SOLUTION TO LOSSY SHORT TERM HYDROTHERMAL COORDINATION PROBLEM WITH LIMITED ENERGY SUPPLY UNITS BY USING GENETIC ALGORITHM

Salih Fadıl
Department of Electrical Engineering
Osmangazi University
Batı Meşelik, 26480, Eskişehir, TURKEY
Tel: (222) 239 1074, E-mail: sfadil@ogu.edu.tr

Uçman Ergün
Department of Electrical Engineering
Afyon Kocatepe University
64300 Uşak, TURKEY
E-mail: uergun@aku.edu.tr

ABSTRACT

A *lossy* electric power system including normal and limited energy supply thermal units and hydraulic units is considered in this paper. The total thermal cost during total operation period is minimized under possible electric, hydraulic and fuel constraints. The minimization of the total thermal cost is achieved by specifying all units' active and reactive generations by means of a genetic algorithm. The application of the genetic algorithm to the problem is explained in detail. A visual simulation program in Delphi programming language is also prepared and the simulation results are presented.

1. INTRODUCTON

The operation period for a short term hydrothermal coordination problem can range from one day to a week. During the operation period, system load values and the units which will supply those loads are assumed to be known. The total operation period is divided into subintervals where the system load values remain constant.

Determination of reactive generations in optimal manner in a power system decreases system active transmission loss. Because of this, active generation of the unit connected to the system swing bus decreases. Therefore, a further decrease in the total system thermal cost is achieved. The reactive power generation optimization is also performed to make system bus voltage magnitudes stay within their limits.

In the literature, the short term *lossless* hydrothermal coordination problem was solved by using various solution methods. Some of those methods utilize dynamic programming [1-2], linear programming and network flow algorithm [3-6], nonlinear programming [7-8], functional analysis [9-10] and neural network algorithm [11]. The *lossless* hydrothermal coordination problem was also solved by using a genetic algorithm [12]. Serial and parallel hydraulic coupling among hydraulic units and the relationship between hydraulic units' input-output curves and their reservoirs' net head are considered in the solution. The effect of some genetic algorithm parameters on the solution algorithm performance was also discussed.

The main differences between the genetic algorithm and the other classical solution methods can be summarized as follows. The genetic algorithm works on coded parameter set, instead of the real problem parameters. It searches solution point in different parts of the solution space simultaneously, instead of searching the solution in one point. It does not need the derivative and other auxiliary information values instead, it only needs fitness value of the solutions. In transition from one solution point to the another, it does not need any predefined transition rule instead, it uses general probabilistic transition rules. Because of having those properties, the genetic algorithm can find global optimum point in highly constrained difficult nonlinear optimization problems. The most important disadvantage of the genetic algorithm is that it generally needs more solution time and computer memory compared to the other classical solution methods [13].

We assumed that the limited energy supply thermal units in the system are fueled under *take-or-pay* fuel contract. Under this type of fuel contract, minimum value of the total fuel amount to be spent by the limited energy supply thermal units during the operation period is determined in advance. The utility company agrees to use this minimum amount, or failing to use this amount it agrees to pay the cost of the minimum fuel amount. While the limited energy supply units' total fuel consumption is below the minimum, the system excluding the limited energy supply thermal units should be scheduled to minimize the total thermal cost subject to the total fuel consumption for the operation period for the limited energy supply thermal units is equal to the minimum amount [14].

2. PROBLEM FORMULATION

Formulation of the optimization problem is divided into two parts as active and reactive power optimization problem. In the active power optimization, active generations of all units (except the one connected to the swing bus) in all subintervals are determined by means of the genetic algorithm. The reactive generations of all units (except the one connected to the swing bus) in all subintervals are taken equal to predefined values and they are not changed during the active power optimization. In the reactive power optimization, active generations of all units (except the one connected to the swing bus) in all subintervals are taken equal to the optimal values that were found in the active power optimization. Only reactive generations in all subintervals are determined by means of the genetic algorithm. Consequently, at the end of the reactive generation optimization, all reactive and active generations in all subintervals giving minimum total thermal cost and also satisfying all electric, hydraulic and fuel constraints within their predefined tolerance values are obtained.

2.1 Active Power Optimization

Active power optimization problem considered in this paper can be given as follows.

