Short-Term Hydrothermal Generation Scheduling Model Using a Genetic Algorithm

Esteban Gil, *Student Member, IEEE*, Julian Bustos, *Senior Member, IEEE*, and Hugh Rudnick, *Fellow, IEEE*

***Abstract*—A new model to deal with the short-term generation scheduling problem for hydrothermal systems is proposed. Using genetic algorithms (GAs), the model handles simultaneously the subproblems of short-term hydrothermal coordination, unit commitment, and economic load dispatch. Considering a scheduling horizon period of a week, hourly generation schedules are obtained for each of both hydro and thermal units. Future cost curves of hydro generation, obtained from long and mid-term models, have been used to optimize the amount of hydro energy to be used during the week. In the genetic algorithm (GA) implementation, a new technique to represent candidate solutions is introduced, and a set of expert operators has been incorporated to improve the behavior of the algorithm. Results for a real system are presented and discussed.**

***Index Terms*—Genetic algorithms, hydrothermal systems, short-term hydrothermal scheduling.**

I. Introduction

THE efficient scheduling of available energy resources for satisfying load demand has became an important task in modern power systems. The generation scheduling problem consists of determining the optimal operation strategy for the next scheduling period, subject to a variety of constraints. For hydrothermal systems, the limited energy storage capability of water reservoirs, along with the stochastic nature of their availability, make its solution a more difficult job than for purely thermal systems. The well-timed allocation of hydro energy resources is a complicated task that requires probabilistic analysis and long-term considerations, because if water is used in the present period, it will not be available in the future, increasing in this way the future operation costs.

So, the hydrothermal generation scheduling problem (HGSP) is usually decomposed into smaller problems in order to solve it [1]. In this way, the HGSP involves three main decision stages, usually separated using a time hierarchical decomposition (Fig. 1): the hydrothermal coordination problem (HCP), the unit commitment problem (UCP), and the economic load dispatch problem (ELDP). The model proposed in this paper handles simultaneously the subproblems of short-term HCP, UCP, and ELDP.

The HGSP is a nonlinear optimization problem with high dimensionality, continuous and discrete variables, a nonexplicit objective function, with equality and inequality constraints. Besides, it is a large multi modal and nonconvex problem. Most of the conventional optimization techniques are unable to produce near-optimal solutions for this kind of problem. Moreover, conventional methods usually require certain suppositions that force them to work with simplified instead of realistic models. In order to deal with the HGSP in a more efficient and robust way, this paper proposes an optimization model using a genetic algorithm (GA) to solve it.

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E. Gil was and J. Bustos is with the Department of Electrical Engineering, Universidad Técnica Federico Santa María, Valparaíso, Chile (e-mail: julian.bustos@vra.utfsm.cl).

H. Rudnick is with the Department of Electrical Engineering, Universidad Católica de Chile, Santiago, Chile (e-mail: h.rudnick@ieee.org).

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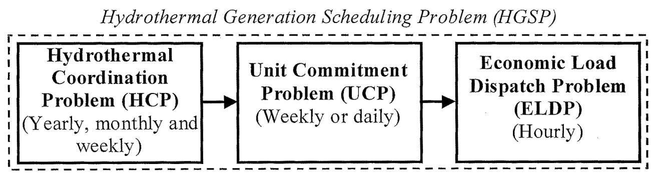

Fig. 1. Time hierarchical decomposition for the HGSP.

A GA is a metaheuristic technique inspired on genetics and evolution theories [4]. During the last decade, it has been successfully applied to diverse power systems problems: optimal design of control systems [5], [6]; load forecasting [7]; OPF in systems with FACTS [8]–[10]; FACTS allocation [11]; networks expansion [12]–[14]; reactive power planning [15]–[17]; maintenance scheduling [18], [19]; economic load dispatch [20], [21]; generation scheduling and its subproblems [22]–[34].

Section IV presents an overview of GA, and describes the implementation of the proposed model using a GA, and Section V shows tests results for test systems. Finally, Section VI presents the main conclusions of the paper.

II. Problem Formulation

A. Hydrothermal Coordination Problem (HCP)

It is the first stage in the solution of the HGSP. The HCP consists of determining the optimal amounts of hydro and thermal generation to be used during a scheduling period [1], [2]. The HCP is also decomposed in long-, mid-, and short-term models [35], depending on the reservoirs storage capacity.

Decisions in hydrothermal systems are coupled in time. In other words, the operating costs in the future depend on the amount of hydro generation during the present period [36]. According to the kind of output of the model, HCP approaches can be classified in two principal categories:

- fixed reservoir storage level for each stage: the use of the water in each stage is determined strictly by the model;
- future cost functions (FCF): future or opportunity cost of the water used during the present stage, versus the storage level at the end of the scheduling period.

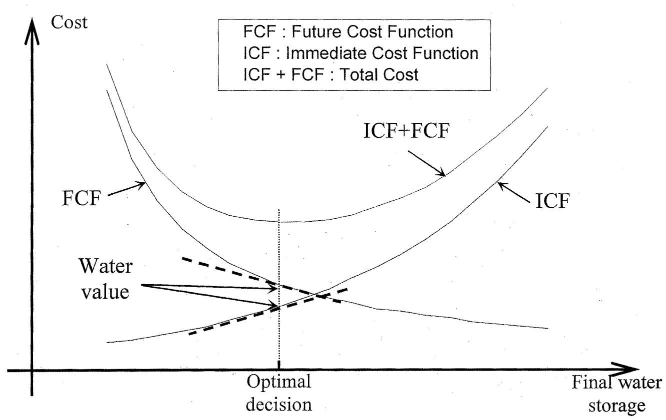

Fig. 2. Immediate and future cost functions [36].

