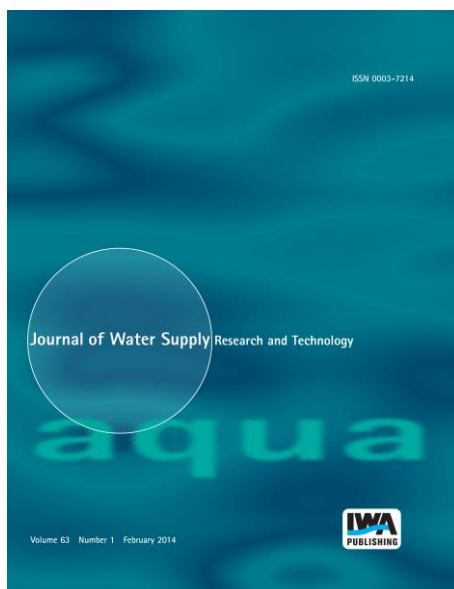


## ELECTRONIC OFFPRINT

Use of this pdf is subject to the terms described below



This paper was originally published by IWA Publishing. The author's right to reuse and post their work published by IWA Publishing is defined by IWA Publishing's copyright policy.

If the copyright has been transferred to IWA Publishing, the publisher recognizes the retention of the right by the author(s) to photocopy or make single electronic copies of the paper for their own personal use, including for their own classroom use, or the personal use of colleagues, provided the copies are not offered for sale and are not distributed in a systematic way outside of their employing institution. **Please note that you are not permitted to post the IWA Publishing PDF version of your paper on your own website or your institution's website or repository.**

If the paper has been published "Open Access", the terms of its use and distribution are defined by the Creative Commons licence selected by the author.

Full details can be found here: <http://iwaponline.com/content/rights-permissions>

Please direct any queries regarding use or permissions to [aqua@iwap.co.uk](mailto:aqua@iwap.co.uk)

# Merged two-level optimization for optimal pump operation of large scale urban water distribution system

Xi Jin and Wenyan Wu

## ABSTRACT

Subsequent to the least cost design problem of water distribution systems (WDSs), optimal operation is probably the most explored topic. Since 1970 a variety of methods have been developed to address this problem. Although the proposed methods give theoretic ways for solving optimal operation problems of WDSs, there are little successful application cases in practice, especially when the methods were used to large scale WDSs due to too many decision variables. In consideration of using fewer decision variables, the two-level optimal method is adopted in this paper. By abstracting pump stations into high level reservoirs, the water distribution system hydraulic model can be modified into a modality, which can be used in first optimal level of two-level optimal method. Also, by building on feasible pump combination database, a new optimal method in the second optimal level will be proposed, and the proposed new method in the second optimal level will be embedded into the first optimal level, so that the problem of results discordant in different levels will be solved. By introducing new concepts and improving present optimal methods, a more practical optimal operation method of water distribution system will be established. By applying in a large scale practical water distribution system, the proposed method has been evaluated.

**Key words** | decision support system, genetic algorithm, pump operation, water distribution system

**Xi Jin** (corresponding author)  
School of Civil Engineering and Architecture,  
Wuhan University of Technology Wuhan,  
Hubei,  
China  
E-mail: jinxi@whut.edu.cn

**Wenyan Wu**  
Faculty of Arts and Creative Technologies,  
Staffordshire University,  
Stafford,  
UK

## INTRODUCTION

The operational cost of pumps in a water distribution system (WDS) represents a significant fraction of the total expenditure incurred in the operational management of WDSs worldwide. Pumps consume large amounts of electrical energy for pumping water from source to storage tanks and to demand nodes. Therefore, the goal of a pump scheduling problem is to minimize the total pump operational cost, while guaranteeing a competent network service. In most cases, this problem is equivalent to the minimization of pumping cost, while supplying water to consumers at adequate pressures (López-Ibáñez *et al.* 2008). In recent years, a significant amount of research has been focused on optimizing pump operation schedules. Since 1970, a variety of conventional methods such as dynamic programming, linear programming (LP) and nonlinear programming were developed to address this problem. A review of some early

optimization approaches to pump scheduling can be found in Ormsbee & Lansey (1994). Price & Ostfeld (2013) developed an algorithm which enables iterative linearization of increasing or decreasing convex nonlinear equations and incorporating them into LP optimization models, which results in short solution times. However, the discrete (binary) nature of some variables and the size of the solution space are among the main difficulties of optimizing water distribution systems operation (Van Dijk *et al.* 2008). Conventional optimization methods are not directly applicable for solving such problems, because these methods are suitable mostly for optimization problems which have only continuous variables, therefore population based methods such as evolutionary algorithms and various meta-heuristics were introduced to deal with the optimal pump scheduling problem. Mackle *et al.* (1995) presented a single objective

optimization (electric energy cost) using genetic algorithms (GAs). Then, *Savic et al. (1997)* proposed a hybridization of a GA with a local search method, in order to optimize two objectives: electric energy cost and pumps maintenance cost. *Fang et al. (2011)* solved optimization of the pump system with constant and variable speed pumps with multi-objective evolutionary algorithms (MOEAs) combined with a repair mechanism. As a result, evolutionary computation has proven to be a powerful tool to solve optimal pump-scheduling problems (*Benjamin et al. 2005*). Although the methods mentioned above give theoretic methods for solving the optimal pump scheduling problem of WDSs, population based algorithms have the following drawbacks. First, they require a large number of the objective and constraint function evaluations which are not acceptable when these evaluations are expensive. Second, they are inefficient for solving large scale problems. Third, these algorithms sometimes cannot locate a solution with high accuracy and as a result, they may produce only suboptimal solutions (*Bagirov et al. 2012*). In this situation, a two-level optimal concept was addressed on better effectiveness and efficiency of solving the optimal pump scheduling problem. In a methodology based on a two-level optimal concept, the optimal outflow and head of source nodes or elevated storage trajectory are determined in the first optimal level, and the optimal pump schedules will be determined in the second level, so that a complex optimal problem is divided into several relative simpler optimal problems. *Ormsbee et al. (1989)* proposed a two-level optimal methodology using elevated tank trajectory as the first level objective, and pump combinations as the second level objective. The optimal trajectory is determined using dynamic programming while the associated pump combination is determined using an explicit enumeration scheme. *Kevin & Kofi (1994)* developed a two-level optimal methodology based on Ormsbee's concept, and considered pump switches as a constraint of optimization model. Pump combinations were solved by dynamic programming. Due to the problem of the variables dimension, these methods are only applicable to small to mid-size systems with elevated storage. *Zheng (1997)* developed a two-level optimal methodology regarding outflow and head of source nodes as the decision variables of the first level optimal problem. The first level optimal problem is solved by the variable-metric method, and the pump combination result is obtained by the enumeration

