$$\frac{1}{2^{n\ell}}.$$

This population is presented by an $n \times \ell$ array

$$P = [x_{ij}] \;\; 1 \le i \le n, 1 \le j \le \ell, \qquad (1)$$

where each x_{ij} is either 0 or 1 assumes each of these values with a probability ½. The matrix P is called the *initial* population.

In the future, *any* array of the form (1) will be referred to as a population. The rows of the array will be denoted by $A_1, \ldots, A_n$, respectively.

With each member A_i of a population P, is associated a measure of the degree of fitness of A_i. This measure, denoted by p_i, is given by

$$p_i := \frac{f_i}{\sum_{j=1}^{n} f_j},$$

where

$$f_j = f(A_j), j = 1, \ldots, n.$$

Note that

$$\sum_{j=1}^{n} p_j = 1.$$

It follows that the assignment

$$i \rightarrow p_i$$

defines a probability measure on the population P.

3.2.4 Selection according to fitness

A genetic algorithm always contains a routine, which, given a population P as in (1), will randomly select some member A_i of the population P where the randomness is controlled by the probability distribution ($i \rightarrow p_i$) on the population $A_1, \ldots, A_n$.

The underlying idea for the design of this procedure is the following: In most programming languages, one has available the faciltiy of simulating the uniform and random selection of a real number in the unit interval. For real numbers a,b with $a < b$, write $[a,b)$ for the interval $\{x \in \mathbf{R} : a \leq x < b\}$. Now divide the interval $[0,1)$ into subintervals of the form $[a,b)$, which have lengths, when schanned for left to right, $p_1, \ldots, p_n$, respectively. If the randomly generated real number lies in the jth interval, the routine will simply output the member A_j, of the population. In the sequel, this routine will be denoted by

Select (P,f).

Here f is the objective function in terms of which the probabilities pj have been defined.

3.2.5 Crisscrossing

Suppose A,B are two binary strings of length ℓ, that j is a natural number and Z is a (j-1) x ℓ binary array. If $j = 1$, it is assumed that Z is λ, the empty array. The following random procedure

Crisscross (A,B,Z,j)

is an abbreviation for the following procedure: Select, in a random and uniform manner, an integer k in the interval $[1, \ell)$. (That is, each $k \in [1, \ell)$, is chosen with probability $1/(\ell-1)$. It is assumed, with no loss of generality, that $\ell > 1$. Suppose

$$A = x_1 \ldots x_\ell$$

$$B = y_1 \ldots y_\ell$$

Then attach

$$A' = x_1 \ldots x_k y_{k+1} \ldots y_\ell$$

$$B' = y_1 \ldots y_k x_{k+1} \ldots x_\ell$$

as rows j and $j + 1$ to Z and output the $(j + 1) \times \ell$ array thus obtained.

3.2.6 Random crisscrossing

In most cases, crisscrossing takes place only with a certain probability $p = p_c$, where $0 < p_c \leq 1$. The decision as to what the value of p_c might be, requires empirical study. Call p_c the *crisscrossing probability*. In this case the procedure is denoted by

Crisscross(A,B,Z,j,p).

Here, p denotes the crisscrossing probability. This procedure is based on a random procedure that outputs, for input $p \in (0,1)$, a Boolean value $X(p)$ with the value *true* assumed with probability p. One can then program **Crisscross**(A,B,Z,j,p) as follows:

If $X(p)$ then Crisscross (A,B,Z,j)

else attach A, B to Z

Output the $(j + 1) \times \ell$ array thus obtained.

3.2.7 Reproduction

Given a population P, one generates a new population P' by repeated crisscrossing of randomly selected mates from the population P. One can do this as follows:

$j \leftarrow 1$
$Z \leftarrow \lambda$
$p \leftarrow p_c$

repeat

matel $\leftarrow$ Select (P,f)
mate2 $\leftarrow$ Select (P,f)
$Z \leftarrow$ Crisscross(matel, mate2, Z,j,p)
$j \leftarrow j + 2$

until j $size$ (P)

Here size (P) *denotes the number of elements of the population* P. *The genetic algorithm iterates this procedure and measures*

$$\max_{A \in P} f(A).$$

at each step. In many cases this maximum will converge to the real maximum after a few iterations.

3.2.8 Mutation

Some genetic algorithms also make provision for "mutations" (changing 0 to 1 or 1 to 0) after crisscrossing has taken place. This frequently leads to an improved performance of the algorithm.

3.3 Analysis

3.3.1 Schemes and deceptiveness

A schema describes a subset of strings with similarities at certain string positions. For example, consider strings of length 3 over the alphabet {0,1}. The two strings

011

111

are similar in the sense that they are identical when the first position is ignored. Regarding * as a symbol which may be instantiated to either 0 or 1, the set consisting of these two strings may therefore be represented by the single string

*11.

Strings over the alphabet {*,0,1} represent so-called *schemata*, and play a central role in analyzing genetic algorithms.

Set $\Omega = \{0,1\}^\ell$ and let P be a finite population drawn from Ω. Let f be the real-valued fitness (objective) function

$$f : \Omega \rightarrow \mathbf{R}$$

For any schema H, define the utility of H with respect to P as

$$f_P(H) = \frac{1}{|H \cap P|} \sum_{x \in P \cap H} f(x)$$

and define the utility of H as $f_\Omega(H)$ regarding P, changing under the influence of the genetic algorithm, let P_t denote the population after t steps. The famous Scheme Theorem is the inequality

$$E(|H \cap P_{t+1}|) \geq |H \cap P_t| \frac{f_P(H)}{f_p(\Omega)}(1 - \alpha(H,t) - \beta(H,t)),$$

where E is the expected value operator, and α, respectively β, approximates the probability that an instance of the scheme H will be destroyed by crossover, respectively mutation. (Note that Ω = *...* (ℓ times)). The functions α and β are usually taken to be constants estimated in terms of properties provided by the concrete representation of H. A proof of this inequality is given in Goldberg (1989) [4].

In some sense, schemata represent the direction of the genetic search. It follows from the schema theorem that the number of the instances of the schema H for which $f_P(H)$ $f_P(\Omega)$ is expected to increase in the next generation when $\alpha(H,t)$ and $\beta(H,t)$ are small. Therefore, such schemata indicate the area within Ω which the genetic algorithm explores. Hence it is important that, at some stage, these schema contain the object of search. Problems for which this is not true, are called *deceptive*.

The importance of the choice of the encoding e : $\Omega \rightarrow \mathbf{R}$ can perhaps be explained in terms of the so-called "Building blocks hypothesis". This hypothesis asserts that a genetic algorithm search proceeds not from individual chromosone to individual chromosome, but rather from high utility schemata with few fixed bits to high utility schemata with many fixed bits. If in the chosen encoding, the function optima does not lie in the schemata which are of high utility, genetic search might mislead.

3.3.2 Utilizing Walsh functions to indicate deceptiveness

The first published study of deceptiveness was undertaken by Bethke (1981) [1]. His analysis made use of the Walsh functions as a basis for the set of real-valued functions on Ω. If $j = j_1 = j$th Walsh function, w_j, is given by

$$w_j(x) = (-1)^{j.x}, x \in \Omega,$$

where

$$j.x = \sum_{j=1}^{\ell} j_i x_i$$

when $x = x_1 \ldots x_\ell$.

Given a function $f : \Omega \rightarrow \mathbf{R}$, define the jth Walsh coefficient $\hat{f}_j$ by

$$\hat{f}_j = 2^{-\ell/2} \sum_{x \in \Omega} f(x) w_j(x).$$

One then has the following inversion formula:

$$f(x) = 2^{-\ell/2} \sum_{j \in \Omega} \hat{f}_j w_j(x).$$

REMARK: The mathematically inclined reader will note that this is a special case of the Fourier inversion formula for a finite abelian group. In this case, the group is $A := Z_2^\ell$ and the Walsh functions are all the group characters of A.

It follows that the utility of the schema H with respect to the function f can be expressed as:

$$f_\Omega(H) = \frac{1}{|H|2^{\ell/2}} \sum_{j\in\Omega} \hat{f}_g \sum_{x\in H} w_j(x). \qquad (2)$$

Indeed, by the inversion formula

$$\frac{1}{|H|}\sum_{x\in H} f(x) = \frac{1}{|H|2^{\ell/2}} \sum_{x\in H}\sum_{j\in\Omega} \hat{f}_j w_j(x)$$

and the identity follows from a reversal of the order of summation.

The number of ones in $j \in\Omega$ is called the order of j and will be denoted by $o(j)$. The order, $o(H)$, of a schema H is the number of fixed positions of H. Two schemata are said to be competing if they have the same order, with *s in the same positions and possibly different fixed bits. This means that two schemata are competing if they differ at most in their fixed positions. Let H_1 *and* H_2 *be two distinct competing schemata such that, for all fixed positions* i, it is the case that if the ith position of H_2 is 0, the same holds for the ith position of H_1. It follow from (2) that if $\hat{f}_j = 0$ when $1 < o(j) \le o(H_1)$ and if $\hat{f}_j > 0$ when $o(j) = 1$, then $f_\Omega(H_1) > f_\Omega(H_2)$.

Definition 1 *Let f be a real valued function on* Ω. *Write O for the* x *set of global optima of f. Then f is deceptive of order d iff, for some x not in O, it is the case that whenever* H_1 *and* H_2 *are distinct competing schemata of order at most d, we have*

$$x \in H \Rightarrow f_\Omega(H_1) > f_\Omega(H_2)$$

It is now possible to provide Bethke's construction. Let d be an even number which is strictly less than ℓ. The previous discussion implies the existence of a constant $c_d < 0$ (depending on d) such that if we define f by

$$f(x) = 2^{-\ell/2} \sum_{j\in\Omega} a_j w_j(x)$$

where

$$a_j = \begin{Bmatrix} 1 \; if \; o(j) = 1 \\ c_d \; if \; o(j) = d + 1 \\ 0 \; otherwise \end{Bmatrix}$$

for j $\in \Omega$, then f has a maximum value at 1…1 and is deceptive of order d.

Definition 2 *Let f be a real valued function on Ω with unique global maximum at x^* and let x^c be the binary complement of x^*. The function f is fully deceptive if, whenever H_1 and H_2 are distinct competing schemata of order less than ℓ, we have*

$$x^c \in H_1 \Rightarrow f_\Omega(H)_\ell > f_\Omega(H_2).$$

Liepins and Vose (1991) [6] constructed fully deceptive problems for all string lengths ℓ > 2. They are given by:

$$f(x) = \begin{Bmatrix} 1 - 2^{-\ell} & if \; o(x) = 1 \\ 1 - (1 + o(x))/\ell & if \; 0 < o(x) < \ell \\ 1 & otherwise \end{Bmatrix}$$

3.3.3 Intermediate deceptiveness

Let x be point in Ω. A shema path at x is a nested sequencs of schemata

$$H_0 \subset \ldots \subset H_n$$

containing x such that o(H_i) = i for every i. Intuitively, deceptiveness occurs whenever a "good path" leads to a "bad point" or a "bad path" leads to a "good point".

Definition 3 Let $x \in \Omega$ *at let* J *be a schema path at* x. *Then* f *is decreasing at* x *along* J *of order* (a, b) *iff whenever* H_1 *and* H_2 *are schemata in* J.

$$a \leq o(H_1) < o(H_2) \leq b \Rightarrow f_\Omega(H_1) > f_\Omega(H_2).$$

If $a = 0$ the term "decreasing along J of order b" will be used. The definitions for increasing along J are analogous.

Observe that fully deceptive functions have a unique optimal x^* and are increasing at x^* of order ℓ - 1 along all schema paths.

Attention can now be turned to the existence of classes of functions of intermediate deceptiveness. We assume that the functions have a unique optimal which, without loss of generality is at 0...0. By using the so-called hyperplane transport introduced by Holland (1989) [5], one can show that each of the following classes are nonempty:

- functions with several schema paths at the optimal, some of them increasing of order ℓ and others decreasing of order ℓ - 1;
- functions all of whose schema paths at the optimal are increasing for some order $d < \ell - 1$ and decreasing thereafter (except at order ℓ;
- functions all of whose schema paths at the optimal are decreasing for some order $d < \ell - 1$ and increasing thereafter.

These classes are interesting because real problems could presumably have some paths, which are deceptive, and other paths, which are not, or could have some regions of deceptiveness either preceded or followed by regions, which are not deceptive. Intuitively, one might expect that the density of non-deceptive paths or the depth of deceptiveness is related to whether a genetic algorithm discovers an optimum or not.

4. INTRODUCTION TO GENETIC ALGORITHMS (GA's)

4.1 Background

An algorithm is any procedure that takes in data and modifies it according to a step-by-step set of instructions. Every program ever written is an example of an algorithm. Genetic Algorithms are programs that stimulate the logic of Darwinian selection, if one understands how populations accumulate, differences over time due to the environmental conditions acting as a selective breeding mechanism, then you understand GAs. Put another way, understanding a GA means understanding the simple, iterative process that underpin evolutionary change. The issue, of course, is how best to get that "selection pressure" translated into a program procedure and applied to your problem.

Holland (1975) the pioneer of Genetic Algorithms defines the evolutionary nature of the algorithm as follows:

- Start with an initial population that is randomly generated, but contains the variability parameters characteristic of the population.

- The fitness of each individual in the population is assessed according to a fitness function.

- The probability of each individual to survive is proportional to its fitness.

- The individuals of the next generation are selected on probability and through a genetic transformation process of crossover and mutation, ensuring that the solution is not localized within the solution environment.

GAs are suited to solve problems that are not vulnerable to attack by brute force methods because the sheer number of potential solutions defies the possibility of testing them all. Such problems are typically multi-constrained, that is the solution must be a balance of conflicting or synergistic properties. When considering a problem with multiple dependencies you are normally forced to admit the possibility of isomeric solutions i.e. solutions that give the same result using different processing routes. So for some problems there is no such thing as the "best solution" but instead you are looking for members of a fuzzy set of solutions that can be defined as "good enough".