Hydro generation has an opportunity cost associated to the thermal generation displaced. As seen in Fig. 2, if a larger amount of water is used during the present stage, the immediate cost (obtained by solving the UCP and the ELDP for the present stage) decreases, and the water available in the future (final water storage) decreases. Hence, if less water will be available, future costs will increase.

The FCF can be obtained by calculating recursively the system operation costs in the future (starting from the end of the period under analysis) considering different starting values of water storage. This can be achieved using stochastic dual dynamic programming (SDDP) [36]–[39].

The FCF allows uncoupling the long/mid-term from the short-term hydrothermal coordination activity. This is the approach used in this paper.

B. Unit Commitment Problem (UCP)

Once the hydroelectric generation for each hour is determined, thermal units must meet the load not covered by hydroelectric generation. The UCP deals with the decision on which of the thermal units will be running or not during each hour of the scheduling period [1], [3]. The committed units must be able to meet the system load at minimum operating cost, subject to a variety of constraints. The UCP is a NP—complete optimization problem.

C. Economic Load Dispatch Problem (ELDP)

Once the running units for an hour have been determined by the solution of the UCP, it is necessary to distribute the load demand solving the ELDP. The ELDP consists of finding the optimal allocation of power demand among the running thermal units, satisfying the power balance equations and the unit's operation constraints.

When the ELDP is solved in the context of the online operation of the system, transmission losses are usually included in the optimization process, and sometimes even an optimal power flow is executed. However, in the context of the selection of an optimal schedule, there is evidence that losses do not have much influence and they are not included.

D. Mathematical Formulation for the Short-Term HGSP

The main objective of the short-term HGSP is to determine the optimal generation level for each hydro and thermal unit for each hour over an entire period (a day or week), subject to a large set of equality and inequality constraints.

The objective function of the short-term HGSP is represented by (1). The objective function is set as to minimize the total operation costs $(\text{immediate costs} + \text{future costs})$ plus a penalty factor (feasibility measure). (Please see the equation at the bottom of the page.) Where

z_T	total system operation cost;
y_t	fuel costs for hour t obtained from the ELDP;
T	number of hours for the time horizon;
N_{UGT}	number of thermal units;
N_{UGH}	number of hydraulic reservoirs;
$E_{i,t}$	status of thermal unit i during the hour t (1 for up and 0 for down);
$Pt_{i,t}$	power output for the thermal unit i during the hour t;
$Ph_{j,t}$	power output for the reservoir j during the hour t;
$CC_i(Pt_{i,t})$	fuel cost for the thermal unit i during the hour t with a power output $Pt_{i,t}$ (using a quadratic cost function);
$C_{\mathrm{su},i}$ and $C_{\mathrm{sd},i}$	start-up and shut-down costs for the thermal unit i during the entire scheduling horizon;
$\mathrm{Vol}_{j,t}$	volume for reservoir j during the hour t;
$\mathrm{Vol}_{j,T}$	volume for reservoir j at the end of the horizon;
$\mathrm{FCF}_j(\mathrm{Vol}_{j,T})$	future cost of thermal units as a function of the volume of reservoir j at the end of the scheduling horizon;
Penalty	penalty factor.

Immediate costs are calculated as the sum of the energy production costs and the start-up and shutdown costs, during the present time horizon (from 1 to T). The energy production cost

$$z_T = \min \left\{ \overbrace{\underbrace{\sum_{t=1}^{T} \left(\min \sum_{i=1}^{\mathrm{N_{UGT}}} E_{i,t} \cdot CC_i(Pt_{i,t}) \right)}_{y_t} + \sum_{i=1}^{N_{\mathrm{UGT}}} (C_{\mathrm{su}\ i} + C_{\mathrm{sd}\ i})}^{\text{Immediate Cost}} + \overbrace{\sum_{j=1}^{\mathrm{N_{UGH}}} \mathrm{FCF}_j(\mathrm{Vol}_{j,T})}^{\text{Future Cost}} + \text{Penalty} \right\} \quad (1)$$

(y_t), for a given hour t, corresponds to the solution of the ELDP for that hour, considering only the dispatched units.

On the other hand, the future cost for each reservoir is calculated using the respective FCF, as a function of the volume at the end of the time horizon.

The penalty factor is directly proportional to the level of violation of constraints. In this way, it works as a feasibility measure.

From (1), it can be appreciated that the objective function is not explicit, because the value of y_t is obtained through the solution of the ELDP, instead of a direct function evaluation.

The short-term HGSP presents a large set of units and system constraints, which are taken into account in this paper, as follows:

1) Demand satisfaction for each hour t:

$$\sum_{i=1}^{N_{\mathrm{UGT}}} E_{i,t} \cdot Pt_{i,t} + \sum_{j=1}^{N_{\mathrm{UGH}}} Ph_{j,t} = \mathrm{Dem}_t + \mathrm{Loss}_t - G_{HP\,t} \quad \forall t \tag{2}$$

where $\mathrm{Dem}_t, G_{HP\,t}$ and Loss_t are the total load demand forecasted for the hour t, total power output of hydraulic units without water storage capacity during the hour t and the total losses estimated for the system during hour t, respectively.