scheme. *Zhang et al. (2000)* presented a method using different algorithms to solve optimal pump combination problems for pump stations with or without variable speed pumps in the second level, so that the pump rotary speed can be regarded as decision variables and more rational and efficient pump combinations can be obtained. *Yuan et al. (2010)* proposed a two-level methodology which determines outflow variables in the first level using the Wilson–Han–Powell method, and determines pump combination and pump rotary speed with a reduced gradient method. With the development of the two-level methodology, more effective and efficient optimal models addressed on large scale WDS optimal operation problems are presented. However, there are still some problems that hinder the optimization method to be applied in practice. In these problems, the most outstanding ones are as follows. (1) Since there is no determined pump schedules, only meta-models can be used in the first level optimization. However, the meta-model is not as robust as a hydraulic model, so the reliability of optimization result is low. (2) Another problem of the two-level optimization is discordant of results in different levels. Since the two levels are solved in totally different phases, the feasibility of the first level result cannot be examined by pump combination information. So sometimes there is no feasible pump combination that can match the result of the first level.

For the purpose of solving these problems, a modified hydraulic model and pump combination database are introduced into the two-level method. By regarding pump stations as high level reservoirs, the hydraulic model of WDSs can be modified into a modality that can be used in the first optimal level of the two-level method, so that the defects of poor effect and low reliability of optimal results of the first optimal level solved with meta-models will be resolved. By building a database on feasible pump combination, a new optimal method in the second optimal level will be proposed. The solving process of the second optimal level will be embedded into the first optimal level, so that the problem of discordant results in different levels will be solved.

---

## OPTIMAL MODEL FORMULATIONS

The only purpose of optimal operation of WDSs is to reduce the electricity cost while meeting hydraulic constraints. In

the single objective optimization method, constraints will be added into the evaluation value by the weighting method or punish functions. Previous studies (Mackle *et al.* 1995; Boulos *et al.* 2010) dealt with constraints by penalizing the objective function. This requires the definition of a penalty function and appropriate penalty values. Moreover, different penalty values are required for different types of constraints and the degree of violation of some of these constraints cannot be easily quantified. To avoid this, a multi-objective optimal model is built with three objectives: minimum electricity cost, minimum amount of lower pressure service nodes and minimum error between two optimal levels. A multi-objective oriented solving method is used in the optimization.

## Objectives

The pump energy cost depends on the energy price as well as on the amount of energy consumed. The minimum electricity cost objective can be expressed by Equation (1):

$$\text{Min: } C = \sum_{i=1}^S P_i \cdot T \cdot t \quad (1)$$

where  $S$  is the set of source nodes,  $P_i$  is the power consumed by the  $i$ th pump (kw),  $T$  is the electricity tariff in the current period (¥/kwh),  $t$  is the length of the hydraulic time step (1 h).

The objective of minimum number of lower pressure service nodes is expressed by Equation (2):

$$\text{Min: } M = \sum_{i=1}^N \beta_i \quad \text{where: } \beta_i = \begin{cases} 0 & \text{if } H_i \geq H_{\min} \\ 1 & \text{if } H_i < H_{\min} \end{cases} \quad (2)$$

where  $N$  is total demand nodes number,  $H_i$  is pressure of  $i$ th node, and  $H_{\min}$  is the minimum service pressure required at demand node.

The third objective value is the error between two optimal levels. During the second level optimal process, a candidate pump combination will be selected for each solution according to the first optimal level result. In the pump combination database, discrete running conditions of all different pump combinations are recorded. Since

decision variables (outflow and head of source nodes) of first optimal level are continuous variables, it is hard to match the first optimal level result by a record from pump combination database exactly. So a neighbourhood region has to be generated by using the hydraulic results of each solution from the first level as central point and a designed length as the broader range. Records that fall into this neighbourhood region can be regarded as candidate pump combinations of this solution, and the flow difference between running conditions of the pump combination record and hydraulic result is the error between two optimal levels of this solution. This objective represents the rationality of the second optimal result. The less the error is, the more rational the second optimal result is. This error can be regarded as a measurement of difference between the modified hydraulic model simulation result and original hydraulic model simulation result. The error objective can be expressed by Equation (3):

$$\text{Min: } E = \sum_{i=1}^S \varepsilon_i \quad \text{where} \quad (3)$$

$$\varepsilon_i = \begin{cases} \infty & \text{if } F'_i \notin (F_i - \theta, F_i + \theta) \\ |F_i - F'_i| & \text{if } F'_i \in (F_i - \theta, F_i + \theta) \end{cases}$$

where  $F_i$  is the outflow of the  $i$ th source node of the hydraulic result of solution,  $F'_i$  is the outflow of the candidate pump combination.  $\theta$  is the broader range that is set before the optimization process.  $\infty$  is a very large number as a penalty for when no pump combination records fall into the neighbourhood region, it means that for the  $i$ th source node, there is no feasible pump combination that can match the first optimal level results.

## Constraints

In order to obtain feasible pump schedules, the optimization model must satisfy system constraints that represent its performance criteria. These include hydraulic constraints representing conservation of mass and energy, minimum and maximum limits on tank storage levels, minimum pressures requirements at demand nodes, and a balance between supply and demand from tanks. The hydraulic simulator implicitly handles some of these constraints. In the

proposed method, the minimum pressure requirement is regarded as an objective value, so there are no constraints about demand nodes pressure criteria in the optimal model. In this study, EPANET is used as the hydraulic simulator for handling the constraints.