Minimize

$$F_{TOT} = \sum_{j=1}^{j_{max}} \Big(\sum_{n \in N_S} F_n(P_{GS,nj}) + \sum_{k \in N_T} F_k(P_{GT,kj}) \Big) t_j \qquad (R)^{1} \quad (1)$$

subject to electric, hydraulic and fuel constraints

---

[1] R represents fictitious monetary unit

$$P_{load,j} + P_{loss,j} - \sum_{n\in N_s} P_{Gs,nj} - \sum_{m\in N_H} P_{GH,mj} - \sum_{k\in N_T} P_{GT,kj} = 0,$$

$$j = 1,\cdots,j_{max} \quad (2)$$

$$P_{Gs,n}^{min} \le P_{Gs,nj} \le P_{Gs,n}^{max}, \quad n \in N_s, \quad j = 1,\cdots,j_{max} \quad (3)$$

$$P_{GT,k}^{min} \le P_{GT,kj} \le P_{GT,k}^{max}, \quad k \in N_T, \quad j = 1,\cdots,j_{max} \quad (4)$$

$$P_{GH,m}^{min} \le P_{GH,mj} \le P_{GH,m}^{max}, \quad m \in N_H, \quad j = 1,\cdots,j_{max} \text{ or}$$

$$q_m^{min} \le q_m(P_{GH,mj}) \le q_m^{max}, \quad m \in N_H, \quad j = 1,\cdots j_{max} \quad (5)$$

$$V_m^{min} \le V_{mj} \le V_m^{max}, \quad m \in N_H, \quad j = 1,\cdots,j_{max} \quad (6)$$

$$V_{m0} = V_m^{start}, \quad V_{mj_{max}} = V_m^{end}, \quad m \in N_H. \quad (7)$$

Since inflow water rate into the m^{th} hydraulic unit's reservoir in the j^{th} subinterval, r_{mj} *(acre-ft/h)*[2], is known, (7) gives rise to the following equation.

$$\sum_{j=1}^{j_{max}} q_m(P_{GH,mj})t_j = q_{TOT,m}, \; q_{TOT,m} = V_m^{start} - V_m^{end} + \sum_{j=1}^{j_{max}} r_{mj}t_j, \; m \in N_H \quad (8)$$

$$\sum_{j=1}^{j_{max}} \sum_{k\in N_T} A_k(P_{GT,kj})t_j = A_{TOT} \quad (9)$$

In the above equations,

F_{TOT} = total thermal cost, *(R)*,

j, j_{max} = subinterval index and number of subintervals,

$P_{Gs,nj}, P_{GH,mj}, P_{GT,kj}$ = the n^{th} normal thermal, the m^{th} hydraulic and the k^{th} limited energy supply thermal unit's active generations in subinterval j, *(MW)*,

$F_n(P_{Gs,nj}), F_k(P_{GT,kj})$ = cost rate of the n^{th} normal thermal and the k^{th} limited energy supply thermal unit in the j^{th} subinterval when their active output powers are $P_{Gs,nj}$, $P_{GT,kj}$ respectively, *(R/h)*,

t_j = length of subinterval j, *(h)*,

$P_{load,j}, P_{loss,j}$ = total system active load and loss in the j^{th} subinterval respectively, *(MW)*,

$P_{Gs,n}^{min}, P_{Gs,n}^{max}$ = lower and upper active generation limits of the n^{th} normal thermal unit, *(MW)*,

$P_{GH,m}^{min}, P_{GH,m}^{max}$ = lower and upper active generation limit of the m^{th} hydraulic unit, *(MW)*,

$P_{GT,k}^{min}, P_{GT,k}^{max}$ = lower and upper active generation limit of the k^{th} limited energy supply thermal unit, *(MW)*,

$q_m(P_{GH,mj})$ = water rate of the m^{th} hydraulic unit when its active output power is $P_{GH,mj}$, *(acre-ft/h)*,

q_m^{min}, q_m^{max} = lower and upper water rate limits for the m^{th} hydraulic unit, *(acre-ft/h)*,

V_{mj} = stored water volume in the m^{th} hydraulic unit's reservoir *at the end of* the j^{th} subinterval, *(acre-ft)*,

V_m^{min}, V_m^{max} = lower and upper reservoir storage limits of the m^{th} hydraulic unit, *(acre-ft)*,

