A genetic algorithm modelling framework and solution technique for short term optimal hydrothermal scheduling — Source link

S.O. Orero, Malcolm R. Irving

Institutions: Brunel University London

Published on: 01 May 1998 - IEEE Transactions on Power Systems (IEEE)

Topics: Meta-optimization, Water transport and Genetic algorithm

A GENETIC ALGORITHM MODELLING FRAMEWORK AND SOLUTION TECHNIQUE FOR SHORT TERM OPTIMAL HYDROTHERMAL SCHEDULING

S.O. Orero and M.R. Irving

Brunel Institute of power Systems, Brunel University, Uxbridge, UB8 3PH, U.K.

***Abstract*: A Genetic algorithm is applied to the problem of determining the optimal hourly schedule of power generation in a hydro thermal power system. A multi-reservoir cascaded hydro-electric system with a non-linear relationship between water discharge rate, net head and power generation is considered. The water transport delay between connected reservoirs is also taken into account. The main control parameters that affect the genetic algorithm performance are discussed and a summary of the theoretical basis of the genetic algorithm method is presented. It is shown that a multiple step genetic algorithm search sequence can provide the optimal hourly loading of the system generators.**

I. INTRODUCTION

Economic operation and control of interconnected power systems involves the solution of difficult optimisation problems that require good computational tools. Evolutionary computation is one such tool that has shown its ability in solving complex problems. Evolutionary computational methods mimic biological population genetics in a search for the optimal solution, and can be implemented in various forms such as genetic algorithms [1], evolutionary programming [2] and evolution strategies [3]. In this work, the genetic algorithm is applied in the solution of the problem of optimal generation scheduling in a hydrothermal power system.

PE-188-PWRS-0-12-1997 A paper recommended and approved by the IEEE Power System Engineering Committee of the IEEE Power Engineering Society for publication in the IEEE Transactions on Power Systems. Manuscript submitted June 20, 1996; made available for printing December 16, 1996.

The optimal scheduling of generation in a hydrothermal system involves the allocation of generation among the hydro-electric and thermal plants so as to minimise total operation costs of thermal plants while satisfying the various constraints on the hydraulic and power system network. In short term scheduling it is normally assumed that the target dam levels at the end of the scheduling period have been set by a medium term scheduling process that takes into account longer term river inflow modelling and load predictions. The short term scheduler then allocates this water (power) to the various time intervals in an effort to minimise thermal generation costs while attempting to satisfy the various unit and reservoir constraints.

The main constraints include: the time coupling effect of the hydro sub problem, where the water flow in an earlier time interval affects the discharge capability at a later period of time, the varying system load demand, the cascade nature of the hydraulic network, the varying hourly reservoir inflows, the physical limitations on the reservoir storage and turbine flow rate and the loading limits of both thermal and hydro plants. Further constraints could be imposed depending on the particular requirements of a given power system, such as the need to satisfy activities including; flood control, irrigation, fishing, water supply etc.

The hydrothermal scheduling problem has been the subject of intensive investigation for several decades now. Most of the methods that have been used to solve the hydro-thermal co-ordination problem make a number of simplifying assumptions in order to make the optimisation problem more tractable. Some of these solution methods include: variational calculus based techniques [5], dynamic programming [6-7], functional analysis [8-10], network flow and linear programming [11-14], non-linear programming [15-16], mathematical decomposition [17-19], heuristics, expert systems and artificial neural networks [20-23]. Genetic algorithms have a number of advantages over other conventional optimisation and search techniques. In the present work, the genetic algorithm technique is applied to the hydro-thermal scheduling problem. The GA has attractive features such as: the simplicity of the algorithm, the ability to handle all sorts of functional representations of problems, including problems with very complex inter-functional and intra-functional relationships and its robustness, enabling one set of general GA control parameters to solve a wide range of problems.

II. PROBLEM STATEMENT

A. Notation

F	Composite cost function
F_i	fuel cost of i^{th} thermal unit
$P_s(i,t)$	loading of i^{th} thermal unit at time t
$P_h(i,t)$	generation level of i^{th} hydro unit at time t
$V_h(i,t)$	storage volume of i^{th} reservoir at time t
$Q_h(i,t)$	water discharge rate of i^{th} reservoir at time t
$P_D(t)$	load demand at time t
$P_L(t)$	total transmission line losses at time t
$S_h(i,t)$	spillage of of i^{th} reservoir at time t
$I_h(i,t)$	inflow rate of i^{th} reservoir at time t
$H_i(t)$	net head of i^{th} reservoir at time t
α, β, γ	thermal generation cost coefficients
C_{i1},..,C_{i6}	hydro power generation coefficients
$\tau_{i,m}$	water transport delay from reservoir σ to i
R_u	set of upstream units directly above i^{th} hydro plant
R_h / R_s	set of hydro / thermal plants in the system
i, m	reservoir index, index of reservoirs upstream of the i^{th} reservoir
t, T	time index, scheduling period
$V,_i^{begin}$	initial storage volume of i^{th} reservoir
$V,_i^{end}$	final storage volume of i^{th} reservoir

B. Mathematical Formulation

Hydro-thermal scheduling involves the optimisation of a problem with a non-linear objective function, with a mixture of linear, non-linear and dynamic network flow constraints. The problem difficulty is compounded by a number of practical considerations and unless several simplifying assumptions are made, this problem is difficult to solve for practical power systems. The basic optimal hydrothermal scheduling in the short term, involves minimising the thermal cost function, F, over a given scheduling period, T,

$$Min\sum_{t\in T}\sum_{i\in R_s} F_i\Big(P_s(i,t)\Big) \tag{1}$$

subject to a number of unit and power system network equality and inequality constraints. These constraints include:

B. 1 System active load balance

The total active power generation must balance the predicted power demand plus losses, at each time interval over the scheduling horizon

$$\sum_{i\in R_s} P_s(i,t)+\sum_{i\in R_h} P_h(i,t)=P_D(t)+P_L(t) \qquad t\in T \tag{2}$$

B. 2 Thermal plant loading limits must be satisfied,

$$P_s(i,t)^{min} \le P_s(i,t) \le P_s(i,t)^{max} \qquad t\in T \tag{3}$$

B. 3 Hydro plant loading limits must be satisfied,

$$P_h(i,t)^{min} \le P_h(i,t) \le P_h(i,t)^{max} \qquad t\in T \tag{4}$$

B. 4 Hydraulic network constraints

The hydraulic operational constraints comprise the water balance (continuity) equations for each hydro unit (system) as well as the bounds on reservoir storage and release targets. These bounds are determined by the physical reservoir and plant limitations as well as the multipurpose requirements of the hydro system. These constraints include:

- physical limitations on reservoir storage volumes and discharge rates,

$$\begin{gathered} V_{h\,i,t}^{\;min} \le V_{h\,i,t} \le Vh_{i,t}^{\;max} \\ Q_{h\,i,t}^{\;min} \le Q_{h\,i,t} \le Q_{h\,i,t}^{\;max} \\ t\in T \end{gathered} \tag{5}$$

- The desired volume of water to be discharged by each reservoir over the scheduling period,

$$\begin{gathered} V_{h\,i,t}\big|^{t=0} = V_{h,i}^{\;begin} \\ V_{h\,i,t}\big|^{t=T} = V_{h,i}^{\;end} \\ i\in R_h \end{gathered} \tag{6}$$

- The continuity equation for the hydro reservoir network

$$\begin{gathered} V_h(i,t)=V_h(i,t-1)+I_h(i,t)-Q_h(i,t)-S_h(i,t) \\ +\sum_{m=1}^{R_u}\Big[Q_h\big(m,t-\tau(i,m)\big)+S_h\big(m,t-\tau(i,m)\big)\Big] \\ i\in R_h \;\; and \;\; t\in T \end{gathered} \tag{7}$$

B. 5 Power generation characteristics

The power generated from a hydro plant is related to the reservoir characteristics as well as the water discharge rate. A number of models [4] have been used to represent this relationship. In general, the hydro generator power output is a function of the net hydraulic head, H, reservoir volume, V, and the rate of water discharge, Q,

$$P_h(i,t)=f\left(Q_h(i,t)\,,V_h(i,t)\right) \quad \text{and } V_h(i,t)=f\left(H_{i,t}\right) \tag{8}$$

The model can also be written in terms of reservoir volume instead of the reservoir net head, and a frequently used functional is

$$\begin{aligned} P_h(i,t)=&C_{1,i}\,V_h(i,t)^2+C_{2,i}\,Q_h(i,t)^2 \\ &+C_{3,i}\left(V_h(i,t)\right)\cdot\left(Q_h(i,t)\right) \\ &+C_{4,i}\,V_h(i,t)+C_{5,i}\,Q_h(i,t)+C_{6,i} \\ &i\in R_h \end{aligned} \tag{9}$$

Net head variation can only be ignored for relatively large reservoirs, in which case power generation is solely dependent on the water discharge. In setting the generation levels of the thermal plants, a quadratic cost function is used to model the fuel input / power output characteristic of thermal units.