In order to accomplish this rule, the model incorporates a fictitious unit, whose cost function corresponds to the failure cost for the system.

2) Technical operation limits of each unit

$$Pt_{\min\,i} \le Pt_i \le Pt_{\max\,i} \quad \forall i \quad \forall t$$
$$Ph_{\min\,j} \le Ph_{j,t} \le Ph_{\max\,j} \quad \forall j \quad \forall t \tag{3}$$
$$\left(T_{i,t-1}^{\mathrm{up}} - \mathrm{Tminup}_i\right) \cdot (E_{i,t-1} - E_{i,t}) \ge 0 \quad \forall i \quad \forall t$$
$$\left(T_{i,t-1}^{\mathrm{down}} - \mathrm{Tmindown}_i\right) \cdot (E_{i,t} - E_{i,t-1}) \ge 0 \quad \forall i \quad \forall t \tag{4}$$

where $Pt_{\min\,i}$ and $Pt_{\max\,i}$ are the minimum and maximum power output of the thermal unit $i; Ph_{\min\,j}$ and $Ph_{\max\,j}$ are the minimum and maximum power output of the hydro unit $j; T_{i,t-1}^{\mathrm{up}}$ and $T_{i,t-1}^{\mathrm{down}}$ are the up and down-time at hour $t-1$ for the thermal unit i; Tminup_i is the minimum up time for thermal unit i and $\mathrm{Tmindown}_i$ is the minimum down time for thermal unit i.

3) Hydraulic dynamic of each reservoir j for each hour t

$$\mathrm{Vol}_{j,t+1} = \mathrm{Vol}_{j,t} + \mathrm{infl}_{j,t} - Q_j(Ph_{j,t}) - \mathrm{filt}_{j,t} - \mathrm{ev}_{j,t} - \mathrm{spil}_{j,t} \tag{5}$$

where $\mathrm{infl}_{j,t}$ is the forecasted inflow; $Q_j(Ph_{j,t})$ is the discharge for a power output $Ph_{j,t}$; $\mathrm{filt}_{j,t}$ is the filtration; $\mathrm{ev}_{j,t}$ is the evaporation; and $\mathrm{spil}_{j,t}$ is the spillage.

Each hydrothermal power system has its own particular hydraulic restrictions, depending mainly on geographical and hydrological conditions. Sometimes, water discharge from one reservoir can affect availability in another reservoir, the so-called hydraulically coupled units.

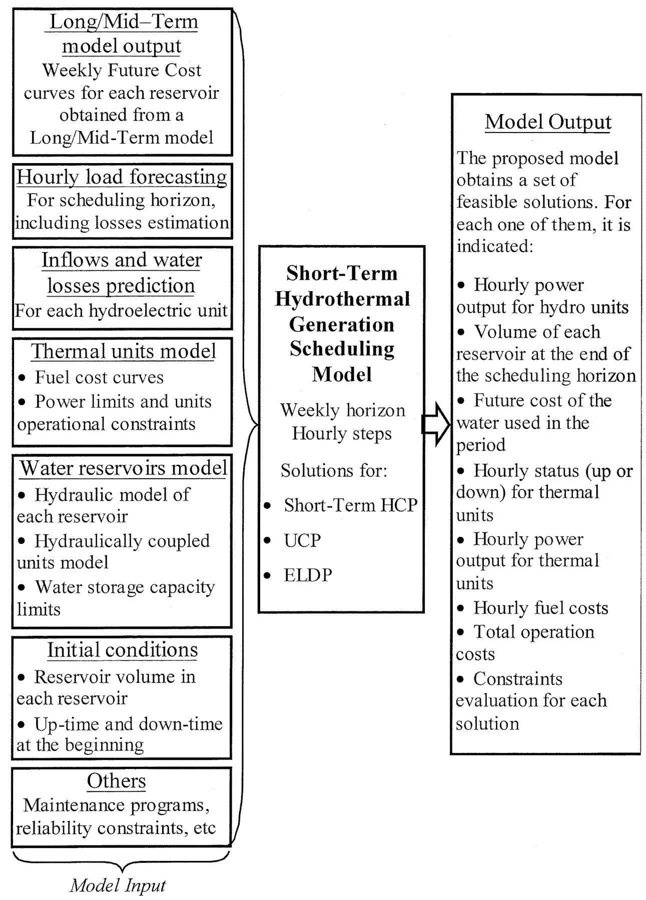

Fig. 3 Proposed model.

4) Limit storage capacity for each reservoir j

$$\mathrm{Vol}_{\min\,j} \le \mathrm{Vol}_{j,t} \le \mathrm{Vol}_{\max\,j} \quad \forall j \quad \forall t \tag{6}$$

where $\mathrm{Vol}_{\min\,j}$ and $\mathrm{Vol}_{\max\,j}$ are the minimum and maximum feasible volumes for reservoir j.