$q_{TOT,m}$ = total water amount that should be used by the m^{th} hydraulic unit during the operation period, *(acre-ft)*,

r_{mj} = inflow water rate into the m^{th} hydraulic unit's reservoir in the j^{th} subinterval, *(acre-ft/h)*,

V_m^{start}, V_m^{end} = starting and ending stored water volume of the m^{th} hydraulic unit, *(acre-ft)*,

$A_k(P_{GT,kj})$ = fuel consumption rate of the k^{th} limited energy supply thermal unit in the j^{th} subinterval, *(ton/h, m³/h, ccf/h,* etc.*)*[3],

A_{TOT} = total fuel amount that should be used by all limited energy supply thermal units during the operation period, *(ton, m³, ccf,* etc.*)*,

N_s, N_T, N_H = sets which contains all normal thermal, limited energy supply thermal and hydraulic units in a given power system respectively.

2.1.1. Coding and Mapping Mechanism

A solution to the active power optimization is formed by concatenating all solutions (substrings) which belong to each subinterval. A solution to a subinterval is also formed by concatenating all binary coded active generation values (except the one which belongs to the unit connected to the swing bus) in that subinterval. Binary coding and linear mapping for active generation of normal thermal unit *n* is done according to

$$\underbrace{00\ldots\ldots0}_{\ell_n} \rightarrow P_{Gs,n}^{min}, \qquad \underbrace{11\ldots\ldots1}_{\ell_n} \rightarrow P_{Gs,n}^{max} \quad (10)$$

where ℓ_n represents the number of binary digits used in the coding. ℓ_n is chosen according to the desired resolution. Similarly, binary coding and linear mapping for the m^{th} hydraulic and the k^{th} limited energy supply thermal units' active generations are done according to the following equations

$$\underbrace{00\ldots\ldots0}_{\ell_m} \rightarrow P_{GH,m}^{min}, \qquad \underbrace{11\ldots\ldots1}_{\ell_m} \rightarrow P_{GH,m}^{max} \quad (11)$$

$$\underbrace{00\ldots\ldots0}_{\ell_k} \rightarrow P_{GT,k}^{min}, \qquad \underbrace{11\ldots\ldots1}_{\ell_k} \rightarrow P_{GT,k}^{max} \quad (12)$$

All active generations determined by the genetic algorithm remain within their respective limits due to the used linear mapping mechanism. Therefore inequality constraints given in (3)-(5) are satisfied automatically.

2.1.2 Fitness Function

Fitness value of a solution in the active power optimization is calculated according to

$$f^P = c_{max}^P - \left\{ \sum_{j=1}^{j_{max}} TCR_j t_j + \sum PF^P \right\} \quad (13)$$

where

[2] 1 *acre-ft* = 1233.5 m^3

[3] 1 *ccf* = 10^3 ft^3 = 27.317 m^3

$$TCR_j = \sum_{n \in N_s} F_n(P_{Gs,nj}) + \sum_{k \in N_T} F_k(P_{GT,kj}) .$$

$\sum PF^P$ in (13) represents sum of the various penalty functions and it is calculated according to

$$\sum PF^P = PF_{P_{sw}} + PF_V + PF_{V^{end}} + PF_{A_{TOT}} \qquad (14)$$

$PF_{P_{sw}}$ in (14) represents sum of penalty functions for the active generation of the unit connected to the swing bus. It is calculated according to the following equation.

$$PF_{P_{sw}} = \begin{cases} \sum\limits_{j \in \{P_{Gs,swj} < P_{Gs,sw}^{min}\}} K_{P_{sw}} (P_{Gs,sw}^{min} - P_{Gs,swj})^2 \\ \sum\limits_{j \in \{P_{Gs,swj} > P_{Gs,sw}^{max}\}} K_{P_{sw}} (P_{Gs,swj} - P_{Gs,sw}^{max})^2 \\ 0 \text{ if } P_{Gs,swj}^{min} \le P_{Gs,swj} \le P_{Gs,swj}^{max},\ j = 1, \cdots, j_{max} \end{cases} \qquad (15)$$

