Journal of Environmental Management 115 (2013) 189–197

Contents lists available at SciVerse ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

# Multi-objective optimization of water quality, pumps operation, and storage sizing of water distribution systems

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ARTICLE INFO

*Article history:*
Received 10 May 2012
Received in revised form
19 November 2012
Accepted 26 November 2012
Available online 20 December 2012

*Keywords:*
Design
Operation
Storage
Sizing
Multi-objective
Optimization
Water distribution systems
Water quality

ABSTRACT

A multi-objective methodology utilizing the Strength Pareto Evolutionary Algorithm (SPEA2) linked to EPANET for trading-off pumping costs, water quality, and tanks sizing of water distribution systems is developed and demonstrated. The model integrates variable speed pumps for modeling the pumps operation, two water quality objectives (one based on chlorine disinfectant concentrations and one on water age), and tanks sizing cost which are assumed to vary with location and diameter. The water distribution system is subject to extended period simulations, variable energy tariffs, Kirchhoff's laws 1 and 2 for continuity of flow and pressure, tanks water level closure constraints, and storage-reliability requirements. EPANET Example 3 is employed for demonstrating the methodology on two multi-objective models, which differ in the imposed water quality objective (i.e., either with disinfectant or water age considerations). Three-fold Pareto optimal fronts are presented. Sensitivity analysis on the storage-reliability constraint, its influence on pumping cost, water quality, and tank sizing are explored. The contribution of this study is in tailoring design (tank sizing), pumps operational costs, water quality of two types, and reliability through residual storage requirements, in a single multi-objective framework. The model was found to be stable in generating multi-objective three-fold Pareto fronts, while producing explainable engineering outcomes. The model can be used as a decision tool for both pumps operation, water quality, required storage for reliability considerations, and tank sizing decision-making.


## 1. Introduction

In reality, most problems are of a multi-objective contradictory nature. The most common goal of an engineering analysis is to select the best tradeoffs among competing objectives. Frequently, such problems are structured as single objective problems by lumping all goals into a single minimization or maximization framework. This type of analysis might be beneficial for gaining insights to a considered problem. However, it is not suited for a clear tradeoff among the utilized objectives. Contrary to that, in a multi-objective formulation there is no single optimal solution, but sets of non-dominated solutions which form a Pareto trade-off curve among all goals.

In recent years, several methods have been developed which extend single objective optimization schemes to multi-objective algorithms. Three of the more utilized algorithms are the multi-objective genetic algorithm (MOGA) (Fonseca and Fleming, 1993), the non-dominated sorting genetic algorithm II (NSGAII) (Deb et al., 2002), and the strength Pareto evolutionary algorithm II (SPEA2) (Zitzler et al., 2001).

Research on multi-objective optimization for water resources and for water distribution systems management is relatively new. Wen and Lee (1998) developed a neural network model coupled with a multi-objective optimization scheme to simulate decision-making preferences in a river basin for water quality management. Halhal et al. (1999) introduced a multi-objective model to solve a water distribution systems design problem through minimizing network cost versus maximizing the hydraulic benefit of the system. Erickson et al. (2002) utilized a multi-objective optimization algorithm for groundwater water quality management through remediation by pump-and-treat. Kapelan et al. (2003) used a multi-objective genetic algorithm to find sampling locations for optimal calibration. Keedwell and Khu (2003) applied a hybrid multi-objective evolutionary algorithm to the optimal design problem of a water distribution system, where the hybrid approach employed a non-dominated sorting genetic algorithm coupled with a neighborhood search methodology. Prasad and

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http://dx.doi.org/10.1016/j.jenvman.2012.11.030

Park (2004) applied a non-dominated sorting genetic algorithm for minimizing the network cost versus maximizing a reliability index. Park and Aral (2004) suggested to control salt intrusions into coastal aquifers by determining pumping rates and well locations through a multi-objective optimization model. Babayan et al. (2005) used a multi-objective genetic algorithm framework to solve the design problem of a water distribution system under demands uncertainty. Bau and Mayer (2007) presented a multi-objective formulation to design and manage pump-and-treat remediation strategies through planning site characterization programs for reducing subsurface parameter uncertainty. Baltar and Fontane (2008) explored multi-objective particle swarm optimization for reservoir operation. Perelman et al. (2008) extended the combinatorial optimization Cross Entropy (CE) method (Rubinstein, 1999) to multi-objective optimization through minimizing the network capital and operational costs versus the maximization of the network hydraulic performance. Huang and Liu (2010) coupled a hybrid genetic algorithm with an artificial neural network in a multi-objective framework for calibrating surface water quality models. Wu et al. (2010) used multi-objective optimization to tradeoff cost and greenhouse gas emissions for water distribution systems optimal design. Alfonso et al. (2010) developed a multi-objective optimization model for water quality decision making in water distribution systems in case of a contaminant intrusion. Nikolos et al. (2010) combined single and multi-objective differential evolution algorithms with an artificial neural network for exploring demand operational strategies in the northern part of the Rhodes Island, Greece. Chang et al. (2010) employed multi-objective optimization to enhance negotiations on discounting ratios on water deficit impacts between irrigation and public sectors stakeholders. Wu et al. (2011) developed a pump power estimation method using a false position methodology based optimization for incorporating variable speed pumps in design and planning of water distribution systems.

In this work water quality, pumping cost, and tank sizing objectives are integrated in a one framework together with constraints on threshold storage-reliability. This assimilated formulation is new and can provide a new decision support tool to support decisions on trading-off pumps operation versus tank sizing versus water quality and versus surplus storage requirements. The developed methodology is demonstrated on EPANET (USEPA, 2012) Example 3 system.

The study provides a tool for enhancing engineering decision making through: (1) a multi-objective scheme for water distribution systems tanks design by mutually optimizing operational costs, disinfectant residuals/water age, and tanks sizing, (2) a quantitative model for exploring tanks sizing significance on water quality and operational costs objectives, (3) a methodology for investigating the relative distribution significance of storage throughout the system, and (4) a method to quantify the implication of residual storage requirements on operational costs and water quality considerations.

## 2. Problem formulation

This section defines the mathematical models solved in this work followed by the solution methodology.