Some problems have a "Best" solution but is lost in a vast result space. Brute force techniques can and do work in situations like this, that's why machines can now beat chess masters, but the problem with any brute force method is its almost complete lack of scalability. If you manage to build a computer large enough to solve a reasonably constrained problem, then adding just one more constraint will probably require another 10 similar computers to deal with additional calculations. Add another row of squares to a chessboard and the number of possible moves expands dramatically. One of the great strengths of GAs is that it does not have to evaluate all the possible solutions. This means that increasing the number of possible solutions has little impact on the run time of a GA – the logic has already sacrificed absolute confidence in the result for the ability to get any sort of workable result at all.

Typically you will see that GAs use bit-strings to represent the state of an object model. Manipulations of the values of these bit-strings can be translated back into changes to the associated objects' instance-data. Once freed by this abstraction into bit-strings the GA-coder can apply biologically analogous processes such as *Replication*, *Crossover* and *Mutation* to the bit-strings, which can then be translated back to the objects themselves. In this way the GA-coder can evolve the instance-state of the components within an object model.

Many people believe random mutation is the engine of evolution but this is not strictly true. Although mutation does provide populations with a steady trickle of novelty in unexpected places the real engine of evolution is *Useful Variation*. Variation stems from mutation but only useful variation is amplified and preserved. This amplification rests on the GAs ability to select members of the population with high fitness values (or their children) and use them to replace members with low fitness values. Selective breeding and selective replacement act together to steadily *ratchet* the mean population fitness remorselessly upwards. Only those members that are good enough, according to the definition of "fit", can survive to breed.

Selection pressure and random mutation may get you to a solution but this is not a GA (it is called a "random walk"). Vital to a GAs amazing efficiency at searching through huge result spaces is the ability to exchange sequences between different, pre-tested (they are still alive) solutions. Generating variety through sequence swapping ensures that you are less likely to lose beneficial groups of bits through sheer bad luck but instead give them a chance to recombine in novel ways. The biological term for this safe shuffling is "Crossover".

The final fundamental component of a GA is its *Fitness Test*. This is usually a simple set of calculations that consumes an object's current state, and assigns to the object a Fitness Value based on that state. Each member of the population must be presented for a Fitness re-evaluation whenever any of the Fitness-Implicated properties change their value.

Now that is known that a GA is a search procedure based on the mechanics of natural selection and natural genetics and it is geared to handle complex multi objective problems with a large solution space, a brief overview of the functioning of a GA, will be provided in this section.

Goldberg (1989) indicated that a GA differ from the traditional search methods in the following ways:

- GAs work with coding of the parameter set, not the parameters themselves.
- Search for population of points, not a single point.

- GAs use objective functions (payoff) information not derivatives or other auxiliary knowledge to determine the fitness of the solution.
- GAs use probabilistic transition rules not deterministic rules.

Goldberg (1989) provide the following examples to illustrate the working of a genetic algorithm.

4.2 Genetic Algorithms at work – A simulation by hand

Let's apply our simple genetic algorithm to a particular optimisation problem step by step. Consider the problem of maximizing the function $f(x) = x^2$, where x is permitted to vary between 0 and 31. To use a genetic algorithm, the decision variables of our problem as some finite-length string must first be coded. For this problem, the variable x simply is coded as a binary unsigned integer of length 5. Before proceeding with the simulation, the notion of a binary integer is briefly reviewed. For example, the five-digit number 53,095 may be thought of as

$$5 \cdot 10^4 + 3 \cdot 10^3 + 0 \cdot 10^2 + 9 \cdot 10^1 + 5 \cdot 10^0 = 53{,}095.$$

In base 2 arithmetic, there are of course only two digits to work with, 0 and 1, and as an example for the number 10 the decoding will result in a string 011. Another example is given below.

$$1 \cdot 2^4 + 0 \cdot 2^3 + 0 \cdot 2^2 + 1 \cdot 2^1 + 1 \cdot 2^0 = 16 + 2 + 1 = 19$$

With a five-bit (binary digit) unsigned integer, numbers between 0 (00000) and 31 (11111) can be obtained. With a well-defined objective function and coding, a single generation of a genetic algorithm with reproduction, crossover, and mutation is now simulated.

To start off, select an initial population at random. Select a population size 4 by tossing a fair coin 20 times. Looking at this population, shown at the left-hand side of Table 4.1, it can be observed that the decoded x values are presented along with the fitness or objective function values $f(x)$. To ensure how the fitness values $f(x)$ are calculated from the string representation, take a look at the third string of the initial population, string 01000. Decoding this string as an unsigned binary integer, note that there is a single one in the $2^3 = 8$'s position. Hence for string 01000, $x = 8$ is obtained. To calculate the fitness or objective function, simply square the x value and obtain the resulting fitness value $f(x) = 64$. Other x and $f(x)$ values may be obtained similarly.

This discussion simply reinforces one of the strengths of the genetic algorithm: by exploiting similarities in codings, genetic algorithms can deal effectively with a broader class of functions than can many other procedures. A generation of the genetic algorithm begins with reproduction. Select the mating pool of the next generation by spinning the weighted roulette wheel four times. Actual simulation of this process using coin tosses has resulted in string 1 and string 4 receiving one copy in the mating pool, string 2 receiving two copies, and string 3 receiving no copies, as shown in the center of **Table 4.1**. Comparing this with the expected number of copies (n pselect,) it has been obtained what can be expected, the best get more copies, the average stay even, and the worst die off.

TABLE 4.1 : A Genetic Algorithm simulation by Hand

String No	Initial Population (Randomly generated)	X Value (Unsigned Integer)	$f(x)$ x^2	Pselect $\frac{f_i}{\sum f}$	Expected count $\frac{f_i}{\bar{f}}$	Actual Count (Roulette Wheel)
1	0 1 1 0 1	13	169	0.14	0.58	1
2	1 1 0 0 0	24	576	0.49	1.97	2
3	0 1 0 0 0	8	64	0.06	0.22	0
4	1 0 0 1 1	19	361	0.31	1.23	1
Sum			1170	1.00	4.00	4.0
Average			293	0.25	1.00	1.0
Max			576	0.49	1.97	2.0

Mating after Reproduction (Cross Site Shown)	Pool Mate (Randomly Selected)	Crossover Site (Randomly Selected)	New Population	X Value	$f(x)$ x^2
1 1 0 0 0	1	4	1 1 0 0 1	25	625
0 1 1 0 1	2	4	0 1 1 0 0	12	144
1 0 0 1 1	3	2	1 0 0 0 0	16	256
1 1 0 0 0	4	2	1 1 0 1 1	27	729
	Sum				1754
	Average				439
	Max				729

NOTES:

1) Initial population chosen by four repetitions of five coin tosses where heads = 1, tails = 0
2) Reproduction performed through 1 part in 8 simulation of roulette wheel selection (three coin tosses)
3) Crossover performed through binary decoding of 2 coin tosses (TT = 00_2 = 0 = cross site 1, HH = 11_2 = 3 = cross site 4)
4) Crossover probability assumed to be unity p_c = 1.0
5) Mutation probability assumed to be 0.001, p_m = 0.001, expected mutations = 5·4·0.001 = 0.02%. No mutations expected during a single generation. None simulated.

With an active pool of strings looking for mates, simple crossover proceeds in two steps: (1) strings are mated randomly, using coin tosses to pair off the happy couples, and (2) mated string couples cross over, using coin tosses to select the crossing sites. Referring again to **Table 4.1**, random choice of mates has selected the second string in the mating pool to be mated with the first. With a crossing site of 4, the two strings 01101 and 11000 cross and yield two new strings 01100 and 11001. The remaining two strings in the mating pool are crossed at site 2; the resulting strings may be checked in the table.

The last operator, mutation, is performed on a bit-by-bit basis. Assume that the probability of mutation in this test is 0.001. With 20 transferred bit positions it is expected that $20 \times 0.001 = 0.02$ bits will undergo mutation during a given generation. Simulation of this process indicates that no bits undergo mutation for this probability value. As a result, no bit positions are changed from 0 to 1 or vice versa during this generation.

Following reproduction, crossover, and mutation, the new population is ready to be tested. To do this, simply decode the new strings created by the simple genetic algorithm and calculate the fitness function values from the x values thus decoded. The results of a single generation of the simulation are shown at the right of **Table 4.1**. While drawing concrete conclusions from a single trial of a stochastic process is, at best, a risky business, it becomes clear how genetic algorithms combine high-performance notions to achieve better performance. In **Table 4.1**, note how both the maximal and average performance has improved in the new population. The population average fitness has improved from 293 to 439 in one generation. The maximum fitness has increased from 576 to 729 during that same period. Although random processes help cause these happy circumstances, indicating that this improvement is no fluke. The best string of the first generation (11000) receives two copies because of its high, above-average performance. When this combines at random with the next highest string (10011) and is crossed at location 2 (again at random), one of the resulting strings (11011) proves to be a very good choice indeed.

This event is an excellent illustration of the ideas and notions analogy developed in the previous section. In this case, the resulting good idea is the combination of two above-average notions, namely the sub strings 11--- and ---11. Although the argument is still somewhat heuristic, it is clear that genetic algorithms effect a robust search.

The intuitive viewpoint developed thus far has much appeal. A comparison has been made between the genetic algorithm and certain human search process, commonly called innovative or creative. Furthermore, hand simulation of the simple genetic algorithm has given some confidence that indeed something interesting is going on here. Yet, something is missing. What is being processed by genetic algorithms and how is it known whether processing it (whatever it is) will lead to optimal or near optimal results in a particular problem? Clearly, as scientists engineers, and business managers it is required to understand the what and the how of genetic algorithm performance.

In any genetic algorithm the following functional procedures are used:

- Reproduction
    - copy according to objective function, maintaining the optimal strings for the next generation (bias roulette wheel)

- Crossover
    - parent pairs exchange there gene bits creating new gene stings that contain the characteristics of the parent stings

- Mutation
    - protects against loss of useful genetic material and forces the search for the optimal solution to a different place in the solution space (secondary mechanisms)

Repetitive uses of these functions of the genetic algorithm have been used in the optimisation of a variety of problems. Some of these applications are discussed in the next section.

5. REVIEW OF THE APPLICATION OF GENETIC ALGORITHMS (GA's)

5.1 Introduction

Researchers, covering a wide range of water engineering related topics have discussed various applications of genetic algorithms. Some of these contributions are summarized below. The articles are grouped according to specific work fields that are handled by engineers and influence their decision on a number of optimisation problems, associated with water supply and distribution.

The groupings that are used here are:

- Rainfall forecasting
- Runoff estimation
- Yield assessment of surface reservoirs
- Optimisation of the system components during he planning and design stage
- Operational optimisation
- Network rehabilitation
- Optimisation of operations of water purification plants and pump stations

5.2 Rainfall forecasting

The complexity and unpredictability of the performance and variance within a big system such as the climatology system is well understood. It however remains essential to be informed as soon as possible about possible natural disasters and therefor weather forecasting remains an integral part of the data that is reviewed by people on a daily basis. Predicting what the outcome of a complex system will be needs the creation of relationships between all these factors that might influence the outcome from a current status. The more extended the data record becomes the more difficult it becomes to create relationships between the dominant parameters that determine the future climate and the less possible it becomes to evaluate all the combinations of these parameters utilizing enumerative procedures.

5.3 Runoff estimation

Liong *et al* (1995) demonstrated the use of genetic algorithms in determining the catchment parameters for a widely used runoff simulation model (SWMM). The study was conducted on a catchment in Singapore with an area of 6,11 km^2. Three measured storm events were evaluated to determine the catchment parameters. These parameters used to create the runoff were then compared with three other gauged storm events and it was found that the error ranged from 0,045 to 7,265 %.

Schutze *et al* (1999) combined the qualitative and quantitative variables of urban stormwater systems parameters to determine an optimal control strategy. Starting with the rainfall that generates runoff and by incorporating a control strategy that has been generated by an optimisation module. The results are fed back to the optimisation module and a new control strategy is developed based on the acceptance of the results that were obtained. The author indicated that by applying the optimisation techniques, there has been an improvement in the outcomes of the integrated control of urban stormwater systems.

5.4 Yield assessment of surface reservoirs

Balascio et. al, 1998, illustrates the application of GA in estimating the calibration parameters of a short time interval rainfall-runoff model that is used for flood analysis. The author's main objective is to show the use of GA in combination with Multi Objective Programming and the formation of a specific Multi Objective Function (MOF) as the "fitness" function for the GA operation. The MOF was developed to measure the goodness of fit with respect to three aspects; the peak runoff rate, runoff volume (for a particular flood) and the time when the peak occurs. Weighting coefficients were used to give the user the opportunity to influence the importance of each of the three terms of the MOF. A specific methodical calibration approach was also adopted, where selected parameter values were estimated first and where only certain of the error terms were allowed to be transferred to the next set of selected parameters. The authors concluded that the application of the GA and the particular MOF improved the calibration and indicated that significant saving of time was achieved compared to the manual optimisation method.

In summary, this paper illustrated the following aspects:

- GAs can be used to assists in the calibration of models. As described in **Section 6.3** the rainfall-runoff (WRSM90) and the Water Quality Calibration (salinity) models could be possible applications of GAs.
- It is possible to develop Multi Objective Functions that captures the statistical and "visual" fitness of a simulation compared to recorded data.
- A methodical approach where certain parameters are calibrated first was found to be beneficial.
- The use of the GA improved the calibration and the time required to calibrate the model was considerably reduced compared to the manual calibration process.