$P_{Gs,swj}$, $P_{Gs,sw}^{min}$, $P_{Gs,sw}^{max}$ in (15) denote for the active generation of the unit connected to the swing bus, the lower and upper active generation limits of this unit respectively. $K_{P_{sw}}$ in (15) is a constant coefficient. PF_V in (14) represents sum of the penalty functions which belong to reservoir storage constraints of the hydraulic units. It is calculated according to

$$PF_V = \begin{cases} \sum\limits_{\substack{j,m \in \{V_{mj} < V_m^{min}\} \\ j \ne j_{max}}} K_{V_m} (V_m^{min} - V_{mj})^2 \\ \sum\limits_{\substack{j,m \in \{V_{mj} > V_m^{max}\} \\ j = j_{max}}} K_{V_m} (V_m^{max} - V_{mj})^2,\ \forall m \in N_H \\ 0 \text{ if } V_m^{min} \le V_{mj} \le V_m^{max},\ j = 1, \cdots, j_{max} - 1 \end{cases} \qquad (16)$$

where K_{V_m} in (16) represents a constant coefficient for the penalty function of the m^{th} hydraulic unit's stored water amount. $PF_{V^{end}}$ in (14) denotes for sum of all penalty functions which belong to water amounts left in the hydro units' reservoirs at the end of the last subinterval. It is calculated as

$$PF_{V^{end}} = \sum_{m \in N_H} K_{V_m^{end}} (V_{mj_{max}} - V_m^{end})^2 \qquad (17)$$

where $K_{V_m^{end}}$ represents a constant coefficient of the penalty function which belongs to the m^{th} hydraulic unit. $PF_{A_{TOT}}$ in (14) represents the penalty function which belongs to the fuel amount which is consumed by the all limited energy supply thermal units during the operation period. It is calculated as

$$PF_{A_{TOT}} = K_{A_{TOT}} \left(\sum_{j=1}^{j_{max}} \sum_{k \in N_T} A_k (P_{GT,kj}) t_j - A_{TOT} \right)^2 \qquad (18)$$

where $K_{A_{TOT}}$ is the coefficient of this penalty function.

In the solution procedure, c_{max}^P value in (13) is taken equal to the highest value of $\sum_{j=1}^{j_{max}} TCR_j\, t_j + \sum PF^P$ which is calculated at the current iteration of the genetic algorithm. Since the genetic algorithm is formulated according to maximization problem and the considered problem in this paper is a minimization problem, the fitness value of each solution is calculated according to (13).

In the genetic algorithm, constraints which can not be considered by means of the coding and mapping mechanism is added into the solution procedure via penalty functions. In order to get efficient contributions of the penalty functions to the fitness value, each penalty function is multiplied by a coefficient. Those coefficients should be selected according to their penalty funtions' relative weight to the total thermal cost value.

Stored water volume in the m^{th} hydraulic unit's reservoir at the end of the j^{th} subinterval is calculated according to the following equation:

$$V_{mj} = V_{mj-1} + \left[r_{mj} - q_m(P_{GH,mj}) \right] t_j \qquad (19)$$

If there are some hydraulic units which are hydraulically coupled (series or parallel) with unit m in the upstream of unit m, equation (19) should be modified accordingly.

2.1.3 General Structure of the Used Genetic Algorithm

The general structure of the used genetic algorithm is shown in Figure 1. At first, a random initial solution set is generated. Active generations of each subinterval in each solution should satisfy the following inequality.

$$K_{load}^P P_{load,j} < \Big(\sum_{\substack{n \in N_s \\ n \ne sw}} P_{Gs,nj} + \sum_{m \in N_H} P_{GH,mj} + \sum_{k \in N_T} P_{GT,kj} \Big) < P_{load,j},$$

$$j = 1, \cdots j_{max} \qquad (20)$$

K_{load}^P in (20) is a coefficient satisfying $0 < K_{load}^P < 1$. The value of this coefficient is selected according to the active generation upper limit of the unit connected to the swing bus and total active load in each subinterval. Selection of K_{load}^P in this manner makes the unit connected to the swing bus run as a generator and it also causes the penalty function in (15) to take zero or small values. After that a Newton-Raphson load flow calculation is performed for each subinterval of each solution. Since the active generation of the unit connected to the swing bus in each subinterval of each solution is known at this point, fitness value of each solution is calculated. Later, a new solution set is generated by using fundamental operations of the genetic algorithm. A solution is taken from the new set and its fitness value is compared with the worst (the lowest) fitness in the old set. If it is better, this solution is written over the worst solution in the old set. If it is not, this solution is discarded. This comparison procedure is done for all solutions in the new solution set. The procedure explained so far is repeated as many times as the number of iterations.