5) Spinning reserve requirements

$$\sum_{i=1}^{N_{\mathrm{UGT}}} E_{i,t}(Pt_{\max\,i} - Pt_{i,t}) + \sum_{j=1}^{N_{\mathrm{UGH}}} (Ph_{\max\,j} - Ph_{j,t}) \ge \beta \cdot \mathrm{Dem}_t \quad \forall t \tag{7}$$

where β corresponds to the percentage of the load demand to be used as reserve ($\beta = 0.1$ in this case).

III. Proposed Model

A scheme of the proposed model is given in Fig. 3. As input information, the proposed model uses the FCF obtained from a long/mid-term model, detailed information on the hourly load demand, the reservoir inflows and water losses, models of the hydro and thermal generating units and initial conditions, among others.

The proposed model uses this input information, handling simultaneously the subproblems of short-term hydrothermal coordination, unit commitment, and economic load dispatch. Con-

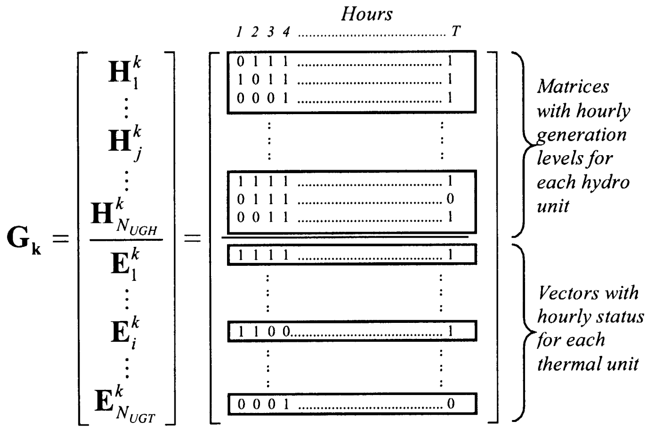

Fig. 4. Candidate solution representation (matrix $\mathbf{G}_\mathrm{k}$).

TABLE I
BINARY CODIFICATION EXAMPLE USING 3 b

% Phmax j	0	40	50	60	70	80	90	100
Binary codification	0	0	0	0	1	1	1	1
	0	0	1	1	0	0	1	1
	0	1	0	1	0	1	0	1

sidering an analysis horizon period of a week, the proposed model obtains hourly generation schedules for each of the hydro and thermal units.

IV. IMPLEMENTATION OF THE MODEL USING GA

The GA is a search technique inspired on genetics and evolution theory. They are described in [4], [45]–[48]. The implementation of the proposed model using a GA includes the following stages.

A. Representation of Candidate Solutions

Each candidate solution is represented by a binary matrix $\mathbf{G}_\mathrm{k}$, (Fig. 4), by means of an adequate codification of the decision variables. Each matrix representing a candidate solution must contain all of the information necessary to be distinguished from another one, and necessary to evaluate its fitness. The decision variables are

1) Power output of each hydroelectric unit for each hour: it is a continuous variable, which is discretized using a 3-bit code. So, there are eight possible discrete power generation levels for each unit. The generation levels for each 3-bit combination are assigned arbitrarily, as seen in Table I. Then, each candidate solution $\mathbf{G}_\mathrm{k}$ contains a set of binary submatrices $\mathbf{H}_k^j$ with size (3, T) for each hydro unit j.
2) Status of each thermoelectric unit for each hour: 1 if the unit is running, 0 if the unit is down. Then, each candidate solution $\mathbf{G}_\mathrm{k}$ contains also a set of binary vectors $\mathbf{E}_k^j$ with length T for each thermoelectric unit i.

B. Initialization

An initial population of candidate solutions is created randomly, and "seeded" with some good solutions obtained by means of heuristic rules based on the expert knowledge of the system and using a priority list.

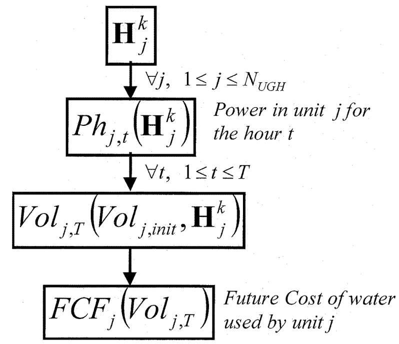

Fig. 5. Future cost calculation process for the hydraulic unit j.

C. Fitness Evaluation

To compare different solutions, a fitness (or cost) evaluation of each candidate solution must be done. It is achieved by means of the decoding of the strings and the evaluation of the objective function (1) for each candidate solution. In order to achieve the fitness evaluation, the following steps are executed for each candidate solution.

1) For each hydro sub-matrix $\mathbf{H}_k^j$, (from 1 to N_UGH), columns are decoded and final volume for each reservoir is calculated. Then, weekly FCFs for hydro generation have been used to obtain the opportunity cost due to the use of hydro energy during the week (Fig. 5).
2) Generation of hydro units is discounted from total load demand for each hour. Thermal demand (total minus hydro) must be satisfied by running thermal units at least cost. Then, for the running thermal units for each hour (obtained from vectors $\mathbf{E}_k^i$), an economic load dispatch is achieved. The ELDP is solved using Lagrange multipliers [1]. Production costs for each thermal unit over the week are calculated.
3) Analyzing each vector $\mathbf{E}_k^i$, start-up and shutdown costs are calculated using (8). As in [23], [25], and [34], $C_{\mathrm{sd}\,i}$ is equal to 0 for each thermal unit i, and $C_{\mathrm{su}\,i}$ is equal either to the cold start cost $(C_{\mathrm{su\ cold}\,i})$ or to the hot start cost $(C_{\mathrm{su\ hot}\,i})$, depending of the time that the unit has been down (t_down)

$$C_{\mathrm{su}\,i} = \begin{cases} C_{\mathrm{su,cold}\,i}, & \text{if} \quad t_\mathrm{down} \le T_{\mathrm{cold\ start}\,i} \\ C_{\mathrm{su,hot}\,i}, & \text{if} \quad t_\mathrm{down} > T_{\mathrm{cold\ start}\,i} \end{cases}. \tag{8}$$

4) Specialized subroutines determinates if each constraint is violated, and penalty factors are calculated.