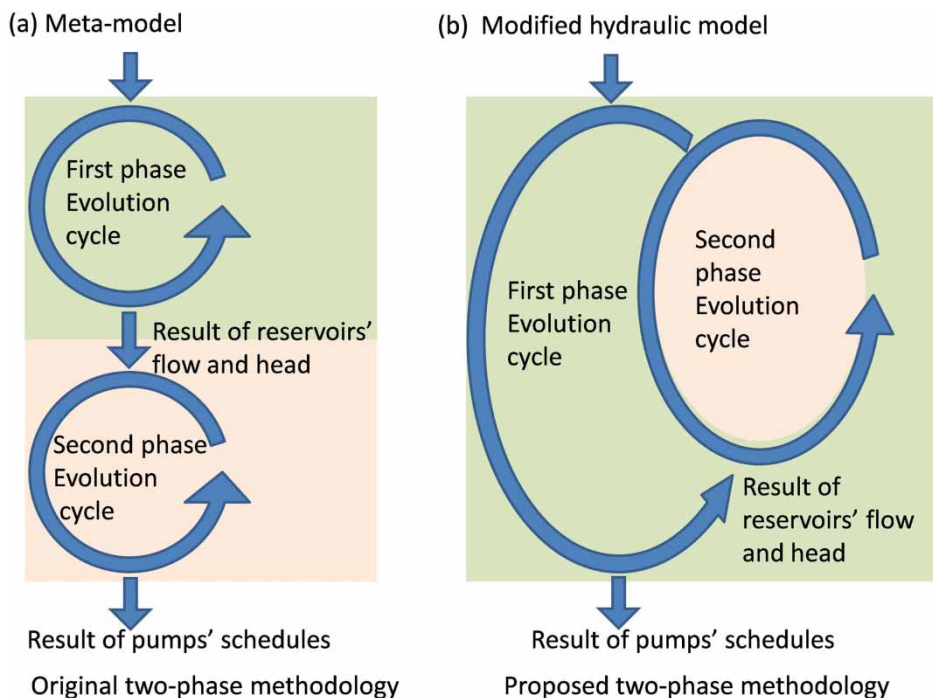
## SOLVING METHODOLOGY

In the two-level optimal methods of previous studies, the first level and second level is totally divided as two parts. The second level will be run after the first level has been done. Since there are no detailed pump schedules in the first optimal level, so the cost objective value can only be calculated based on an average pump efficiency parameter assigned beforehand, and only a meta-model can be used to evaluate fitness of candidate solutions in the first optimal level. The introduction of an average pump efficiency parameter may lead to an error between cost objective values of the first optimal level and the second optimal level, and cannot guarantee the first level result is an optimal one. The meta-model can only be trained by historical data, so it cannot be used directly after WDS expansion or

rehabilitation, and cannot be used to forecast WDS running condition in scenarios that have not happened, and cannot evaluate hydraulic constraints of the candidate scheme in detail, for example, the meta-model can only evaluate pressure constraints for certain nodes in WDS. These shortcomings of the meta-model make the two-level optimal method not a robust methodology. To avoid these shortcomings, a merged two-level optimal method with a hydraulic simulator is proposed. In order to use a hydraulic simulator in the first level, a modification has to be carried out to the original WDS hydraulic model by transforming the pump stations into elevated reservoirs. In order to avoid the problem of discordance between two levels' results, the second optimal level process will be embedded into the first optimal level, and executed to each candidate solution in every evolved step. The difference between the proposed two-level optimal method and the previous two-level optimal method is shown in [Figure 1](#).

### Building pump combination database

The pump combination database will be used in the second optimal level. The records of running conditions of each



**Figure 1** | Differences between proposed two-level optimal method and previous two-level optimal method.

pump combination are stored in the database. For each source node, the pumps will first be organized into a set of pump combinations. Then the characteristic curves (Q-H, Q-E curves) of the parallel pump running conditions of each pump combination will be calculated by using characteristic curves of each pump of the combination. In the database, the characteristic curves for each pump combination are recorded by discrete running condition sample points. In each running condition point, the parameters of flow, head, efficiency and power are recorded. The detailed process of building a pump combination database is described below. In general, it is rare to run all pumps in one pump station simultaneously, so a maximum amount of running pumps can be set for the pump station. With this limitation, the records in the pump combination dataset will be smaller, and the efficiency of the enumeration algorithm for the pump combination selection can be enhanced. The pumps and combinations of example pump station are shown in Table 1.

In the example pump station, there are three pump types A, B and C and the maximum number of running pumps is 4. The total combinations are listed in the ‘combination’ column. Each element in the ‘combination’ column is combined by pump type and its number (the number in brackets after the pump type), and there is no number and bracket if the number is 1.

For each pump combination, the running condition sample points of the Q-H characteristic curve will be calculated by Q-H characteristic curves of pumps in combination, according to the rule of ‘flow added in each head sample point’. The efficiency of each pump at running condition sample points can be obtained by the pump’s Q-E curve and its flow parameter. The power of each pump at running condition sample points can be obtained by flow, head and

efficiency parameters. The total power is a summary of power of each pump in this pump combination. The total efficiency is the ratio of effective power and total power. The calculation concept of Q-H sample points of pump combination and efficiency sample points of each pump is illustrated by an example of pump combination ‘AB’ in Figure 2.