2.2 Reactive Power Optimization

The reactive power optimization considered in this paper can be given mathematically as follows:

$$\text{Minimize } F_{TOT}^{sw} = \sum_{j=1}^{j_{max}} F_{sw}(P_{Gs,swj}) t_j \qquad (R) \qquad (21)$$

subject to

$$Q_{load,j} + Q_{loss,j} - \sum_{y \in N_Q} Q_{G,yj} = 0, \quad j = 1, \cdots j_{max} \qquad (22)$$

$$P_{load,j} + P_{loss,j} - \sum_{n \in N_s} P_{Gs,nj} - \sum_{m \in N_H} P_{GH,mj} - \sum_{k \in N_T} P_{GT,kj} = 0,$$

$$j = 1, \ldots, j_{max} \qquad (23)$$

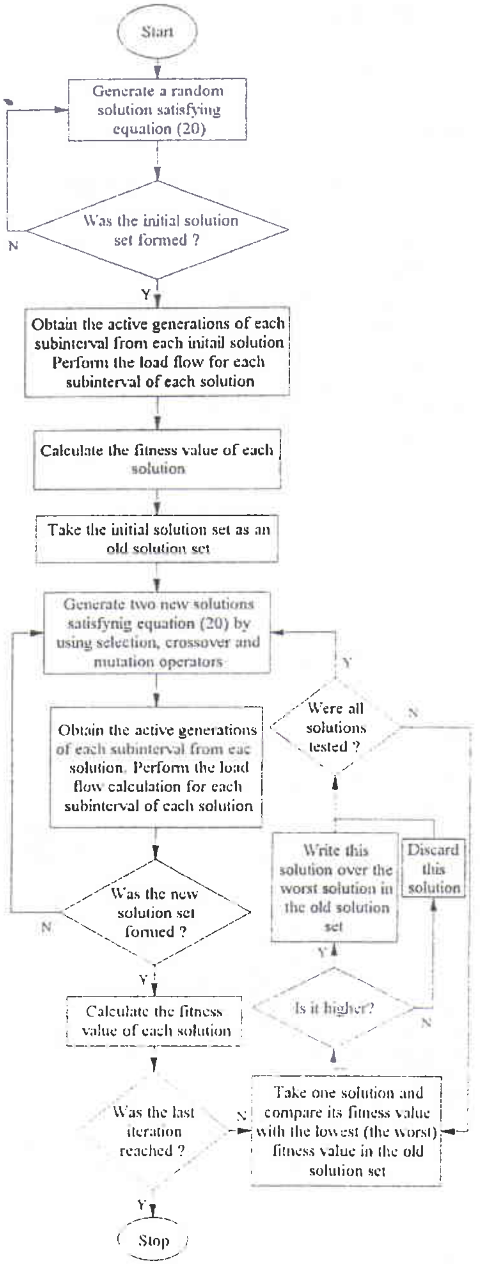

Figure 1 Flow chart of the used genetic algorithm.

$$Q_{G,y}^{min} \le Q_{G,yj} \le Q_{G,y}^{max}, \quad y \in N_Q, \quad j = 1,\cdots,j_{max} \tag{24}$$

$$P_{Gs,sw}^{min} \le P_{Gs,swj} \le P_{Gs,sw}^{max}, \quad j = 1,\cdots,j_{max} \tag{25}$$

$$\left|U_i\right|^{min} \le \left|U_{ij}\right| \le \left|U_i\right|^{max},$$

$$i \in \left\{\begin{matrix} All\ system\ buses\ execept\ swing \\ bus\ and\ voltage\ controlled\ buses.\end{matrix}\right\}, \ j = 1,\cdots j_{max}. \tag{26}$$

In the above equations,

F_{TOT}^{sw} = total cost for the normal thermal unit connected to the swing bus, *(R)*,

$F_{sw}(P_{Gs,swj})$ = cost rate of the normal thermal unit connected to the swing bus in the j^{th} subinterval when its output active power is $P_{Gs,swj}$, *(R/h)*,