III. GENETIC ALGORITHM SOLUTION METHOD

A. Overview of Genetic Algorithms

Genetic Algorithms (GA) are evolutionary computation techniques that work with a population of potential solutions to a problem, mimicking some of nature's evolutionary process. Individuals in the GA population mate and reproduce as in nature. Different population members are assigned reproduction rates proportional to their fitness. The fitness is derived from the problem objective function. A GA solution to a problem frequently uses a representation similar to biological gene structures. The population of a GA is a subset of a larger set of individuals whose members include all the possible solutions to the problem. This larger set of possible solutions is usually too large to be enumerated and hence the need for a technique such as GA to sample this large search space. A GA uses a combined set of genetic operators to search for an optimal solution over the coded parameter space. A flow chart for a simple genetic algorithm cycle is shown in figure 1.

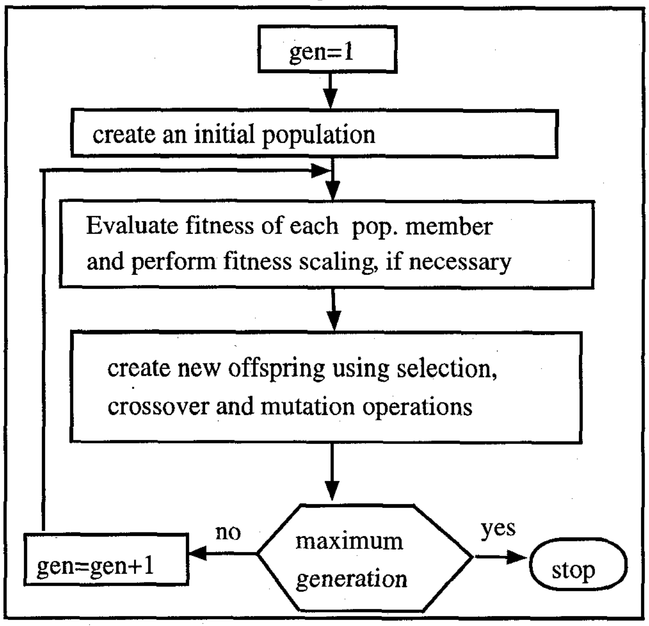


Fig 1. A basic genetic algorithm cycle

A brief description of the main components of the genetic algorithm process is presented in the following sections.

A. 1 Selection

The selection step of the GA cycle is the process of determining the number of copies of each individual parent that can participate in the reproduction or mating process. There are several ways of implementing the selection mechanism. The main ones are; 'roulette wheel' selection [24], tournament selection [25] and stochastic remainder selection [26]. The stochastic remainder selection approach has been used in this work. Fitness scaling is usually applied to the fitness values to prevent premature convergence, which is caused by a lack of diversity in the population due to a decrease in the variance of fitness.

A. 2 Crossover and mutation

The crossover operator is mainly responsible for the global search property of the GA. The operator basically combines substructures of two parent chromosomes to produce new structures, with a chosen probability. The most commonly used crossover methods are single point, two point and uniform crossover [27]. The main reason for using the mutation operator is to prevent the permanent loss of any particular bit value, as without a mutation there is no possibility of re-introducing a missing bit value.

A. 3 Population Size and Initialisation

A genetic algorithm is a population based search technique that derives its power from the fact that it advances its search based on feedback obtained from a number of potential solutions to the problem, each searching different regions of the search space at the same time. The initial population of solutions is usually generated randomly, although sometimes the search can benefit from inclusion of good previous solutions, if available, but this must be done with utmost care, since lack of sufficient diversity in the initial population can easily result in premature convergence. The size of the population is one of the major GA control parameters. A number of theoretical and empirical studies [28] provide guidelines on the choice of appropriate population sizes. However there is no empirical formulae linking the population size to other GA variables or any problem specific parameters. In this study the population size is chosen as a function of the string length, and the value used has been set after a number of empirical trials.

A. 4 Parent replacement method

In moving from one generation to the next, the old population should be replaced by the newly created offspring population in some optimal way that keeps the search for better solutions on the appropriate track. This step is important for the GA because it determines the degree of exploitation of the new search material in the advancement of the search for the optimal solution. Sometimes, it is good to keep track of the best solution obtained so far as the optimisation progresses. This is achieved in GA by an "elitist" strategy that retains intact a copy of the best solution in successive generations.

B. Theoretical Basis of Genetic Algorithms

Although genetic algorithms have shown high success rates in solving a number of complex problems previously unsolved by other methods, the theoretical basis of their performance is still the subject of intensive research.

B. 1 Schema Analysis

The genetic algorithm uses a population of candidate solutions to the problem, which individually and in combination with other members of the group provide information about the various sub-structures making up the complete solution string. Through the process of selection and recombination, the number of instances of a substring (building blocks), changes in proportion to the relative observed performance of each string in each generation. If a fitness proportional selection method is used, as is usually the case, then an exponentially increasing number of copies are made of the substrings of above average fitness, enabling them to dominate future populations. The basic explanation of the robust performance of the genetic algorithm is based on the schema theorem, [1], which postulates that while the fitness function is evaluated based on the performance of the whole string, information is gathered about all the component parts that make up the string.

A schema is a subset of strings in a population with similarities at certain string positions. The schema theorem provides a lower bound for schema growth in a GA population. Consider a schema H existing in a population at a given time t. After selection, schema numbers change according to

$$M(H,t+s) \geq M(H,t)\left[f(H,t)/f_{avg}\right] \tag{10}$$

and after crossover, mutation and other operators

$$M(H,t+1) \geq M(H,t)\left[f(H,t)/f_{avg}\right] \times \left[1-\epsilon(H,t)\right] \tag{11}$$

where

$M(H,t)$ is the number of strings with schema H at time t, $M(H,t+s)$ the number of strings with schema H after selection, f_{avg} the average fitness of the strings in the population and $\varepsilon(H,t)$ the probability that a schema has been disrupted by an operator such as crossover or mutation. Using the theorem, the minimum proportion of a particular schema that is expected to be present in the succeeding generation of the trial can be evaluated.

Although the schema theorem has provided many insights on GA performance and has enabled tremendous advancement of the work on genetic algorithms, it does not give an exact distribution of the schemata in the population. The mathematical expression is an inequality that ignores string gains created by crossover and underestimates the string losses. It is based on a normally distributed population, a condition that is only accurate in the first generation before the population is biased by selection and other GA operators, thus it can only accurately predict the GA behaviour in the first generation. Markov chain analysis can be used to complement and extend the schema theorem and provide better insights into the GA process.

B. 2 Modelling GA Performance With Markov Chains

Since a GA uses stochastic control parameters to guide the search in a random initial population, random process theory can be used to model its behaviour. A Markov process is specified by a matrix of transition probabilities which give the probability of moving from one state to the next. The GA can be modelled as a Markov process in which the state of the GA in any given generation is given by the contents of the current population [29-30]. The size of the matrix will depend on the granularity of the modelling required, for example it can be at string level, schema level or class level, where a class is a group of schema or strings sharing a common property. The state space of all possible population members representing any given problem solution provides the total region to be searched by the GA and an analysis of the population trajectories as the GA search proceeds should provide some insights into the algorithm performance.

The main limitation of the Markov chain analysis method is the high computation burden implied by the treatment of the large matrices used for computing the transition probabilities, that are crucial in determining the population trajectories. Such models become unwieldy with increasing population size and string length, since the size of the transition matrix grows exponentially with increasing string length. However, Markov chain modelling of GAs on small scale systems has provided important insights into the fundamental functioning of GAs. Using matrix analysis, without manipulating the individual matrix elements [29] provide a steady state convergence analysis based on the assumptions of infinite population size, while [30] perform an analysis of the transient behaviour of a finite population GA that attempts to answer questions pertinent to GA performance such as: the probability that a GA will contain a copy of the optimum solution at generation k, the probability that a GA will have a fitness value greater than some value at generation k and what is the expected best individual at generation k.

