Near real-time, optimal, and joint operation of pressure reducing valves and pumps for improving the operational efficiency of water distribution systems

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ABSTRACT

The new environmental paradigms imposed by climate change and urbanization processes are leading cities to re-think urban management services. Propelled by technological development and the internet of things, an increasingly smart management of cities has favored the emergence of a new research field, namely the smart city. Included in this new way of considering cities, smart water systems are emerging for the planning, operating, and managing of water distribution networks (WDNs) with maximum efficiency derived from the application of data analysis and other information technology tools. Considering the possibility of improving WDN operation using available demand data, this work proposes a hybrid and near real-time optimization algorithm to jointly manage pumps and pressure reducing valves for maximum operational efficiency. A near real-time demand forecasting model is coupled with an optimization algorithm that updates in real time the water demand of the hydraulic model and can be used to define optimal operations. The D-town WDN is used to validate the proposal. The number of control devices in this WDN makes real-time control especially complex. To cope with this feature, computational methods must be carefully selected and tuned. In addition to energy savings of around 50%, the methodology proposed in this paper enables an efficient system pressure management, leading to significant leakage reduction.

List of Symbols, Variables, and Acronyms

ANN - Artificial neural network;

DMA - District metered area;

NARX - Non-linear autoregressive neural network with exogenous input;

NSGA II - Non-dominated sorting genetic algorithm II;

PRV - Pressure reducing valve;

PSO - Particle swarm optimization;

VSD - Variable speed drive;

WDN - Water distribution network;

UKF - Unscented Kalman filter;

b^h - Bias of hidden layer;

b^o - Bias of output layer;

C - Pump operational costs;

c_t - Energy cost at time step t;

c_1 - Cognitive parameter;

c_2 - Social parameter;

d_x - Index for number of exogenous components;

d_y - Index for number of delay elements;

$F(\cdot)$ - State function;

$f_h(\cdot)$ - Activation function for hidden layer;

$f_o(\cdot)$ - Activation function for output layer;

$g(\mathbf{s})$ - Constraint function calculated for a solution vector s;

$H(\cdot)$ - UKF function;

$H(\alpha_{p,t})$ - Hydraulic head added by pump p at time step t;

$K_{v,t}$ - Setpoint of the valve v at the time step t;

$L_{k,max}$ - Maximum tank level of tank k;

$L_{k,min}$ - Minimum tank level of tank k;

$L_{k,t}$ - Tank level of tank k at time step t;

m_{max} - Maximum number of switches allowed during the operational horizon;

m_p - Number of switches during the operational horizon for pump p;

Nn - Number of nodes in the network;

$\mathbf{n}_t$ - Measurement noise;

P_e - Operational horizon;

$P_{j,t}$ - Pressure at node j at time step t;

P_{min} - Minimum operational pressure allowed;

$Q(\alpha_{p,t})$ - Flow pumped by pump p at time step t;

r_1 and r_2 - Random numbers.

$\mathbf{v}_t$ - Process noise;

w - Inertia weight;

w_h^o - Weight h for output layer;

w_i^h - Weight i for exogenous data in hidden layer;

w_j^h - Weight j for delay data in hidden layer;

$x(i)$ - Component of exogenous input vector;

$\mathbf{x}_t$ - exogenous input for time step t;

$y(k)$ - Output value at time k;

$\mathbf{y}_t$ - Output value for time step t;

$\alpha_{p,t}$ - Speed of pump p at time step t;

$\mathbf{\Gamma}^t$ - Global best position at iteration t;

γ - Specific weight of water;

Δt - Duration of the time step;

δ_t - State vector at time step t;

ζ_i^t - Position of particle i at iteration t;

$\eta(\alpha_{p,t})$ - Efficiency of pump p at time step t;

λ_i^t - Local best position at iteration t;

v_i^t - Velocity of particle i at iteration t;

$\rho(\mathbf{s})$ - Penalty function calculated for a solution vector s;

INTRODUCTION

Operational decisions in water distribution systems should be made to supply consumers under safe conditions, and address growing environmental challenges. It is critical to develop consistent methods for decision-making in water distribution systems to reduce operating costs and energy consumption, while maintaining sufficient quality of service and also recovering energy when possible. Operational rules for pumps and valves can bring significant improvements to the hydro-energetic efficiency of water distribution networks (WDNs) (Abkenar et al., 2013; Bene et al., 2013; Skworcow et al., 2014; Brentan et al., 2015; Lima et al., 2017).