$Q_{load,j}$, $Q_{loss,j}$ = total system reactive load and loss in the j^{th} subinterval respectively, *(MVA r)*,

$Q_{G,y}^{min}$, $Q_{G,y}^{max}$ = lower and upper reactive generation limits of the y^{th} reactive power generation source, *(MVA r)*,

$\left|U_{ij}\right|$ = voltage magnitude of bus i in the j^{th} subinterval, *(kV)*

$\left|U_i\right|^{min}, \left|U_i\right|^{max}$ = lower and upper voltage magnitude limits for bus *i*, *(kV)*,

N_Q = set containing all buses to which reactive power generation sources are connected.

The coding and mapping mechanism in the reactive power optimization resembles the one given in the active power optimization:

$$\underbrace{00.......0}_{\ell_y} \rightarrow Q_{G,y}^{min}, \ \underbrace{11.......1}_{\ell_y} \rightarrow Q_{G,y}^{max} \tag{27}$$

where ℓ_y represents the number of binary digits used in coding of $Q_{G,yj}$. ℓ_y is chosen according to the desired resolution. Since reactive generations of the reactive power sources connected to voltage controlled buses are determined in the load flow calculation, those reactive generations are not determined by the genetic algorithm.

The fitness value of a solution in the reactive power optimization is calculated according to

$$f^Q = c_{max}^Q - \left\{\sum_{j=1}^{j_{max}} F_{sw}(P_{Gs,swj})\,t_j + \sum PF^Q\right\} \tag{28}$$

where $\sum PF^Q$ denotes for sum of various penalty functions and it is calculated as

$$\sum PF^Q = PF_{P_{sw}} + PF_{Q_{sw}} + PF_{|U|}. \tag{29}$$

$PF_{Q_{sw}}$ in (29) represents sum of penalty functions for the reactive generation of the unit connected to the swing bus. It is calculated as

$$PF_{Q_{sw}} = \begin{cases} \sum\limits_{j \in \left\{Q_{Gs,swj} < Q_{Gs,sw}^{min}\right\}} K_{Q_{sw}}(Q_{Gs,sw}^{min} - Q_{Gs,swj})^2 \\ \sum\limits_{j \in \left\{Q_{Gs,swj} > Q_{Gs,sw}^{max}\right\}} K_{Q_{sw}}(Q_{Gs,swj} - Q_{Gs,sw}^{max})^2 \\ 0 \ if \ Q_{Gs,sw}^{min} \le Q_{Gs,swj} \le Q_{Gs,sw}^{max}, \ j = 1,\cdots,j_{max} \end{cases} \tag{30}$$

where $K_{Q_{sw}}$ is a constant coefficient. $PF_{|U|}$ in (29) is sum of penalty functions for voltage magnitudes of the system buses, and it is calculated as

$$PF_{|U|} = \begin{cases} \sum\limits_{\substack{i,j \in \left\{U_{ij} < U_i^{min}\right\} \\ i \ne sw,vc}} K_{|U_i|}(\left|U_i\right|^{min} - \left|U_{ij}\right|)^2 \\ \sum\limits_{\substack{i,j \in \left\{U_{ij} > U_i^{max}\right\} \\ i \ne sw,vc}} K_{|U_i|}(\left|U_{ij}\right| - \left|U_i\right|^{max})^2 \\ 0 \ if \left|U_i\right|^{min} \le \left|U_{ij}\right| \le \left|U_i\right|^{max}, i \in \left\{\begin{matrix} All\ buses \\ i \ne sw,\ vc \end{matrix}\right\} \\ j = 1,\cdots j_{max} \end{cases} \tag{31}$$

$K_{|U_i|}$ in (31) is the coefficient of the penalty function for voltage magnitude of bus i. vc index in (31) is used to designate voltage controlled buses.

Like in the active power optimization, c^{Q}_{max} value in (28) is taken equal to the highest value of $\sum_{j=1}^{j_{max}} F_{sw}(P_{Gs,sw,j})t_j + \sum PF^Q$ which is calculated at the current iteration of the genetic algorithm.