There are six running condition sample points for this pump combination. The sample points are selected by dividing the common head area of all pumps in pump combination by a certain head step, for example 1 or 0.5 m. The smaller the head step is, the more detailed the characteristic curves will be described, however the larger the database is, the worse the efficiency of the second optimal level. So a feasible head step should be set before the characteristic curves calculation. After setting the head step, the head sample points can be obtained, and then the intersection points between the head sample points (represented by the gray dashed line) and Q-H curves of each pump can be found, and the outflow value of intersect points with the same head value will be used to calculate the outflow value of the running condition of the pump combination by summation. The Q-H curve of the pump combination is formed by points that comprise of the head sample value and the calculated outflow value. The horizontal gray arrows indicate the calculation of the Q-H curve of the pump combination. Using the intersect point of the Q-H curve of each pump, the efficiency of that pump at that running condition can be indicated by the intersecting point at the Q-E curve. The vertical gray arrows indicate the process of finding the pump efficiency. The total power and total

Table 1 | Pump combination of example pump station

Pump type and number	Max number of running pumps	Combinations
A(3)	4	A,B,C; A(2), B(2), C(2), AB, AC, BC; ABC,AB(2), AC(2), A(2)B, A(2)C, A(3), BC(2), B(2)C,B(3); AB(2)C, ABC(2), A(2)BC, A(2)B(2), A(2)C(2), A(3)B, A(3)C, B(2)C(2), B(3)C
B(3)		
C(2)		

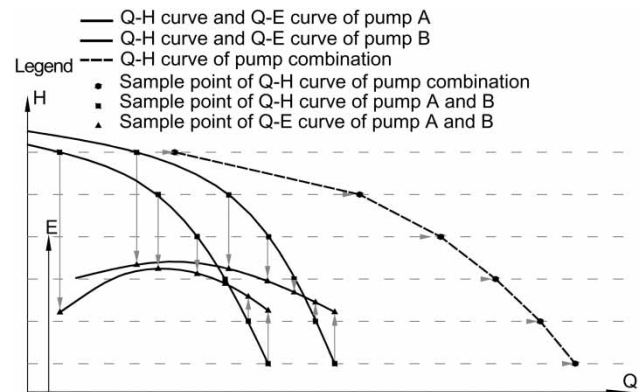


Figure 2 | Calculation concept of running condition points of pump combination.

efficiency of the pump combination can be calculated by Equations (4) and (5):

$$P_i = \sum_{k \in \Phi} \frac{\rho g H_{ki} Q_{ki} n_k}{e_{ki}} \tag{4}$$

where  $P_i$  is the power of the  $i$ th sample point of the pump combination,  $\Phi$  is the set of pump types in the pump combination,  $\rho$  is the density of water and  $g$  is the acceleration of gravity,  $H_{ki}$   $Q_{ki}$  and  $e_{ki}$  are head, flow and efficiency of the pump  $k$  at the  $i$ th sample point,  $n_k$  is the pump amount of type  $k$  in the pump combination.

$$e_i = \frac{\sum_{k \in \Phi} \rho g H_{ki} Q_{ki} n_k}{P_i} \tag{5}$$

where  $e_i$  is the efficiency of the  $i$ th sample point of the pump combination.

After calculation of all parameters of sample points in the pump combination characteristic curves, the results will be stored in database in the format shown in Table 2.

### Optimization method

In the case of multi-objective optimization, instead of obtaining a unique optimal solution, a set of equally good (non-dominating) optimal solutions is usually obtained (Pareto sets). Several methods, such as meta-heuristic algorithm (Kim *et al.* 2004), versions of GA (Khu & Keedwell 2005; Alvisi and Franchini 2006), NSGA-II (Deb *et al.* 2002) and particle swarm optimization algorithm (Liu *et al.* 2008) are available to solve multi-objective optimization problems. NSGA-II is used here to obtain the Pareto set.

Table 2 | The example records of pump combination scheme database

Pump station name	Pump combination name	Head	Flow	Power	Efficiency
Pump station 1	AB	H1	F1	P1	e1
		H2	F2	P2	e2
		H3	F3	P3	e3
		...	...	...	...
		...	...	...	...

### Coding and decoding

Since only the head of elevated reservoirs are decision variables, so the number of genes in chromosomes is equal to the number of reservoirs. Because different reservoirs may have different head ranges, each reservoir’s head range is discretized into  $n$  points by equal intervals, so that the gene code of each reservoir can be coded from a uniform integer gene code pool which is composed of integers from 0 to  $n$ , and the searching space becomes smaller. The chromosome string can be represented by an integer array, and each element of the integer array stores a gene code of the chromosome string, and each gene code belongs to the set of (0, 1, 2 ...,  $n$ ). The decoding process is to calculate the head of each reservoir from the gene code, and can be expressed by Equation (6):

$$H_i = H_{i\min} + (H_{i\max} - H_{i\min}) \frac{g_i}{n} \tag{6}$$

where  $g_i$  is the  $i$ th gene code in the chromosome,  $H_i$  is the head of the  $i$ th reservoir calculated from  $g_i$ ,  $H_{i\min}$  and  $H_{i\max}$  is low and up boundary of the head of the  $i$ th reservoir,  $n$  is the size of the gene code pool.

### Calculation of individual’s objective values and fitness

In the evolving process, the three objective values of each solution are obtained in different levels. In the first optimal level, by decoding chromosome string into reservoirs’ water level and by hydraulic simulation, the objective value of lower pressure service nodes amount can be obtained. Since the outflow of each reservoir is calculated in hydraulic simulation, so the optimal pump combination for each reservoir can be selected from the pump combination database according to outflow, head and neighbourhood region. After the pump combination is selected, the electricity cost objective value and error objective value can be calculated. The pump combinations of the simulated period are determined. The pump combinations will be stored in the individual of each solution. After calculation of objective values, solutions will be sorted by a non-dominated sorting method, and assigned rank value.

**Genetic operations**

The roulette wheel selection, one point crossover and real valued mutation are used in GA operation of this study. For optimization problems, the termination condition is also an important aspect that impacts the algorithm’s performance. In traditional ways, errors between the last iterations’ results can be used as the termination condition. For example, when the error between the last two iterations’ results is less than a designated value then the iteration stops. However, for GAs these kinds of termination conditions may cause a premature termination

when GA converges to a local optimal solution. So assignment of a large generation number is a popular method of termination condition in GAs, and this method is used in the proposed merged two-level optimal method. The whole optimal methodology framework is shown in Figure 3.