Several works have been proposed in the literature as solutions for optimal pump scheduling. These proposed techniques include: linear programming (Jowitt and Xu, 1990); dynamic programming (Jowitt and Germanopoulos, 1992); and evolutionary algorithms, such as genetic algorithms (GAs) (Farmani et al., 2007) and particle swarm optimization (PSO) (Brentan and Luvizotto Jr, 2014).

With the development of computational hydraulic models, many optimization algorithms may be coupled with various hydraulic models. As an example, Sakarya and Mays (2000) presents a non-linear optimization method coupled with EPANET (Rossman, 2000) to determine the optimal operation of pumps, while considering water quality. The authors, using an hourly discretization of time, find the pump statuses (switch operations) for each time step. Pump optimization using suitable switch operation has been exploited to reduce energy consumption and reduce the number of pump switches, as presented by Tang et al. (2014). The authors render the pump optimization process into a general optimal control (GOC) procedure and use PSO to solve the optimization problem.

The use of bio-inspired algorithms can also be highlighted for pump scheduling problems. (Wegley et al., 2000) presents pump scheduling optimization with variable speed drives (VSDs). The authors highlight the efficiency of the method to control pressure and reduce energy costs for WDN operation. López-Ibáñez et al. (2008) propose the ant colony optimization algorithm to define optimal maneuvers of pumps, comparing the results for two networks, and concluding that computational efficiency is improved. Brentan and Luvizotto Jr (2014) apply a modified version of PSO, with two levels, to define the optimal pump scheduling for pump stations with VSDs. In the first level, the algorithm determines the pumps that will operate at each time-step, and in the second level, the method finds the optimal speed for each pump. Recently, the optimal control of pumps working with VSDs was exploited from the control theory viewpoint, as presented by (Page et al., 2017). The authors highlight the benefits of a hybrid approach (hydraulic and control theories) for optimal pump control.

In addition to pumps, optimal operation can be applied to pressure reducing valves (PRVs), which, if well operated, enable the reduction of water loss through pressure management. Some works are proposed in the literature to define the optimal location and operational point of control valves, with the focus on PRVs (Araujo et al., 2006; Dai and Li, 2014; Brentan et al., 2017c; Fontana et al., 2017).

The optimal placement of valves using GAs is addressed by Reis et al. (1997). In this work, the authors define the number of PRVs and the location of each. Nazif et al. (2010) propose a hybrid model using GAs and artificial neural networks (ANNs) to estimate the hydraulic state of a WDN. The authors aim to improve pressure management. Dai and Li (2014) present an optimal valve placement by mixed integer and non-linear programming, addressing the physical and operational constraints of the hydraulic problem using penalty functions. De Paola et al. (2017) present an effective methodology for PRV placement and control solved with the harmony search algorithm. Leakage is minimized as a result of the improved operation of PRVs.

Most recently, interest in dividing WDNs into district metered areas (DMAs) has gained space in WDN analysis. Such a division enables not only a better management of the system, but also the determination of specific rules that can improve the hydraulic and energetic efficiency of systems (Abraham et al., 2017; Campbell et al., 2016). Aiming to improve pressure management, Brentan et al. (2017c) present a network community detection algorithm coupled with a multi-level optimization technique for the optimal placement and definition of operational set-points for PRVs. According to the authors, the multi-level optimization process reduces computational effort during optimization. In the first level, the optimal placement of the valves work with integer variables, while in the second level, that is to say, for the optimal operational point, the process works with continuous variables.