C. Genetic Algorithm Problem Representation

The solution to the short range hydrothermal scheduling problem can be defined by specifying the actual load allocated to various hydro and thermal plants at each time step, over the scheduling period. In hydro generation, the basic performance curve is expressed in terms of the water input versus power output hence the turbine water discharge can be used as the problem decision variable. In this work, it is assumed that the thermal unit commitment decision is known *a priori* and that the thermal generation provides the generation that cannot be supplied by the hydro sub-system. The basic optimal hydrothermal scheduling sequence is: assuming a given thermal unit commitment, load demand, and hydraulic inflows, allocate load to the various hydro and thermal units, while satisfying the individual unit loading limits, hydraulic constraints and power network constraints so that the total operation cost is minimised. Included with hydraulic constraints is the desire to satisfy *end point* conditions for the scheduling period in order to conform to medium term water release targets. For the GA solution method, the water discharge through the turbines during each optimisation interval is used as the main control variable. Knowing the water discharge at each plant, the reservoir inflows and the unit characteristic equations, the change in reservoir storage and the hydroelectric power outputs can easily be evaluated. In the GA binary problem representation, the various water discharge rates at each reservoir for each time interval are represented by a given number of binary strings. The number of binary bits representing each reservoir depends on the required (resolution) accuracy within which the turbine discharge level can be varied. The total solution string length is obtained by concatenating all the sub-strings that represent the individual reservoirs in the various time intervals.

In a GA optimisation process using binary encoding, the solution accuracy depends on the number of bits used to represent the decimal equivalent of the control parameter. The higher the number of bits used, the finer the resolution. The precision required is chosen according to the solution accuracy desired. The binary solution string must represent the whole scheduling period, to take into account the river flow dynamics resulting from the hydraulic coupling effects between hydro plants on the same stream.

D. Fitnes Function

A genetic algorithm conventionally searches for the optimal solution by maximising a given fitness function, and therefore an evaluation function which provides a measure of the quality of the problem solution must be provided. For the hydrothermal co-ordination problem, the evaluation function is a combination of the thermal cost function and penalty function terms that take into account the various system, unit and hydraulic network constraint violations. The evaluation function should differentiate between good and poor solutions, both in the feasible and infeasible search domains. The fitness value is critical to the functioning of the genetic algorithm, since it is this function that determines an individual's ability (chance) to undergo selection hence propagate its features to future generations. Since a GA maximises the fitness function, the minimisation objective function must be transformed into a maximisation problem. Solution of the scheduling problem involves a minimisation of the composite function, F;

$$F=\sum_{i\in R_s} F_i\left(P_{s,i}\right)+\sum_{i\in R_h}\Phi\left(V_{h,i}\right)+\sum_{i\in R_h}\Psi\left(V_{h,i}(end)\right) + \sum_{i\in R_h}\Omega\left(P_{h,i}\right)+\sum_{i\in R_s}\theta\left(P_{s,i}\right) \tag{12}$$

where:

$F_i\,(P_{s,i})$ is the optimal dispatch cost of the thermal plants, Φ, the penalty function for reservoir storage capacity limits violation, Ψ, the penalty function for final (end conditions) reservoir levels violation, Ω, the penalty function for hydro unit loading limit violations, and θ, the penalty function for thermal unit loading limit violations.

The thermal fuel cost is implicitly related to the sum of the hydro power generation (hence discharge) and the load demand according to the system load balance given in equation 2. The fuel cost / power output characteristics of the composite thermal plant is represented by,

$$F_i\left(P_{s,i}\right) = 5000 + 19.2 P_{s,i} + 0.002 P_{s,i}^{2} \quad \text{and} \quad 500 \le P_{s,i} \le 2500 \tag{13}$$

while the power output of a hydro unit during any given time interval as a function of reservoir volume and discharge is given by equation 9.

The decoded binary solution string gives the actual decimal values of the plant discharge over the whole scheduling period, which is then used to obtain the fitness function value through a sequence of events as shown in figure 2.

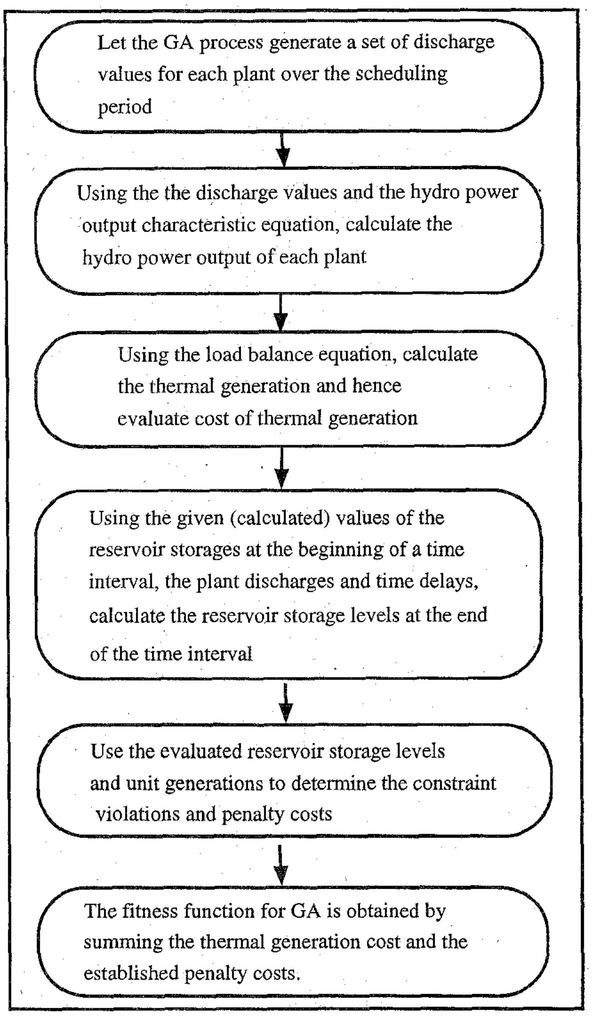


Fig 2. The hydrothermal Scheduling GA evaluation sequence

D. 1 Penalty Function Approach For Constraint Handling

Finding a solution that satisfies all the hydrothermal scheduling problem constraints is quite difficult. A penalty function approach [31-32] that takes into account the violation of the problem constraints is adopted in this work. The penalty functions try to force the unconstrained optimum towards the feasibility boundary by incorporating penalty terms into the fitness function to penalise strings that violate the constraints.

With the penalty function, the evaluation function, f, can be written in the generic form,

$$f = c(x) + \sum_{i=1}^{m} \lambda_i \phi_i(x) \tag{14}$$

where $c(x)$ is the thermal cost function λ_i and Φ_i the i[th] penalty coefficient and penalty functions respectively, for the m constraints. The choice of the penalty term can be significant, for, if the penalty term is too harsh, infeasible strings that carry useful information for the GA, but lie outside the feasible region will largely be ignored and their information lost while if the penalty term is not strong enough, the GA may search only among infeasible strings, and miss out on the feasible solutions.

A quadratic penalty function is adopted in the present work and the penalty terms are set so that all feasible strings are always awarded a higher fitnes than infeasible ones, an approach that avoids the difficulties usually encountered in choosing appropriate penalty coefficients, λ_i, while allowing infeasible solutions into the population.

The penalty boundaries for the hydraulic reservoir are shown in figure 3. For example, the same violation of either the reservoir maximum or minimum storage levels must be awarded the same penalty cost, otherwise if one side is penalised more, the population will tend to drift towards the less penalised side. The GA treats the desired final reservoir levels (end volume) as soft constraints which can be violated or relaxed, while the maximum (minimum) allowable reservoir levels must not be violated. Similarly the hydro and thermal unit loading limits must not be violated. The plant discharge limits are never violated because they are implicitly made to vary within their allowable limits as the encoded GA decision variable.