The pump operation schedules of each reservoir in the simulated period will be obtained after a run of the merged two-level optimal method. For an extended period of pump schedules operation, the merged two-level optimal method should be run several times equal to time steps in total duration.

A merged two-level optimal method

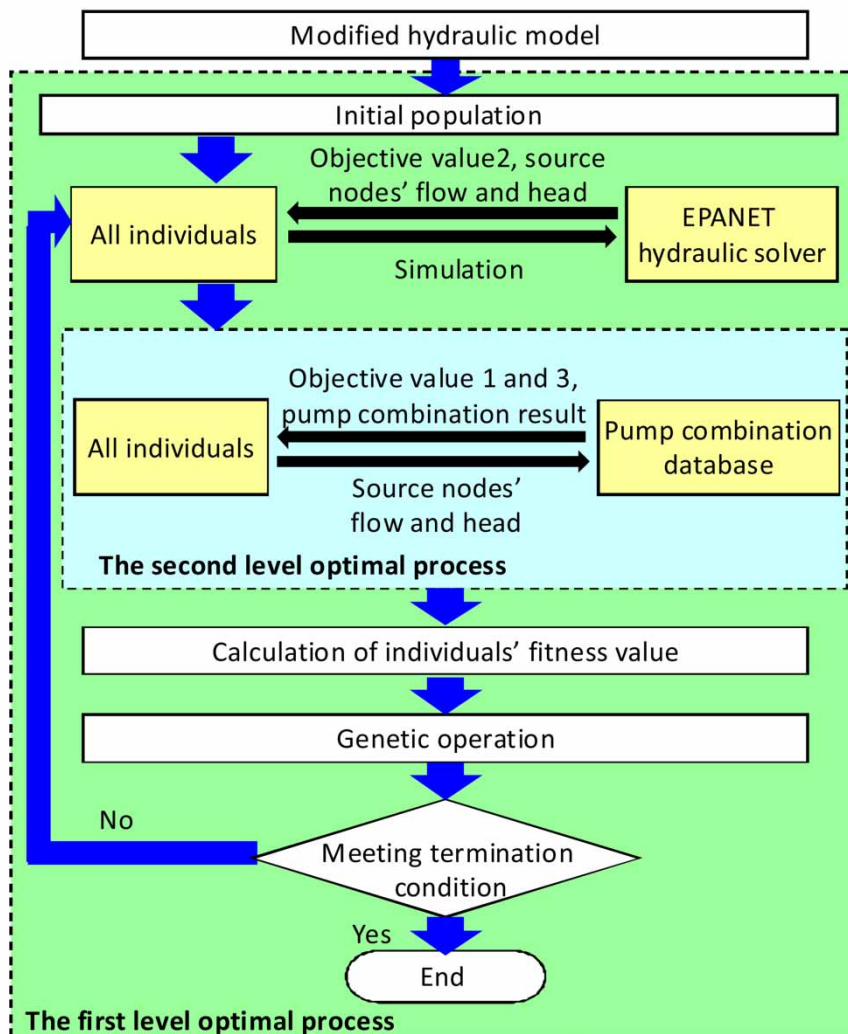


Figure 3 | Flow chart of merged two-level optimal method.



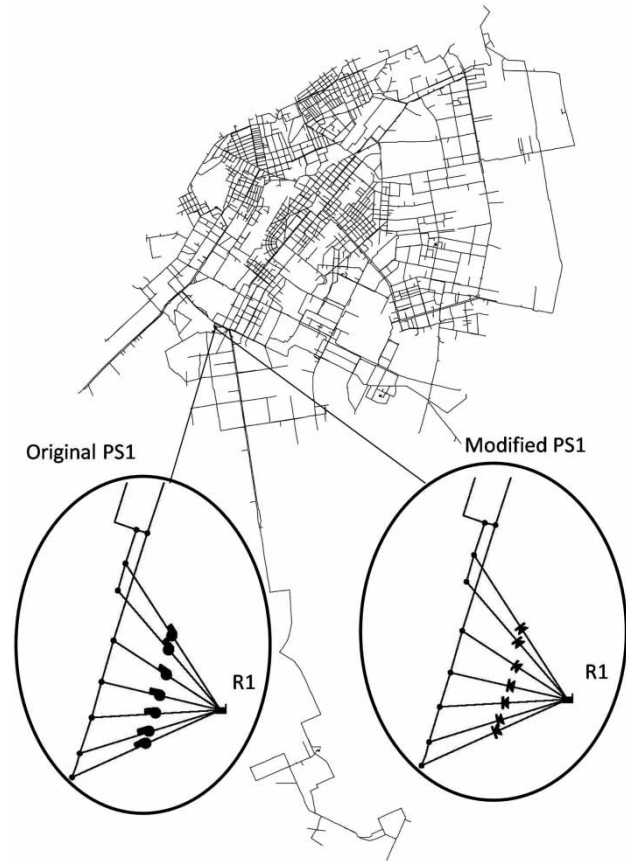
## CASE STUDY

A real WDS in North China is used here as a case study network. This WDS serves a population of nearly 3 million. Daily water consumption is in the range of 0.7–0.9 million  $\text{m}^3$ . In the daily water consumption pattern, there are two consumption peaks, generally at 10 am and 7 pm. The studied WDS has seven pump stations (each pump station has a reservoir) and 48 pumps. In total, the network consists of 3732 nodes and 4522 links with a total length of 764.76 km. Details of the pump stations are shown in Table 3.

Before running of the merged two-level optimal method, the hydraulic model needs to be modified. The modification method is replacing pump links which connect reservoirs with pipe network by pipe links with a check valve. Figure 4 shows the layout of the network. PS1 is used as an example to show the modifications to the pump stations. In this case, a typical 24 h scheduling period is used to test optimal methodology, and the period is divided into 24 1-hour simulation steps. So the merged two-level optimal model solved by NSGA-II will run 24 times obtain pump schedules for the typical 24 h period. In order to evaluate the average performance of the merged two-level optimal model, 10 runs of 24 h pump scheduling optimization were conducted using different random seeds. Each run is executed with the same GA parameters setting: population size is 100, generation size is 100, crossover probability is 0.6 and mutation probability is 0.1.