Although optimal operation of WDNs has been approached with different techniques, the joint optimal rule definition for valves and pumps has not yet been fully exploited. AbdelMeguid (2011) presents the modulation of PRVs and the optimal operation of pumps for reducing leakage and improving the energetic efficiency of the WDN. Gao et al. (2014) present an algorithm to reduce energy costs and water loss through the optimal control of pumps and valves. The authors added the costs related to the lost water volume on top of the energy cost in the worse pressure management scenario. Tricarico et al. (2014) propose a joint operation of pumps and valves and also pumps as turbines (PATs) for the optimal management of water systems. A multi-objective analysis was conducted, minimizing the energy costs, the difference between the minimal allowed pressure and the operational pressure, and maximizing the energy recovered by the PATs. In this case, the Pareto front must be analyzed by the operators, who, using their practical skills, can identify the best operational solution.

In addition to this joint control, an analysis during a suitable operational horizon must be taken into account to find overall optimal control rules. This horizon is paramount because water demand oscillates during the day, and optimal control rules can rapidly become outdated for a new set of demands. Near real-time control can bring improvements to WDN management. Kang (2014) presents a joint pump and valve control in near real-time. The authors define the statuses of the pumps (ON/OFF) controlling the maximum and minimum pressures with feedback of the hydraulic state from a supervisory control and data acquisition (SCADA) system. A GA coupled with EPANET was used to update the demand data by means of a demand forecaster model. Skworcow et al. (2010) present a predictive control approach to operate pumps and valves at near real-time by processing on-line SCADA data and finding operational rules to minimize energy costs and leakage. The authors highlight the benefits of on-line predictive control when compared with the off-line control.

Following the line of optimal control in near real-time, Eker and Kara (2003) consider pump control for distribution tanks. The model also receives feedback from the hydraulic state and generates the action rules for the control devices. The approach presented by Shamir and Salomons (2008) uses on-line control for optimal management of the real network in Haifa. The optimal rule algorithm, developed with GAs, is coupled with a SCADA system that updates the hydraulic information each time step. Despite the high quality results, the real-time approach is impaired by the computational time burden.

Multi-objective algorithms have also been applied for the optimal control of pumps. Odan et al. (2015) develop a model with two calculation cores. The first is responsible for estimating the water demand in real-time. This demand is communicated to the second core for optimization, where the Pareto front is determined for two objectives: minimum energy consumption and maximum operational reliability.

Recently, a systematic literature review about optimal operations in WDNs presented by Mala-Jetmarova et al. (2017) highlighted efforts (during the last decade) to address the joint control of pumps and valves with near real-time optimization algorithms. More than one hundred published papers on the optimal operation of WDNs were revised. The authors pinpoint that only 15% of optimal operation papers take into account pumps and valves jointly. Furthermore, only 5.5% of the published papers use meta-heuristic algorithms to solve operational problems. The authors conclude their review on the future of the operational optimization by highlighting the need to incorporate uncertainty parameters (such as water demand and pipe roughness), as well as the need to develop efficient computational models to solve genuine real-time problems. The real-time control of various devices (pumps and valves) using the predictive approach is a research field still to be explored.

Considering the need to invest in optimal operation research, this work presents a near real-time methodology to find optimal joint operations for pumps working with VSD and PRVs. The methodology is a compound of two main cores: the water demand forecasting core and the optimal operation core. In the former, the algorithm estimates the water demand based on climatic and social information, together with past hydraulic states. Taking this estimated demand, the optimization core is triggered to define new operational rules to minimize energy consumption and water losses. A study on warm solutions that reduces the computational effort for finding new optimal solutions is also presented.

The proposed methodology is applied to the D-town network (Marchi et al., 2012), presented in the Battle of Networks II. This network exposes the optimization algorithm to a large problem, thus enabling a robust performance evaluation. Furthermore, as this network has been widely studied by different works, a comparison of control performance is also conducted.