### 2.1. Decision variables

The decision variables in this study are operational and design: the speed of each pump $v_i$ and the disinfectant concentrations $u_i$ at each treatment plant (operational), and the diameter $\mathrm{td}_i$ of each tank (design). The pumping and concentration schedules are expressed as patterns with durations corresponding to the control evaluation horizon $H_p$.

The pumps speed and the plants concentration are restricted to a continuous range $u_i \in \langle u_{\min}; u_{\max}\rangle$ and $v_i \in \langle v_{\min}; v_{\max}\rangle$, respectively, where the tanks diameter can receive values from discrete sets $\mathrm{td}_i \in \{\mathrm{td}_i^1, \mathrm{td}_i^2, \ldots, \mathrm{td}_i^n\}$. Those constitute the decision variables of the considered problems:

$$\mathbf{U} = \left[\{u_i(1), \ldots, u_i(H_p)\} \text{ for } i \in \mathbf{R}\right] \quad (1)$$

$$\mathbf{V} = \left[\{v_i(1), \ldots, v_i(H_p)\} \text{ for } i \in \mathbf{P}\right] \quad (2)$$

$$\mathbf{Td} = [\mathrm{td}_i \text{ for } i \in \mathbf{T}] \quad (3)$$

The vector $\mathbf{U}$ corresponds to the concentration pattern at the reservoirs (sources) which belongs to the set $\mathbf{R}$. Next, the vector $\mathbf{V}$ is associated with the pumps speed schedules: for each pump belonging to the set $\mathbf{P}$ a schedule of $H_p$ elements (24 in this study for 24 h) is computed. Lastly, $\mathbf{Td}$ is the vector of the tanks diameter, where for each tank a diameter is selected from the set $\mathbf{T}$.

### 2.2. Objectives

Pumps operational cost, water quality, and tanks sizing are formulated herein as the model objectives.

#### 2.2.1. Operational cost

The first objective $J_1(v,\mathrm{td})$ is the overall energy consumed by the pumps during the control evaluation horizon $H_p$. Different energy tariffs for each pump can be considered:

$$J_1(v, \mathrm{td}) = \sum_{k=1}^{H_p} \sum_{i \in P} \eta_i(k) E_i(k) \quad (4)$$

where $\eta_i(k)$ is the energy cost of pump $i$ over time period $k$, and $E_i(k)$ is the energy consumed by pump $i$ over time period $k$ (constant).

The operational cost objective will drive the system to minimize the amount of pumping during peak energy tariffs and utilize the systems storage for reducing energy cost.

#### 2.2.2. Water quality

Two different water quality objectives are considered in this work. The first is based on disinfectant concentrations, where the second on water age.

*2.2.2.1. Water quality objective based on disinfectant concentrations.* For each of the nodes in the system (including the tanks) the concentration of chlorine is evaluated using a penalty-based function (Ewald et al., 2008) as described in Fig. 1. This is different from the

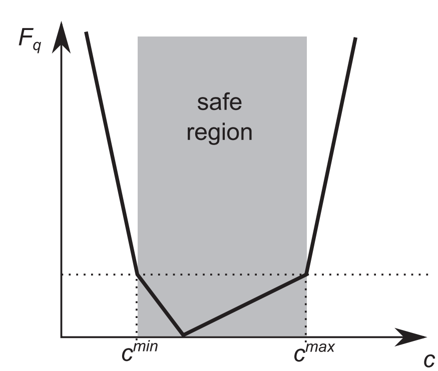


**Fig. 1.** Water quality evaluation function (following Ewald et al., 2008).

common approach of introducing hard ranged water quality constraints $\langle c_{\min}; c_{\max}\rangle$ at each node of the system. In case of the later, the distribution of chlorine within the network cannot be forced to meet the required range constraints at all nodes (Tryby et al., 2002).

The formulation utilized in this study for disinfectant concentration is:

$$J_2^1(v, u, \mathrm{td}) = \sum_{k=1}^{H_p} \sum_{j \in \mathbf{J}} F_{\mathrm{q}}(c_j(k)) \tag{5}$$

where $\mathbf{J}$ is the subset of the monitored nodes, $F_{\mathrm{q}}(\cdot)$ is the quality evaluation function (see Fig. 1), and $c_j(k)$ is the disinfectant concentration at node $j$ at time instant $k$. Note that the subset of nodes considered can be altered, and the quality evaluation function parameters adjusted (e.g., for nodes which constitute higher bacteriological hazards risks).

*2.2.2.2. Water quality objective based on water age.* The second water quality objective is based on water age (Salomons et al., 2012). It is aimed at minimizing the age of water below a certain threshold for all nonzero demand nodes:

$$J_{2l}^2(v, \mathrm{td}) = \frac{\sum_{k=1}^{H_p} \sum_{i \in \mathbf{J}} s_i(k) d_i(k) a_i(k)}{\sum_{k=1}^{H_p} \sum_{i \in \mathbf{J}} d_i(k)} \tag{6}$$

where $d_i(k)$ is the demand at node $i$ at time instant $k$, $a_i(k)$ is the age of water at node $i$ at time instant $k$, and $s_i(k)$ is a variable defined as:

$$s_i(k) = \begin{cases} 1, & \text{if } \mathrm{a}_i(k) \geq a_{\mathrm{th}} \\ 0, & \text{if } \mathrm{a}_i(k) < a_{\mathrm{th}} \end{cases} \tag{7}$$

where $a_{\mathrm{th}}$ is the water age threshold ($a_{\mathrm{th}} = 12$ h in this study).

This objective attempts to set the water age at consumer nodes below the threshold $a_{\mathrm{th}}$, prioritizing nodes with higher demands. Considering only the demand nodes while neglecting the tanks may lead to unexpected results. This will be further elaborated in the example application section.

*2.2.3. Tanks cost*

The third objective $J_3(\mathrm{td})$ corresponds to the cost of erecting tanks at desired locations, which is assumed to be a function of both the tank location and its diameter:

$$J_3(\mathrm{td}) = \sum_{i \in \mathbf{T}} f_{t,i}(\mathrm{td}) \tag{8}$$

where $\mathbf{T}$ is the subset of tanks in the system, and $f_{t,i}(\cdot)$ is the tanks cost function defined as:

$$f_{t,i}(\mathrm{td}) = \beta_i \cdot \mathrm{td}^2 + \gamma_i \tag{9}$$

where $\beta_i$ and $\gamma_i$ are the design coefficients for the size and tank location, respectively. The assumed shapes for (9) utilized in this study for the example application below, are presented in Fig. 2.