D. Offspring Creation

Creation of new individuals is a fitness-dependant activity, due to solutions with best fitness have more probabilities to be selected as parents. The offspring creation process used in this paper (Fig. 6) involves three groups of genetic operators.

1) Crossover Operators: The crossover operators select randomly (but better solutions have more chances to be selected) two parent solutions and then combine their respective

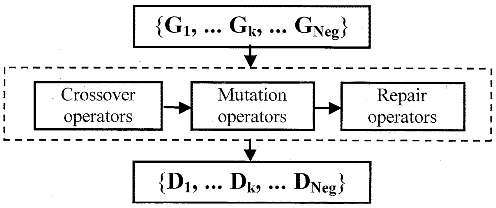

Fig. 6. Offspring creation process.

strings based in some rules, generating new population members. To achieve the parent selection, tournament selection has been used.

Three different kinds of crossover operators were used (one at a time), performed with probabilities p_{c1}, p_{c2}, and p_{c3}, respectively, (with $p_{c1} + p_{c2} + p_{c3} = 1$).

Window Crossover: For two selected parents, it selects randomly a "window" formed by two rows and two columns, and interchanges the bits inside the window between the parents. The better solution must transfer more information (bits) to the descendant [34].

2 Points Crossover: It is a particular case of the window crossover. It selects randomly two columns, and the parents interchange the bits between the columns.

Daily Crossover: this specialized operator takes advantage that hourly demand has a similar behavior for different weekdays. When the scheduling is being achieved for a week, this operator interchanges 24-h blocks between parents to create an offspring. It is a particular case of the two points crossover.

2) Mutation Operators: They are applied to avoid premature convergence of the algorithm, and are achieved over the created descendants. Two mutation operators has been used in this paper, performed with probabilities p_{m1} and p_{m2}, respectively.

Standard Mutation: it randomly changes a bit of the matrix.

Swap Mutation: this operator selects arbitrary an hour t, and search for the most expensive unit i_1 that is ON and the most cheaper unit i_2 that is OFF. Then, with probability 0.7, unit i_1 is turned OFF while unit i_2 is turned ON [34].

3) Repair Operators: The offspring creation process often produces unfeasible solutions due to violations of restrictions described in (4) and (6). To avoid the creation of too many unfeasible solutions, two repair operators have been included:

Repairing of Minimum Up/Downtime Constraints: This operator goes across each one of the vectors $\mathbf{E}_k^j$ evaluating the consecutive time that a thermal unit has been up or down. If a minimum up or down time constraint is violated for a given hour, the state of the unit at the hour is changed. An analysis of this operator and its benefits can be seen in [34].

Repairing of Storage Capacity Constraints: This operator tracks each submatrix $\mathbf{H}_k^j$, decodes it, and recursively calculates the water volume for each hour using (5). If at a given hour the constraint is violated, the operator randomly changes a bit of $\mathbf{H}_k^j$ for that hour until the violation is fixed.

If more feasible solutions are created on each generation, the process of replacement of the population members becomes more competitive, and the exploration of more zones of the search space is allowed. To investigate the effect of the repair operators, a sensibility analysis was performed in a small test system with four units (not shown in this paper). It could be seen that the inclusion of repair operators implies a faster convergence and solutions closer to the optimal.

E. Replacement of the Population Members

In order to create a new and improved population of solutions, a parents versus descendants competition is achieved, where best solutions survive and bad solutions disappear. The replacement procedure used is the $(\mu + \lambda)$ selection, used successfully in [34]. It can be described as:

Step 1) For each solution G of the present population, select randomly (using an uniform distribution) an offspring $\mathbf{D}$.

Step 2) If $\mathrm{Cost}(\mathbf{G}) < \mathrm{Cost}(\mathbf{D})$, then add $\mathbf{G}$ to the new population. If $\mathrm{Cost}(\mathbf{G}) > \mathrm{Cost}(\mathbf{D})$, then add $\mathbf{D}$.

Step 3) Remove $\mathbf{G}$ and $\mathbf{D}$ from the selectable offspring and repeat the process for the next solution $\mathbf{G}$.

This procedure is described in more detail in [48].

F. Convergence Criterion

If a fixed number of generations is reached, the algorithm stops, else it goes back to stage D. The maximum number of generations depends on the size of the system (number of units).

V. Case Results

The algorithm was programmed using MATLAB 5.3, and the simulations were performed using a 1-GHz Athlon processor. For tuning the parameters of the GA, it was previously tested using a purely thermal test system. After, the model was tested for a hydrothermal system.