The remainder of the paper is organized as follows. The next section presents the tools proposed to tackle near real-time demand forecasting. A new section then develops the optimization process, including the concept of warm solutions. The D-town network and the results obtained are then presented. Finally, an insightful discussion together with conclusions is provided. The References section closes the paper.

NEAR REAL-TIME DEMAND FORECASTING

A central element in near real-time control of WDNs must be the highly accurate estimation of water demand. Accurate demand estimation is essential for building a computer routine able to produce control strategies to meet demand.

Several works are found in the literature for short-term water demand forecasting. Frequently, time-series are used for this task (Jain et al., 2001). Maidment et al. (1985) present a development of temporal series based on rain and temperature data, including a Box-Jenkins type transfer function (Box et al., 2015). Seasonal autoregressive integrated moving average (SARIMA) models also are applied for demand forecasting, as found in (Cutore et al., 2008; Mombeni et al., 2013). However, according to Voitcu and Wong (2006), average models are not always able to estimate demand, mainly because of the linear modelling associated with the mean value.

With the increase of machine learning tools, new models for short-term water demand forecasting have flourished in the literature (Bougadis et al., 2005; Adamowski and Karapataki, 2010; Herrera et al., 2010; Xu et al., 2011; Brentan et al., 2017d). The possibility of processing highly non-linear correlations of the demand variable has situated machine learning methods in an outstanding position within the state estimation research field.

However, the usual (static) approaches of machine learning tools have difficulties considering new data arriving from real-time measurements and network monitoring, and, as a result, new information must be stored until new training and tuning of the obsolete tool is performed. The use of this information frequently requires the re-training from scratch of the forecaster model. As a result, these types of static models lose valuable time training to avoid becoming outdated, mainly when the data structure changes, thus impairing the forecasting process (Brentan et al., 2017d).

Transforming static into dynamic models, thus allowing quick decision-making (Montalvo and Deuerlein, 2014), is a growing research field. Dynamic models emerge as a link between acquisition systems and static models, and can improve the final results of demand forecasting (Herrera et al., 2014). The development of dynamic models requires high computational efficiency. Van Vaerenbergh et al. (2006) proposes a sliding data window applied to a kernel regression algorithm, which updates the model parameters step by step. Brentan et al. (2017d) also present a sliding data window for a hybrid model using support vector machines and Fourier series for real-time demand estimation.

Taking into account the need for a highly accurate demand forecasting model to define in near real time the optimal maneuvers, this section presents an alternate method based on a hybridization process of an ANN, namely a non-linear auto-regressive with exogenous input ANN (NARX), and an unscented Kalman filter (UKF). The NARX is able to process the climatic and social information in the data, thus estimating the demand with good accuracy, while the UKF assimilates new data by adjusting the error of the NARX.

Non-linear auto-regressive with exogenous input - NARX

Several ANNs have been proposed in the literature to synthesize dynamic spaces, that is to say, spaces considering temporal relationships. The modification of feedforward networks with recurrence features is a common approach to tackle dynamic processes. Recurrence relationships are internal loops in the ANN, which enable using the output of a layer as an input for other previous layers. Starting from the architecture of a multi-layer perceptron (MLP), several recurrence relations can be considered that define various recurrent networks.

Among these recurrent networks, the NARX (Lin et al., 1996) creates just one loop, using the final output, y, as input for the first layer, thus contributing with the temporal trend of (in our case) water demand, as observed in figure 1. The number $d_y + 1$, of past output data transformed into input is called delay, while the input vector including the last $d_x + 1$ observations, $(x(k), x(k-1), \ldots, x(k-d_x))$ is the so-called vector of exogenous variables (Brentan et al., 2017a).

The output $y(k+1)$ of a NARX is calculated similarly to the output of an MLP, and corresponds to a multi-process with activation functions, f_o for the output layer and f_h for the hidden layer, acting on the products between the input vectors and the weight vectors. However, the NARX adds the contribution of the delay data, as shown:

$$y(k+1) = f_o\left(\sum_{h=1}^{N} w_h^o \cdot f_h\left(\sum_{i=0}^{d_x} w_i^h \cdot x(k-i) + \sum_{j=0}^{d_y} w_j^h \cdot y(k-j) + b^h\right) + b^o\right). \tag{1}$$

Here N is the number of neurons in the hidden layer; w_h^o are the weights of the output layer; w_i^h and w_j^h are the weights of the hidden layer corresponding to exogenous input and delays, respectively; and b^h and b^o are the biases for the hidden and output layers, respectively.