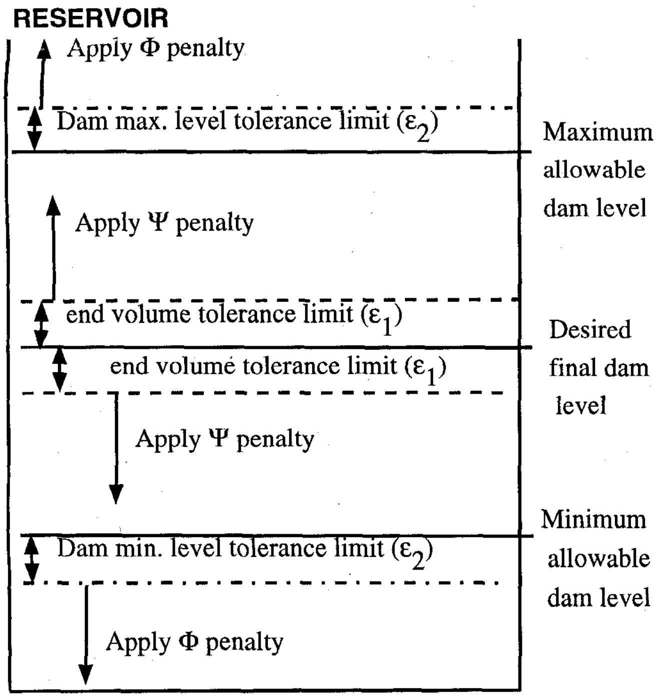


Fig 3. Reservoir Constraint Penalty Boundaries

From figure 3, it should be noted that the Ψ penalty is only invoked in the final time interval, while the Φ penalty is applied to all the time intervals in the scheduling period.

E. Implementation of Hydro-Thermal Genetic Algorithm

Once a method of awarding a fitness to each member of the population has been determined, the standard GA search sequence of population creation, selection, crossover, mutation and parent replacement can be applied to the chosen GA model. A canonical GA model, based on Holland's genetic plan [1] has been implemented for the hydrothermal co-ordination problem. In addition to the usual GA techniques of GA control parameter tuning, a number of enhancements, mainly derived from the hydrothermal scheduling problem structure, have been incorporated in the standard GA search mechanism to enable it to solve a wide range of hydrothermal scheduling problems.

In any optimisation process, an appropriate step length for changing each parameter variable at each stage of the optimisation sequence, must be chosen. If the step lengths are too small, it can take a large number of iterations to reach the optimal solution, while if step lengths are too large, the optimum solution can only be crudely approached and the optimisation can easily get stuck at a local optimum. For a GA search, the smaller the resolution, the longer the string lengths, which results in longer solution times.

The GA can performance can be greatly enhanced by performing a multiple step search using different string lengths for different stages of the optimisation. This allows a coarse grained search in the initial stages of the GA process, which are used as starting points for later runs with finer resolutions. These enhancements are described in the next section.

E. 1 Multiple Step GA Using Variable Time Steps

Exploiting the relationships between the hydrothermal scheduling problem structure over successive time intervals can reduce the problem size, by providing approximate solutions based on an intuitive time decomposition. This basically involves varying the step time interval for the scheduling process. For example two hour time intervals can be used instead of one hour, reducing the problem size by half. The solutions obtained from the longer time interval are then used as the optimisation starting point for the desired final time step, a process that should result in a shorter overall solution time, with possible improvements in the solution quality. It is to be expected, that the longer the time interval, the less accurate the results, due to the loss of precision in modelling of the load demand and river inflows. However, the longer time intervals are able to reach the more promising areas of the search space much faster, because of the smaller problem dimension, and their results can be used as favourable starting points for the searches based on shorter time intervals, resulting in a speed up of the overall optimisation process.

E. 2 Multiple Step GA Using Variable Control Parameter Resolution

The multiple step search uses different string lengths (parameter resolutions) for the various stages of the GA run. This involves a change in discharge resolution, in which the search starts off with short string lengths, which are progressively increased in the course of the optimisation. If a binary representation is used, then at the end of each step, the best solution already obtained is converted to the equivalent binary representation required for the next step of the GA run.

The performance of the GA depends on the resolution chosen for the control variable. If, the resolution is too large, the GA will tend to converge prematurely, while if it is too fine, the convergence might take too long, and therefore a reasonable balance must be made between the resolution accuracy and the convergence time.

Using multiple steps in the search reduces the computation time, and often leads to improved solutions over single resolution runs, but the appropriate resolution steps and number of generations for each step must be carefully chosen. The variation of the size of the scheduling time intervals and parameter resolution can be combined in an optimal manner to produce an efficient GA search mechanism able to solve a wide range of hydro-thermal scheduling problems.

E. 3 Genetic Algorithm Control Parameter Settings

While the fitness function is derived from the problem objective function, as has been described in the previous section, the other GA control parameters such as selection method, population size, crossover method, crossover rate and mutation rate, are chosen based on the theoretical foundations of GA, guidance from previous experience in the application of GA in other problem domains and performance of empirical trial runs on the hydro-thermal scheduling problem. The genetic algorithm operators used for the hydrothermal scheduling are summarised in table 1.

Table 1. GA parameter list for the hydrothermal scheduling problem

Parameter	Type / Method	Value
population size	random initialisation	variable (up to size of string length)
selection	stochastic remainder	
fitness scaling	sigma (truncation)	std. dev.=1.0
crossover	uniform	rate =1.0
mutation	flip bit	set to 1/string length
parent replacement	generational replacement	replace all parents
elitism	replace randomly chosen children	10% of children population
generations	variable	

F. Test System

The test system [17], [19] used to evaluate the performance of the GA consists of a multi-chain cascade of 4 hydro units, and a number of thermal units represented by an equivalent thermal plant. The scheduling period is 24 hours, with one hour time intervals. The cost of thermal generation can be obtained in two ways:

1. by using a standard economic dispatch technique to find the optimal operation cost of the on-line thermal generators, or
2. by assuming the thermal generation is represented by an equivalent single plant, whose characteristics can be determined as described in [33].

The hydraulic sub-system is characterised by the following:

- a multi-chain cascade flow network, with all the plants on one stream,
- river transport delay between successive reservoirs,
- variable head hydro plants,
- variable natural inflow rates into each reservoir,
- variable load demand over scheduling period.

The hydro sub-system configuration and network matrix including the water time delays are shown in figure 11, in appendix. This hydraulic test network models most of the complexities encountered in practical hydro networks. The load demand, hydro unit power generation coefficients, river inflows and reservoir limits for the test network are also given in tables 7, 8 and 9 respectively, in the appendix.

IV. SIMULATION AND RESULTS

A genetic algorithm provides a final population of solutions. The best solution, in terms of the fitness function, is usually taken as the optimal solution. This mathematically best solution might not necessarily be the best option for the decision makers, who may wish to take some other factors, not implementable in the mathematical formulation, into account. The GA can act as a decision support tool by providing the analyst with a range of optimal or near optimal solutions upon which they can base their judgement.

In the short term hydrothermal scheduling problem, the two important parameters that can be allowed to vary are the satisfaction of the final reservoir storage levels and the cost of thermal generation. These two objectives can be conflicting and by providing final solutions showing the best of both variables, the decision maker can be helped in making better decisions. A number of tests were carried out to validate the performance of the hydrothermal scheduling GA on the test network. In one set of experiments, each GA trial was allowed to run for 2000 generations, while in the other set, the GA run was terminated after 5000 generations. Each experiment was run 10 times, starting with a different random initial population. Further tests were carried out to determine the combined effects of multiple parameter resolution and variable time step GA search sequence.

A. Multiple Resolution, Single Time Step GA

The effect of using different parameter resolutions for different stages of the GA was investigated. Table 2 shows the GA performance for 5000 generations, for the single and multiple step resolution respectively. The column showing the violation of reservoir end volume indicates the sum of the violations of all the plants. The corresponding variations between the schedule cost and total final reservoir storage violations are shown in figure 4. The results show that the multiple resolution GA performs significantly better than the single resolution algorithm, and also takes less cpu time to obtain the results given.

From figure 4 it can be seen that the GA with multiple resolution consistently performs better than that with single resolution in terms of scheduling cost and also takes much less cpu time to obtain improved results. It is also worth noting that the best cost solution does not necessarily result in the least violation of end volume storage requirements. The decision maker should be able to choose the best solution from those provided by the GA.

When the performance of multiple parameter resolution GA for runs terminated after 2000 and 5000 generations were compared, it was found that increasing the number of generations of the run from 2000 to 5000 provides a 0.57 percent average improvement in scheduling cost and a slight improvement in meeting the end volume constraints. This improvement, was however accompanied by almost an 80% increase in computation time. The GA user must decide the degree of accuracy required of the solutions, as well as the computation time which can be tolerated, since the solution quality is usually improved by increasing the number of generations

Table 2. Scheduling results (Multiple parameter resolution, 5000 generations)

Trial	Single resolution		Multiple step resolution	
	Thermal cost	Total violation in end volume	Thermal cost	Total violation in end volume
1	947,846	0.091	939,734	0.215
2	945,221	0.086	936,451	0.169
3	942,600	0.071	935,721	0.493
4	943,024	0.099	936,625	0.233
5	946,611	0.079	938,551	0.445
6	946,767	0.093	936,567	0.219
7	945,768	0.098	938,420	0.376
8	951,087	0.140	937,141	0.221
9	948,513	0.134	937,749	0.204
10	948,654	0.122	932,734	0.115
Average resolution [0.1], Number of bits [696], Average cpu time [32 min.], Generations [5000]		Average resolutions [2.7, 1.2, 0.1] Number of bits, [240, 336, 696] Generations per stage [710, 1430, 2860], Total Cpu time [20 min.]		