*2.3. Constraints*

There are three kinds of constraints for this problem. The first are constraints derived from the network physics which the decision variables should meet, such as flows, pressures, continuity, etc. In this work the network is evaluated using the quantity-quality simulation program EPANET (USEPA, 2012) which incorporates the system's dynamics.

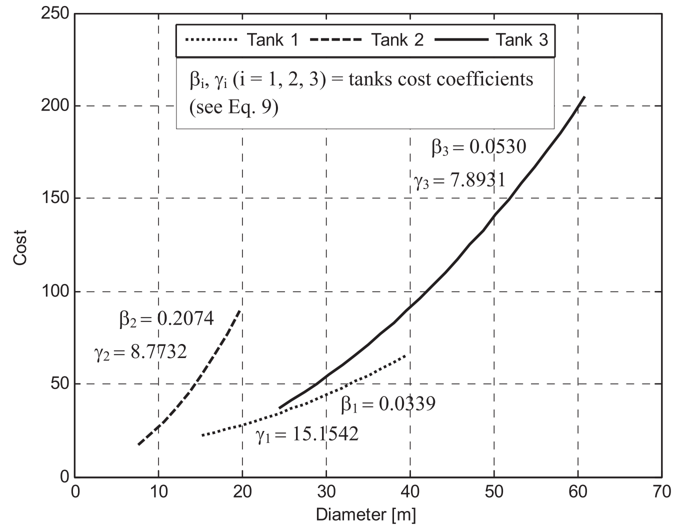


**Fig. 2.** Tanks cost functions.

For each simulation step EPANET returns a warning code indicating whether the simulation was successful or not. That information is then used for determining if the evaluated solution is feasible or not, thus introducing the first constraint:

$$\sum_{k=1}^{H_p} w(k) = 0, \tag{10}$$

where $w(k)$ is the warning code returned by EPANET. Note that (10) implies a positive pressure constraint at all nodes (Kurek and Brdys, 2007, 2010). Explicit additional minimum and maximum pressure constraints could be added at all or some of the nodes at different time steps $k$. As the results for the example application revealed satisfactory pressure outcomes for all cases [i.e., a minimum of 10 m, an average of 33 m, and a maximum of 67 m] such constraints were not implemented.

The next constraints enforce periodical operation of the network which is required for its reliable operation. Those impose terminal constraints on the tank levels:

$$\max\{0, |p_t(H_p) - p_t(1)| - \alpha p_t(1)\} = 0, \quad \forall t \in \mathbf{T} \tag{11}$$

where $p_t(k)$ is the head at tank $t$ at time instant $k$, $\alpha$ is the coefficient that relaxes the terminal constraint introducing tolerance to the constraint, and $\mathbf{T}$ is the set of all tanks in the network. In this study $\alpha$ was set to 0.1.

The third type of restrictions is storage-reliability constraints for guaranteeing that a sufficient amount of water is stored in the system at any time. The rational behind this constraint is for ensuring that for every time instant $k$ the amount of water stored in the tanks is equal or greater than the demand predicted for the next $D$ time steps. This results in $H_p$ constraints defined as:

$$\sum_{l \in \mathbf{T}} \left[ \left( \frac{\mathrm{td}_l}{2} \right)^2 \pi p_l(k) \right] - \sum_{m=k+1}^{k+D} \left[ \sum_{j \in \mathbf{J}} d_j(k) \right] \geq 0, \quad \text{for } k = 1 : H_p \tag{12}$$

where $\mathrm{td}_l$ is the diameter of tank $l$, $p_l(k)$ is the pressure in tank $l$ at time $k$, and $d_j(k)$ is the demand at node $j$ at time $k$.

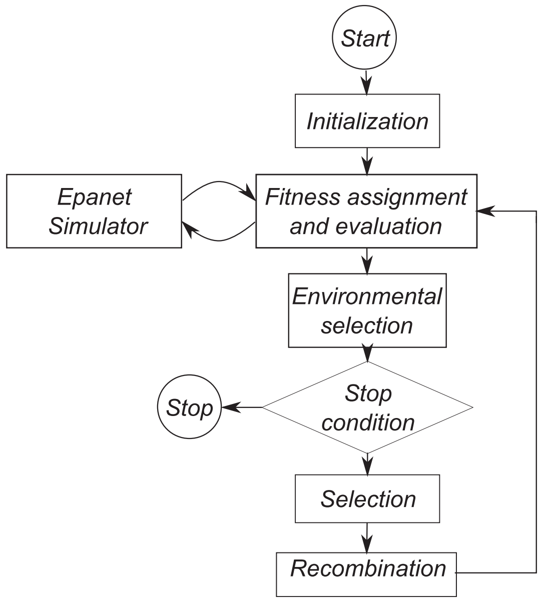


**Fig. 3.** Solution procedure flowchart.

## 3. Optimization problems

Assembling the above objectives and constraints yields the following two multi-objective optimization problems (13) and (14):

$$\underset{v\in \mathbf{V},u\in \mathbf{U},td\in \mathbf{Td}}{\text{Minimize}} \left\{J_1;J_2^1;J_3\right\} \qquad (13)$$
$$\text{Subject to}: \ (10),(11),(12)$$

$$\underset{v\in \mathbf{V},u\in \mathbf{U},td\in \mathbf{Td}}{\text{Minimize}} \left\{J_1;J_2^2;J_3\right\} \qquad (14)$$
$$\text{Subject to}: \ (10),(11),(12)$$

The difference between (13) and (14) is not only in the water quality objective. As (14) is based on water age there is no need to optimize the disinfectant concentrations at the system inlets, thus the overall number of decision variables is reduced.

