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Optimal operation of water supply systems with tanks based on genetic algorithm*

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Abstract: In view of the poor water supply system's network properties, the system's complicated network hydraulic equations were replaced by macroscopic nodal pressure model and the model of relationship between supply flow and water source head. By using pump-station pressure head and initial tank water levels as decision variables, the model of optimal allocation of water supply between pump-sources was developed. Genetic algorithm was introduced to deal with the model of optimal allocation of water supply. Methods for handling each constraint condition were put forward, and overcome the shortcoming such as premature convergence of genetic algorithm; a solving method was brought forward in which genetic algorithm was combined with simulated annealing technology and self-adaptive crossover and mutation probabilities were adopted. An application example showed the feasibility of this algorithm.

Key words: Water supply system, Optimal operation, Genetic algorithm, Tank
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INTRODUCTION

With increased urbanization and consumer demand, most water distribution systems and efficient scheduling of pump operation have become increasingly complex. Several optimization methods are used to find optimal pump schedules. Because of the complex water distribution systems, simple calculations are no longer possible. The main methods used at present are linear programming (Crawley and Dandy, 1993), dynamic programming (Yeh *et al.*, 1992; Nitivattananon *et al.*, 1996), network flow programming (Sun *et al.*, 1995) and non-linear programming (Ormsbee and Reddy, 1995; Sakarya and Mays, 2000; Liu *et al.*, 2003).

For multisource-multitank systems, and dual-level optimization models were developed by many researchers. Such methods first determine the optimal discharge or added head associated with each pump station. The pump-operation schedules associated with the resulting optimal discharges or pump heads are then determined by solving a secondary series of discrete optimization problems. This paper presents an attempt to solve the upper-level optimal pump-station discharge problem by using genetic algorithm (GA).

MODEL DESCRIPTION

Generally speaking, the optimal policy should result in the lowest total operating cost for a given set of boundary and system constraints. So, objective function and constraints are needed for optimal scheduling model.

Objective function

In a typical water distribution system, the en-

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ergy-consumption cost incurred by the pumping facility depends on the rate at which water is pumped, the associated pump head, the duration of pumping, and the unit cost of electricity. Mathematically the objective function may be expressed as

$$F_1 = \sum_{i=1}^{I}\sum_{t=1}^{T}(ER_{it})CQ_{it}(HS_{it}) \tag{1}$$

where F_1 is total energy cost to be minimized; I is number of pump-stations; T is number of time intervals which constitute the operating horizon; ER_{it} is electric rate of pump-station i during time period t; C is conversion coefficient; Q_{it} and HS_{it} are discharge and pressure head of pump-station i during time period t.

For a given network configuration, when nodal demand, the pressure head associated with each pump-station and each tank are given, the discharge of each pump station and each tank can be obtained by satisfying the conservation of mass and conservation of energy, which are defined as the hydraulic equilibrium equations, whose solutions require knowledge of the topology relation of pipe network, pipe diameter, pipe length, pipe material and nodal demand. Based on the current foundation conditions, it is difficult to obtain the values for the topology relation and basic parameters of some pipe networks, especially because of the limitations of monitor equipment condition, the nodal demand cannot be dynamically acquired accurately, the method of adopting microcosmic model can hardly satisfy the demands of optimal scheduling of water supply system in China now. On the other hand, the hydraulic equilibrium equations include a series of nonlinear equations whose solution, for large-scale water supply network, involves much calculation time. Consequently, we adopt macroscopic model, i.e. nodal pressure macroscopic model and the model of the relationship between water supply flow and head of water source, to replace the cumbersome hydraulic equilibrium equations. Based on Support Vector Machine (SVM) approach (Yu, 2004), the macroscopic model can be expressed as

$$Q_{it} = f_i(HS_{1t},\cdots,HS_{It},HR_{1t},\cdots,HR_{St},Q_{Dt}),\quad i=1,\cdots,I \text{ and } t=1,\cdots,T \tag{2}$$

$$QR_{st} = f_s'(HS_{1t},\cdots,HS_{It},HR_{1t},\cdots,HR_{St},Q_{Dt}),\quad s=1,\cdots,S \text{ and } t=1,\cdots,T \tag{3}$$

where HR_{st} is water level of tank s during time period t; S is number of tanks; Q_{Dt} is total water demand of system during time period t; QR_{st} is flow to or from tank s during time period t.

