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EXTENDED ABSTRACT

Performance Analysis of PSO Algorithm for Setting the Hazen Williams Coefficients of Water Distribution Network Models

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1. Introduction

Gradually, with the urban population growth and development of cities, water distribution networks (WDNs) gain significant importance. So the need for computerized modeling of WDNs is felt more than ever to understand the behavior of these systems. The most important problem with modeling of WDNs is consistency between the calculated and measured data. Setting the coefficients of the model via measured data is necessary. Model parameters include Hazen-Williams coefficients in the pipes, base demand and demand pattern coefficients at the nodes. The calculated and measured data mainly include pressure head at nodes, tank levels, and flow in pipes, that can be considered either in steady state or in an extended period condition. The aim of this paper is to investigate the performance of PSO algorithm for setting the Hazen Williams coefficients of WDN Models. For this purpose, five models of the PSO algorithm and three models of the ACO algorithm were made. The proposed method tested on a two-loop test example and a real water distribution network.

2. Methodology

In this paper, the particle swarm optimization algorithm and ant colony optimization algorithm are used to adjust the model parameters by minimizing the Errors between the model-predicted and the field-observed data that are coupled with EPANET. In the PSO algorithms, the position and velocity of each particle (X_i (t) and V_i(t)) are initialized by random vectors. The new position and velocity of the particles (X_i(t+1) and V_i(t+1)) in the simple PSO algorithm are updated by these equations (Kennedy and Eberhart, 1995):

$$\mathrm{X_i} = \mathrm{X_i}\,(\mathrm{t}) + \mathrm{V_i}(\mathrm{t}+1) \tag{1}$$

$$\mathrm{V_i}(\mathrm{t}+1) = C_1 * \mathrm{Rand_1} * \left(\mathrm{P_{i\,.best}} - \mathrm{X_i}(\mathrm{t})\right) + \mathrm{C_2} * \mathrm{Rand_2} * (\mathrm{P_{g\,.best}} - \mathrm{X_i}(\mathrm{t})) + \mathrm{W} * \mathrm{V_i}\,(\mathrm{t}) \tag{2}$$

Where C1 and C2 are called the acceleration coefficients, Rand 1 and Rand 2 are two uniformly distributed random numbers, $P_{i\,.best}$ denotes the personal historically best particle for the ith particle, $P_{g\,.best}$ denotes the best position that the whole swarm has found. In the hybrid SPSO (HSPSO) model, the genetic algorithm mutation operator is added to the SPSO model. In the meta PSO model, the model has several particle swarm instead of one particle swarm. The new velocities of the particles in this model are updated by this equation (Wang et al, 2010):

$$\mathrm{V_{ij}}(\mathrm{t}+1) = C_1 * \mathrm{Rand_1} * \left(\mathrm{P_{ij\,.best}} - \mathrm{X_{ij}}(\mathrm{t})\right) + \mathrm{C_2} * \mathrm{Rand_2} * (\mathrm{P_{g\,.best}} - \mathrm{X_{ij}}(\mathrm{t})) + \mathrm{C_3} * \mathrm{Rand_3} * (\mathrm{S_{gj\,.best}} - \mathrm{X_{ij}}(\mathrm{t})) + W_{ij} * \mathrm{V_{ij}}\,(\mathrm{t}) \tag{3}$$

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Where $S_{gj\,.best}$ denotes the best position that the jth swarm has found. In the hybrid MPSO (HMPSO) model, the genetic algorithm mutation operator is added to the MPSO model. In the HMPSO1 model, the mutation operator is added to some particles, but in the HMPSO2 model the mutation operator is added to all particles.

The probability function of the ACO algorithms (Zecchin et al., 2006) is as following equation:

$$P_{\mathrm{ij}}(\mathrm{k},\mathrm{t}) = \frac{[T_{\mathrm{ij}}(\mathrm{t})]^{\alpha}[U_{\mathrm{ij}}(\mathrm{t})]^{\beta}}{\sum_{\mathrm{j}=1}^{\mathrm{J}}[T_{\mathrm{ij}}(\mathrm{t})]^{\alpha}[U_{\mathrm{ij}}(\mathrm{t})]^{\beta}} \qquad (4)$$