A. Test Results for Purely Thermal Systems

The generation scheduling for a purely thermal system (or unit commitment problem) is a particular case of the short-term HGSP. The simulations were performed over a 24-h demand schedule for 10, 20, and 40 thermal units systems, which are described in [25]. Probabilities for the GA were set to $\mathrm{p_{c1}} = 0.5, \mathrm{p_{c2}} = 0.5, \mathrm{p_{m1}} = 0.001$ per bit and $\mathrm{p_{m2}} = 0.3$.

Results were compared with test results reported in [23], [25], and [34], as seen in Table II, where the cost for the better, the average, and the worst solution over ten runs are shown. It can be seen that the results from the simulations are competitive with previously reported results. The convergence process is shown in Fig. 7, with the average, over ten runs, of the minimum population cost, normalized by the minimum cost known for the system.

B. Test Results for a Hydrothermal System

The hydrothermal test system is a reduced version of the Chilean Central Interconnected System (see Appendix). It consists of six water reservoirs (11 hydro units, any of them hydraulically coupled) and ten thermal units.

Probabilities for the GA were set to $\mathrm{p_{c1}} = 0.3, \mathrm{p_{c2}} = 0.3, \mathrm{p_{c3}} = 0.4, \mathrm{p_{m1}} = 0.001$ per bit and $\mathrm{p_{m2}} = 0.3$.

TABLE II
TEST RESULTS FOR PURELY THERMAL SYSTEMS

Method	Problem	P1	P2	P3
	Number of units	10	20	40
	Search Space	1.70E+72	2.90E+144	8.30E+288
Dynamic Prog. [34]	Optimum	565827	No	No
Lagrangian Relaxation (LR) (5000 iterat.) [34]	Better	566107	1128362	2250223
	Average	566493	1128395	2250223
	Worst	566817	1128444	2250223
	Variation (%)	0.13	0.01	0.00
GA [25]	Better	565825	1126243	2251911
	Worst	570032	1132059	2259706
GA [34]	Better	565866	1128876	2252909
	Average	567329	1130160	2262585
	Worst	571336	1131565	2269282
	Variation (%)	0.96	0.24	0.72
Memetic Algorithm (MA) [34]	Better	565827	1127254	2252937
	Average	566453	1128824	2262477
	Worst	566861	1130916	2270361
	Variation (%)	0.18	0.32	0.77
MA seeded with LR [34]	LR (100 iterations)	567663	1129633	2250223
	Better	566686	1128192	2249589
	Average	566787	1128213	2249589
	Worst	567022	1128403	2249589
	Variation (%)	0.06	0.02	0.00
GA and LR [23]	LR	565825	1130660	2258503
	GA	565825	1126243	2251911
	LR + GA	564800	1122622	2242178
Proposed GA	**Better**	**565169**	**1128075**	**2252201**
	Average	**566045**	**1129328**	**2254329**
	Worst	**567117**	**1130899**	**2260114**
	Variation (%)	**0.34**	**0.25**	**0.35**

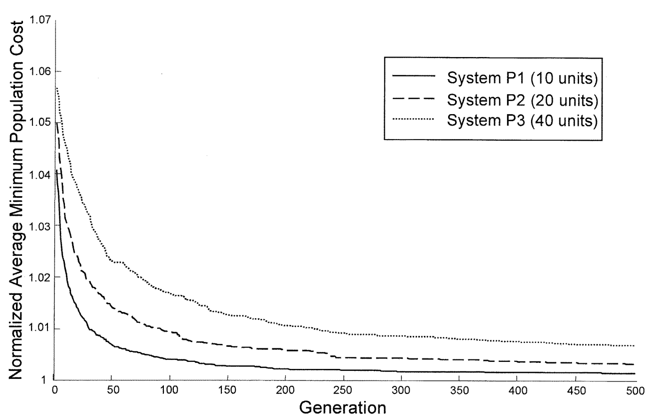

Fig. 7. Convergence process for a purely thermal system.

The simulation converged (Fig. 8) to a population of feasible solutions. From the analysis of the matrix $\mathbf{G}$ for the best solution, it could be observed that the two cheaper thermal units were ON for the entire scheduling period, while the most expensive were only turned on to satisfy demand peaks. Also, running thermal units were operating near their respective maximum efficiencies.

As seen in Fig. 9, total thermal generation is flattened by the effect of the hydro generation. In this way, hydro generation displaces the most expensive thermal generation. Besides, it can be observed the similar behavior of generation for different days of the week, mainly due to the effect of the "daily crossover."

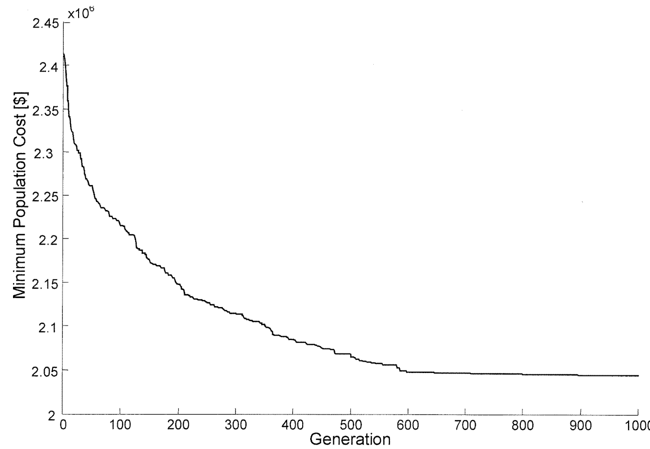

Fig. 8. Convergence process for hydrothermal system.