In addition, tank level is updated through Eq.(4)

$$HR_{s(t+1)} = HR_{st} + \frac{QR_{st}}{A_{st}}\Delta T,\quad s=1,\cdots,S \text{ and } t=1,\cdots,T \tag{4}$$

where A_{st} is area of tank s during time period t; ΔT is length of time period.

Constraints

(1) Consider the constraint conditions for daily water supply capability of each pump station

$$\sum_{t=1}^{T} Q_{it} \le Q_{\max i},\ i=1,2,\cdots,I \tag{5}$$

where $Q_{\max i}$ is maximum allowable flow of pump station i in one day.

(2) Ensure water pressure at each node within the scope of technical demand so that

$$H_{\min jt} \le H_{jt} \le H_{\max jt},\ j=1,2,\cdots,N,\ t=1,2,\cdots,T \tag{6}$$

where $H_{\min jt}$ and $H_{\max jt}$ are maximum and minimum allowable pressure head at nodal j; N is number of nodes. The node pressure H_{jt} can be obtained by establishing network behavior model (Yu *et al.*, 2005):

$$H_{jt} = f_j''(HS_{1t},\cdots,HS_{It},Q_{1t},\cdots,Q_{It},HR_{1t},\cdots,HR_{St}),\quad j=1,2,\cdots,N;\ t=1,2,\cdots,T \tag{7}$$

(3) Bound constraints of tank level

$$HR_{\min st} \le HR_{st} \le HR_{\max st},\ s=1,2,\cdots,S; t=1,2,\cdots,T \tag{8}$$

The maximum allowable water level $HR_{\max st}$ will normally be the top of the tank, the minimum allowable water level $HR_{\min st}$ will normally be somewhere above the tank bottom in order to provide some residual storage for potential fire suppression activities.

In addition to these normal tank level constraints, most optimal control policies are constructed to result in a set of tank trajectories that begin and end at specified target elevations. In most cases the beginning and ending levels will be the same. For such an operating strategy the following additional tank level constraints would be required:

$$HR_{s1} - e_s \le HR_{sT} \le HR_{s1} + e_s,\ \ s = 1, 2, \cdots, S \qquad (9)$$

where e_s is allowable water level offset.

Thus it can be seen that when HR_{s1} and HS_{it} are determined, other variables can be solved uniquely by Eqs.(2), (3), (4), (7). Therefore the model of optimal allocation of water supply between pump-sources can be generalized as:

$$\min\ F(HR_{s1}, HS_{it}) \qquad (10.1)$$

$$\text{s.t. } g(HR_{s1}, HS_{it}) \le 0 \qquad (10.2)$$

Genetic algorithms are search methods based on the mechanics of natural selection and natural genetics, combining an artificial survival of the fittest with genetic operators abstracted from nature (Goldberg, 1989). Genetic algorithms differ from other search techniques in that they search among a population of points and use probabilistic rather than deterministic transition rules. As a result, genetic algorithm searches more globally and efficiently, and is a promising method for solving problems with complicated constraints and multiple objectives, and so, was adopted in this paper to solve optimal operating model.

GENETIC ALGORITHM FOR OPTIMAL OPERATING MODEL

During applying of GA, how to express the decision variables of optimal operation for water supply system as GA chromosomes, how to select a fitness function and how to design genetic operators are the keys to success in applying GA for optimizing strategy of water supply system.

The following section describes the application of GA to optimal operation of large-scale water supply system and discusses the possibilities of improving their performance with an example.