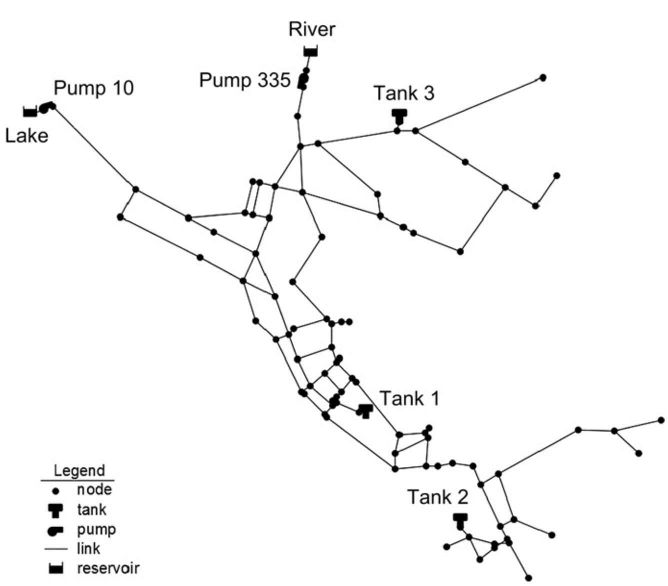


**Fig. 4.** Example application.

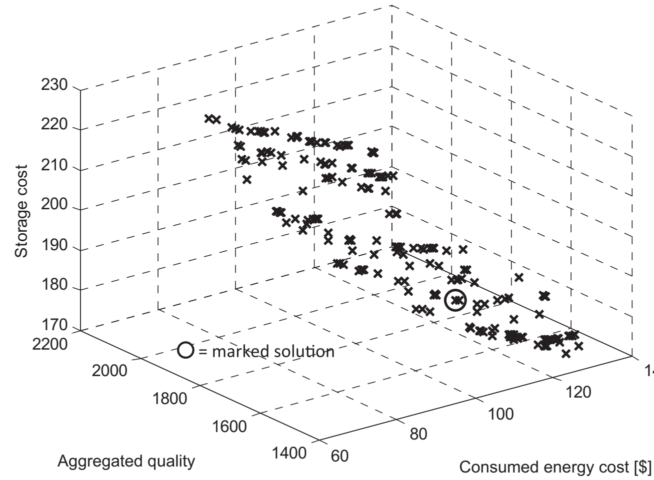


**Fig. 5.** Pareto set for a storage-reliability constraint of 6 h.

## 4. Solution procedure

The optimization problems defined in (13) and (14) require a multi-objective scheme for searching the Pareto optimal set. In this work SPEA2 (Zitzler et al., 2001) is utilized due to its superior diversity preservation mechanism based on a modified *k*-nearest neighbor approach. Its operation is based on a strength Pareto approach where the non-dominated set is determined by the strength of the dominators. Additionally, SPEA2 is also equipped with an external archive which allows preservation of the already obtained Pareto set approximation. The solution procedure flowchart is described in Fig. 3.

The algorithm starts with a random initialization of both the real variables and the binary coded tank diameters. Each solution residing in the working population is assessed for computing its corresponding objective function values and constraints, where the system behavior is simulated using EPANET. Once the entire population is evaluated, the strength of each solution is computed. A solution strength is expressed by the number of individuals which are dominated by the considered solution out of the combined archive and the current population. Next, the raw fitness of an individual is assessed as the sum of the strength of the solutions, which dominate it. Following this scheme the non-dominated individuals are assigned a raw fitness value of zero. This approach allows SPEA2 to take into account the quality of both the dominated and non-dominating solutions when assigning a fitness to an individual. To provide an efficient niching mechanism, the raw fitness is augmented with an adaptation of the *k*-th nearest neighbor algorithm.

Subsequently, a new archive is created by copying the non-dominated solutions from the merged archive and the current population. In case the size of the Pareto set exceeds the size of the archive, the solutions which occupy the most crowded regions of the Pareto set are neglected. Otherwise, if the size of the set is

**Table 1**
Impact of storage requirement on the span of the Pareto set approximations.

| Storage requirement (h) | Objective function | | | | | |
|---|---|---|---|---|---|---|
| | Operational cost | | Disinfectant concentration | | Tanks cost | |
| | Min | Max | Min | Max | Min | Max |
| 4 | 73.56 | 123.06 | 1350.17 | 1901.54 | 145.42 | 200.70 |
| 6 | 77.52 | 129.47 | 1425.46 | 2000.75 | 170.62 | 225.12 |
| 8 | 83.70 | 152.47 | 1253.56 | 2032.85 | 221.62 | 282.82 |

**Table 2**
Selected solutions for comparison based on the distance from the utopian solution.

| Storage requirement (h) | Utopian solution | | | Selected solution | | | Corresponding tank diameters (m) | | |
|---|---|---|---|---|---|---|---|---|---|
| | $J_1$ | $J_1$ | $J_2$ | $J_3$ | $J_2$ | $J_3$ | Tank 1 | Tank 2 | Tank 3 |
| 4 | 73.56 | 1350.17 | 145.42 | 102.24 | 1473.75 | 151.92 | 27.4 | 10.7 | 38.53 |
| 6 | 77.52 | 1425.46 | 170.62 | 104.99 | 1530.56 | 188.82 | 24.4 | 10.7 | 47.2 |
| 8 | 83.70 | 1253.56 | 221.62 | 108.48 | 1493.87 | 231.42 | 18.3 | 10.7 | 56.4 |

smaller than the archive, it is complemented by the best solutions with regard to their fitness. Once the new archive is populated a stopping condition is invoked to determine whether the algorithm should terminate. In this study a stopping condition based on a fixed number of generations is utilized. The number of generations was selected based on the performance of the algorithm during an extensive testing phase.

If the algorithm is to evaluate the next generation, then the selection of parent individuals is performed based on a constrained tournament (Deb, 2000). The conception of the constrained tournament is based on comparing first the constraint violation of the solution and later on comparing their fitness. Following this procedure feasible solutions are in favor to infeasible.

For the binary variables a single-point crossover and random mutation is used. In case of a real variable a simulated binary crossover (SBX) and polynomial mutation were selected (Deb, 2001). Once completed, the new population is evaluated and fitness values are assigned to the obtained solutions and for the ones from the archive.