Yu-Ming Chen, (1997) describes the application of GAs to optimise the management of an irrigation project. The total scheme consisted of six irrigation districts all receiving water from the same water resource. A stepped approach was followed where the optimum parameters of each irrigation district was first found separately and these results were used for the initial population of the genes or binary strings used for the main problem. The authors developed economic functions to describe the 'fitness' of a solution. Different methods of crossover and mutation were introduced. The paper only describes the concepts. The application will be described in a subsequent publication.

In summary, this paper illustrates the following aspects:

- The concept of first solving sub-problems and then using these results for the initial population of the main problem may be useful to reduce computational requirements.
- Variations in the basic crossover and mutation operations could be of value to improve efficiency in deriving the optimum solution.

5.5 Optimisation of the system components during the planning and design stage

Feng C and Lin J (1999) developed a Sketch Layout Model (SLM) to assist planners in generating alternative sketch maps for the development of a piece of land where provision for all land users are made. These alternative layouts reflecting the Pareto optimum are then used to develop the detailed designs. In the reported case study the environmental harmony and the development efficiency was (doubled) improved considerably.

Lek S and Guegan J F (1999) compared different non-linear programming structures, that have been presented at the International Workshop, on the application of Artificial Neural Networks and concluded that the utilization of these procedures provide better insight in the handling of complex environmental decisions.

In determining the relevance of certain parameters influencing water quality, large amounts of relevant data has to be evaluated simultaneously, competing objectives have to be satisfied and non-quantifiable factors with non-linear characteristics and uncertainty has to be evaluated. Chen *et al* (1998) used genetic algorithms to search for the optimal strategy that are used as benchmarks for decision-making. The authors evaluated the use of genetic algorithms for the management of the Tseng-Wen river basin in south Taiwan. The competing management objectives were to maximize the assimilative capacity, minimize the treatment cost for water pollution control and maximize the recreational economic value of the river. The authors indicated the application of genetic algorithms in determining a management strategy to strive for the best compromised solution.

Montesinos P *et al* (1999) also investigated the New York water supply problem and found that by modifying the genetic algorithm used by previous researchers the cheapest published solution for this problem was obtained. The modified genetic algorithm used by the authors firstly ranked the strings in order of fitness. The least fit strings are then eliminated and replaced by duplicates of the fittest individual chromosome strings. Since the intermediate strings remain in their ranked positions and by excluding the first two strings from crossover, results in the fittest strings being maintained in the gene pool for the next generation. The paper also highlights the fact that there is no defined metrology for the evaluation of the penalty. A variable was defined to indicate the number of constrained failures. The variables are directly related to cost of the selected solution. The authors also modified the mutation operation and the mutation of a string will occur at a random position along the bits (individual elements of the gene) of the string.

Reis *et al* (1997) used genetic algorithms to determine the location and setting of pressure control valves in a distribution system, the objective being to minimize leakage for certain reservoir levels. The approach used by Reis *et al* (1997) was first to determine the best location for the valves for a representative demand and then to use these valve locations and demand patterns to determine the optimal setting of these valves to reduce leakage. It was established that valve location is strongly dependent on the demand (nodal) distribution.

Yeo M F, *et al* (1998) indicated the application of GAs on a number of engineering problems such as the finite analyses of a structure, extraction of pollutants from an aquifer, positioning of wells for optimum abstraction and minimizing pumping rates and overall costs. The authors indicated the flexibility of GAs as an optimisation technique and its applicability in practical engineering problems.

5.6 Operational optimisation

Lapa C M F *et al* (2000) developed a method for the scheduling of preventative maintenance to increase the average availability of the system. The procedures were evaluated by assessing a two-looped pressurized water reactor and it was found that the failure probability was minimized. It was indicated that certain shortcomings and limitations of the parallel genetic algorithm would be investigated further.

Runoff to the combined sewerage pump station originates from sewerage and natural runoff. Selecting the required pumping rates are determined by fuzzy inference and fuzzy control rules resulting from the application of genetic operations. Yagi S and Shiba S (1999) found that the utilization of genetic algorithms provided an effective way of establishing a reasonable fuzzy rule base. Furthermore it was determined that the inclusion of additional information such as the sewer water quality not only reduced pollution, but also the potential of flooding in the drainage area.

Wardlaw R and Sharif M (1999) indicated that a four-reservoir problem can be handled effectively by utilizing genetic algorithms with real value coding with tournament selection, uniform crossover and modified uniform mutation. The authors are the first to use uniform crossover, which allows each gene to crossover. They also indicated that real value coding is significantly faster than binary coding which gives better results.

Morshed J and Kaluarachchi J J (1998) indicated the complexities of flow and contaminant modeling of groundwater resources and reflected the usefulness of artificial neural networks in solving groundwater problems. Reference to the use of genetic algorithms as a robust mechanism in solving non-linear, optimisation problems are made. Training of artificial neural networks can be obtained through the use of genetic algorithms to prevent the system from focusing on a local optimal solution. The comparison of genetic algorithms (GA) and back propagation algorithm (BPA) suggests that the BPA is superior although the author quantifies the findings as inconclusive due to insufficient results.

Barros A S *et al* (1998) indicated the difficulty to establish which of the variables should be included in a multivariate regression model. The problem that arose here was the assessment of a large number of measurements taken from a set of samples with the independent variable not being mutually independent (linear dependant vectors or co-linearity). The authors showed that genetic algorithms provided a global optimal selection of variables in a reasonable time but warned that the initial selection of strings was important to ensure convergence.

Olivera and Loucks (1997) proved in a very useful and descriptive way that GAs could be used to optimise the operating rules of multi reservoir systems. The authors illustrate the formation of real-valued chromosomes as opposed to binary strings for the functioning of the GA. The 'fitness' function derived for the GA was based on a function of the average deficit of water supply or energy. This was derived from a simulation of a selected time series using a reservoir simulation model. The GA was tested and compared with other optimisation methods and found to produce acceptable optimum solutions for the operating rules. The conclusion from the paper is that the use of GA as a tool to derive optimum operating rules seems to be a practical and robust method. Possible refinements to the optimisation approach are also suggested.

In summary, this paper illustrated the following aspects:

- The research showed the application of the GA to derive optimum operating rules for multi reservoir system is possible and the technique seems to be robust and practical.
- The application of real-value chromosomes are illustrated and thoroughly documented.

- The concepts described in the paper is applicable to the water resource analysis techniques used in South Africa and could be used to develop an algorithm for optimizing the operating rules of water resource systems.
- The water resource system used in the research is far less complex than the integrated systems used in South Africa and the challenge will be to use the technology to derive optimum rules for these large interdependent systems.

Huang C *et al* (1997) indicated that genetic algorithms could be used in the search for optimum pumping rates and discrete spacing of wells in an aquifer with homogeneous or non-homogeneous characteristics.

5.7 Network rehabilitation

Gupta I *et al* (1999) developed a methodology based on the use of genetic algorithms for the development of lower cost designs and augmentation of existing water distribution systems. A comparison with other mathematical programming techniques was made. The program that was developed had a limitation of 200 pipes, 175 nodes and 2 reservoirs. Gupta found that the non-linear programming converged faster than the genetic procedure but that the genetic algorithm in general obtained a more cost-effective solution. For larger more complex systems the benefit of genetic algorithms will be prominent.

Halhal D *et al* (1997) indicated that in network rehabilitation, expansion and replacement it is difficult to determine the correct improvements to be achieved with a limited capital budget if conventional optimisation techniques (linear programming) are applied. A multi-objective function approach was applied by using capital cost and benefit as the objective function to determine the required changes to the system. The two examples that are discussed showed the value of this technique.

Walters D A *et al* (1999) presented a procedure to assist with the decision in the rehabilitation and expansion of existing networks. This procedure is tested against the benchmark problem ("Anytown"). In the evaluation of the benchmark problem, tank levels were defined as independent variables and all the nodes have been specified as potential sites for new storage tanks. Allowance was also made for the pump sizes to vary. The solutions that were obtained by evaluating a 24 h extended period, resulted in a cheaper solution than determined before. It was found that the required storage was more than what other researchers have determined.

6. POTENTIAL USE OF GENETIC ALGORITHMSS IN THE WATER SECTOR

6.1 Planning and design

In the literature study reference has been made to a number of problems that have been evaluated by using GAs. The benefit of the optimisation has been proven and further application of this technique now remains the challenge.

In the planning and design stages of any project, alternative solutions have to be compared and optimised. Those optimisation problems frequently encountered are:

- The selection of pipelines in a distribution network to be incorporated for rehabilitation.
- Decision support for the abandoning or replacements of pipelines.
- Determining the stages of a phased development of infrastructure for different development horizons.
- Cost effective development of infrastructure with cognizance of alternative service levels and affordability of service.
- Optimisation of reservoir sizing and pump capacity.

The optimisation decision is always taken against the background of a number of uncertainties, such as:

- what will be the influence of escalation on operational and capital replacement cost,
- how will natural phenomena like floods and droughts influence the choice of the system components,
- how will affordability of services for the consumers influence the design standards and
- how will demand variance and increase influence the selection of the capacity of system components.

6.2 Operational optimisation

Operational optimisation is paramount since the total operation cost during the lifetime of a project can ion real terms be larger than the capital cost of the project. In the water supply industry there are a number of decisions that can influence the efficiency and effectiveness of the operation. Some of these decisions are:

- When should pumps of different capacity been switched on to ensure an uninterrupted supply, maximum pump and motor life and minimum cost.
- What units of a package type purification plant should be operational to ensure sufficient supply.
- When should alternative resources be used and how should they be incorporated into the water supply for optimal yield.

6.3 Water Resources Assessment

6.3.1 Introduction

In order to identify the possible applications of GAs in the Water Resources Assessment studies it is required to describe the current practices and technology used in this field.

In South Africa, water resource management and development planning is mainly undertaken by the Department of Water Affairs and Forestry (DWAF). In some cases other Water Supply Authorities including Water Boards, Municipalities, and Irrigation Boards also carry out studies usually in collaboration with DWAF. In the field of water resource management and planning numerous opportunities exist in apply optimisation techniques that ranges from the selection of the best parameter sets for simulation models to finding optimal solution to augment a water resource system. The latter may involve the development of major infrastructure projects or the implementation of demand management and conservation measures to postpone the need for further infrastructure development projects.

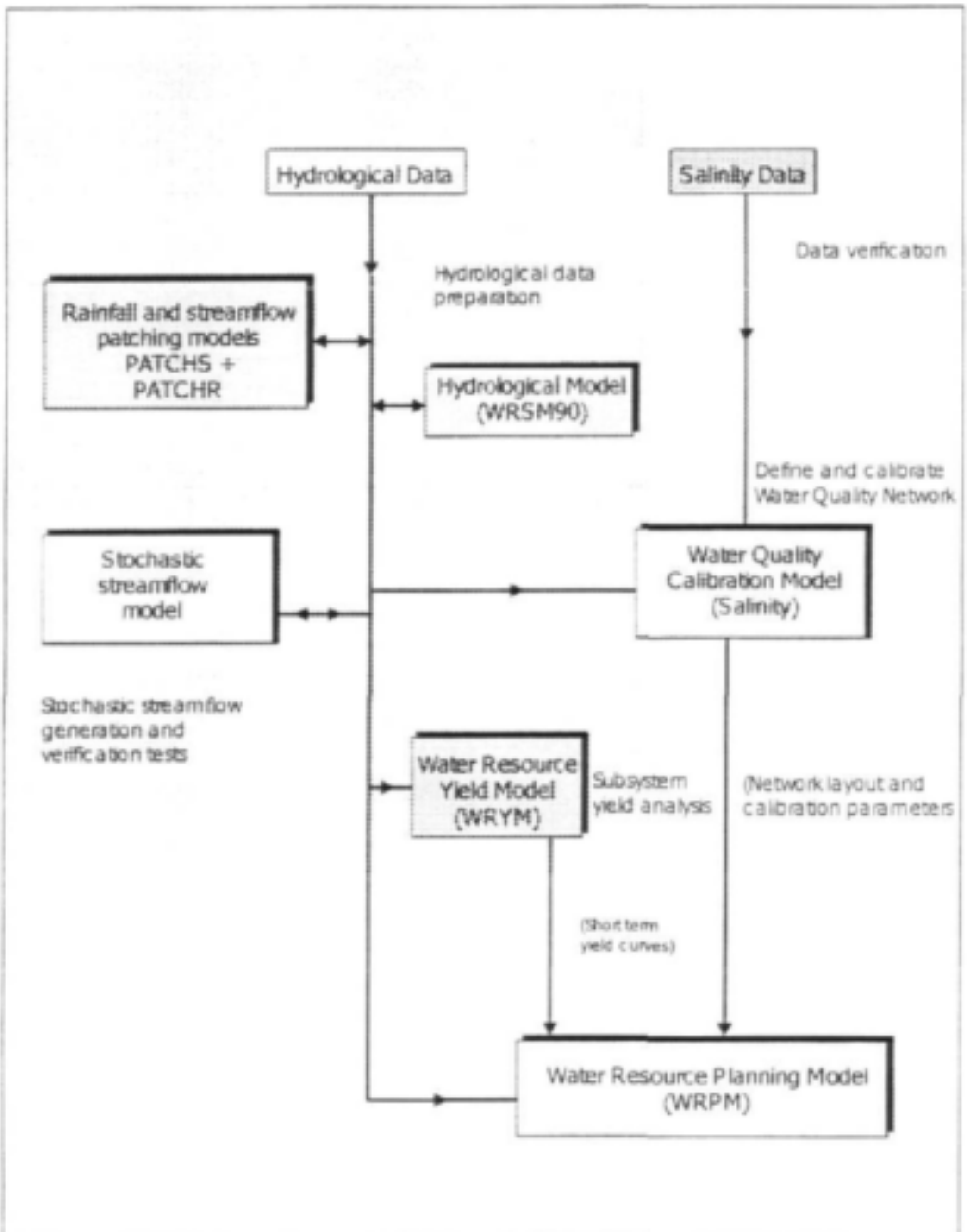
In order to define the needs for optimisation in the field of water resource assessments one is required to consider the different processes applied and studies undertaken.