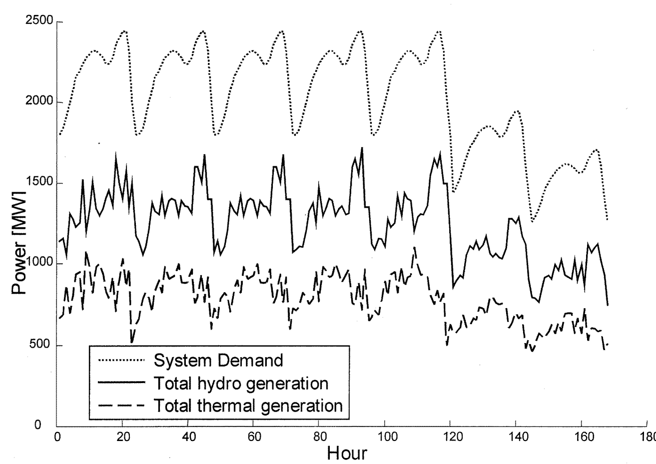

Fig. 9. Total hydro and thermal hourly generation scheduling for a week.

VI. CONCLUSION

This paper proposes and develops a new model for dealing with the short-term HGSP, incorporating, as a whole, three problems traditionally analyzed separately: short-term HCP, UCP, and ELDP.

Hydrothermal systems are coupled in time. In order to uncouple the long/mid-term models from the short-term model, FCFs have been used. In this way, FCFs work as the link between the short and the mid/long-term models.

The definition of the decision variables, the representation of candidate solutions, and the fitness evaluation are the basis for implementing a GA. They act like the connection between the electric/economic model and the GA. Once these aspects are solved, the solution through GAs is fundamentally a programming problem.

Promising results obtained from the computational simulation have been presented. The proposed GA, using new specialized operators, have demonstrated excellent performance in dealing with this kind of problem, obtaining near-optimal solutions in reasonable times and without sacrificing the realism of the electric and economic models.

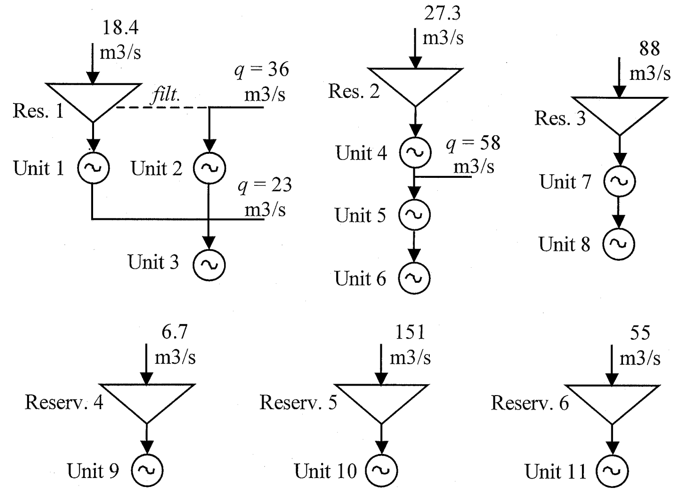

Fig. 10. Hydraulic configuration of hydro units in Chilean system.

TABLE III
INPUT/OUTPUT CHARACTERISTICS FOR HYDRO UNITS

Unit	Qmin [m3/s]	Qmax [m3/s]	Ph(Q) [MW]
1	5	92	Ph = k·Q (See values for k in Table IV)
2	0	90	Ph = 1.2·Q
3	0	192	Ph = 1.63·Q
4	0	40	Ph = k·Q (See values for k in Table IV)
5	0	84	Ph = -15.89+Q*(1.495-0.588e-2*Q)
6	0	84	Ph = Q·(0.833+Q·(0.715e-3+Q·(0.951e-4-Q·0.891e-6)))
7	56.5	310	Ph = k·Q (See values for k in Table IV)
8	56.6	310	Ph = Q·(0.359-Q·(0.235e-3+0.370e-6·Q))
9	0	83	Ph = k·Q (See values for k in Table IV)
10	0	578	Ph = k·Q (See values for k in Table IV)
11	115	315	Ph = k·Q (See values for k in Table IV)

TABLE IV
RESERVOIRS CHARACTERISTICS

Reservoir	1	2	3	4	5	6
Associated unit	Unit 1	Unit 4	Unit 7	Unit 9	Unit 10	Unit 11
Init.volume [Mm3]	1866	41.7	946.2	662.8	198.05	106.6
Inflow [m3/s]	18.4	27.3	88	6.7	151	55
Volume1 [Mm3]	500	7.5	384	224.9	142.65	103
k1 [MW/m3/s]	4.5494	2.62	1.204	1.9197	0.6209	1.7322
Filt1 [m3/s]	17.98	0	0	0	0	0
Volume2 [Mm3]	1768.1	49.29	666.1	435.03	215.32	110.66
k2 [MW/m3/s]	4.6974	2.63	1.343	1.9602	0.6447	1.7494
Filt2 [m3/s]	24.87	0	0.07	0	0	0
Volume3 [Mm3]	3036.2	91.07	984.2	645.15	287.99	118.32
k3 [MW/m3/s]	4.8149	2.64	1.440	1.9996	0.6549	1.7663
Filt3 [m3/s]	31.77	0	3.4	0	0	0
Volume4 [Mm3]	4304.3	132.86	1230	855.28	360.65	125.98
k4 [MW/m3/s]	4.9154	2.65	1.513	2.0389	0.664	1.775
Filt4 [m3/s]	40.2	0	7.02	0	0	0
Volume5 [Mm3]	5572.4	174.64	1512	1065.4	433.32	133.64
k5 [MW/m3/s]	5.0026	2.66	1.582	2.0389	0.672	1.78
Filt5 [m3/s]	50.33	0	10.13	0	0	0