Fig.1 shows the hypothetical water distribution system composed of two pump stations and one tank. The total water demand was 50000 m^3/d. The maximum hourly node demand of the pipe network is shown in Table 1, all junctions have the same demand pattern factor listed in Table 2. With allowance for deposit water for accidents or fires, the cylindrical water tank with cross-sectional area of 1153.85 m^2,

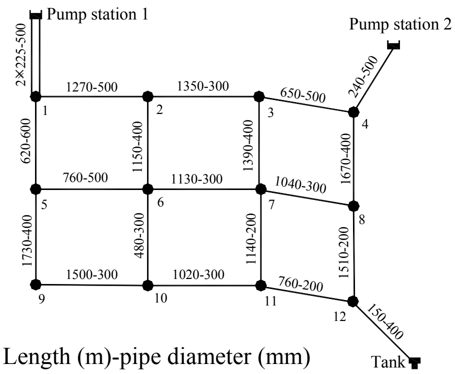

Fig.1 Hypothetical water distribution system

Table 1 The maximum hourly node demand of pipe network

Node code	Water demand (L/s)	Node code	Water demand (L/s)
1	36.2	7	198.7
2	36.8	8	66.1
3	82.5	9	50.6
4	36.4	10	43.2
5	48.7	11	105.8
6	81.5	12	35.5

Table 2 Demand factor

Node code	Demand fator (%)	Node code	Demand fator (%)
1	2.53	13	5.09
2	2.54	14	4.81
3	2.50	15	4.99
4	2.53	16	4.70
5	2.57	17	4.62
6	3.09	18	4.97
7	5.31	19	5.18
8	4.92	20	4.98
9	5.17	21	4.39
10	5.10	22	4.17
11	5.21	23	3.12
12	5.21	24	2.48

bottom height of 27.4 m, adjustable capacity of 1730.775 m^3, had allowable minimum and maximum water levels of 27.4 and 28.9 m.

Coding

Implementation of a genetic algorithm begins with coding decision variables as chromosomes. As mentioned above, HR_{s1} and HS_{it} are taken as decision variables so the genetic algorithm must code these variables into a binary string. As for examples, each continuous variable HS_{it} is represented by a nine-bit binary sub-string, HR_{s1} is represented by an eight-bit binary sub-string, and the chromosome string total length is 440 bits. The previous eight bits represent HR_{s1} (the initial tank level), in the next 18 bits, the former nine bits and the latter nine bits represent the pressure heads of pump-station 1 and pump-station 2 at the first time period respectively; the ordinal next 18 bits represent the pressure heads of the two pump-stations at each time period; there are 24 time periods altogether.

The maximum and minimum pressure heads provided by the lower-level optimal pumps scheduling should be considered in the value scope of pressure head of pump-stations, and according to the limits of pressure head of each pump, $29.5 \le HS_{1t} \le 48.5$ and $28 \le HS_{1t} \le 42$ can be obtained. Therefore the coding discrete precisions are Π=(48.5−29.5)/(2^9−1)= 0.0372 m and Π=(42−28)/(2^9−1)=0.0274 m respectively. The initial tank level range is $27.4 \le HS_{11} \le 28.9$, so its coding discrete precision is Π=(28.9−27.4)/ (2^8−1)=0.005882 m, which can satisfy the needs of proper scheduling.

Handling of constraints and calculation of fitness

The key to applying genetic algorithm to the problem of constraining optimization is the handling of constraints. Suppose the solution is obtained for problem without constraint, then the value of the objective function is calculated during the search process, and constraints are checked for violation. No violation indicates that it is a feasible solution, and then fitness is chosen for it according to the objective function; else, it is an infeasible solution, with zero fitness value. Except for some simple boundary constraints, such treatment is impractical in fact, since it is hard to find a feasible solution, so that some information is needed to be found from infeasible solutions. Therefore, the method of penalty function is used for incorporating constraints into the fitness function in this paper.

According to the coded scope of initial tank level, the levels at later time are calculated by Eq.(4), if the levels calculated are more than the maximum allowable level of 28.9 m, then 28.9 m is taken, and if it is less than the minimum allowable level of 27.4 m, then 27.4 m is taken.