## 5. Example application

The optimization problems (13) and (14) were tested on EPANET (USEPA, 2012) Example 3 (Fig. 4). The system consists of two reservoirs (sources) (a Lake and a River), three elevated tanks, 120 pipes, 94 nodes, and two pumping stations. The example full input file is freely available with the EPANET software from USEPA (2012).

SPEA2 was invoked with a population size of 300 and an external archive of 200, with nine binary (three per tank), and 96 real variables corresponding to the pumping schedules and the concentration set points for problem (13), and 48 real variables for problem (14). The mutation probability was set to 0.1, the crossover probability to 1, and the SBX crossover parameter to 1.5. The number of generations was selected as 500, allowing repetitive stable approximations of the Pareto sets. All computations were conducted on an Intel Core i5-2430M processor with 4 GB of RAM. A single run for generating the Pareto set took approximately 4 h.

The tanks diameter ranges were set to (15.2–39.6 m), (7.6–19.8 m), and (24.4–60.9 m), for Tank 1, 2, and 3, respectively, with eight equally spaced discrete diameters in-between each range. These ranges were selected based on the existing tank diameters of 26 m, 15.2 m, and 50 m, for Tank 1, 2, and 3, respectively.

### 5.1. Multi-objective problem (13)

Fig. 5 describes the Pareto set obtained for the case where water quality is expressed using disinfectant concentration [problem (13)]. This set corresponds to a storage-reliability constraint [Eq. (12)] of 6 h. It can be seen from Fig. 5 that the obtained Pareto set approximation is uniformly spaced in the objective space indicating a successful run of SPEA2.

The impact of the reliability-storage constraint is presented in Table 1. It can be seen from Table 1 that the less water is required the smaller is the energy and tank costs. With the increase of the required storage the energy and tanks cost increase. The water quality objective is comparable for all cases as the water circulation in the system is similar.

For comparing solutions which carry similar properties, a selection procedure based on an utopian solution is introduced (Miettinen, 1999). Likewise, other comparison methodologies could be employed (e.g., through utilizing game theory techniques as described in Salazar et al., 2007). Following Miettinen (1999) the utopian solution $z^*$ is first constructed using the minimum values of all objective functions (see Table 2).

$$z^* = \{\min\{J_1\}, \min\{J_2\}, \min\{J_3\}\} \tag{15}$$

Next, the span of the front $\Delta J_i$ for each of the considered objectives is computed:

$$\Delta J_i = \max\{J_i\} - \min\{J_i\}, \quad \text{for} \quad i = 1\ldots3, \tag{16}$$

Subsequently, for removing any preferences in the selection, the fronts are normalized using their span in the objective space, and finally a solution having the minimum distance to the utopian solution is selected for comparison.

$$\min_{p\in\Omega}\left\{\left[\left(\frac{J_1 - z_1^*}{\Delta J_1}\right)^2 + \left(\frac{J_2 - z_2^*}{\Delta J_2}\right)^2 + \left(\frac{J_3 - z_3^*}{\Delta J_3}\right)^2\right]^{\frac{1}{2}}\right\} \tag{17}$$

where $\Omega$ is the Pareto set resulting from solving the problem (13) or (14), and $p$ is the selected "balanced" solution.

In case of the Pareto set for 6 h of storage-reliability, the selected "balanced" solution is marked (Fig. 5). The values of all objective functions and their corresponding tank sizes are given in Table 2. Notice, that the main storage corresponds to Tank 3. Tank 2, due to its small size and location at the far end of the network, is kept