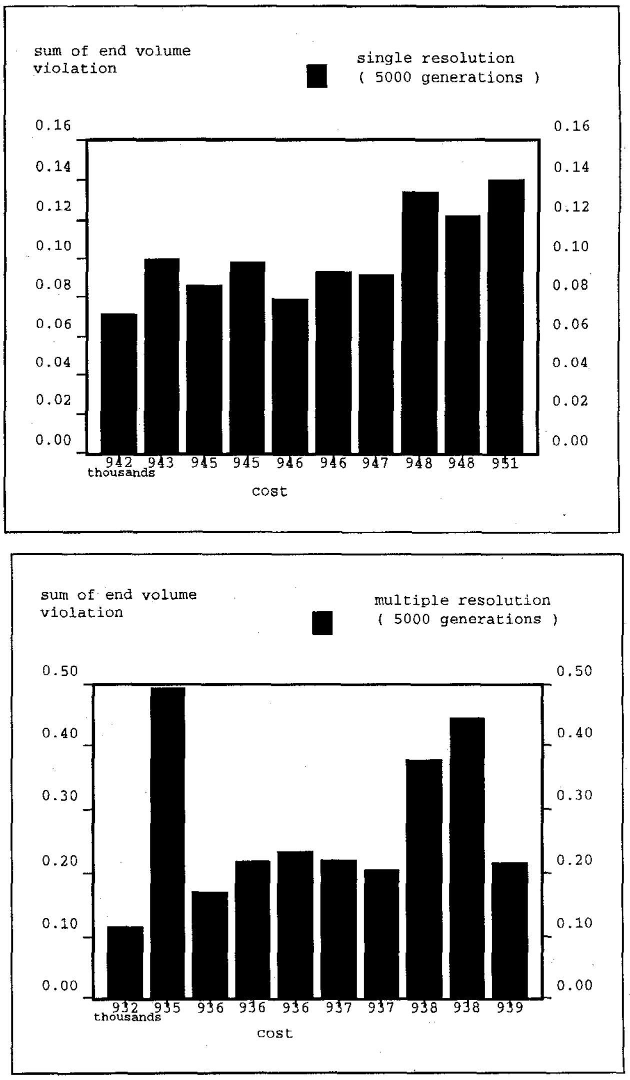


Fig 4. Relationship between total reservoir final volume violation and cost of thermal generation

Figure 5 shows the variation of the scheduling cost with the number of generations, while Figure 6 shows the variation of the total *end volume* violations with the number of generations. From figure 6, it can be seen that the GA has nearly converged by generation 500, after which the scheduling cost changes very slowly as the number of generations is increased. It is important to observe the effects of the end volume constraints as well, as shown in figure 6, otherwise the GA might be prematurely terminated before optimal results that also satisfy the problem constraints are obtained.

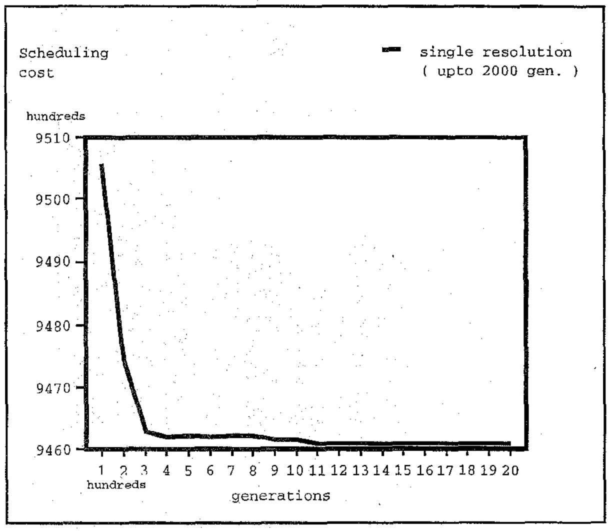


Fig 5. Variation of hydrothermal scheduling cost with the number of generations

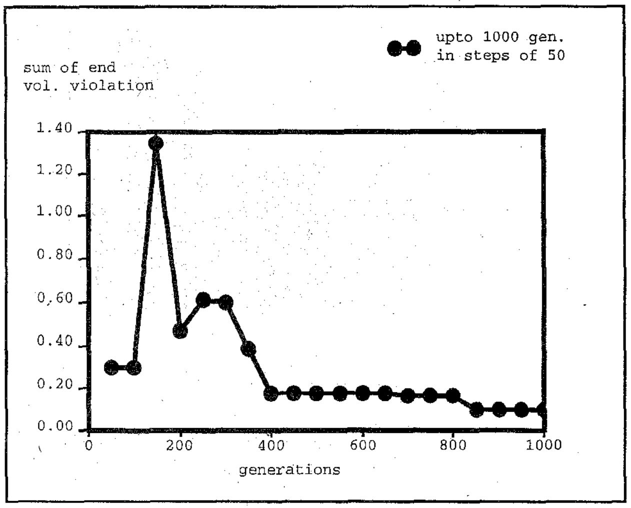


Fig 6. Variation of total end volume violations with number of generations

B. Multiple Time Step, Single Resolution GA

Table 3 shows the results of a 3 stage GA run with different time intervals at each stage, for a total GA run of 5000 generations, with the number of generations at each stage shown in the table. The corresponding variations between the scheduling cost and total reservoir end storage violation are shown in figures 7 and 8.

Table 3. Scheduling results (multiple time step GA, 5000 generations)

Trial	Single time step		Multiple time step	
	Thermal cost	Total violation in end volume	Thermal cost	Total violation in end volume
1	947,846	0.091	945,402	0.100
2	945,221	0.086	938,577	0.114
3	942,600	0.071	939,798	0.104
4	943,024	0.099	940,269	0.106
5	946,611	0.079	939,789	0.110
6	946,767	0.093	938,370	0.134
7	945,768	0.098	941,046	0.114
8	951,087	0.140	944,006	0.113
9	948,513	0.134	945,942	0.119
10	948,654	0.122	943,734	0.122
Average resolution [0.1], number of bits [696], Average cpu time [32 min.], Generations [5000]			Time steps (hours) [3, 2, 1] Number of bits, [232, 348, 696] Generations per stage [710, 1430, 2860], Cpu time [22 min.]	

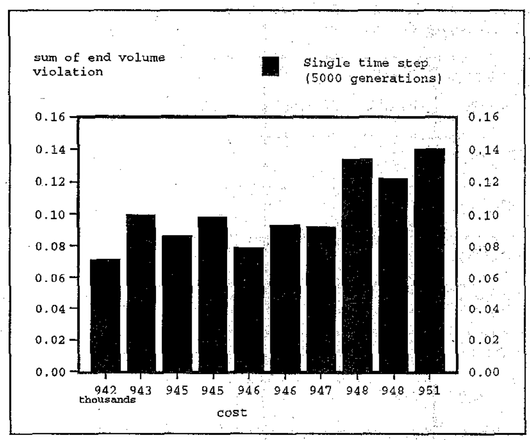


Fig 7. Relationship between reservoir end volume violation and cost of thermal generation (single time step)

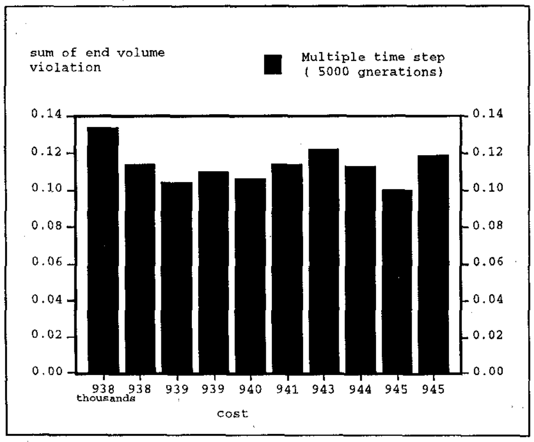


Fig 8. Relationship between reservoir end volume violation and cost of thermal generation (multiple time step)

C. Results of Combined Effects of Multiple Resolution, Multiple Time Step GA Search

The variation of the size of the scheduling time intervals and parameter resolution can be combined in an optimal manner to produce improved results. Table 4 shows the results obtained by incorporating both a multiple control parameter resolution and a variable time step search in the GA. The results demonstrate the superior performance obtained by combining the multiple time step and multiple resolution GA search mechanisms.