The following sections therefore briefly describe the processes and procedures applied in water resource studies and highlight the areas where optimisation is already applied. Further potential applications of optimisation techniques, in particular relevant to GAs, are also identified and described.

6.3.2 General overview of current practice in water resource analysis

Since the commissioning of the Vaal River System Analysis Study in the early nineteen eighties, where the foundation for the current water resource analysis practices were developed, all major water resource systems in South Africa have been analysed based on the procedures presented in **Figure 6.1**.

Figure 6.1: Schematic presentation of water resource analysis procedure



The analysis procedure consists of four main components namely; hydrological assessment, water resource yield analysis, water quality assessment and water resource planning with the emphasis on providing decision support to water resource managers. As illustrated in **Figure 6.1** the hydrological data preparation involves collating, patching and checking rainfall, streamflow and land use data that is used to compile the base hydrology of a water resource system. Rainfall-runoff modelling are undertaken using the Water Resource Simulation Model 90 (WRSM90) to extend the streamflow time series records back in time to where reliable rainfall data exists (usually from around the nineteen twenties).

The need to determine the assurance of water supply at 1:100 or 1:200 year recurrence intervals requires stochastic streamflow modelling. This is undertaken by a suite of programs designed to estimate the required parameter values and perform verification and validation checks.

The next step in the assessment of a water resource system is to compile a simulation model, which represents the physical characteristics of the infrastructure and uses either the historical or the synthetically generated stochastic data to quantify the yield capability of a system. This is undertaken with the Water Resource Yield Model (WRYM)

In some systems where high Total Dissolved Solids (TDS) concentrations have been identified as a problem, salinity modelling is undertaken. This involves (in addition to the hydrological data) collecting, collating, patching and checking salinity time series data that is used to calibrate the Water Quality Model modules, which are configured to represent the particular layout of a system. These calibrated modules, the hydrological data and the short-term yield characteristics are fed into the Water Resource Planning Model (WRPM). The WRPM is a decision support system capable of simulating various management options relating to the water quantity and quality (salinity).

The WRYM and WRPM are used to provide information to the water resource managers regarding the operation and development planning of the water resource systems. Typical aspects of water resource management where the technology is used are:

- Determine if the water requirements imposed on a system can be supplied by the water resource. Reconciliation of water requirements and yield availability. This also involves determining when augmentation will be required in future or what the influence of water demand management will be on the projected balance of water supply and requirements.

- Balancing is undertaken for users with different reliability requirement that is supplied from the same system.
- Develop optimum operating rules with the objective to maximise system yield but also minimise the operating costs, mainly energy or pumping costs.
- Determine the influence operating rules to improve the water quality (usually blending and dilution) will have on the assurance of supply from the system.
- Derive drought curtailment or restriction operating rules with the purpose to conserve water by reducing supply to low priority uses to ensure water is secured for higher priority (more essential) uses.
- Undertake sensitivity analysis to evaluate the impact a change to a particular variable (of which the projected value is uncertain) could have on the ability of a system to satisfy the needs of user requirements. For example different water requirement projection scenarios can be analysed.

The following sections elaborate further on the processes followed in water resource assessments and describe where optimisation is applied and GAs can possibly be used.

6.3.2 Hydrological assessments

This process involves compiling the hydrological database used in the analysis of water resource systems. Several mathematical models are applied to manipulate and produce the required rainfall and streamflow time series records. Optimisation techniques are used in these models to (for example) determine correlation parameters to patch missing rainfall and streamflow data. The optimisation or search techniques used in these models are well established and therefore do not warrant the application of GAs.

One of the activities of a hydrological study is applying the rainfall-runoff model (WRSM90) to generate sufficiently long records of natural stream flow time-series-data. Prior to generating these stream flow records, one is required to calibrate the rainfall-runoff model against recorded data. This activity is undertaken through an interactive process where the model user has to select values for various calibration parameters and adjust those in order to obtain the "best fit" between the recorded and the simulated data. The objective of this process is to obtain the model parameter values that give the best "goodness of fit" statistics but also to obtain an acceptable visual match between the recorded and simulated (peak and base) flows.

The above described calibration process is typically the type of problem that could be optimised with Genetic Algorithms. It is accepted that the judgement of an experienced model user (hydrologist) could not be replaced, however, the efficiency at which a solution is derived could possibly be improved by applying Genetic Algorithms. The GA will generate a vast number of iterations with varying combinations of parameters and in doing so expand the search space which would not have been covered by the model user due to time constraints. This will have the associated benefit that the model user will be able to observe the results of a wide range of situations and select the best options for detail evaluations and checking. As in all the applications of GAs, it is required to undertake research to derive the most appropriate fitness function and coding method for this application.

6.3.3 Stochastic streamflow generation

Due to the relatively short length of available streamflow data and the need to quantify the reliability of supply from a water resource system, stochastic streamflow generation is undertaken in system analysis studies. The process of deriving stochastic hydrology requires obtaining the best set of model parameter values that represent the character of the natural historical data. The mathematical models used for the parameter estimation employ well-established optimisation techniques that have been proven in practice to be robust and efficient.

6.3.4 Water quality modelling (salinity)

In various water resource systems in South Africa, water quality modelling (in particular salinity) is undertaken to simulate quality driven management options and the effect those have on the supply capability of the water resource system. This process requires compiling the water quality modules that represent the system configuration and involves calibration where model parameters are adjusted interactively by the model user until the simulated concentration and salinity loads are statistically and visually similar to those of recorded data.

This is another possible application of GAs and is similar to the process of calibrating the rainfall runoff model described in a previous section. It should be noted that to automate the parameter selection process a new procedures would have to be developed to undertake a number of related calculations that are currently carried out by the model user during each interactive iteration step.

6.3.5 System analysis

Yield analysis or system analysis involves configuring a mathematical network model to simulate the water balance and estimate the supply capability of a water resource system. An important aspect of this activity is finding the optimal operating rule for a system. In general, deriving the best operating rule requires balancing two opposing objectives; to maximise the yield of the system and minimising the operating costs mainly related to pumping or energy costs. In most cases the main objective is to maximise the yield, however, the question is always asked whether an alternative operating rule exists that would yield "close to the maximum" but still with energy costs savings.

Other variables need to be optimised when development planning is considered. Development planning requires analysing new system components, dams and transfer conduits that can be gravity or pumping links. Usually the proposed infrastructure transfers water into an existing water resource system, which means the operation of the extended system also needs to be included in the optimisation process.

During the initial Vaal River System Study of the early nineteen eighties Dynamic Programming (DP) techniques were used to determine the optimum operating rules of some of the sub-systems of the larger Integrated Vaal River System (DWAF, 1986). The DP results were compared to those derived from rules that were obtained through trail-and-error simulations and it was found the latter method produced results close to the optimum answer. The DP analysis was only undertaken for the critical period of the historical record and applied to sub-systems (subsets) of the larger Vaal River System.

In order to create an understanding of the need for optimisation in system analysis, it is required to describe the extent of the water resource systems. For the purpose of this discussion the Vaal River System is used, since it is by far the most important and complex system in South Africa. **Figure 6.2**, therefore, gives the basic schematic diagram of the Integrated Vaal River System and shows the different sub-systems, which are all linked through various inter-basin transfers. As an example, the Komati River Sub-system consists of the Nooitgedacht and Vygeboom dams, two diversion structures and related transfer conduits. The Usutu River sub-system comprises of Westo, Jericho and Morgenstond dams that are connected using gravity and pumping links designed to support mainly the coal fired electricity-generating power stations located along the Highveld coalfields.

A combination or reservoirs and transfer conduits supports the Gauteng region, supplied mainly in bulk by Rand Water who abstracts water from the Vaal Dam and Vaal Barrage. The Vaal Dam is supported by Sterkfontein Dam, which is fed from the Woodstock Dam through the Thukela-Vaal Transfer scheme. Another major source of water is the Lesotho Highlands Water Project, diverting water through a series of gravity tunnel from Katse Dam into the Liebenbergsvlei River, which is upstream of Vaal Dam.

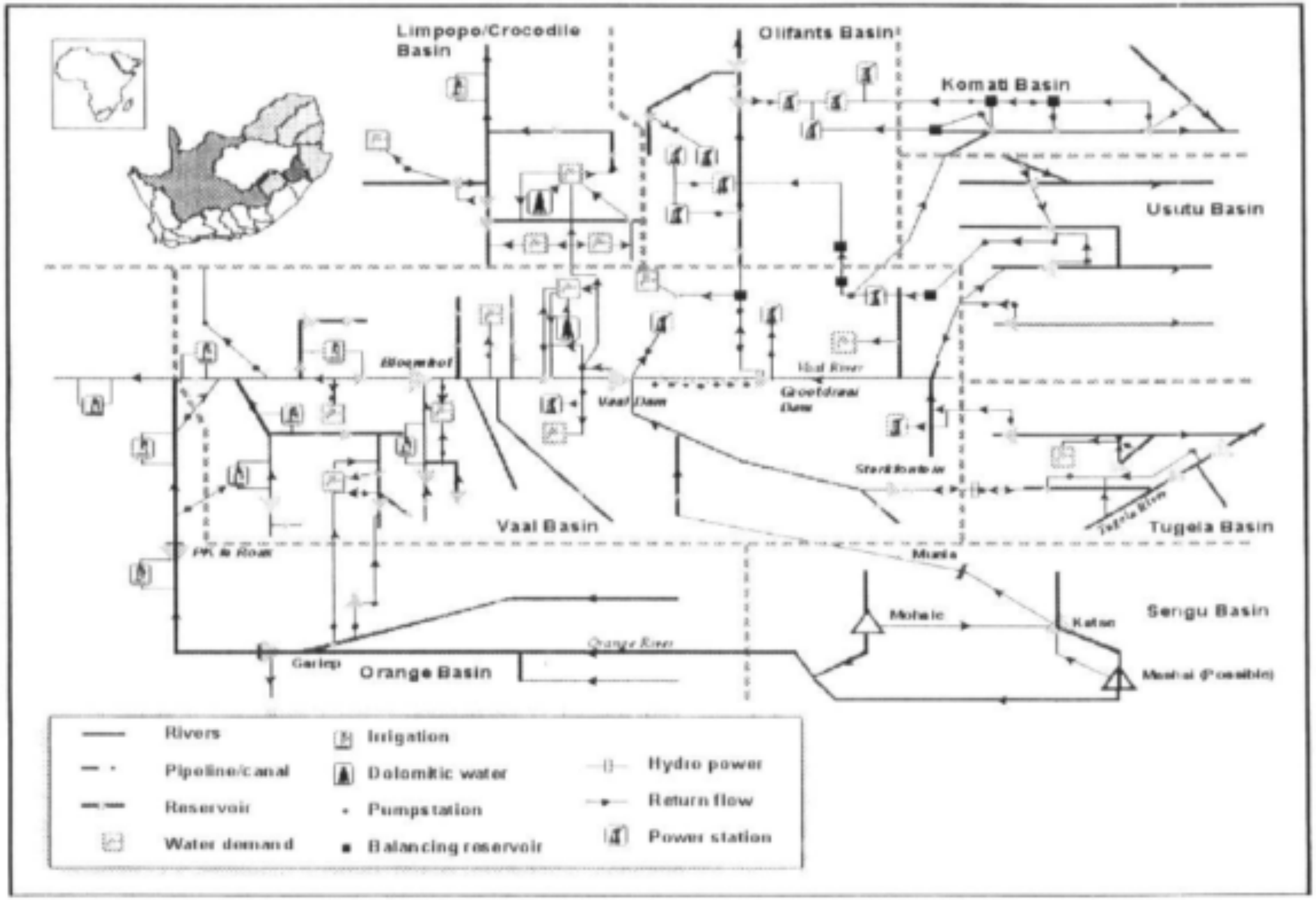


Figure 6.2 Schematic diagram of integrated Vaal River System

The following sections describe how the models for the Vaal River were configured and where optimisation was carried out.

Configuration of systems models and operating rule optimisation

The process used to configure the water resource network models was to first compile system networks for the seven different sub-systems Komati, Usutu, Heyshope, Zaaihoek, Grootdraai, Bloemhof Sub-system which include the Vaal River system down to Bloemhof Dam and the Senqu Sub-system consisting of Katse Dam and transfer tunnels. Optimisation of the **inter-reservoir operating rules** was undertaken in the cases of the Komati and Usutu sub-systems. The Grootdraai-Heyshope-Zaaihoek sub-systems were also combined to determine the transfer-operating rule to Grootdraai Dam.

These operating rules are defined by selecting different storage zones in each reservoir and specifying the sequence according to which water is abstracted from these zones. **Figure 6.3** shows the reservoir zone definitions of the rule adopted for the Usutu Sub-system. The circled numbers represent the sequence in which water is abstracted from the different zones.