**Table 3** | Information of pump stations

Name	Reservoir name and head boundaries (m)	Pump type and count
PS1	R1 (20–60)	12sh-9(7)
PS2	R2 (20–60)	20LN-26A(7), 12LN-21B(3)
PS3	R3 (20–70)	S500-59(5), 500S-98B(2)
PS4	R4 (20–60)	12sh-9(4), 14sh-13A(1)
PS5	R5 (20–60)	24SA-10A(3), 16SA-9C(3)
PS6	R6 (10–60)	12sh-13(4), 12sh-9A(2)
PS7	R7 (20–60)	10LN-13(7)



**Figure 4** | Layout of network.

## RESULTS AND DISCUSSION

Since the pump schedules result is obtained by an enumeration algorithm with a pump combination database and modified hydraulic model, the optimal result should be examined by the original hydraulic model with a run according to the optimal pump schedules results. Only when simulation results of the original model and the modified model are met can the feasibility of the merged two-level optimal methodology based on the pump combination database and the modified hydraulic model be guaranteed. A comparison between hydraulic simulation results of total outflow from each reservoir of the two hydraulic models is shown in Table 4. There are 10 runs of 24 h pump scheduling optimization, so the maximum, minimum and average values of errors between two models are shown in Table 4. The values in Table 4 are relative errors that were calculated

**Table 4** | Comparison between total out flow from each reservoir of the two hydraulic models

	R 1	R 2	R 3	R 4	R 5	R 6	R 7
Max error	0.021	0.016	0.030	0.048	0.019	0.022	0.029
Min error	0.005	0	0.001	0.003	0.001	0.002	0.002
Average error	0.012	0.004	0.011	0.023	0.009	0.011	0.016

by Equation (7):

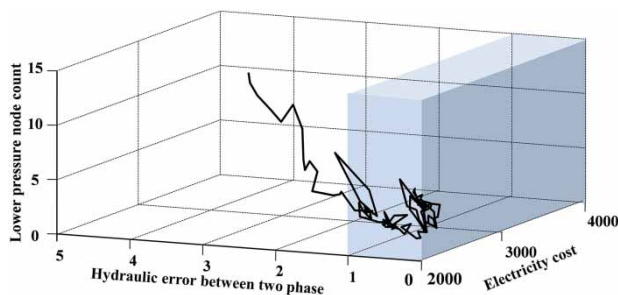
$$\text{error} = \frac{|r_0 - r_m|}{r_0} \quad (7)$$

where  $r_0$  is the simulation result of the original model, and  $r_m$  is the simulation result of the modified model.

In Table 4 the maximum relative error of the two models is less than 0.05. It shows that there is little error between the hydraulic simulation results of the two models. So it is feasible to use a modified model and pump combination database for calculation of objective values in the optimal process as a surrogate of the original hydraulic model.

Figure 5 shows the 3D line which represents the convergence path of the evolution process. Each junction of the 3D line represents the average objective values of one generation. The objective value of ‘hydraulic error between two optimal levels’ has been processed, the integer part of objective value represents the number of reservoirs without a feasible pump combination, and the fraction part represents the relative hydraulic error.

From Figure 5 it can be seen that the hydraulic error objective converges to the feasible solution space rapidly and searches for better solutions in the feasible solution space. The transparent blue box defines the feasible solution space. In this space, the objective value of ‘hydraulic error between two optimal levels’ is less than 1. This means that

**Figure 5** | Converge path of evolve generations.

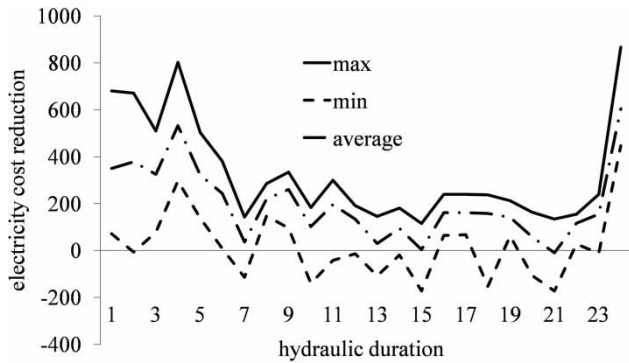
solutions found in this space all have feasible pump combinations for every reservoir of WDS. Generally, after 30–40 generations evolution the average objective values can enter the feasible solution space, and use the rest of the evolving process to search the feasible solution space thoroughly. If considering the best solutions generated during the evolving process, some best solutions reach the feasible solution space much earlier than the average solutions, so the search process in the feasible solution space should start much earlier than the situation shown in Figure 5. This performance is a result of merged two-level optimization. By embedding the second optimal level into the first optimal level, the solutions without a feasible pump combination and solutions with poor hydraulic performances are eliminated in the initial generations of the evolving process, and lead the search direction to the feasible solution space. This prevents the possibility of generating unfeasible results in the whole optimal process.

The second concern is the quality of the optimal result. The quality of the optimal result can be evaluated from two aspects: electricity cost and hydraulic performance of WDS. A comparison between the optimized optimal pump schedules and the original pump schedule from the aspect of electricity cost is shown in Table 5.

The original pump schedule is used in the case study WDS in the summer water consumption pattern, and is corrected by years of running experience. With years of correction it is nearly perfect and has little scope to be optimized by experience. Finding better pump schedules for the case study WDS is a challenge of the proposed optimization method. From Table 5 it can be seen that each run of the optimal method finds a lower electricity cost pump schedule, and the average reduction of electricity cost is more than 5%. So the proposed method has the ability to find a better pump schedule for WDS's electricity cost reduction. Figure 6 shows the electricity cost reduction of 10 runs of the two-level optimal method.