Table 4. Final results for multiple resolution, multiple time step GA search

Reservoir	**1**	**2**	**3**	**4**
Final storage	119.96	70.03	170.03	140.0
Expected final storage	120	70	170	140
Thermal generation cost = **926,707,** Total end volume violation = **0.10**				
GA parameters: [popsize=100, p_{cross}=1.0, p_{mut}=0.001, elitist copies =10] Other simulation variables: Time steps (hours) [2, 1], Generations per step [500, 500] Parameter resolution [2, 1, 0.5, 0.25, 0.125] Generations per stage [1000, 2000, 4000, 8000, 16000] Average cpu time [1 hr: 12 min.],				

In addition to the turbine discharge, which is given as the hydrothermal scheduling GA solution, it is also useful to provide as an output, quantities such as reservoir storage levels, total thermal generation and hydro unit power outputs, during each time interval. These quantities are calculated using the water discharge rates, the hourly river inflows, water transport delays and the load demand at each time interval, over the scheduling period. The hourly unit power outputs and the water discharge levels for the sample results in table 4 are given in tables 5 and 6, while the hourly turbine discharge and hydro power generation trajectories are given in figures 9 and 10 respectively.

Table 5. Hydro plant power outputs and total thermal generation

Hour	**hydro power generation (MW)**				**Thermal gen. (MW)**
	plant 1	plant 2	plant 3	plant 4	
1	72.4	49.6	43.3	205.8	999.0
2	72.9	50.7	0.0	194.0	1072.4
3	82.6	52.1	34.5	180.8	1010.0
4	86.7	67.9	0.0	165.4	970.0
5	85.4	53.8	0.0	161.4	989.4
6	84.0	54.6	40.1	176.8	1054.4
7	69.8	69.2	0.0	191.0	1320.0
8	73.9	61.5	38.7	204.4	1621.5
9	83.9	79.5	18.3	222.4	1835.9
10	69.7	66.1	35.6	230.8	1917.9
11	74.0	73.7	39.2	245.2	1798.0
12	76.9	78.3	38.7	252.0	1864.2
13	77.5	62.6	40.9	261.6	1787.4
14	88.7	67.0	25.0	276.9	1742.4
15	74.5	69.6	25.5	262.8	1697.6
16	70.5	73.6	36.6	255.9	1633.4
17	90.6	73.5	26.4	297.6	1642.0
18	73.0	73.7	46.5	296.0	1650.9
19	68.2	70.6	48.9	288.0	1764.3
20	90.2	72.7	48.5	298.2	1770.4
21	70.7	73.5	51.0	293.3	1751.7
22	62.7	41.0	54.8	290.6	1670.8
23	65.7	43.6	56.0	267.7	1417.1
24	64.7	50.8	58.4	305.3	1110.7

Table 6. Hourly plant discharge (x 10^4 m^3)

Hour	Hydro Reservoirs 1	2	3	4
1	7.519	6.000	19.960	13.000
2	7.519	6.000	30.000	13.000
3	9.094	6.000	19.411	13.000
4	10.039	8.267	30.000	13.000
5	10.039	6.000	29.921	13.000
6	10.039	6.000	13.137	13.000
7	7.519	8.267	28.823	13.000
8	8.149	7.133	13.764	13.000
9	10.039	10.535	20.039	13.000
10	7.362	8.055	15.019	13.000
11	7.834	9.401	13.764	13.755
12	8.149	10.535	15.176	13.755
13	8.149	7.700	15.019	14.511
14	10.039	8.409	20.039	16.023
15	7.519	8.834	20.039	14.511
16	6.889	9.685	17.529	13.755
17	10.039	9.968	20.039	19.047
18	7.204	10.535	11.254	19.047
19	6.574	10.464	12.509	17.629
20	10.039	11.669	15.019	19.047
21	6.968	12.803	10.313	18.291
22	5.944	6.141	12.509	18.291
23	6.259	6.283	11.098	15.929
24	6.102	7.275	12.823	23.677

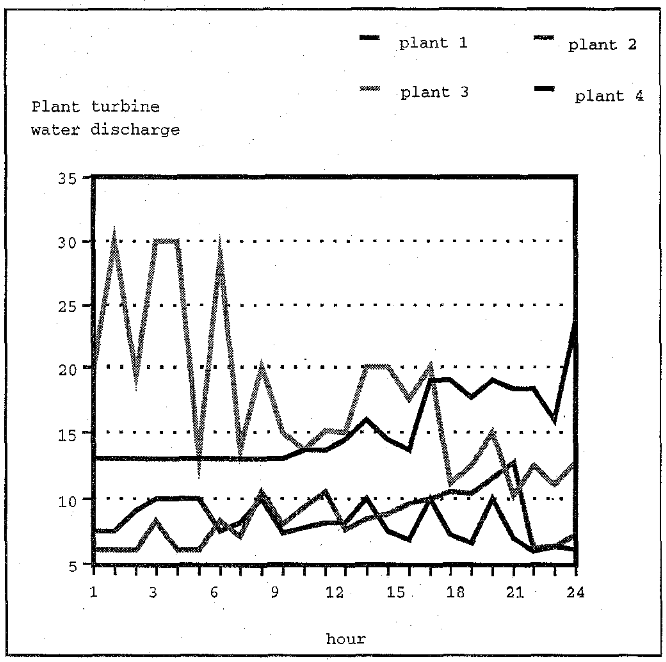


Fig 9. Hourly plant discharge trajectories

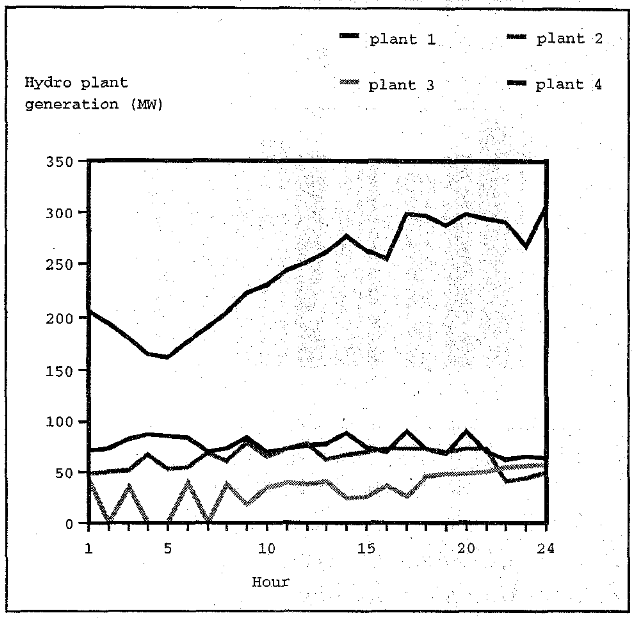


Fig 10. Hourly hydro plant power generations

V. DISCUSSION

The empirical success of genetic algorithms on hitherto unsolved complex problems has made them very attractive for the solution of difficult non-linear optimisation problems. The GA, must however be carefully designed in order to be able to solve any particular class of problems. This design involves the appropriate choice of the GA control parameters and problem representation. The GA is best applied in an innovative way to any specific problem, by using as much problem knowledge as possible. For example, as has been shown in this work, a single change in the GA such as the use of multiple resolution instead of single resolution results in vast improvements in solution quality. Further tuning of the GA control parameters such as population size, crossover and mutation rates can also result in improved solutions. Most of these GA parameters are set after considerable experimentation, and it is the lack of a solid theoretical basis for their setting which is one of the main drawbacks of the GA method. Theoretical research is continuing on the appropriate choice of GA parameters and if this succeeds, the GA method will become much more acceptable for industrial applications, as the design of the algorithm will no longer be an exclusive domain for the GA expert.

The GA method is able to provide a number of quasi-optimal solutions to a problem, either by repeated trials with different initial populations or by taking a sample of the best solutions from the final generation. These alternative solutions can sometimes provide some very practical solutions that might otherwise have escaped the attention of the analyst.

The nature of the GA allows their implementation on parallel computers, with possible significant decreases in computation time.