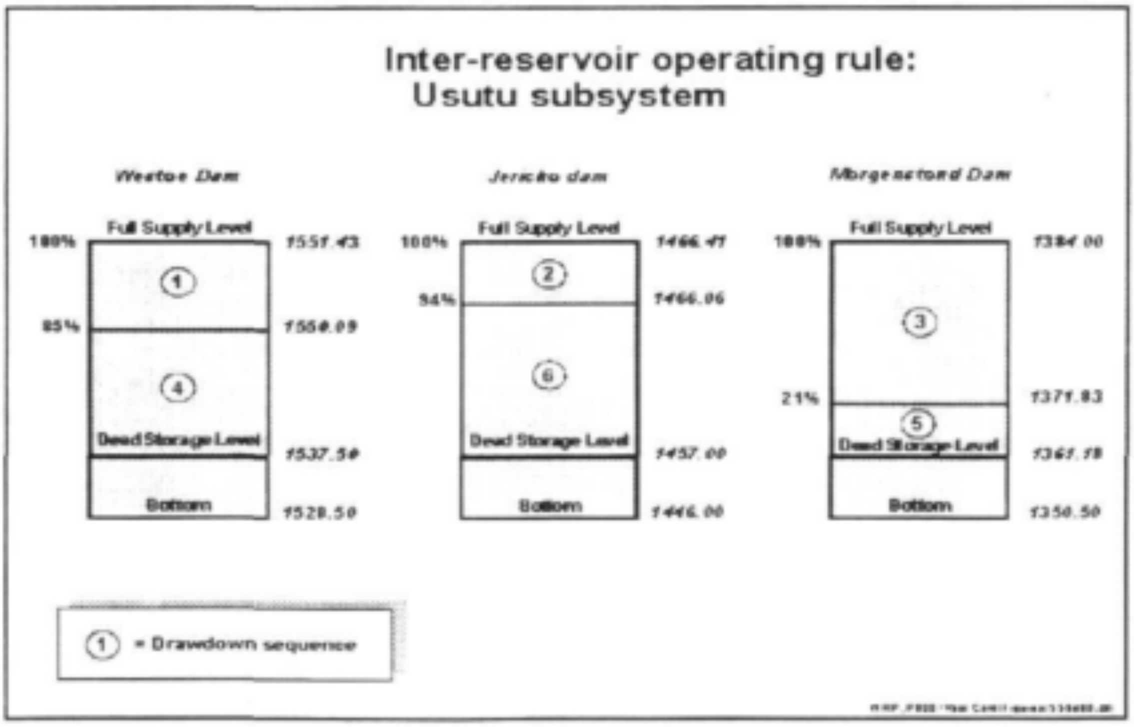
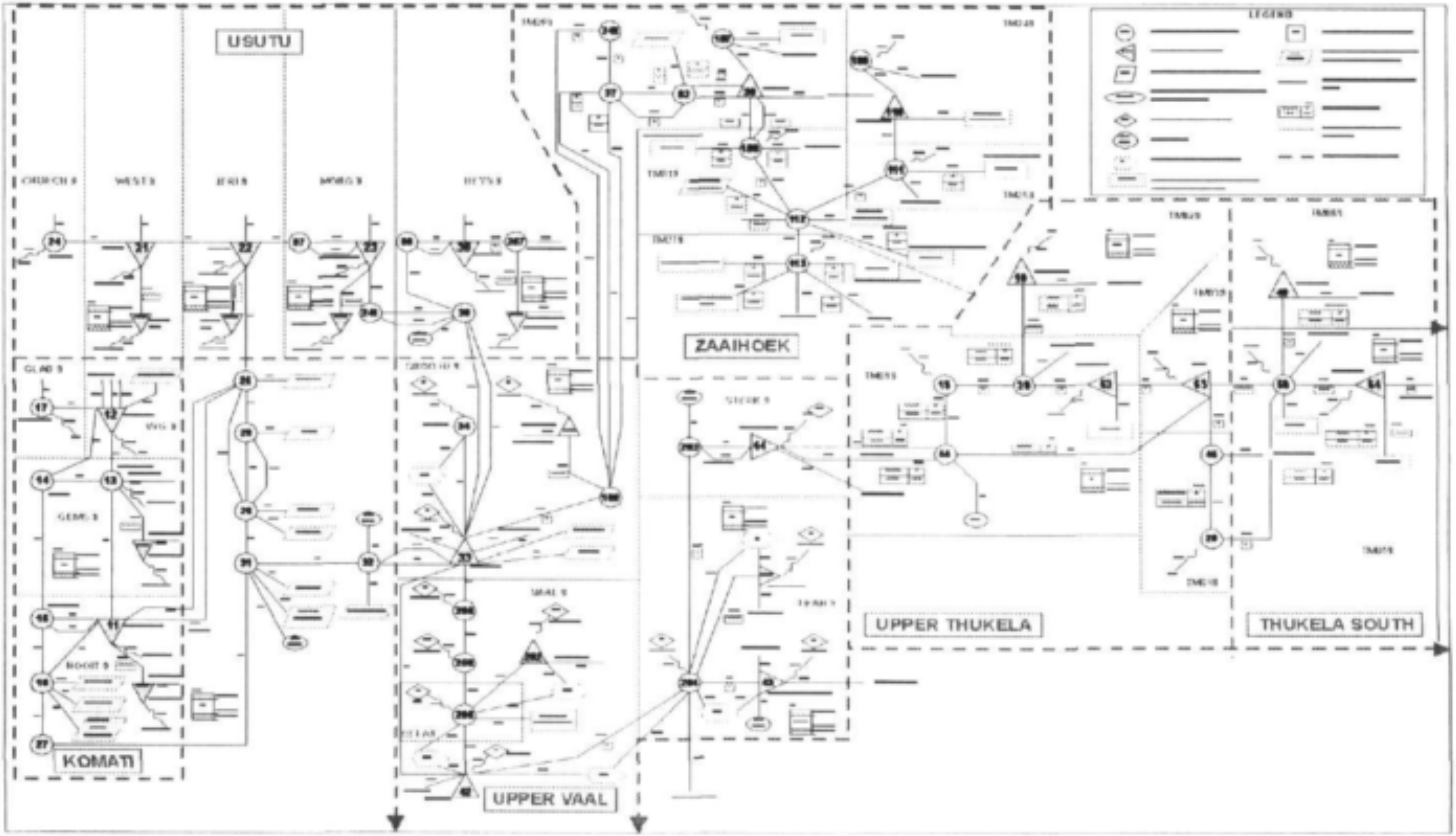


Figure 6.3: Example definition of the operating rule for the three dams in the Usutu sub-system

The optimum inter-reservoir operating rules are determined through a trail and error process where the model user select different settings for these zones and determine the yield for each scenario as well as the average transfer volumes through the pumping links. These optimisation analyses are first undertaken using the historical streamflow sequence, to analyse a wide range of settings and once the options are narrowed down, stochastic analyses are undertaken of the most promising rule options. The criteria used in the optimisation process are primarily to maximise the yield of the system but also (as a secondary objective) to minimise the pumping costs. In some cases it was found that a rule exists that gives slightly lower than the maximum yield but with significant reductions in pumping costs.

Once the inter-reservoir rules are defined within each sub-system, the integrated system is configured by linking the sub-systems using the WRPM. **Figure 6.4** gives the schematic layout of the network model of the eastern part of the Integrated Vaal River System and illustrate the complexity of the system. In the WRPM the **inter sub-system operating rule** are defined using the allocation algorithm.



WRPM SCHEMATIC DIAGRAM: UPPER VAAL, KOMATI, USUTU, THUKELA NORTH, UPPER THUKELA AND THUKELA SOUTH SUB-SYSTEMS

Example System Schematic Diagram

Fig6.4

The allocation algorithm has two main functions, calculate curtailments during drought periods and control the transfer or support between sub-systems. **Figure 6.5** presents schematically the functioning of the allocation algorithm and show the required input and results of the model. The allocation decisions are calculated by balancing the short term yield capability of the sub-systems with the projected water requirements imposed on the system. The calculation is carried out at least once a year using the storage state of the sub-systems at the decision date to select the appropriate short term yield curves (the short-term yield is dependant on the storage volume in the dams of a sub-system). The user support definition defines what users (water demand centre) can be supplied, by what sub-systems and in what sequence should the sub-systems support a particular users. Typically when the storage states in the reservoirs of the sub-systems are high there is sufficient yield (short-term) to support the water requirements of the users from the first sub-system in the sequence. As an example the power stations (Komati, Arnot, Hendrina and Duvha) will, under high storage conditions be fully supplied from the Komati Sub-system and no support will be transferred from the Usutu or Grootdraai sub-systems.

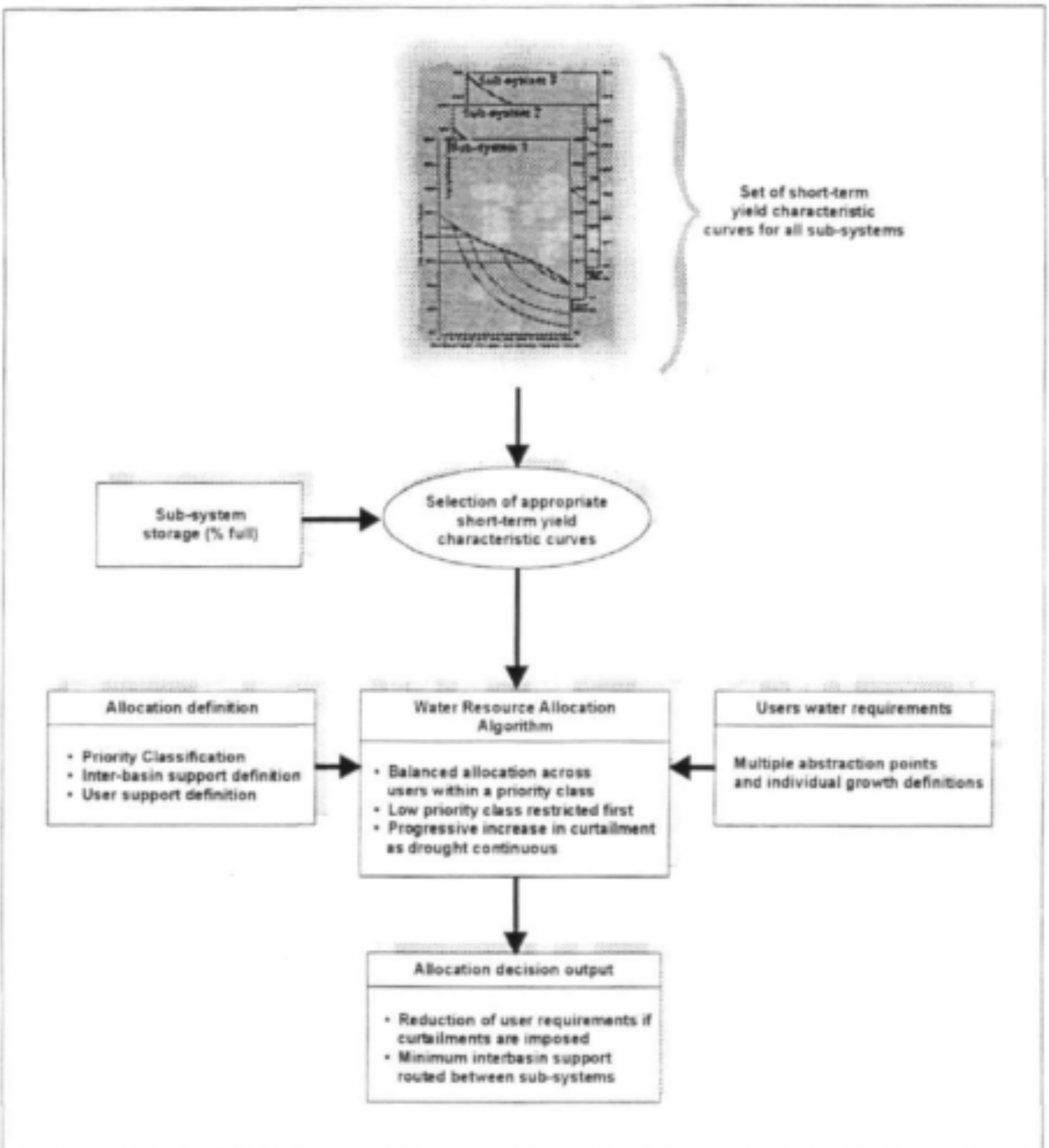


Figure 6.5: Schematic diagram of the functioning of the Water Resource Allocation Algorithm

When the reservoir levels are drawn down, during dry conditions, the short term yield of the sub-system will also decrease to the point where the water requirements are more than the sub-system yield. In such cases the allocation model will "search" for yield by following the sequence of potential supporting sub-systems (define by the user support definition). When it is found that support is available the allocation algorithm instructs the network simulation model to route the calculated volume from one sub-system to another.

The procedure described above is effectively a methodical approach that is followed to define the inter sub-system rules. In the past simulation analyses were carried out to test the behaviour of the system under these rules and in some cases adjustments were made. The rules were in general accepted without undertaking further optimisation or considering alternatives. It has only been in later years (since 1998) that refinements of the inter sub-system support rules have been undertaken where the cost of transfer (pumping) has been taken into account. This was made possible by increased processing capacity of computers, which allowed analysing various scenarios in a reasonable period of time.

Hydropower generation operating rules

Another potential application of GAs could be the operation of hydropower generation systems. In South Africa hydropower generation makes up a small portion of the electricity requirements and the largest installations are located in the Orange River system at Gariep and Vanderkloof dams. Operating rules have been developed for this system using scenario simulations (Eskom, 1995). An important aspect of this system is that the water is primarily used to support irrigation schemes and secondly to generate hydropower. Although there may be room to further optimise these operating rules, it would require significant development work to create an optimisation tool that has limited further application due to the absence of other large hydropower generation facilities in the country.

In summary, the status of optimisation in water resource system analysis field is as follows:

- Scenario simulations through and iterative process implemented manually by the model user is carried out to determine the optimum operating rules of sub-systems. This is achieved by defining the transfer rules between individual reservoirs to be dependant on the storage in each reservoir.