**Table 5** | Summary of electricity cost reduction

Electricity cost of original pump schedule (¥)		Electricity cost of optimal pump schedule (¥)	Reduction ratio
86308	Best	79893	0.071
	Average	81262	0.056
	Worst	82461	0.042



**Figure 6** | Electricity cost reduction.

The solid line and dashed line express the maximum and minimum electricity cost reduction among 10 runs. The area between the two lines is the band that represents the electricity cost potentiality found by the merged two-level optimization. Most of the band area is above the abscissa axis, it means in most cases the optimal method found pump combinations with lower electricity cost. For the case network, most cost reductions were achieved at night. This indicates that the original pump schedule for the night hours has room for improvement.

Table 6 shows the comparison of lower service pressure nodes between the original pump schedule and the optimal pump schedules.

It can be seen from Table 6 that lower service head nodes in the test network with optimal pump schedules are much less than the situation with the original pump schedule. It shows that the proposed method has the ability to find solutions which not only reduce the electricity cost but also enhance the hydraulic performance of WDS. By transforming the lower service pressure constraint into an objective function in the optimal process, better solutions in both cost saving and hydraulic performance enhancement were found. Since there are no penalty functions or weighted coefficients used in the optimal process, the

**Table 6** | Comparison of lower service pressure nodes

Time period	Result of original pump schedule	Result of best optimal run	Result of worst optimal run	Result of average of 10 runs
1	20	0	12	1.6
2	20	6	7	1.4
3	16	0	19	6.4
4	0	9	0	4.4
5	0	0	3	1.3
6	0	0	1	0.4
7	19	0	9	5.0
8	31	0	9	6.6
9	56	0	4	4.0
10	40	0	6	4.8
11	44	3	30	7.3
12	11	3	10	3.4
13	0	1	6	2.8
14	0	0	0	0.7
15	28	3	0	1.7
16	32	0	19	3.6
17	0	0	3	0.4
18	3	0	1	0.4
19	0	0	2	0.3
20	12	0	0	1.4
21	2	0	4	1.5
22	283	0	0	0.2
23	18	0	0	0.4
24	43	0	0	0
Total	678	25	145	60

unreasonable setting of penalty functions or weighted coefficients is avoided. This makes the merged two-level optimal method a robust method in finding better solutions of lower cost and high hydraulic performance.

One thing that should be considered but is not discussed in this study is pump ON/OFF switch times. Because the optimization for each 1-hour simulation step is implement isolated, so the pump switch times during the 24 h pump scheduling optimization could not be concerned in the optimal process. Table 7 shows the average times of each pump type in the pump stations. Since the optimal result is shown in the format of pump combination with pump type and its number for each pump station, the optimal result does not give the operation schedule for each pump, so the average times of

**Table 7** | Pump switch times result

Pump station	Pump type and count	Max	Min	Average	Original schedule
PS1	12sh-9(7)	3.14	2.00	2.70	0.14
PS2	20-LN-26A(7)	2.00	1.14	1.47	0.28
	12-LN-21B(3)	0.33	0	0.03	0
PS3	S-500-59(5)	3.00	1.40	2.32	0.4
	500S-98B(2)	2.5	0	0.70	0
PS4	12sh-9(4)	3.75	1.50	2.85	0.25
	14sh-13A(1)	7.00	4.00	5.40	0.33
PS5	24SA-10A(3)	4.67	2.67	3.57	1.00
	16SA-9C(3)	4.67	2.33	3.60	0.25
PS6	12sh-13(4)	3.50	2.00	2.60	0
	12sh-9A(2)	1.75	0.50	1.18	0.50
PS7	10-LN-13(7)	1.57	0.71	1.04	0.14

each pump type in the pump station is used here to evaluate pump switch times. Average times of each pump type is calculated by dividing total switch times of certain pump type by pump number of that pump type. There are 10 runs of optimal method, and the maximum, minimum and average values of ‘average switch times of each pump type’ is shown in Table 7, and the average pump switch times of original pump schedule are also shown as a comparison.

From Table 7 it can be seen that the pump switch times of optimal result is obviously higher than switch times in the original pump schedule. A reasonable explanation for the increase of pump switch times is that to meet the objective of electricity cost reduction, the selected pump combination for each 1-hour simulation step should meet the water consumption in WDSs more precisely, so that running pumps can stay in a high efficiency state, however, this can also cause a situation of high frequency of ON/OFF switches of pumps. So when consumption demand changes the pump combination tries to find a high efficiency pump combination to attain the minimum electricity cost objective. The important thing is that the pump switch times should stay in an acceptable range. Since there is no tradeoff between electricity cost reduction and pump switch times, so the result of high pump switch times occurred in the proposed methodology. Although the pump switch times are higher than the original pump schedule, the optimal schedules of most pump stations are acceptable. The maximum number of simultaneously running pumps in each pump station in the

WDSs is set as 4, so certain pump types with spare pumps have a relatively lower average pump switch time because the total switch times can be shared by relatively more pumps, for example, there are seven pumps of type 10-LN-13 in PS7, and the maximum pump switch times of this type is 11 during a whole 24 h pump schedule period. Divided by seven, each pump only experienced 1.57 ON/OFF occurrences in 1 day. An extreme case of high switches is the pump of 14sh-13A in PS4, because there is only one pump of that type in the pump station, so all switches will act on this pump. In this case, an operation schedule modification for certain pumps should be carried out manually.

The computational effort required by the merged two-level optimal method was measured when run on a Core 2 Duo T6500 (2.10 GHz) with 2048 kb of cache size running under Windows XP. The mean computation time required for one run of one hydraulic simulation step of the case network was 1198 s, while it was 7.99 hours for a 24 h pump schedules optimization with a hydraulic step of 1 h. Since each optimal process for every simulation step is run totally separately, the total computation time can be shortened by parallel runs of optimal program in one computer or several computers.