VI. CONCLUSIONS

In the hydro-thermal scheduling problem, the complexity introduced by the cascade nature of the hydraulic network, the scheduling time linkage, non-linear relationships in the problem variables and the water transport delay factors, has made the problem very difficult to solve using standard optimisation methods. This problem is *epistatic* in GA terms, since a schedule at an earlier time interval affects that at a later time, and therefore the whole scheduling period must be treated as a single solution or entity. The GA, on the other hand is able to take into account all the problem variables without making the usual simplifying assumptions, required by conventional techniques. Once the problem has been formulated in the GA framework, the only other issue to be resolved is the choice of GA control parameters. Large scale hydrothermal scheduling problems can be solved using intuitive techniques such as multiple resolution in parameter variables or multiple time interval decomposition, to speed up the search process.

The genetic algorithm approach provides a good solution to the short term hydrothermal scheduling problem and is able to take into account the variation in net head and water transport delay factors. Once good GA control parameters have been obtained, the solution to the problem under different operation scenarios can easily be obtained. The genetic algorithm method results in a simple hydro-thermal scheduling problem formulation and solution method which can easily be extended to other challenging operation and control problems facing electricity utilities.

VII. BIOGRAPHIES

Shadrack Orero received both the B.Sc. and M.Sc. degrees in Electrical Engineering from Nairobi University, Kenya in 1984, and 1989 respectively. He is currently a Ph.D student at the Brunel Institute of Power Systems, Brunel University, U.K. His current research interests include the applications of Evolutionary Computation Techniques to Power System Optimisation and Control.

Malcolm Irving received a B.Eng. degree in Electrical Engineering from the University of Sheffield, U.K., in 1974, and the degree of Ph.D in Control Engineering, also from the University of Sheffield in 1977. He has been researching in power systems for over 20 years and is presently the Director of the Brunel Institute of Power Systems, Brunel University, U.K.

VIII. REFERENCES

[1] Holland, J.H., "Adaptation in Natural and Artificial Systems.", *Ann Arbor: University of Michigan Press*, 1975.

[2] Fogel, L.J., Owens, A.J., Walsh, M.J., "Artificial Intelligence Through Simulated Evolution.", *John Wiley*, 1966.

[3] Back, T., Hoffmeister, F., Schwefel, H.-P., "A survey of evolution strategies." *In R.K. Belew, L.B. Booker (Eds.), Proc. of the Fourth Int. Conf. on Genetic Algorithms*, 1991, pp. 2-9.

[4] El-Hawary, M.E., Christensen, G.S., "Optimal Economic Operation of Electric Power Systems.", *Academic press*, New York, 1979.

[5] Chandler, W.G., Dandeno, P.L., Glimn, A.F., Kirchmayer, L.K., "Short range economic operation of a combined thermal and hydroelectric power system.", *AIEE Trans. PAS*, Vol. 72, Part III, 1953, pp. 1057-1065.

[6] Chang., S., Chen, C., Fong, I., Luh, P.B., "Hydroelectric generation scheduling with an effective differential dynamic programming.", *IEEE Trans. PWRS*, Vol. 5, No. 3, 1990, pp. 737-743.

[7] Turgeon, A., "Optimal operation of multi reservoir power systems with stochastic inflows." *Water Resources Research*, Vol. 16, No. 2, April 1980, pp. 275-283.

[8] Papageorgiou, M., "Optimal multi reservoir network control by the discrete maximum principle.", *Water Resources Research*, 21 (2), 1985, pp. 1824-1830.

[9] Soliman, S.A., Christensen, G.S., "application of functional analysis to optimisation of variable head multi reservoir power system for long term regulation.", *Water Resources Research,* 22 (6), 1986, pp. 852-858.

[10] Lee, B.Y., Park, Y.M., Lee, K.Y., "Optimal generation planning for a thermal system with pumped storage based on analytical production costing model.", *IEEE Trans. PWRS*, Vol. 2, No. 2, May 1987, pp. 486-493.

[11] Brannud, H., Bubenko, J.A., Sjelvgren, D., "Optimal short term operation planning of a large hydrothermal power system based on a non linear network flow concept.", *IEEE Trans. PWRS*, Vol. 1, No. 4, Nov. 1986, pp. 75-82.

[12] Wakamori, F., Masui, S., Morita, K., "Layered network model approach to optimal daily hydro scheduling.", *IEEE Trans. PAS*, Vol. 101, No. 9, Sep. 1982, pp. 3310-3314.

[13] Xia, Q., Xiang, N., Wang, S., Zhang, B., Huang, M., "Optimal daily scheduling of cascaded plants using a

new algorithm of non-linear minimum cost network flow concept.", *IEEE Trans. PWRS, Vol. 3, No. 3*, 1988, pp. 929-935.

[14] Piekutowski, M.R., Litwinowicz, T., Frowd, R.J., " Optimal short term scheduling for a large scale cascaded hydro system.", *Power Industry Computer Applications Conference,* Phoenix, AZ, 1993, pp. 292-298.

[15] Saha, T.N., Khapade, S.A., "An application of a direct method for the optimal scheduling of hydrothermal power systems.", *IEEE Trans. on PAS*, Vol. 97, No. 3, 1978, pp. 977-985.

[16] Habibollahzadeh, H., Bubenko, J.A., "Application of decomposition techniques to short term operation planning of hydro-thermal power system", *IEEE Trans. PWRS*, Vol. 1, No. 1, Feb. 1986, pp. 41-47.

[17] Wang, C., Shahidehpour, S.M., "Power generation scheduling for multi-area hydrothermal power systems with tie-line constraints, cascaded reservoirs and uncertain data.", *IEEE Trans. PWRS*, Vol. 8, No. 3, 1993, pp. 1333-1340.

[18] Pereira, M.V.F., Pinto, L.M.V.G., "application of decomposition techniques to the mid and short term scheduling of hydrothermal systems.", *IEEE Trans. PAS*, Vol. 102, No. 11, Nov. 1983, pp. 3611-3618.

[19] Soares, S., Lyra, C., Tavayes, W.O., "Optimal generation scheduling of hydrothermal power system.", *IEEE Trans. PAS*, Vol. 99, No. 3, 1980 1106-1114.

[20] Liang, R.H., Y.Y. Hsu., "Scheduling of hydroelectric generation units using artificial neural networks.", *Proc. IEE, Pt. C*, Vol. 141, No. 5, Sep. 1994, pp. 452-458.

[21] Luo, G.X., Habibollahzadeh, H, Semylen, A., "Short-term hydrothermal scheduling, detailed model and solutions", *IEEE Trans. PWRS*, Vol. 1, No. 4, Oct. 1989, pp. 1452-1462.

[22] Soares, S., Ohishi, T., "Hydro dominated short-term hydrothermal scheduling via a hybrid simulation-optimisation approach: a case study.", *Proc. IEE Pt. C*, Vol. 142, No. 6, Nov. 1995, pp. 569-575.

[23] Wong, K.P., Wong, Y.N., "Short term hydrothermal scheduling. Part I: Simulated annealing approach. ", *Proc. IEE., Pt. C*, Vol. 141, No. 5, 1994, pp. 497-501.

[24] Goldberg, D.E., "Genetic Algorithms in Search, Optimisation, and Machine Learning.", *Reading, MA: Addison-Wesley,* 1989.

[25] Goldberg, D.E., Deb, K., "A comparative analysis of selection schemes used in genetic algorithms.", *In G. J. E. Rawlins (Ed.), Foundations of Genetic Algorithms*, 1991, pp. 69-93.

[26] Baker, J.E. "Reducing bias and inefficiency in the selection algorithm.", *In J.J. Grefenstette(Ed.). Proc. of the Second Int. Conf. on Genetic Algorithms*, 1987, pp. 14-21.

[27] Davis, L., (Ed.), "A Handbook of Genetic Algorithms,", *New York: Van Nostrand Reinhold*, 1991.

[28] Goldberg, D.E., Deb, K., Clark, J.M., "Genetic algorithms, noise and the sizing of populations.", *Complex Systems*, 6, 1992, pp. 333-362.

[29] Nix, A.E., Vose, M.D., "Modelling a genetic algorithm with markov chains.", *Annals of Mathematics and Artificial Intelligence,* Vol. 5, No. 1, 1992, pp. 79-88.