- This same process is followed with respect to development planning where the sizes of the infrastructure components (reservoirs and transfer conduits) and the operating rule need to be determined.
- For the integrated systems a methodical procedure is applied to define the inter sub-system operating rule and in later years scenario analyses were undertaken where the cost of energy (pumping) is taken into consideration. Effectively the status (volume of water in storage) of groups of reservoirs (sub-systems) is used as the independent variable that drives the transfer rule between sub-systems.
- The complexity of the integrated water resource systems, limitations of available optimisation techniques and the associated demand on computing resource were constraints limiting the application of automated optimisation methods in the past.

Given that the GA optimisation technique works well with multi dimensional problems with a large search space and the fact that computer processing capacity has improved considerably, it can be concluded that significant benefits could be achieved in the application of GAs in water resource system analysis. Recent scenario optimisation analyses showed (DWAF,1999) that savings in the order of R7million is achievable through merely adopting an alternative operating rule for the eastern part of the Integrated Vaal River System.

7. TECHNOLOGY TRANSFER - CAPACITY BUILDING IN THE APPLICATION OF GENETIC ALGORITHMS

7.1 Introduction

This section provides a description of the implementation and procedures that had been incorporated in the development of a simple pipeline optimisation program to be used as an educational tool to transfer the use of genetic algorithms in the water field.

Two simple problems had been selected to be evaluated with the program. One being a gravity system with off takes between the supply and the end reservoir and the second is a pumping line problem, with demands between the pump station and the end reservoir. In both these problems objective functions have been declared that reflects the required residual pressure at all the nodes and the maximum permissible flow velocity in the pipes. In both these problems it is assumed that an optimal cost solution, for a selection of pipe diameters that will supply the demand at the required residual pressure and within the velocity constraints set by the designer, does exist.

7.2 Short description of the program, "Genetic Algorithm Pipeline Optimisation Program", GAPOP

The objectives of the simple GA optimisation program, called GAPOP are:

- provide access for the novice in the use and understanding of the working of GA techniques;
- determine an optimal solution for a simple gravity or pumping system.

In the search for the optimal solution the "fitness function" seeks the lowest cost solution. Cost comparison in the case of the pumping system is done based on the Net Present Value

(NPV), (Capital cost, maintenance cost and energy cost) calculated over the analysis period. In the case of the gravity system only the capital cost is compared. Provision has been made for a weighing factor to increase the cost of the solution on the following two grounds:

- the residual pressure is less than the required pressure and
- the flow velocity is more than the acceptable maximum design flow velocity.

In the case of a pumping system the weighing factor, which is applied to increase the total NPV of the cost of the solution (real cost), resulted in a new cost referred to as "comparative cost". The "comparative cost" will always be higher or equal to the real cost of the solution and is only valued to rank the alternatives on a cost basis. This ranking procedure therefore incorporates the physical parameters of the solution, i.e. the residual pressure at the off takes and the flow velocity in the pipe with the cost for the solution. In the case of the gravity system the weighing factor, is applied to the capital cost of the solution to obtain the "comparative cost".

The program can analyse up to 20 pipe sections and 8 different pipe sizes and types. Although the program requires a minimum amount of input it provides the user with an optimised set of solutions to be investigated in more detail. The GAPOP program is available from the WRC website: http:\\www.wrc.org.za/software/GAPOP and also from the University of Pretoria's website: http:\\www.up.ac.za/academic/civil/divisions/water.html.

7.3 Data input required

The program is capable of handling two options, a gravity system or a pumping system. The system type is selected with the option button shown in **Figure 7.1**.

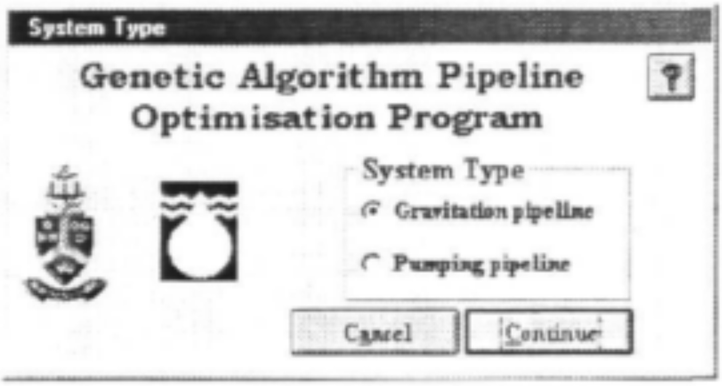


Figure 7.1 : Selection of the system type

The following data is required for a gravity system:

- the project data (project description, designer name and date), general data (the reservoir levels, the pipe length units and the demand units) and the profile data (pipe length, elevation and demand) are provided through **Figure 7.2**

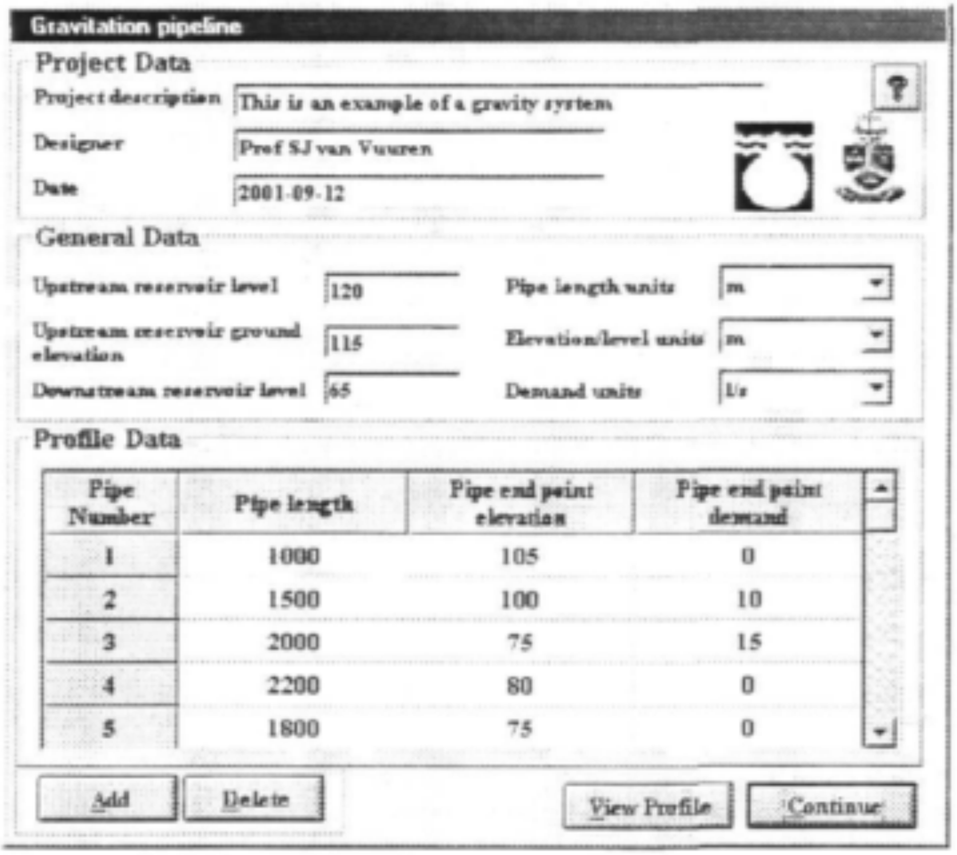


Figure 7.2 : Gravitational project data

- a list of possible pipe types to be analysed, their diameters, a representative roughness parameter for each pipe and their installed cost per meter. Up to 8 pipe diameters can be entered. The units of the diameters and absolute roughness values can be selected. **Figure 7.3** reflects the data requirements.

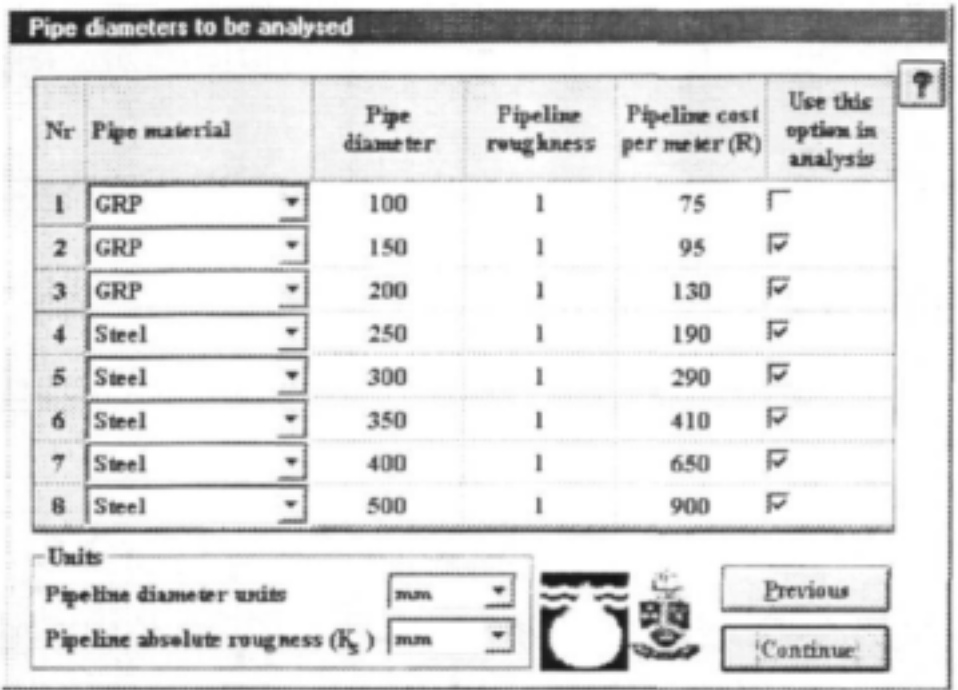


Figure 7.3 : Pipe diameters to be evaluated

- the required minimum residual pressure at all the nodes, the maximum preferred flow velocity in the pipes and the mutation probability is selected in **Figure 7.4**.

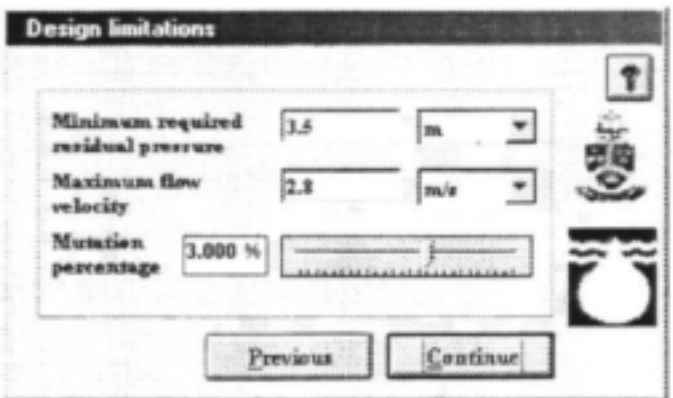
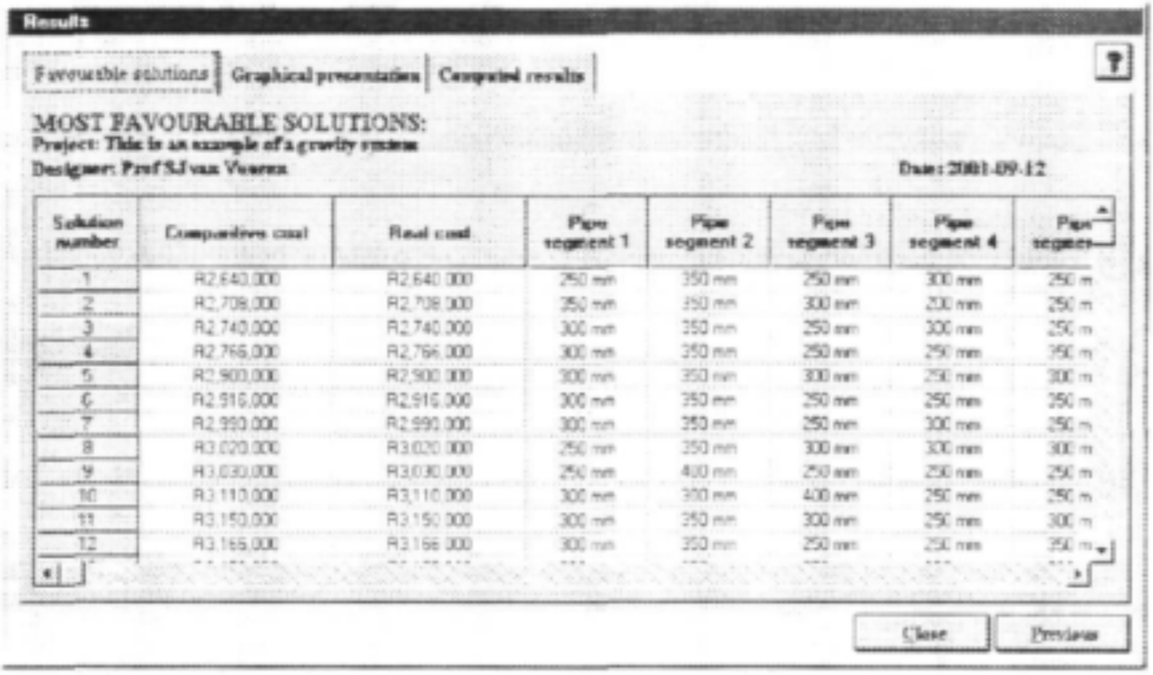


Figure 7.4 : Design limitations

With the above data provided the program will search for the optimum solution. The 20 most favourable results are reflected in a tabular format **Figure 7.5** and a graphical format **Figure 7.6**. By "clicking" the mouse on any of the graphical results shown in **Figure 7.6**, a dropdown Table will be shown that provides details of the specific solution.