The structure of the genetic algorithm used in the reactive power optimization looks like the one shown in Figure 1. The only difference is that solutions generated by the genetic algorithm should satisfy the following inequality

$$K^{Q}_{load} Q_{load,j} < \Big(\sum_{\substack{y \in N_Q \\ y \neq sw,vc}} Q_{G,yj} \Big) < Q_{load,j}, \quad j = 1, \cdots j_{max} \tag{32}$$

instead of the one given in (20). Similarly K^{Q}_{load} in (32) is a coefficient satisfying $0 < K^{Q}_{load} < 1$ and its value is selected according to the reactive generation upper limit of the unit connected to the swing bus and the total system reactive load in each subinterval.

3. SIMULATON PROGRAM AND EXAMPLE

A visual simulation program in Delphi was written to test the proposed solution algorithm. A user can enter necessary data about the considered power system (bus number and type, transmission line parameters, input-output curves of the units, bus load values etc.) and parameters of the genetic algorithm (number of solutions (population), number of iterations, crossover and mutation probability etc.) very easily. Data about the considered system is saved in various files. Therefore, the user can resolve the optimization problem by changing some genetic algorithm parameters without reentering the power system data.

The simulation program was tested on an example power system which has sixteen buses, two limited energy supply natural gas fired thermal units, three normal thermal units and four hydraulic units. Hydraulic coupling among the hydraulic units are taken as shown in Figure 2. Twenty four hours operation period having six equal subintervals was considered.

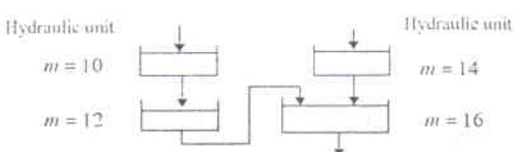

Figure 2. Hydraulic coupling among the hydraulic units in the example power system.

A_{TOT} is taken as equal to 44500 *ccf*. We chose population and number of iteration as 180 in the solution. At first, we ignored the natural gas constraint and applied the active and reactive power optimization to the problem. At the end of active power optimization, total thermal cost and used gas quantity were obtained as 184869 *R*, and 37397 *ccf* respectively. Later we applied the reactive power optimization and the total thermal cost decreased to 184321 *R*. We also resolved the same problem by considering the gas constraint. At the end of the active power optimization, the total thermal cost and used gas quantity were obtained as 177004 *R* and 44490 *ccf*. The total thermal cost was decreased to 176375 *R* at the end of reactive power optimization. We saw that all bus voltage magnitudes remain within their prespecified upper and lower limit values at the end of reactive power optimizations. Relative absolute error values for the water amounts left in the hydraulic units' reservoirs at the end of the operation period are below 0.32 % at the solution points in both solution. Also at the solution point, the stored water amounts at the end of each subinterval in each hydraulic unit's reservoir remain within their storage limits.

We saw from the obtained results that the genetic algorithm gives approximate solution around the fiftieth iteration in both active and reactive power optimization. After the fiftieth iteration, only a small decrease in the total thermal cost occurs.

4. CONCLUSION

Application of the genetic algorithm to *lossy* short term hydrothermal coordination problem including limited energy supply thermal units is given in this paper. A visual simulation program in Delphi was written and it was tested on an example power system. Obtained results from the solution is also summarized. Detailed results will be given in the presentation.

REFERENCES

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

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

[3] Brannud, H., Bubenko, J., A., Sjelvgren, D., Optimal short term operation of a large hydrothermal system based on a non linear network flow concept, *IEEE Trans. PWRS, Vol. 1, No. 4, Nov. 1996, pp.75-82*

[4] 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.*

[5] Xia Q., Xiang, N., Wang, S., Zhang, B., Huang, M., Optimal daily scheduling of cascaded plant using a new algorithm of non-linear minimum cost network flow concept, *IEEE Trans. PWRS Vol. 3, No. 3, 1988, pp. 929-935.*

[6] 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.*

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

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

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

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

[11] 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.*

[12] Orero, S. O., Irving, M. R., A genetic algorithm modeling framework and solution technique for short term optimal hydrothermal scheduling, *IEEE Trans. on Power Systems, Vol. 13, No. 2, May 1998, pp. 501-516*

[13] Goldberg, D. E., *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley Publishing Company, Inc., 1989.

[14] A. J. Wood, B. F. Wollenberg, Power Generation, Operation and Control, New York, John Wiley & Sons, 1984, pp. 65-99.