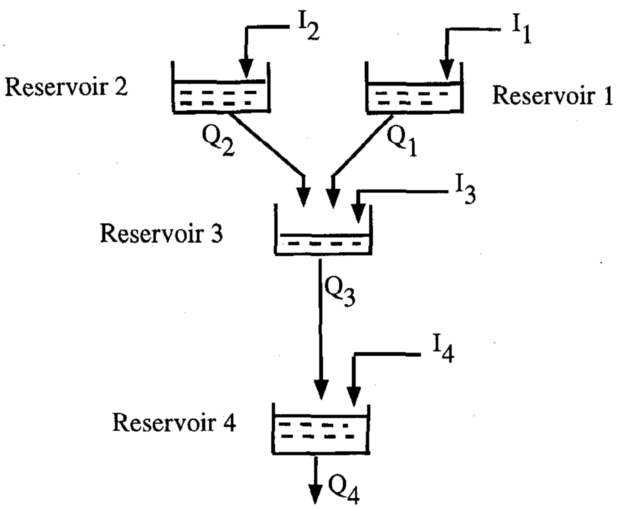
[30] De Jong, K.A., Spears, W.M., Gordon, D.F., "Using markov chains to analyse genetic algorithms for function optimisation, (GAFOS).", *In Whitley, D., Vose, M., (Eds.), Proc. of Foundations of Genetic Algorithm Workshop III,* 1994, Cambridge: MIT Press.

[31] Orero, S.O., and Irving, M.R., "A genetic algorithm for generator scheduling in power systems", *Int. Jnl. of Electric Power and Energy Systems,* Vol. 18, No. 1, 1996, pp. 19-26.

[32] Richardson, J.T, Palmer, M.R., Liepins, G.E., Hilliard, M., "Some guidelines for genetic algorithms with penalty functions.", *In J.D. Schaffer, (Ed.), Proc. of Third Int. Conf. on Genetic Algorithms*, 1989, pp. 191-197.

[33] Wood A.J., Wollenberg, B.F., "Power Generation, Operation and Control.", *John Wiley & Sons,* New York, 1996.

IX. APPENDIX



Where:

I_i - natural inflow to reservoir i

Q_i - discharge of plant i

Plant	1	2	3	4
R_u	0	0	2	1
τ_d	2	3	4	0

R_u - no. of up stream plants
τ_d - time delay to immediate downstream plant

Fig 11. Hydraulic system test network

Table 7. Load demand and hydro power generation coefficients

Load demand (MW)					
hour	load	hour	load	hour	load
1	1370	**9**	2240	**17**	2130
2	1390	**10**	2320	**18**	2140
3	1360	**11**	2230	**19**	2240
4	1290	**12**	2310	**20**	2280
5	1290	**13**	2230	**21**	2240
6	1410	**14**	2200	**22**	2120
7	1650	**15**	2130	**23**	1850
8	2000	**16**	2070	**24**	1590

Hydro power generation coefficients						
plant	c_1	c_2	c_3	c_4	c_5	c_6
1	-0.0042	-0.42	0.030	0.90	10.0	-50
2	-0.0040	-0.30	0.015	1.14	9.5	-70
3	-0.0016	-0.30	0.014	0.55	5.5	-40
4	-0.0030	-0.31	0.027	1.44	14.0	-90

Table 8. Reservoir inflows (x 10^4 m^3)

hour	Reservoir			
	1	**2**	**3**	**4**
1	10	8	8.1	2.8
2	9	8	8.2	2.4
3	8	9	4	1.6
4	7	9	2	0
5	6	8	3	0
6	7	7	4	0
7	8	6	3	0
8	9	7	2	0

Hr.	Reservoir				Hr.	Reservoir			
	1	**2**	**3**	**4**		**1**	**2**	**3**	**4**
9	10	8	1	0	**17**	9	7	2	0
10	11	9	1	0	**18**	8	6	2	0
11	12	9	1	0	**19**	7	7	1	0
12	10	8	2	0	**20**	6	8	1	0
13	11	8	4	0	**21**	7	9	2	0
14	12	9	3	0	**22**	8	9	2	0
15	11	9	3	0	**23**	9	8	1	0
16	10	8	2	0	**24**	10	8	0	0

Table 9. Reservoir storage capacity limits, plant discharge limits, plant generation limits and reservoir end conditions (x 10^4 m^3)

Plant	V_{min}	V_{max}	V_{ini}	V_{end}	Q_{min}	Q_{max}	Ph_{min}	Ph_{max}
1	80	150	100	120	5	15	0	500
2	60	120	80	70	6	15	0	500
3	100	240	170	170	10	30	0	500
4	70	160	120	140	13	25	0	500

Discussion

A. J. Conejo, J. M. Arroyo, N. Jiménez Redondo (Universidad de Málaga, Málaga, Spain): The authors have written an interesting and lengthy paper. We would like them to comment on the following issues:

1. The short-term hydrothermal scheduling considers start-up and shut-down thermal unit decisions (unit commitment problem) simultaneously with hydro scheduling decisions (hydro scheduling problem). To consider these two problems successively renders in general sub-optimal solutions. Quite a few of the cited references considers both problems simultaneously. Could the authors explain why they have chosen to consider thermal unit commitment separately from hydro scheduling?

2. The authors use a penalty strategy to meet constraints. It is well known from optimization theory that relevant numerical instability problems arise as a result of using penalties to handle constraints. Have the authors considered the possibility of using an interior point genetic algorithm based on feasibility heuristic procedures to always preserve the feasibility of the solutions?

3. The authors use a 0/1 coding technique to represent many real variables. This results in high computing times if good accuracy is required. It should be noted that the computing time required for the different numerical experiments performed in the case study is very high. Have they tried alternative coding strategies, such us using the actual real numbers?

4. The number of generations required is about 5000 in some of the numerical experiments performed on the small case study presented. In our experience, a smaller number of generations is usually good enough. Could the authors comment on the sensitivity of the quality of the best solution found with respect to the number of generations considered?

5. The case study presented is a very small example. Have the authors any evidence that the results and conclusions drawn from the analysis of the small example presented will hold for large-scale real-world case studies?

6. The paper would have benefited from a comparison with a conventional procedure able to get either the exact solution or lower and upper bounds of the exact solution. Have the authors tried to compare the performance of their algorithm with the performance of a conventional one?

Manuscript received June 2, 1997.

S.O.Orero and M.R.Irving:

We thank the discussors for their interest in our paper and would respond to their questions as follows:

1. This study assumes that the thermal unit commitment (UC) problem has been solved, and only the dispatch sub-problem is considered, in order to concentrate on the complex problem of the hydro sub-system and to provide a genetic algorithm (GA) model that considers all the non-linearities in the resulting scheduling equations. The UC problem could be incorporated through a co-ordination scheme between the UC and the hydro sub-problem.

2. We are also aware of the numerical instabilities that can arise with the use of penalty functions. This problem is perhaps less severe for GAs, in comparison with conventional optimization theory based techniques, since GAs do not impose stringent requirements on the objective function (e.g. differentiability, continuity, convexity etc.). Nevertheless, it is important to select and grade the penalty terms for each type of constraint carefully. All feasible strings must be awarded a fitness value greater than any infeasible string, and the penalty level should be proportional to distance from the constraint boundary.

3. The 0/1 coding technique was found useful and straightforward in demonstrating the use of the GA technique. There is considerable debate regarding the relative merits of binary and other codings (e.g. real numbers), see for example [reference C1]. There are two basic arguments against the use of real number representation. Firstly, there will be fewer hyperplane partitions, as compared to binary encoding which maximises the number of hyperplanes available for schema processing. Secondly, the alphabetic characters (e.g. real numbers) associated with higher cardinality alphabets will not be as well represented in a finite population, diminishing the effectiveness of the statistical sampling.

4. Figures 5 and 6 of the paper show that good solutions are obtained after about 400 generations, and that there are no significant improvements after 1000 generations. The algorithm was run for 5000 generations simply to illustrate that no further improvements could be obtained. Good solutions can therefore be produced in about one tenth of the reported computer times.

5. The example considered was small, but included all the modelling complexities that provide major challenges in the hydrothermal co-ordination problem. Certainly, one of current problems with GAs is that as problem sizes are scaled up GAs tend to suffer from convergence difficulties (premature convergence). In our approach, we have incorporated modifications such as multiple time step and

multiple step control parameter resolution that should help when solving larger examples.

6. As the discussors mentioned the paper was already a lengthy one, and we felt that comparison with another method would be outside the scope of this paper. We agree that this is an important issue, and look forward to future comparative studies.

[Reference C1] Antonisse, H.J., "A new interpretation of the schema notation that overturns the binary encoding constraint", Proc. Third Int. Conf. on Genetic Algorithms, Morgan-Kaufmann, 1989.

Manuscript received September 16, 1997.