Results

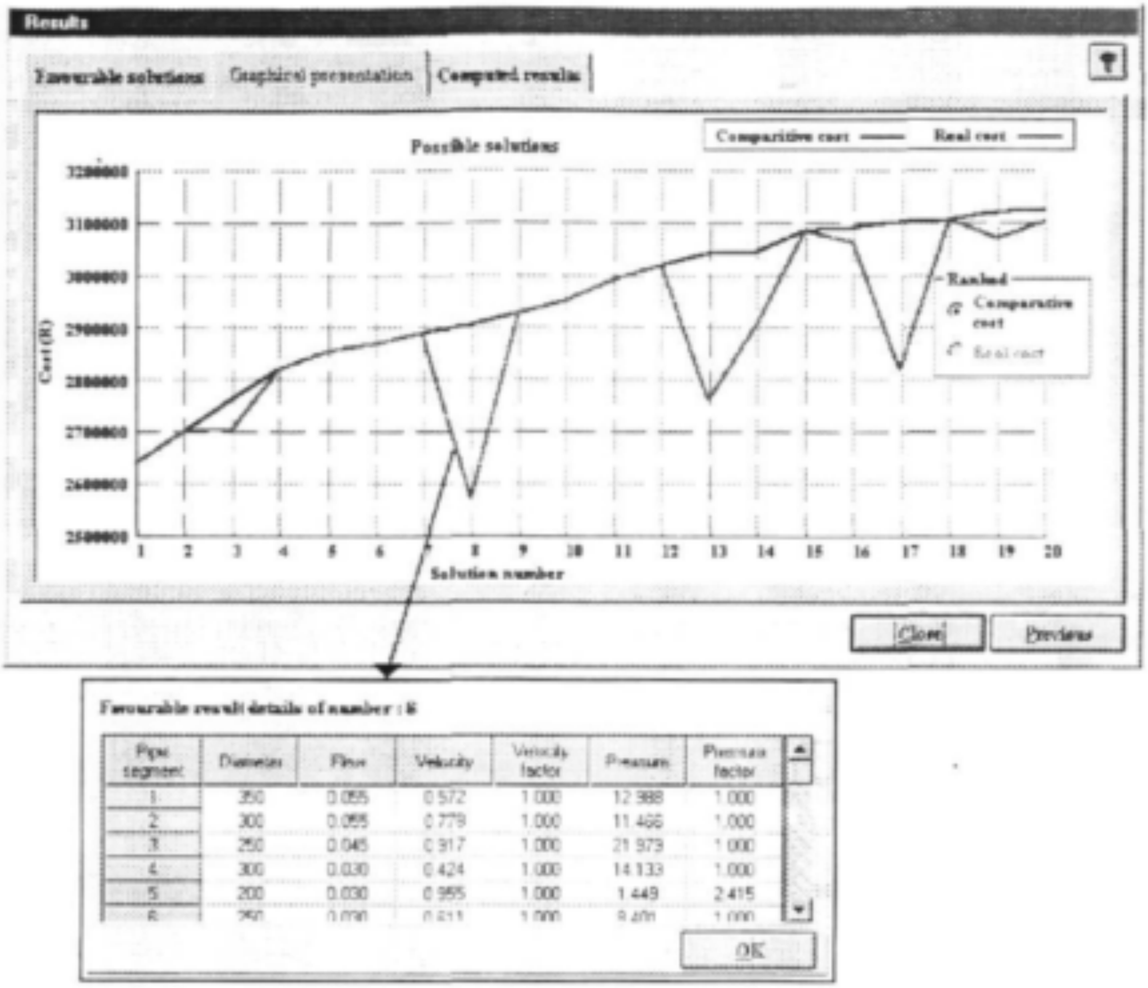
Favourable solutions | Graphical presentation | Computed results

MOST FAVOURABLE SOLUTIONS:
Project: This is an example of a gravity system
Designer: Prof SJ van Vuuren
Date: 2001-09-12

Solution number	Comparative cost	Real cost	Pipe segment 1	Pipe segment 2	Pipe segment 3	Pipe segment 4	Pipe segme
1	R2,640,000	R2,640,000	250 mm	350 mm	250 mm	300 mm	250 m
2	R2,708,000	R2,708,000	350 mm	350 mm	300 mm	200 mm	250 m
3	R2,740,000	R2,740,000	300 mm	350 mm	250 mm	300 mm	250 m
4	R2,766,000	R2,766,000	300 mm	350 mm	250 mm	250 mm	350 m
5	R2,900,000	R2,900,000	300 mm	350 mm	300 mm	250 mm	300 m
6	R2,916,000	R2,916,000	300 mm	350 mm	250 mm	250 mm	350 m
7	R2,990,000	R2,990,000	300 mm	350 mm	250 mm	300 mm	250 m
8	R3,020,000	R3,020,000	250 mm	350 mm	300 mm	300 mm	300 m
9	R3,030,000	R3,030,000	250 mm	400 mm	250 mm	250 mm	250 m
10	R3,110,000	R3,110,000	300 mm	300 mm	400 mm	250 mm	250 m
11	R3,150,000	R3,150,000	300 mm	350 mm	300 mm	250 mm	300 m
12	R3,166,000	R3,166,000	300 mm	350 mm	250 mm	250 mm	350 m

Close | Preview

Figure 7.5 : Tabular results



Pipe segment	Diameter	Flow	Velocity	Velocity factor	Pressure	Pressure factor
1	350	0.055	0.572	1.000	12.988	1.000
2	300	0.055	0.779	1.000	11.466	1.000
3	250	0.045	0.917	1.000	21.973	1.000
4	300	0.030	0.424	1.000	14.133	1.000
5	200	0.030	0.955	1.000	1.449	2.415
6	250	0.030	[illegible]	1.000	[illegible]	1.000

Figure 7.6 : Graphical presentation of the results

The following data is required for a pumping system:

- the project data (project description, designer name and date), general data (the reservoir levels, the pipe length units and the demand units) and the profile data (pipe length, elevation and demand) are provided in **Figure 7.7**.

Figure 7.7 : Project data for a pumping pipeline

- a list of possible pipe types to be used, their diameters, a representative roughness parameter for each pipe and their installed cost per meter. Up to 8 pipe diameters can be entered. The units of the diameters and absolute roughness values can be selected. Similar to the selection of pipes for the gravitational solution according to **Figure 7.3**, the data is provided for the pumping pipeline.

- the energy cost, applicable summer and winter rates, selection of peak, standard and off-peak periods, pumping hours per day options and pumping efficiency. **Figure 7.8** shows the input screen for these data.

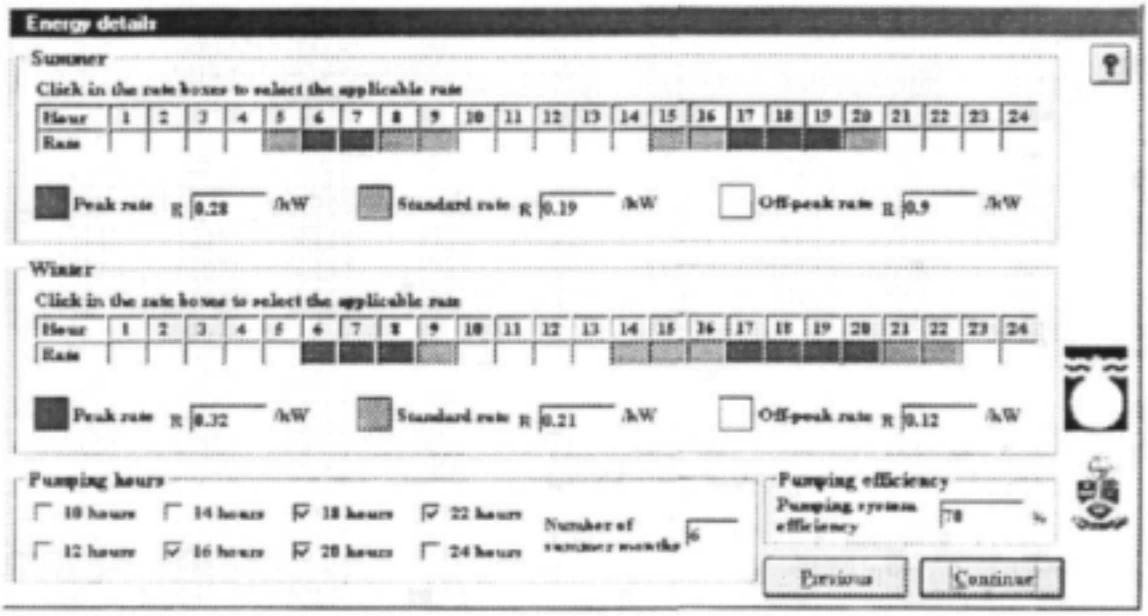


Figure 7.8 : Data for the applicable energy tariff structure

- the mechanical and electrical components of the capital cost based on the energy used, the escalation rates (for future operation, maintenance and energy costs) as well as the discount rate and the analyses period (design life) is defined in **Figure 7.9**.

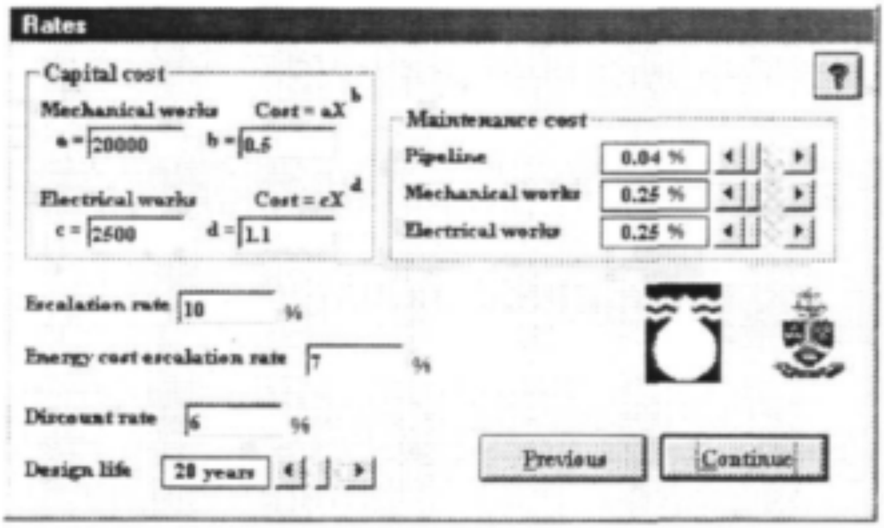


Figure 7.9 : Data for capital components and the escalation rates

- the required minimum residual pressure at all the nodes, the maximum preferred flow velocity in the pipes and the mutation probability as per **Figure 7.10**.

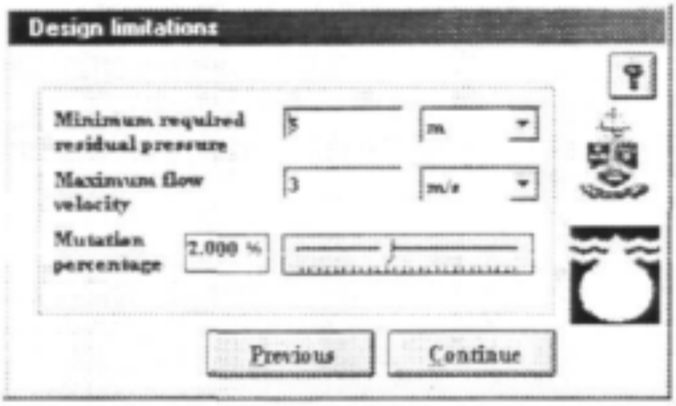


Figure 7.10 : Design limitations (preferences)

This data, required for the pumping system, is used to evaluate different pipe diameters, solving the objective function (lowest total NPV of all the cost) that adheres to the constraints defined for the system. Once the system is analysed the 20 most favourable results (if there are more than 20 possibilities) will be shown as indicated before for as gravity pipeline (**Figures 7.5** and **7.6**). As before a typical graphical result is shown below in **Figure 7.11**.

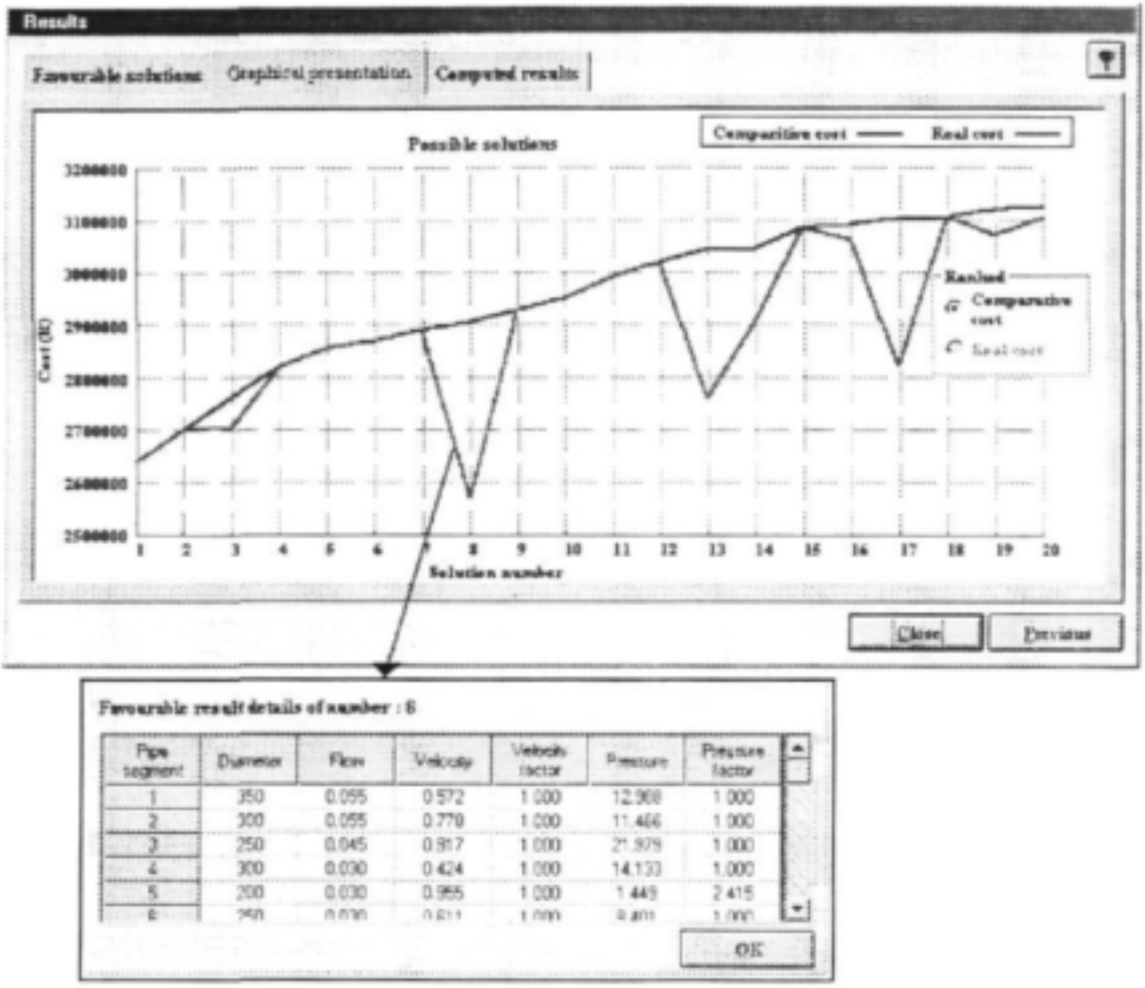


Figure 7.11 : Graphical result for a pumping pipeline

7.4 Summary of the calculation steps used in GAPOP

In the program the calculation steps that were used are reflected below.