Converting the constraint Eq.(5) of daily water supply capability of each pump station to objective:

$$f_{2i} = \begin{cases} 0, & \sum_{t=1}^{T} Q_{it} \le Q_{\max i} \\ \left(\sum_{t=1}^{T} Q_{it} - Q_{\max i} \right) / Q_{\max i}, & \sum_{t=1}^{T} Q_{it} > Q_{\max i} \end{cases} \tag{11}$$

$$F_2 = \sum_{i=1}^{I} f_{2i} \tag{12}$$

Converting the constraint Eq.(6) of node pressure to objective:

$$f_{3jt} = \begin{cases} (H_{\min jt} - H_{jt})/(H_{\max jt} - H_{\min jt}), & H_{jt} < H_{\min jt} \\ 0, & H_{\min jt} \le H_{jt} \le H_{\max jt} \\ (H_{jt} - H_{\max jt})/(H_{\max jt} - H_{\min jt}), & H_{jt} > H_{\max jt} \end{cases} \tag{13}$$

$$F_3 = \sum_{j=1}^{N} \sum_{t=1}^{T} f_{3jt} \tag{14}$$

In Eq.(13), $H_{\max jt} - H_{\min jt}$ is taken as denominator, which will remove the impact of different dimensional units and convert multiple objectives to simple objective.

Converting the constraint Eq.(9) to objective:

$$f_{4s} = \begin{cases} 0, & |HRE_s - HR_{sT}| \le e_s \\ |HRE_s - HR_{sT}| - e_s, & |HRE_s - HR_{sT}| > e_s \end{cases} \tag{15}$$

$$F_4 = \sum_{s=1}^{S} f_{4s} \tag{16}$$

After the above treatment of constraints, the operating model will have been converted into a non-restraint multi-objective optimization problem with four objectives. Simple multiplication method can be adopted to transform multiple objectives into simple objective. Then the problem is changed into the minimum problem without constraint.

$$\min\ F = (\delta + F_1)(1 + F_3)(1 + F_4) \tag{17}$$

where δ is constant, whose function is to prevent each penalty item from losing function when F_1 is zero.

During the evolutionary process, GA does not require derivative information or other supplementary knowledge; only the objective function and corresponding fitness levels influence the search directions. Therefore, the selection of fitness function is very important, and will influence directly the convergence time of GA and whether the optimal solution can be found. The object function F is a function seeking for minimum value, and here it is converted to seek for maximum value:

$$Fit=C/F \tag{18}$$

where C is constant. When Eq.(18) is used to calculate fitness value, it is found that the individuals of maximum fitness occupy more than 90% of total individuals after no more than ten evolutionary generations because individual difference is large during the early stage of operation. When classical roulette wheel selection is adopted, the offspring population is proportional to the fitness of paternal individuals, so in the early stage some very good individuals are prone to overflow the whole population, which will lead to premature convergence. In the latter stage of the genetic algorithm, the population tends to be homogeneous, when excellent individuals are producing offspring, their predominance is not obvious, and so the evolution of population stalls. In this paper, the principle of simulated annealing introduced, and fitness scaling is as Eqs.(19) and (20):

$$Fit_k = \frac{\mathrm{e}^{Fit_k/T}}{\sum_{k=1}^{K} \mathrm{e}^{Fit_k/T}} \tag{19}$$

$$T = T_0(0.99^{1/g}) \tag{20}$$

where Fit_k is fitness of k individual, which can be obtained by using Eq.(18); K is size of population; g is evolutionary generations; T is temperature; T_0 is initial temperature. In Eqs.(19)~(20), when the temperature is high (the early stage of genetic algorithm), the best individuals have lower reproduction probability than they should, and the worst ones have their probability increased. The resulting population is maintained to be more heterogeneous at the beginning of the algorithm, which decreases the risks to be trapped into a local optimum. Then, when the temperature decreases constantly, the scale factor is increased to ensure that the algorithm effectively converges.