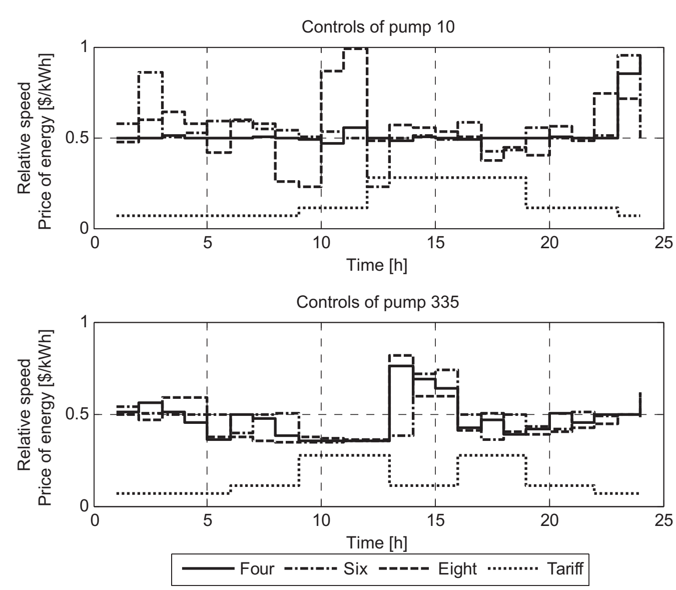


**Fig. 6.** Pump controls for the marked solution (see Fig. 5).

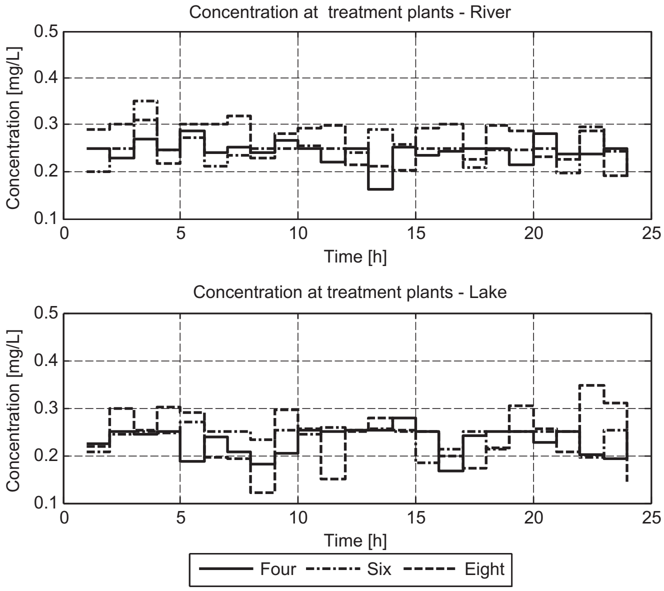


**Fig. 7.** Disinfectant concentration at the treatment plants for the marked solution (see Fig. 5).

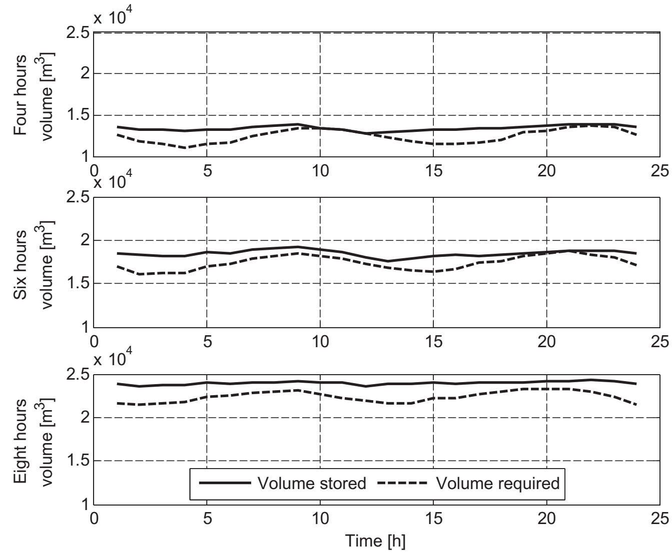


**Fig. 9.** Storage in the network for the marked solution (see Fig. 5).

relatively small, thus enhancing the minimization of water quality issues which might occur in its vicinity.

Next, the control actions corresponding to the balanced solution in Fig. 5 are explored (Figs. 6–10). First the pumping speed in relation to the energy tariff. Each of the pumps in the system is subject to a different energy tariff which clearly reflects its resulted speed (Fig. 6). As anticipated the pumping speed for the most restrictive storage-reliability constraint of 8 h yields the highest pumping speeds. At the same time, notice that pump 335 takes advantage of the midday cheap energy period.

Analogously, the concentration at the treatment plants is examined in Fig. 7. Due to the increased storage in the 8 h solution the corresponding concentration at the input to the system is generally higher. This is especially evident at the river source, and when comparing to the four and 6 h storage requirements.

Sustainable and reasonable tank operation is crucial for proper energy conservation and water quality maintenance within the network. The resulting tank operation over an extended time period is given in Fig. 8 for the balanced solutions presented in Table 2 and in Fig. 5. It can be seen from Fig. 8 that all tanks meet the water level terminal requirement. It might seem odd that the tanks level is the highest during the evening. This is due to the storage constraint, and the high consumer demands during the evening and night. The second tank located at the far end of the system is less influenced by the storage constraint and the tank sizing objective.

Turning the focus to the system storage and the impact of the storage-reliability constraint on it, it can be seen from Fig. 9 that in all cases the balanced solution attempts to minimize the volume of the stored water in the system. This is a valid outcome as storing excessive water would deteriorate the water quality and increase pumping cost. At the same time, the selected tank diameters allow the network to operate under similar pressures, with a mean of approximately 35 (m), a minimum of around 8–10 m, and a maximum of 70–75 m.