APPENDIX
HYDROTHERMAL TEST SYSTEM DESCRIPTION

The hydrothermal test system is a reduced version of the Chilean Central Interconnected System, where a real model of

TABLE V
FUTURE COST FUNCTION FOR RESERVOIR 1

End Volume [Mm3]	500	568.7	824.7	1107.1	1416.0	1784.6	2217.9
Future Cost [M$]	1.45	1.371	1.19	1.041	0.94	0.806	0.724
End Volume [Mm3]	2721.3	3259	3785.5	4294.2	4775.7	5525.0	5572.4
Future Cost [M$]	0.626	0.542	0.494	0.466	0.443	0.412	0.4

TABLE VI
THERMAL UNITS CHARACTERISTICS

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
Ptmin [MW]	80	80	80	40	40
Ptmax [MW]	350	350	300	200	150
a [$/h]	0,0004	0,0004	0,0005	0,002	0,0022
b [$/MWh]	13,19	13,19	14,19	16,6	19,5
c [$/MW2-h]	800	800	780	700	680
min. up time [h]	3	3	3	5	5
min. down time[h]	3	3	3	5	5
hot start cost [$]	1500	1500	1500	550	560
cold start cost [$]	5000	5000	5000	1100	1120
shut down cost [$]	0	0	0	0	0
cold start hrs [h]	5	5	5	4	4
initial status [h]	8	8	8	-5	-5

	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
Ptmin [MW]	40	20	20	55	55
Ptmax [MW]	150	80	50	55	55
a [$/h]	0,0022	0,0071	0,0071	0,0041	0,0041
b [$/MWh]	19,5	22,26	26,26	32,92	32,92
c [$/MW2-h]	680	370	320	650	650
min. up time [h]	5	3	3	1	1
min. down time[h]	5	3	3	1	1
hot start cost [$]	560	170	170	30	30
cold start cost [$]	1120	340	340	60	60
shut down cost [$]	0	0	0	0	0
cold start hrs [h]	4	2	2	0	0
initial status [h]	-3	-3	-1	-1	-1

TABLE VII
HOURLY DEMAND FOR A WEEKDAY

Hour	Demand [MW]	Hour	Demand [MW]	Hour	Demand [MW]
1	1800	9	2280	17	2280
2	1840	10	2300	18	2396
3	1920	11	2320	19	2400
4	2000	12	2320	20	2440
5	2080	13	2300	21	2440
6	2160	14	2280	22	2320
7	2200	15	2240	23	2000
8	2240	16	2240	24	1800

the six most important hydraulic reservoirs (and their associated hydraulic systems) and a reduced set of representative thermal units were incorporated.

The hydraulic configuration of the hydro units in the test system is shown in Fig. 10. It can be seen that three of the hydro units are independent, but the rest are hydraulically coupled. Except for a 2-h time lag between units 7 and 8, no time lags were considered. Input/output characteristics (water discharge/power) for hydro units are given in Tables III and IV. Also, curves for modeling each of the six water reservoirs can be obtained from Table IV.

The FCF for reservoir 1 is indicated in Table V. The FCF for the others reservoirs can be calculated using the respective k values given in Table IV.

Parameters for the quadratic cost functions for each thermal unit (with $CC = a \cdot Pt^2 + b \cdot Pt + c$), along with their technical limits, are summarized in Table VI.

Hourly demand for a weekday is given at Table VII. For Saturday and Sunday, 80 and 70% of a weekday demand have been used, respectively.

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Esteban Gil (S'00) was born in Santiago, Chile. He received the B.Sc. and M.Sc. degrees in electrical engineering from Universidad Técnica Federico Santa María (UTFSM), Valparaíso, Chile, in 1997 and 2001, respectively. He is currently pursuing the Ph.D. degree at Iowa State University, Ames.

His research interests focus mainly on economics, optimization, operation, and planning of electric power systems.

Julian Bustos (SM'94) was born in Santiago, Chile. He graduated as an electrical engineer from Universidad Técnica Federico Santa María (UTFSM), Valparaíso, Chile, and received the M.Sc. and Ph.D. degrees from the University of Pittsburgh, PA.

Currently, he is a Professor at UTFSM and is Vice President for Academic Activities. His research activities include the economic operation, planning, and analysis of electric power systems.

Hugh Rudnick (F'00) was born in Santiago, Chile. He graduated as an electrical engineer from University of Chile, Santiago, Chile. He received the M.Sc. and Ph.D. degrees from the Victoria University of Manchester, Manchester, U.K.

Currently, he is a Professor at Catholic University of Chile, Santiago, Chile. His research activities focus on the economic operation, planning, and regulation of electric power systems.