The weight tuning process (or training) of a NARX can be done using a backpropagation algorithm, as in the training of an MLP. However, the convergence time for a NARX is much longer than for an MLP (Lin et al., 1996). Consequently, a number of adaptations are implemented in the backpropagation algorithm that lead to a gradient descent algorithm which shows good properties in the training process (Haykin and Network, 2004).

Unscented Kalman filter - UKF

Within the field of non-linear filters, the UKF, proposed by Julier and Uhlmann (1997), presents various improvements for the general extended Kalman filters, mainly for the linearization method, which reduce errors and save computational time.

The main idea of a Kalman filter is to estimate a state from a dataset affected with noise and other uncertainties. This state is a compound of unknown variables that tend to be more precise than those based on a single measurement. Typically, a nonlinear dynamic system is described as:

$$\delta_{t+1} = \mathbf{F}(\delta_t, \mathbf{x}_t, \mathbf{v}_t), \tag{2}$$

$$\mathbf{y}_t = \mathbf{H}(\delta_t, \mathbf{n}_t), \tag{3}$$

where δ_{t+1} is the unknown state, the response to an exogenous input $\mathbf{x}_t$, $\mathbf{y}_t$ is the observed signal, $\mathbf{v}_t$ is the process noise, and $\mathbf{n}_t$ the measurement noise.

Hybrid online time-series analysis

The intensive monitoring of systems generates huge amounts of data, requiring advanced tools for exploration and information retrieval from these measurements. Online processing of data can be useful to improve the control of a system, since the introduction of new information on the system state makes control easier. Online water demand forecasting using hybrid models has been proposed with the aim of improving quality and accuracy. However, the use of online machine learning tools can be difficult, since the continuous tuning of parameters as new data arrives requires considerable computation time. The use of hybrid models, as proposed by Brentan et al. (2017d), is useful because the underlying robust machine learning method is only retrained for long intervals, while much less expensive time-series analysis methods perform real-time updating.

In this work, the NARX processes the environmental data to estimate the water demand for a DMA, and the UKF is responsible for the estimation of the error made by the NARX. The UKF is adjusted dynamically, assimilating the new measured values for the demand in the DMA (working with a sliding window). In each time-step, the oldest demand data is disregarded, while the new measurement is assimilated. With the new window of data, the UKF parameters are adjusted and the future value of the error is estimated.

OPTIMAL MANAGEMENT OF PUMPS AND VALVES

Optimization problem statement

The improvement of the hydro-energetic efficiency of the system can be interpreted in two ways: namely, as a reduction of the energy consumption through optimal control of pumps; and as better pressure management, thus reducing physical water losses.

Considering the hydraulic interactions between the set of control devices in the networks and the set of hydraulic states, the joint operation of pumps and PRVs can maximize the hydro-energetic efficiency of the systems, since the operational point of one device will affect the operational points of other devices.

The operational costs C related to pump operation can be written in terms of the associated energy cost. This, in turn, is related to the pump rotational speed α, as shown in equation (4) for a number of pumps N_p operating during P_e periods of time.

$$C = \sum_{p=1}^{N_p} \sum_{t=1}^{P_e} \frac{Q(\alpha_{p,t}) H(\alpha_{p,t}) \gamma}{\eta(\alpha_{p,t})} \cdot \Delta t \cdot c_t. \quad (4)$$

Here, for the rotational speed, $\alpha_{p,t}$, of pump p at time step t, $Q(\alpha_{p,t})$ is the flow through the pump, $H(\alpha_{p,t})$ is the pump head, and $\eta(\alpha_{p,t})$ is the pump efficiency; γ is the specific weight of the fluid, and c_t is the energy cost at time step t.