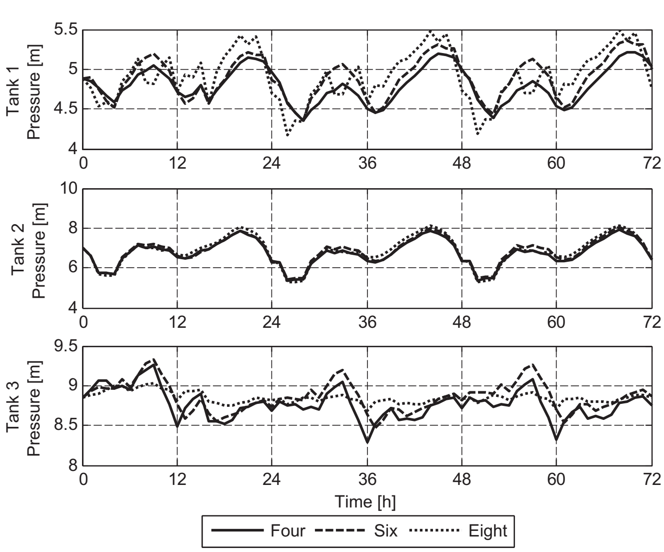


**Fig. 8.** Level at the tanks for the marked solution (see Fig. 5).

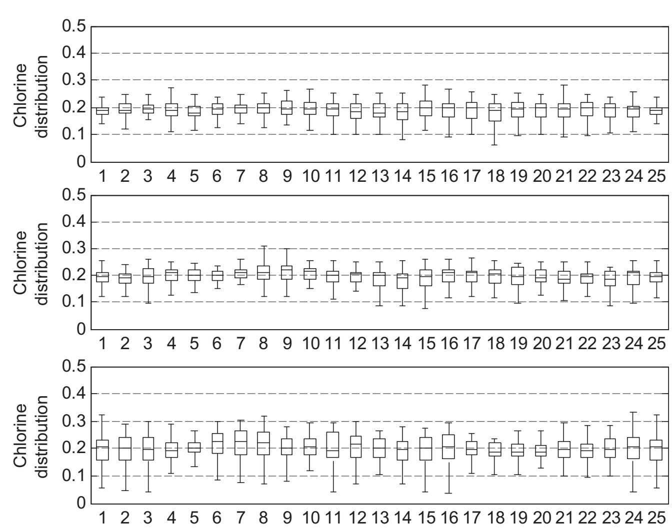


**Fig. 10.** Disinfectant distribution within the network for the marked solution (see Fig. 5).

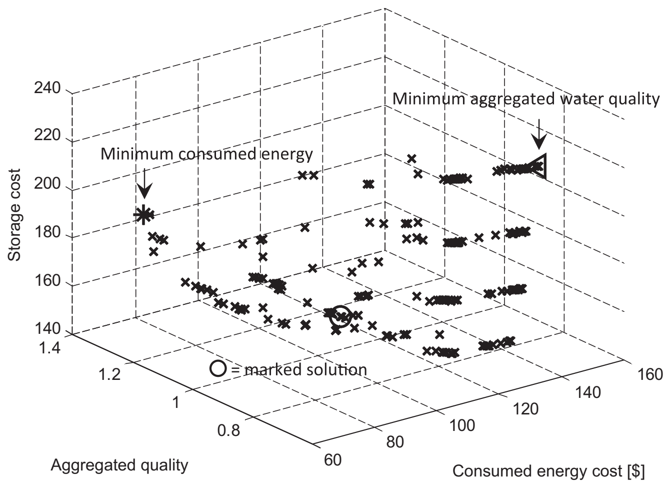


**Fig. 11.** The Pareto set for 4 h storage and water quality age based criterion.

Finally, the distribution of disinfectant within the network is presented if Fig. 10. The top plot in Fig. 10 corresponds to the 4 h storage-reliability constraint, the middle to the 6 h, and the bottom to the eight. The most noticeable influence of the storage constraint on the disinfectant distribution is visible for the 8 h storage requirement. The distribution of chlorine there is "wider" due to a higher storage in the systems, and the corresponding disinfectant deterioration at the tanks. This could be overcome by introducing additional booster chlorination stations within the network.

### *5.2. Multi-objective problem (14)*

In this section the proposed algorithm is demonstrated on the second water quality objective which is based on water age [problem (14)]. In this case a single Pareto set is explored for comparing how the solutions within a single front differ from each other.

Three solutions were selected. One of them marked with a circle in Fig. 11 is the "balanced" solution chosen according to the previously introduced utopian mechanism (Miettinen, 1999). The remaining two solutions (Fig. 11) are those having the minimum value of the water quality function (marked with a triangle) and the minimum value of the consumed energy (marked with *). Additionally, the selected solution values and their corresponding tank sizes are presented in Table 3. Note (see Table 3), that the solution having the best water quality value has also the largest Tank 3 size. This unexpected result will be further explained below.

In Fig. 12 the pumping speeds are presented for the three selected solutions described in Fig. 11. As expected, the solution having the minimum value of energy has smaller pumps speed, which translates to fewer consumed energy. In all cases the energy tariffs are exploited. This is especially visible for pump 335 which encounters an electricity tariff with a cheaper midday period.

In examining the tanks operation (Fig. 13) one can see that the dotted tank operation result, which corresponds to the best water quality solutions, is puzzling. The largest tank in the network (Tank 3) has almost a constant water level. Moreover, the tanks operation is significantly different to what was observed in the case of the disinfectant concentration water quality objective (see Fig. 8).

Could the different water quality measure have this kind of impact on the proposed operation of the system? Looking at the amount of water stored for the selected solutions (Fig. 14), it can be seen that the operation of the system is completely different for the three solutions. The best water quality solution (bottom plot) shows that the algorithm tries to keep the tanks full. Why is that? This is attributed to the assumption in the age based water quality criterion (Eqs. (6) and (7)) that only demand nodes are considered. This obviously overrules the tanks from this evaluation. The tanks influence the water quality only when water is discharged from them. The proposed methodology thus founded a way around this problem: it stores as much as possible water in the tanks so as to limit the amount of water withdrawn from them, which impairs water age.

**Table 3**
The selected solutions for comparison for the water age criterion.

| Storage requirement | Selected solutions | | | Corresponding tank diameters (m) | | |
|---|---|---|---|---|---|---|
| | $J_3$ | $J_2$ | $J_3$ | Tank 1 | Tank 2 | Tank 3 |
| Balanced | 98.11 | 0.90 | 162.5 | 15.2 | 12.2 | 42.7 |
| Best energy | 76.54 | 1.34 | 187.7 | 21.3 | 15.2 | 42.7 |
| Best quality | 141.37 | 0.69 | 221.62 | 15.2 | 9.14 | 56.4 |