Crossover probability and mutation probability

The scaling of fitness function is to ensure that the population has heterogeneous form reproduction behavior. While each individual has the same chromosome and be trapped into local optimization, no matter which scaling is chosen for fitness, it is impossible to produce new individuals and to jump out of local optimization. At this time, mutation probability must be increased properly for improving the ability of mutation operator to produce new individuals. In this paper, the adaptive strategy for updating P_c and P_m developed by Wang and Cao (2002) was adopted:

$$P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1} - P_{c2})(Fit_c - Fit_{\mathrm{avg}})}{Fit_{\max} - Fit_{\mathrm{avg}}}, & Fit_c \ge Fit_{\mathrm{avg}} \\ P_{c1}, & Fit_c < Fit_{\mathrm{avg}} \end{cases}$$

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(Fit_m - Fit_{\mathrm{avg}})}{Fit_{\max} - Fit_{\mathrm{avg}}}, & Fit_m \ge Fit_{\mathrm{avg}} \\ P_{m1}, & Fit_m < Fit_{\mathrm{avg}} \end{cases}$$

where P_{c1}, P_{c2}, P_{m1} and P_{m2} are constants less than 1.0, and $P_{c1}>P_{c2}$, $P_{m1}>P_{m2}$; Fit_c is larger fitness values of the individuals selected for crossover; Fit_m is fitness of the mth chromosome to which the mutation with probability P_m is applied.

Genetic operators

Besides roulette wheel selection, an elitist selection procedure is used in this application. In the elitist procedure, the fittest individual in a population always survives with probability one. The crossover and mutation operators are the same as those in the simple genetic algorithm (SGA) described by Goldberg (1989).

EXAMPLE RESULTS

The calculation was conducted over 24 h using discrete time intervals of 1 h. Two instances of electrical rate were considered. One was a constant 0.514 Yuan/(kW·h) at each time period, the other one was varied under a time of use schedule, in which electrical rate was 0.308 Yuan/(kW·h) at time periods of 1~7, 11~12 and 22~24, 0.679 Yuan/(kW·h) at time periods of 8~10, 13~18 and 22, 0.924 Yuan/(kW·h) at time periods of 19~20. The constraints of daily water supply capability were not considered. $H_{\min jt}$=24 m, $H_{\max jt}$=50 m, δ=100, C=10^6, P_{c1}=0.9, P_{c2}=0.6, P_{m1}=0.1, P_{m2}=0.001, T_0=10, K=100, and the evolution generations=1500. The optimal operation strategies under two instances of electrical rate were calculated respectively. The optimal pressure heads and discharges of two pump stations are listed in Table 2; Fig.2 shows global water demand and total water supply of two pump stations; Fig.3 shows the optimal tank water level trajectory; Figs.4 and 5 show pressure head of nodes.

From Figs.2 and 3, when electricity rate is variable, since time from 1 to 7 is at period of lower electricity rate, water supply is greater than water demand, so the tank water level rises quickly. At the time period of higher electricity rate from 8 to 10, water supply is less than water demand, and the tank supplies insufficient water. At the time of lower electricity rate from 11 to 12, because water demand is very large at this period and a high water level has been maintained in the tank, if the tank water level must be increased, the pump stations should provide water flow larger than water demand. However, for a certain distribution network, the system head loss increases with increase of water supply, so the tank does not store water like it does at the time period of lower electricity rate from 1 to 7 with low water demand, neither does it use a great deal of water in the tank like it does at the time period of higher electricity