Where $P_{ij}(k,t)$: is the probability of the kth ant situated at node j at stage t, to choose an edge i, $T_{ij}(t)$: is the pheromone intensity present on the edge i at node j and stag t, $U_{ij}(t)$: is the desirability factor present on the edge i at node j and stage t, and α , β are the parameters controlling the relative importance of pheromone intensity and desirability for each ant's decision. The pheromone intensity function is as following equation:

$$T_{\mathrm{i,j}}(\mathrm{t}+1) = \rho\, T_{\mathrm{i,j}}(\mathrm{t}) + \vartriangle T_{\mathrm{i,j}}(\mathrm{t}) \qquad (5)$$

Where ρ: is the pheromone evaporation rate (note: 0<ρ<1); $\vartriangle T_{\mathrm{ij}}(\mathrm{t})$: is the pheromone addition on edge i at node j and stage t. The objective function is written as following equation: (Ormsbee, 1989).

$$\mathrm{F} = \sum_{j=1}^{N}\sum_{t=1}^{T}\left(PO_{tj} - PS_{tj}\right)^2 \qquad (6)$$

where N: is the number of observation locations; T: is the number of times that field data has been collected; PO_{tj}: is the observed pressure head; and PS_{tj}: is the calculated pressure head at node j during time t;

In this paper, for verifying and analyzing the performance of the models, a two-loop test example network (Alperovits and Shamir 1977) and a real water distribution network (Dini and Tabesh 2014) were used.

3. Results and discussion

In this paper, to investigate the performance of PSO algorithm for setting the Hazen Williams coefficients of water distribution network models five PSO models and also there ACO models were made. The characteristics of these models are shown in table 1. To set the Hazen Williams coefficients, a combination of EPANET simulator with PSO and ACO algorithms has been used by programming in MATLAB software. All models were investigated in a two-loop test example network. All models were executed three times and each time 20 repetitions. The best results for 20 repetitions are presented in Table 2.

Table 1. The characteristics of five PSO models and there ACO models

parameter	SPSO	HSPSO	MPSO	HMPSO1	HMPSO2	parameter	ACO1	ACO2	ACO3
$Ss*10^9$	167961.6	167961.6	167961.6	167961.6	167961.6	$Ss*10^9$	167961.6	656.1	11.02
Ns	100	100	50	50	50	Nant	100	100	100
Nm	1	1	6	6	6	T_0	40	40	40
C1	2	2	2	2	2	U_0	1	1	1
C2	2	2	2	2	2	α	1	1	1
C3	0	0	2	2	2	ß	1	1	1
W	0.8	0.8	0.6-0.8	0.6-0.8	0.6-0.8	ρ	0.98	0.98	0.98
Nmu	0	1	0	0.2	1	$\vartriangle T_{i,j}$	1	1	1
Rmu	0	0.02	0	0.2	0.02				

Table 2. The characteristics of five PSO models and there ACO models

Indices	SPSO	HSPSO	MPSO	HMPSO1	HMPSO2	ACO1	ACO2	ACO3
Number of consecutive runs	20	20	20	20	20	20	20	20
The number of achievement to optimal answer	11	15	18	19	20	1	13	20
Average step to achieve optimum answer	30	29	24	48	27	415	348	193
Maximum step to achieve optimum answer	44	56	64	134	96	-	446	226
Minimum step to achieve optimum answer	19	15	12	12	9	-	287	148
Average evaluation number of the objective function	3000	2900	7200	14400	8100	41500	34800	19300
Maximum evaluation number of the objective function	4400	5600	19200	40200	28800	-	44600	22600
Minimum evaluation number of the objective function	1900	1500	3600	3600	2700	-	28700	14800
Average Time to Achieve Optimum Answer (s)	20	20	21	47	24	363	259	135
Maximum Time to Achieve Optimum Answer (s)	30	40	57	131	87	-	332	157
Minimum Time to Achieve Optimum Answer (s)	13	11	11	12	8	-	214	103

Comparison of the results for five PSO models showed that the performance of the models with mutation operator or with a multi particle swarm is better than the simple models. For example, the HSPSO and MPSO models find the optimal answer respectively in 15 and 18 runs of 20 consecutive runs, while the SPSO model finds the optimal answer in 11 runs of 20 consecutive runs. All PSO based models have found the optimal answer with a low evaluation of the objective function and in a short time. Among these models, model HMPSO2 has had the best performance, because in all 20 consecutive runs, it has found the optimal answer.