In the second case, the benefits related to pressure management in the system derive from the reduced volume of water losses. This volume is a function of the operational pressure and can be used to calculate the equivalent price of lost water. However, in several countries water is much cheaper than energy. As a result, minimizing the global (associated to energy and water losses) cost of operation using a single objective approach can lead to scenarios where the electrical energy cost is effectively minimized, but overrides the water loss, which is effectively disregarded. However, the minimization of pressure also minimizes leakage flow. Usually, a WDN should be operated at a minimum pressure for a safe and adequate supply to consumers. Taking the minimum pressure as P_{min}, a possible way to minimize the water loss is by bringing the operational pressure $P_{j,t}$ of any node j at any time t as close as possible to the minimum pressure. The final objective function can be written as a sum of dimensionless terms of energy and pressure as:

$$\frac{C}{max(C)} + \sum_{t=1}^{Pe} \sum_{j=1}^{N_n} \frac{|P_{j,t} - P_{min}|}{P_{min}}, \tag{5}$$

where the division by $max(C)$ and P_{min} is used to turn the values dimensionless.

Considering the operational problem in hand, the candidate maneuvers considered in this work are changes in the rotational speed of pumps and/or set-points of modulated PRVs. This means that, at each time step, each pump and each valve may have its settings updated. A set of constraints can be identified to maintain a safe operation. The constraints are linked to the minimum pressure, the fluctuation tank levels, the minimum speed for pumps and the maximum number of switches of pumps. Thus, the operational constraints may be written as:

$$L_{k,min} < L_{k,t} < L_{k,max}, \tag{6}$$

$$L_{k,1} \simeq L_{k,P_e}, \tag{7}$$

$$P_{j,t} > P_{min}, \tag{8}$$

$$m_p < m_{max}, \tag{9}$$

where $L_{k,min}$ and $L_{k,max}$ are the minimum and maximum tank levels for tank k, and $L_{k,t}$ is the tank level at time step t in tank k. As this work considers the possibility of turning off the pumps if the pump speed is lower than the minimum, it is important to define the maximum number of allowed switches during a given period, m_{max}, to avoid spending financial resources on maintenance. The hydraulic simulator EPANET is used to calculate the hydraulic state for the different solutions in the optimization process. Additionally, the possibility of turning off the pumps turns the optimization process into a non-continuous problem, hampering the use of classical optimization tools.

To handle the operational constraints, the use of penalty functions is a common approach for single-objective optimization. In general, the penalty methods use functions that increase the value of the objective function to be minimized, when any constraint is violated (Yeniay, 2005). Typically, for a constraint given by a function $g(\mathbf{s})$ calculated for a solution $\mathbf{s}$, which should be non-negative, a penalty function $\rho(\mathbf{s})$ is defined as:

$$\text{If } g(\mathbf{s}) < 0 \Rightarrow \rho(\mathbf{s}) > 0; \tag{10}$$

$$\text{If } g(\mathbf{s}) \geq 0 \Rightarrow \rho(\mathbf{s}) = 0. \tag{11}$$

From the mathematical point of view, the use of penalty functions modifies the search space and generates deformations along the boundaries between feasible and unfeasible regions corresponding to the violated constraints, thus avoiding the optimization method to find solutions in the unfeasible region. However, the deformation of the search space produces the side effect of creating local minima in the feasible area, so that the use of penalty functions frequently makes the optimization process harder.

Several mathematical approaches have been developed to treat the problems associated with penalty functions (Wu and Simpson, 2002; Van Dijk et al., 2008; Vassiljev et al., 2015). Among them, (Marchiori et al.) present a broad comparison among various penalty functions applied to WDN optimal design. The authors highlight the effects of this approach on various search spaces, and the comparison of eight penalty functions pinpoints the need for deeper studies to find the best approach to handle the constraints.