Table 3 Optimal values of pressure heads and discharges of two pump stations

Time period	Pump station 1				Pump station 2			
	Constant electricity rate		Variable electricity rate		Constant electricity rate		Variable electricity rate	
	HS_{1t} (m)	Q_{1t} (L/s)	HS_{1t} (m)	Q_{1t} (L/s)	HS_{2j} (m)	Q_{2j} (L/s)	HS_{2t} (m)	Q_{2t} (L/s)
1	37.2	170.3	46.5	414.4	40.8	260.4	34.3	17.1
2	38.9	244.6	43.7	406.8	38.7	175.4	30.6	0.0
3	35.3	233.0	39.5	260.5	35.5	178.3	38.8	167.7
4	37.0	147.7	45.4	382.0	41.8	282.3	36.0	52.9
5	35.5	229.3	35.3	307.9	36.0	192.3	31.0	98.0
6	39.0	274.0	46.8	373.6	39.8	234.8	41.8	153.5
7	48.0	593.9	37.5	481.1	35.3	219.2	34.8	296.4
8	30.8	344.5	31.2	393.1	34.7	362.3	32.0	301.3
9	30.8	341.9	39.5	490.4	36.9	405.9	35.4	279.0
10	40.1	473.5	47.0	545.0	37.6	296.3	38.8	250.8
11	48.4	620.6	42.8	530.0	31.2	165.6	35.8	258.9
12	38.9	462.8	44.5	498.8	37.8	317.8	41.9	312.6
13	40.1	463.5	32.0	374.5	38.7	310.4	35.0	361.8
14	34.9	360.1	36.2	436.6	38.0	356.7	34.1	274.1
15	31.0	382.6	48.4	599.5	32.7	328.2	32.4	167.3
16	31.1	418.7	35.4	436.0	28.7	239.3	32.5	253.1
17	36.9	416.0	36.5	455.6	36.6	299.2	31.3	222.4
18	45.0	507.6	47.0	515.5	39.8	271.0	41.3	270.7
19	32.0	450.8	33.1	469.7	30.1	278.4	29.6	260.2
20	45.4	559.7	44.4	479.2	33.4	197.3	41.4	290.9
21	44.8	482.7	33.6	431.0	37.7	213.8	28.3	189.6
22	40.0	399.4	42.0	452.5	38.6	258.6	36.0	204.4
23	44.1	437.7	38.9	295.6	32.7	70.5	39.0	218.8
24	37.5	186.4	38.5	241.0	40.0	237.7	38.6	183.1

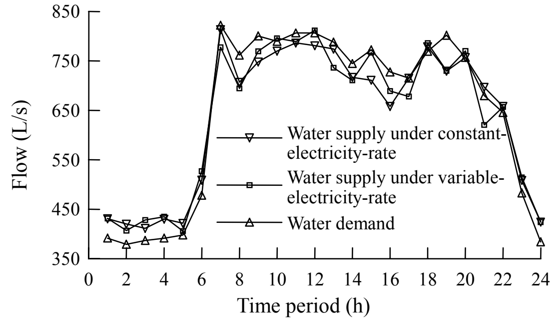

Fig.2 Comparison of water demand and total water supply of two pump stations under two electricity rates