Comparison of the results for three ACO models showed that the performance of the ACO3 is better than ACO2 and ACO1, while the search space of ACO3 is very smaller than the ACO2 and ACO1. Among these models, only ACO1 has a search space similar to PSO models. Comparison of the results for ACO1 and HMPSO2 models showed that the performance of the HMPSO2 is very better than the ACO1. For example, the HSPSO2 finds the optimal answer in 20 runs of 20 consecutive runs, while the ACO1 finds the optimal answer in only one run of 20 consecutive runs.

In the second case study, the Ahar water distribution network was investigated. The Ahar water distribution network has been reduced in size by excluding dispensable pipes. The simplified network includes 192 pipes, 169 nodes, one reservoir, 5 tanks and 3 pumping stations. To simplify the problem, pipe roughness coefficients were classified into limited categories, based on the pipe diameter. HMPSO2 and ACO1 Models are used to setting the Hazen Williams coefficients of water distribution network models. Both models were able to find the optimal answer. Table 3 illustrates the results in three categories and some best optimal answers. The results of some best optimal answers for three categories showed that the minimum calibration data error belonged to the answer 1 of category C3 and the minimum testing data error belonged to the answer 2 of category C3. The value of testing data in answer 2 of category 3 showed that the maximum testing error is 3.9% and the average testing error is 2.6%, which indicate that the proper adjustment of coefficients has been done. To investigate the performance of HMPSO2 and ACO1 for setting the Hazen Williams coefficients of the real water distribution network, each model was executed five times and the results showed in table 4.

Table 3. The results of some best optimal answers for three categories

Coefficients	Category 1	Category 2	Category 3		
			Ans1	Ans2	Ans3
C1	103	104	104	103	104
C2		97	101	101	101
C3		105	86	85	87
C4			94	95	94
C5			107	107	107
C6			150	150	149
E_c	19.11	16.69	14.57	14.62	14.60
E_t	6.25	5.45	5.22	4.60	5.44

Table 4. The results of some best optimal answers for three categories

Run	HMPSO2						ACO1					
	Category 2			Category 3			Category 2			Category 3		
	SN	EN	Time(s)	SN	EN	Time(s)	SN	EN	Time(s)	SN	EN	Time(s)
1	5	1500	11.7	31	9300	72.6	424	42400	622.9	214	21400	317.9
2	6	1800	14.9	32	9600	74.8	479	47900	704.7	151	15100	223.0
3	8	2400	19.6	33	9900	76.7	484	48400	712.5	210	21000	318.4
4	7	2100	18.3	30	9000	69.2	396	39600	591.3	202	20200	302.0
5	10	3000	26.3	54	16200	124.8	345	34500	513.3	244	24400	375.5
Avrrage	7	2160	18	36	10800	84	426	42560	629	204	20420	307

The results of the HMPSO2 and ACO1 for 5 consecutive runs showed that in average model HMPSO2 finds the best answer in less time and the number of evaluations of objective function compared with ACO1. Therefore, PSO algorithm has better performance than the ACO algorithm for setting the Hazen Williams coefficients of water distribution network models.

4. Conclusions

The aim of this paper is to study the performance of PSO algorithm for setting the Hazen Williams coefficients of WDN Models. For this purpose, five PSO algorithm models and three ACO algorithm models were made. The proposed method tested on a two-loop test example network and a real water distribution network. All models were investigated in a two-loop test example network. Comparison of the results for five PSO models showed that the performance of the models with mutation operator or with a multi particle swarm is better than the simple models. Also, all PSO based models have found the optimal answer with a low evaluation of the objective function and in a short time. Among these models, model HMPSO2 has had the best performance. Comparison of the results for three ACO models showed that the performance of the ACO3 is better than the ACO2 and ACO1. Among these models, only ACO1 has a search space similar to PSO models. Comparison of the results for ACO1 and HMPSO2 models showed that the performance of the HMPSO2 is very better than the ACO1. In the second case study, HMPSO2 and ACO1 Models are used to setting the Hazen Williams coefficients of water distribution network models. Results showed that both models were able to find the optimal answer, so that the maximum and the average testing error for answer 2 of category 3 are respectively 3.9% and 2.6%. Also a comparison of the HMPSO2 and ACO1 results for 5 consecutive runs in Ahar water distribution network showed that in average, the HMPSO2 finds the best answer in less time and the number of evaluations of the objective function than the ACO1. Therefore, the PSO algorithm has better performance than the ACO algorithm.

5. References

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