## CONCLUSIONS

By introduction of a hydraulic model and pump combination database, a merged two-level optimal method for WDS optimal pump operation is proposed. By transforming the pump station of the original hydraulic model into an elevated reservoir, the modified model can be used in the first optimal level for evaluation of hydraulic performance of candidate solutions, and the defects of fallibility and incomplete hydraulic performance evaluation of meta-model are avoided and more reliable solutions can be obtained. By building a pump combination database, the enumeration algorithm is used in the second optimal level, and the complexity of second optimal level is reduced significantly. This makes it possible to run the second optimal level process to each solution in each evolving step of evolution algorithms, so that the second optimal level can be embedded into the first optimal level to form a merged two-level optimal methodology. By embedding the second optimal level into the first optimal level, the solutions without a feasible pump combination will be eliminated and lead the solving process

to converge on the feasible solution space so that a generation of impracticable results can be avoided. A multi-objective optimal model and solving method NSGA-II are used in this study, hydraulic constraint of lower service node count and hydraulic errors between two levels are regarded as objectives in parallel with electricity cost objective in the multi-objective model. These measures solve the problems of unreasonable penalty functions or the setting of weighted coefficients that occur in optimization methods using single objective optimal models.

Since there is no limitation for maximum pump switch times in the optimal process, sometimes results with a high frequency of pump switches will be obtained by the proposed method. In this case, a manual modification to optimal results should be carried out before pump schedules are put into effect.

## ACKNOWLEDGEMENTS

The authors acknowledge the support from Seventh Framework Programme (FP7) Marie Curie Actions International Research Staff Exchange Scheme- Smart Water (PIRSES-GA-2012-318985) and FP7-WatERP (EC-318603), and also acknowledge the support from the Project of Construction Science and Technology-Component Based Software Development of Information Management Platform of Water Distribution System (2010-53).

## REFERENCES

- Alvisi, S. & Franchini, M. 2006 *Near-optimal rehabilitation scheduling of water distribution systems based on a multi-objective genetic algorithm*. *Civil Eng. Environ. Syst.* **23** (3), 143–160.
- Bagirov, A. M., Barton, A. F., Mala-Jetmarova, H., Al Nuaimat, A., Ahmed, S. T., Sultanova, N. & Yearwood, J. 2012 A novel approach to optimal pump scheduling in water distribution systems. In: *14th Water Distribution Systems Analysis Conference*, Adelaide, South Australia, pp. 618–631.
- Benjamín, B., von Christian, L. & Aldo, S. 2005 *Multi-objective pump scheduling optimisation using evolutionary strategies*. *Adv. Eng. Softw.* **36** (1), 39–47.
- Boulos, P. F., Zheng, W., Chun, H. O., Michael, M., Paul, H. & Devan, T. 2010 *Optimal pump operation of water distribution systems using genetic algorithms*. In: *Proc., Distribution System Symp.*, AWWA, San Diego, pp. 23–25.
- Deb, K., Pratap, A., Agarwal, S. & Meyarivan, T. 2002 *Fast and elitist multi-objective Genetic Algorithms: NSGA-II*. *IEEE Trans. Evol. Comput.* **6** (2), 182–197.
- Fang, H., Wu, W., Lv, M. & Gao, J. 2011 *Optimising pump system with constant and variable speed pumps: case study*. *Int. J. Modell. Ident. Control* **12** (4), 412–420.
- Kevin, E. L. & Kofi, A. 1994 *Optimal pump operation considering pump switches*. *J. Water Resour. Plann. Manage. ASCE* **120** (1), 17–35.
- Khu, S. T. & Keedwell, E. 2005 *Introducing more choices (flexibility) in the upgrading of water distribution networks: the New York city tunnel network example*. *Eng. Optimiz.* **37** (3), 291–305.
- Kim, J. H., Baek, C. W., Jo, D. J., Kim, E. S. & Park, M. J. 2004 *Optimal planning model for rehabilitation of water networks*. *Water Sci. Technol. Water Supply* **4** (3), 133–147.
- Liu, D. S., Tan, K. C., Huang, S. Y., Goh, C. K. & Ho, W. K. 2008 *On solving multi-objective bin packing problems using evolutionary particle swarm optimization*. *Eur. J. Operat. Res.* **190** (2), 357–382.
- López-Ibáñez, M., Prasad, T. D. & Paechter, B. 2008 *Ant colony optimization for optimal control of pumps in water distribution networks*. *J. Water Resour. Plann. Manage.* **134** (4), 337–346.
- Mackle, G., Savic, D. A. & Walters, G. A. 1995 *Application of genetic algorithms to pump scheduling for water supply*. In: *Proc., Genetic Algorithms in Engineering Systems: Innovations and Applications, GALESA'95, IEEE*, Sheffield, UK, pp. 400–405.
- Ormsbee, L. & Lansley, K. 1994 *Optimal control of water supply pumping systems*. *J. Water Resour. Plann. Manage.* **120**, 237–252.
- Ormsbee, L., Walski, T., Chase, D. V. & Sharp, W. W. 1989 *Methodology for improving pump operation efficiency*. *J. Water Resour. Plann. Manage.* **115** (2), 148–164.
- Price, E. & Ostfeld, A. 2013 *Iterative linearization scheme for convex nonlinear equations: application to optimal operation of water distribution systems*. *J. Water Resour. Plann. Manage.* **139** (3), 299–312.
- Savic, D. A., Walters, G. A. & Schawb, M. 1997 *Multi-objective Genetic Algorithms for Pump Scheduling in Water Supply*. ERASMUS, Exeter, UK/Stuttgart, Germany: School of Engineering of Exeter University/University of Stuttgart.
- Van Dijk, M., Van Vuuren, S. & Van Zyl, J. 2008 *Optimising water distribution systems using a weighted penalty in a genetic algorithm*. *Water SA* **34** (5), 537–548.
- Yuan, Y. X., Zhong, D. & Gao, J. L. 2010 *Optimization operation of water distribution system based on macroscopic model*. *China Water Wastewater* **26** (5), 55–62.
- Zhang, T. Q., Lv, M. & Zhao, H. B. 2000 *Research into optimal control algorithms in water-supply networks*. *J. Zhejiang Uni. (Eng. Sci.)* **34** (4), 428–432.
- Zheng, S. Y. 1997 *Study on the macroscopic model of two-grade optimization operation in urban water supply system*. *J. Sichuan Union Uni. (Eng. Sci. Edn.)* **1** (2), 60–68.