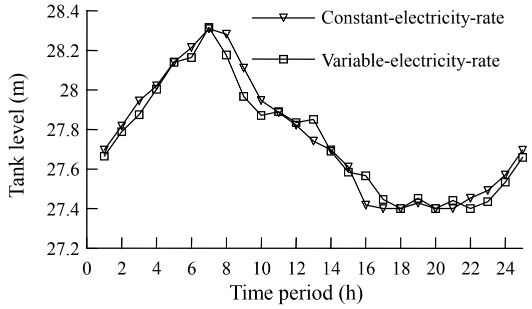

Fig.3 Optimal tank level under two electricity rates

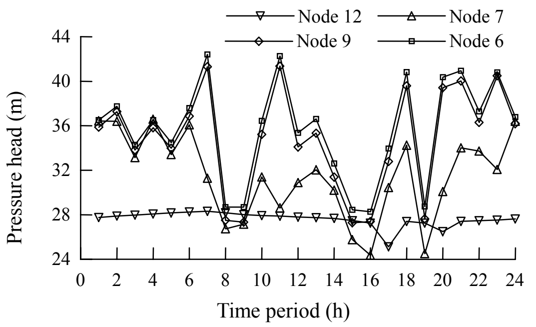

Fig.4 Pressure head of nodes under constant-electricity-rate

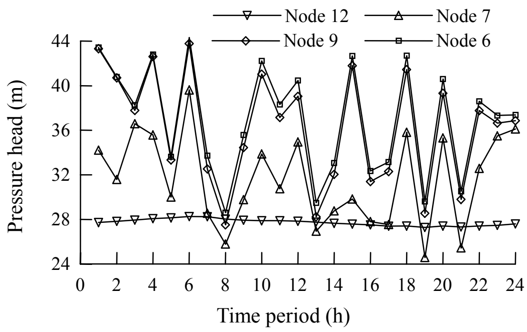

Fig.5 Pressure head of nodes under variable-electricity-rate

rate from 8 to 10, the water supply is almost equal to water demand. At the time period of lower electricity rate from 13 to 18, almost like the time period of lower electricity rate from 8 to 10, water supply of the pump station is less than water demand, the tank water level declines. But this time period, the magnitude of water demand should be considered also. When water demand is low, since system head loss is relatively low, water in the tank should be used as little as possible, so it can be used at higher electricity rate period with high water demand. The time period from 16 to 17 is just this kind of period. At the time period of peak electricity rate from 18 to 21, because the tank water level decreases to the lowest level, the water supply of the pump station is equal to the water demand of the pipe network. At the time period of lower electricity rate from 22 to 24 with low water demand, like the time period from 1 to 7, the tank water level increases to the water level at the first time period.

When electricity rate is constant, only variation of water demand needs to be considered for pump station water supply and tank water level. During time periods with low water demand, as the head loss of the pipe network is small, the pump station should supply more water, so water level rises, like in the time periods of 1~7 and 22~24. During time periods with high water demand, the pump station and tank supply water together, in order to avoid overlarge pipeline flow causing large head loss of the entire pipe network when water supplied by the pump stations only, like that in the time periods 7~13.

At the same time, under the two electricity rate instance, the allowable minimum and maximum head constraints also take effect. When tank pressure head is greater than zero, the constraint conditions of the minimum and maximum head are both not-active constraints. Only when the reservoir level is zero, the constraint of allowable minimum head of some nodes become active constraints. Under constant-electricity-rate, from Fig.4, the minimum head constraint of node 7 is active at time periods 16 and 19, while the minimum head constraint of node 12 become active constraint at time period 17 because two pump-stations have different combination of water supply when the system has different water demand. Under variable-electricity-rate, the minimum head constraint of node 7 is active at time periods 19 and 21.

Comparison of Figs.4 and 5 shows that time periods of active constraints of node 12 at variable-electricity-rate are less than those at constant-electricity-rate because when at variable-electricity-rate, the tank stores more water during off-peak time periods, and the tank supplies more water during peak time periods, so that the head of node 12 must satisfy the demand of flow to (or from) the tank, and high pressure head must be maintained all day.

As calculation efficiency was considered, this example analysis used a PIII 733 PC and 128 M RAM; the algorithm took approximately 165 s in two cases. Although the example has only two pump stations and one tank, as for large-scale water supply system, the workload for solving fitness function that is the main workload of genetic algorithm does not increase much, so the algorithm in this paper can satisfy completely the demand of practical optimization scheduling.

SUMMARY AND CONCLUSION

Although several successful applications of optimal control of water supply system exist in some countries, widespread application in China has been severely limited. The problem is the difficulty in developing well-calibrated network hydraulic models and accurate demand forecast models because of the lack of monitor equipment and network fundamental data, such as pipe length, pipe diameter, and nodal demand. Therefore, this optimal operation research is based on the actual situation in China. In view of the poor water supply system's network properties, the complicated network hydraulic equations were replaced by macroscopic nodal pressure model and the model of relationship between supply flow and head of water source. By using pump-station head and initial tank head as decision variables, the model of optimal allocation of water supply between pump-sources is developed. GA is introduced for solving this model and methods for handling each constraint condition were put forward. In this study, genetic algorithm combined with simulated annealing technology and self-adaptive crossover and mutation probabilities were adopted in order to overcome premature convergence of the genetic algorithm. By example calculation and analysis, the optimal operating model and the effectiveness and feasibility of this algorithm were proved.

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