1. Initial string (seed) – random selection of initial strings (pipe diameters from the selection of possible pipe diameters to be analysed for the 20 pipe segments. A maximum number of 8 different pipe diameters can be analysed.

2. The fitness of these selections were determined based on the comparative costs that were calculated. This analyses is repeated for a number of times, dependent on the

number of pipe sections entered as well as the number of possible pipe diameters in search of the "fittest" solution.

Fitness check and the application of weighting (penalty) factors for each analysis

(a) *From the initial randomly selected string, the diameters are obtained (decoding).*

(b) Calculate the velocity in each pipe segment.

(c) Calculate velocity penalty factor, $\left(\frac{velocity}{\max imum\ velocity}\right) = y$ If $y < 1$ then the velocity penalty factor = 1. If $y > 1$ then multiply the pipe cost with the velocity penalty factor, y.

(d) Calculate hydraulic grade line (friction).

(e) Calculate friction penalty factor, $\left(\frac{\min imal\ residual\ pressure}{calculated\ residual\ pressure}\right) = x$

If $x < 1$ then the friction penalty factor = 1,0. If $x > 1$, then multiply the pipe cost with the velocity penalty factor, x.

(f) If system is incapable to provide the flow, then the friction penalty factor is set to 50, penalizing the system. This penalty factor is also applied when negative pressure occurs at any point in the system.

(g) Calculate cost for these four strings by adding the cost of the individual pipe sections with the incorporation of the friction and velocity penalty factors.

(h) In the case of the gravity system obtain the best solutions for the system. In the case of the pumping system calculate the NPV for the other costs add it to the capital cost and obtain the best solution based on the NPV of all the costs.

(i) Select the 4 parent strings, based on the calculated fitness of the strings (lowest NPV costs) to be used in the following generation.

Pairing (crossover) – gene transfer between two parents

(a) Randomly determine which of the parents should be paired to obtain the offspring strings (children).

(b) Determine (randomly) the position for the crossover to occur in each of the pairs. Implement the crossover.

Mutation – forcing the solution to including gene strings from the total solution space and to steer away from the local optimum

(a) Randomly determine if mutation should occur (mutation probability normally < 2 %).

(b) Mutation will change all the bits in the string that mutates from "1" to "0" or from "0" to "1".

3. Rank the solution based on the comparative costs.

4. Plot costs and write favourable results to a file for review. The results as well as the input data can be printed.

The data input and the results should be user friendly and fun to use.

8. CONCLUSION

Based on the literature that has been reviewed it can be stated categorically that:

- GAs are not used to its full potential in the optimisation in the water industry in South Africa,
- Potential applications of the technique within the South African context are:
  - Hydrology and water resources assessment,
  - Network optimisation,
  - Optimisation of rehabilitation, extension and upgrading of distribution networks,
  - Operation and maintenance scheduling of pumps and purification plants.
- Little formal teaching on GAs are included in the curriculum of civil engineering in South Africa.
- Feedback from Rand Water reflected the need for the development of software utility programs that can be used in practice and stimulate the further exploitation of this technique,
- The pipeline diameter optimisation program (GAPOP) that has been developed has been well accepted in practice.

9. RECOMMENDATIONS

This phase of the study (Phase 1) reflected the value of GAs and the potential utilisation of GAs in the water industry. It is therefor recommended that the following research has to be undertaken in future phases of this project. It is proposed that further research be undertaken in a phased approach as outlined below and described in more detail in subsequent paragraphs:

It is recommended that the following aspects should be researched as part of **Phase 2 (2001 to 2002)**:

- A course be presented on the use of GAs in the water industry. World-renowned leaders in this field must be invited to participate in such a course in South Africa.
- Opportunities for the inclusion of this technique in the graduate program should be promoted.
- Procedures for the implementation of the technique in :
    - Network optimisation
    - Water resources assessment
    - Operational scheduling

  needs to be conceptually defined and developed for implementation.
- The software that have been developed should be extended and distributed through the WRC with the objective to enhance the use and transfer of knowledge regarding the value of GAs in the water sector

- Conceptual development of coding for the application of GA to optimise the operating rules between reservoirs.

Further research that should be considered in the Water Resources Field is defined in the following paragraphs.

The potential applications of GAs in the Water Resource field is to improve the calibration of the rainfall-runoff (WRSM90) and Water Quality models as well as automating the optimisation of operating rules of water resource systems. Considering the potential benefits of applying GAs in these two areas, it is clear that the optimisation of the operating rules of systems would yield the largest benefits. An automated optimisation tool would reduce the time required by the model user and has the potential benefit of reducing pumping costs, which could amount to millions of rands in savings. Optimising the sizes of proposed infrastructure components in combination with optimising the operating rules could also have significant benefits.

It is therefore proposed that further research and development be undertaken to apply GAs in the optimisation of the operating rules and sizing of proposed water resource infrastructure. Although the ultimate aim of such an optimisation tool would be to simulate the large integrated systems, it is proposed that the research and development be carried out in incremental steps to first prove the viability of the development.

Following the findings of **Phase 2**, the research will be extended to include the following:

Phase 3

- Development of a basic software model.
- Testing of parameter values and alternative operators for the GA (mutation percentage, population size, crossover methods ect.).
- Develop a generic inter reservoir optimisation model.

Phase 4: Extend the Phase 3 model to optimise the operating rules of integrated water resource systems.

- Conceptual development of coding and "fitness" functions. The integration of the GA model with the existing water resource allocation algorithm will be important.

- Development of a basic software model.
- Testing of parameter values and alternative operators for the GA (mutation percentage, population size, crossover methods ect.).
- Develop a generic optimisation model.

Phase 5: Incorporate the optimisation of new infrastructure sizing.

This will involve further extending the GA optimisation model to also optimise the sizes of proposed new infrastructure in relation to the operating rules. It will be required to incorporate engineering economic parameters as part of the "fitness" functions to undertake optimisation is this area. The steps required for this phase would be similar to those described for the other two phases.

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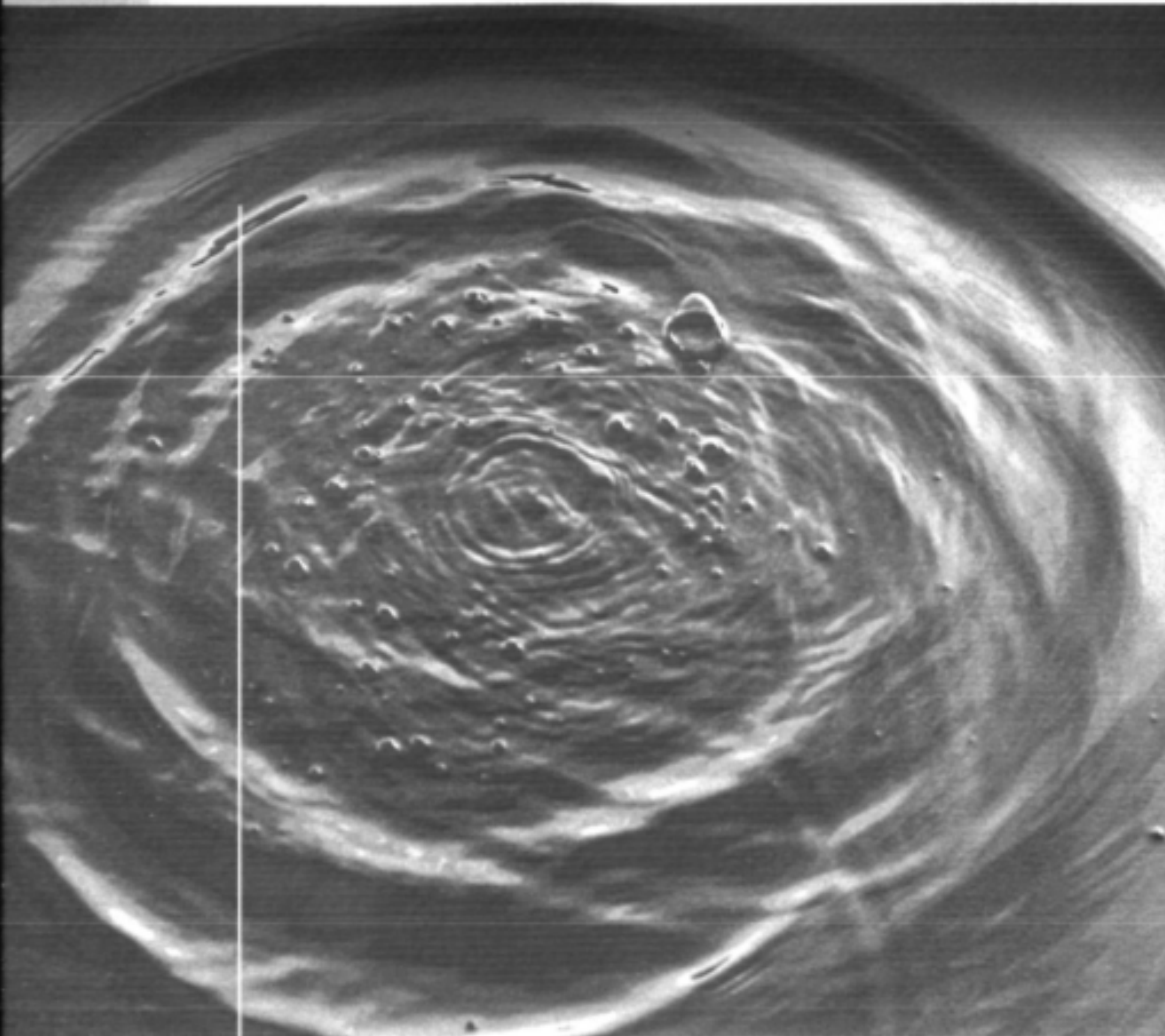

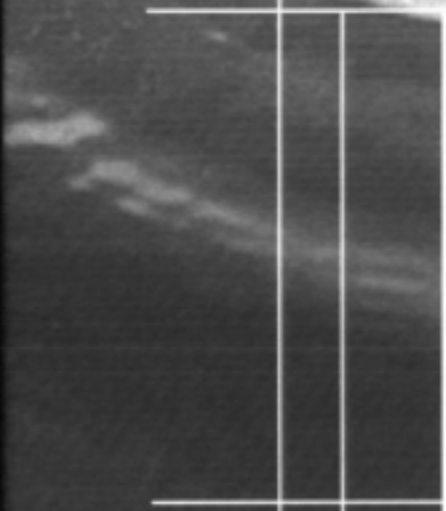

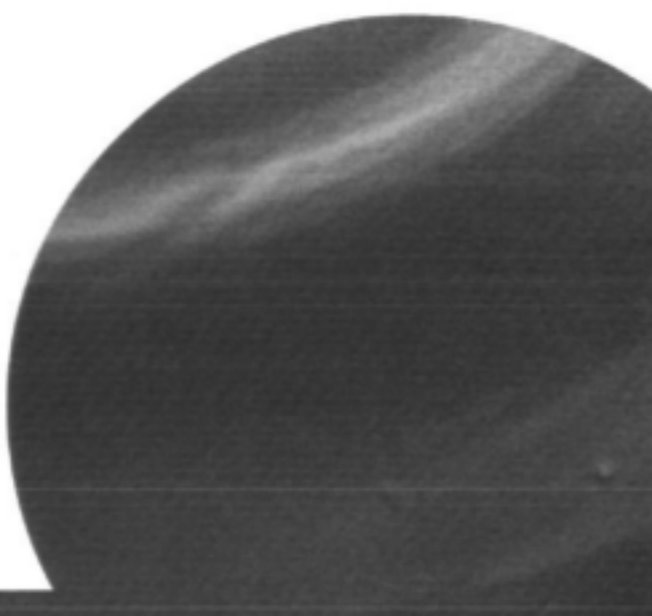

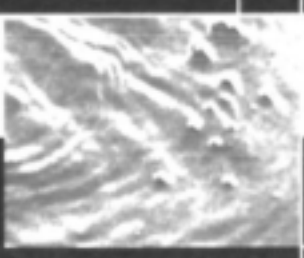

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