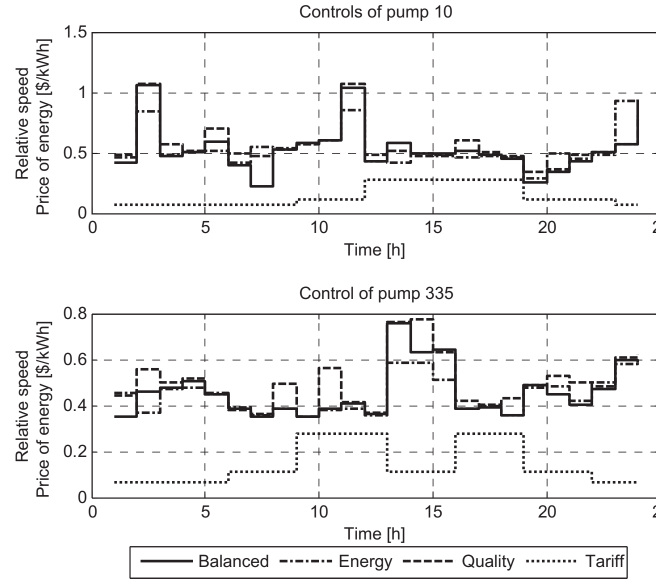


**Fig. 12.** Pump controls for the three selected solutions (see Fig. 11).

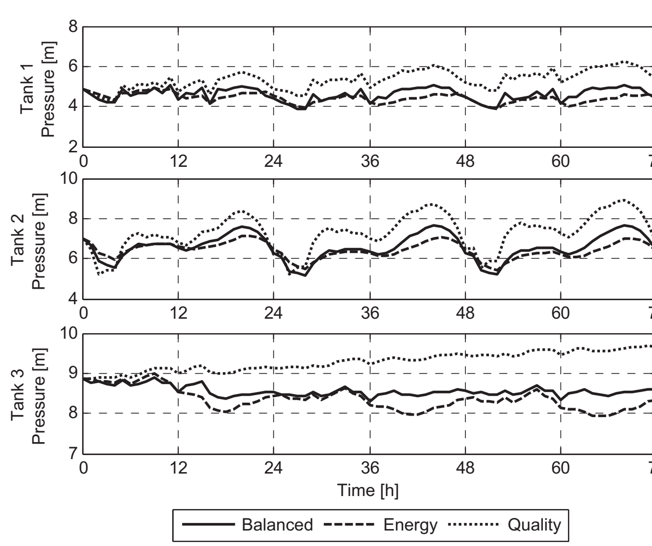


**Fig. 13.** Tanks operation level for the three selected solutions (see Fig. 11).

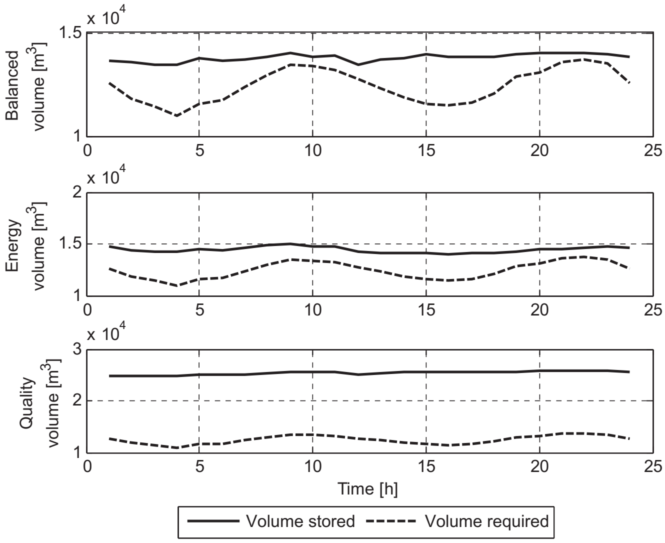


**Fig. 14.** Storage for the three selected solutions (see Fig. 11).

Observing the distribution of water age in the system (Fig. 15), it is apparent that most of the nodes have water age below the 12 h required threshold. However, the outliers on the box plot clearly show that the water age at some nodes rise. Those are the tanks, and the nodes supplied directly from them.

## 6. Discussion

A new integrated approach for storage sizing, water quality, pumps operation, and storage-reliability considerations was developed and demonstrated using two different water quality objectives: one based on disinfectant residuals and the other on water age. The multi-objective evolutionary algorithm SPEA2 was employed for the Pareto set computation while EPANET was utilized for simulating the system's hydraulic and water quality behavior.

All model outcomes were explainable and the Pareto fronts generated stable for all runs. The utilization of the water age objective revealed interesting understandable insights on the model performance, thus strengthening its potential for serving as a decision tool.

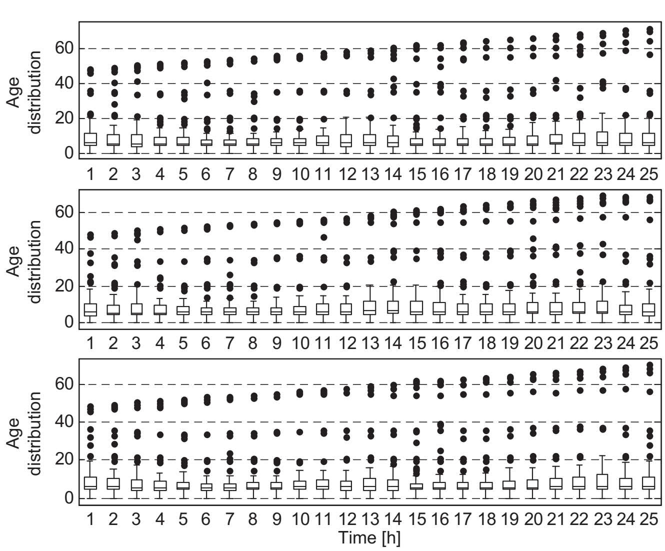


**Fig. 15.** Age of water for the three selected solutions (see Fig. 11).

Possible extensions of this work can include the incorporation of tank sizing at candidate system sites (i.e., not only at existing locations), integration of pumps scheduling at pumping stations, and assimilation of other/additional reliability/risk criteria as constraints or new objectives.

## Acknowledgments

This work was supported by the EU COST ACTION IC0806: Intelligent Monitoring, Control and Security of Critical Infrastructure Systems (IntelliCIS) and Polish MNiSW No. 638/N – COST/09/20/2010/0: Intelligent systems for monitoring, control and security of critical infrastructure plants: methodology, structures, algorithms and applications to drinking water distribution networks – (InSIK). The authors wish to express their gratitude for this support.

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## Glossary

*D:* number of time steps of predicted demand to be stored in the system,
$d_i(k)$: demand at node $i$ at time instant $k$,
$E_i(k)$: energy consumed by pump $i$ over time period $k$,
$f_{t,i}(\cdot)$: tanks cost function,
$F_q(\cdot)$: quality evaluation function,
$H_p$: control evaluation horizon length,
$\boldsymbol{J}$: subset of the monitored nodes,
$J_1(\cdot)$: first objective function corresponding to consumed energy,
$J_2^1(\cdot)$: second objective function corresponding to water quality expressed by disinfectant concentration,
$J_2^2(\cdot)$: second objective function corresponding to water quality expressed by water age,
$J_3(\cdot)$: third objective function corresponding to storage cost,
$p_t(k)$: head at tank $t$ at time instant $k$,
$\boldsymbol{P}$: set of controlled pumps,
$\boldsymbol{R}$: set of reservoirs,
$s_i(k)$: auxiliary variable indicating if the water age at node $i$ exceeds the water age threshold,
$\boldsymbol{T}$: set of tanks in the system,
$td_i$: diameter of tank $i$,
$\boldsymbol{Td}$: vector of tank diameters,
$u_i$: disinfectant concentration at treatment plant $i$,
$u_{min}$: maximum allowable disinfectant concentration,
$u_{max}$: minimum allowable disinfectant concentration,
$\boldsymbol{U}$: concentration patterns at the reservoirs,
$w(k)$: warning code returned by EPANET at time instant $k$,
$v_i$: speed of pump $i$,
$v_{min}$: minimum allowable pump speed,
$v_{max}$: maximum allowable pump speed,
$\boldsymbol{V}$: speed patterns for each pump belonging to set **P**,
$\alpha$: coefficient that relaxes the terminal constraint,
$\beta_i$: cost function coefficient,
$\gamma_i$: cost function coefficient,
$\eta_i(k)$: energy cost of pump $i$ over time period $k$,
$a_i(k)$: age of water at node $i$ at time instant $k$,
$a_{th}$: water age threshold,
$c_i(k)$: disinfectant concentration at node $j$ at time instant $k$.