The following penalty function Parsopoulos and Vrahatis (2002) is used in this research:

$$\rho(\mathbf{s}) = \omega \mid g_{ref} - g(\mathbf{s}) \mid . \tag{12}$$

Here ω is the penalty scale factor, adjusted for each optimization problem, and g_{ref} is the reference value for the considered variable to be compared with $g(s)$ for a given solution s.

Warm solutions

Optimal management of pumps and valves in near real-time requires the optimization process to converge quickly. In general, bio-inspired algorithms use a random initialization of solutions. This random initialization can lead to a large and slow optimization process, mainly caused by the many unfeasible initial solutions. Furthermore, the WDN simulator, which is usually coupled with the bio-inspired optimization algorithm, can also increase the optimization process, due to the time needed to solve the hydraulic equations, which makes the simulator unstable for unfeasible solutions.

Among the many alternatives to improve the efficiency of the optimization process, Wu and Zhu (2009) present a parallel and distributed computation scheme for the pump scheduling optimization and López-Ibáñez et al. (2008) implements a parallel code of the hydraulic simulation of EPANET. To reduce the time to obtain the hydraulic state of the system, some authors propose the use of machine learning techniques, highlighting ANNs trained with a large set of feasible hydraulic scenarios as a surrogate for the hydraulic model during the optimization process (Broad et al., 2005; Rao and Alvarruiz, 2007; Nazif et al., 2010; Behandish, 2013; Behandish and Wu, 2014). The development of warm solutions is also used by Pasha and Lansey (2014) to minimize convergence problems. Warm solutions are nearly optimal solutions. The interesting feature of this type of solution is the high probability of being feasible, thus improving the convergence of the optimization process. The authors compare three strategies to accelerate the optimization problem, concluding that the use of warm solutions is the most efficient, even when compared with the surrogate of a hydraulic model by an ANN or the use of parallel computing.

The proposed methodology to generate warm solutions in this work is based on two scenarios. The first scenario considers the nonexistence of previous optimal solutions and is applied at the start of the optimization process. In this case, an optimization process to define the optimal maneuvers for pumps and valves is performed using the mean demand of a day. For each time step, an initial solution vector is created taking the optimal solution found for the mean demand. This vector is used to initialize the optimization process in real-time. In this process, the mean demand is changed by the forecasted demand and the optimal operation is found by adjusting the warm solution. The second scenario considers the existence of a previous optimized scenario, such as the last day values. In this case, the initialization is performed using the optimal solution of a previous and corresponding time step.

In each time-step, the optimal solution should guarantee full water supply to consumers. The hydraulic states should be obtained at each time-step optimization to evaluate the operational constraints. Simulations are conducted for the entire day by keeping track of the vector containing all the operational rules. At the first time step, the operational vector is only composed of warm solutions. For the following time steps, this vector is composed of a combination of the previously found optimal solutions and warm solutions.

Figure 2 presents the construction of the solution vectors using the warm solutions and the operational vector, which is used to obtain the hydraulic state of the network. Observe that, at each time step t, the vectors are composed of the speed of each pump p, $\alpha_{p,t}$, and the valve set-point $K_{v,t}$ of each valve v.

Particle swarm optimization - PSO

Among several bio-inspired algorithms, PSO, initially proposed by Kennedy and Eberhart (1995), can be highlighted as one of the most efficient evolutionary algorithms in terms of quasi global solution search and processing time. As in the case of other evolutionary algorithms, the solutions are improved in each iteration by comparison with other previously obtained solutions. For a D-dimensional problem, a particle (candidate solution) i, has an associated position, ζ_i, which is written as a vector with D coordinates, $\zeta_i = (\zeta_{i1}, \zeta_{i2}, ..., \zeta_{iD})$. The velocity of the particle can also be written as a vector with D coordinates, $v_i = (v_{i1}, v_{i2}, ..., v_{iD})$.

In each time step, particles compare their positions and save the best position of the group, the so-called gbest, $\mathbf{\Gamma} = (\gamma_1, \gamma_2, ..., \gamma_{iD})$. Each particle also saves its best position during iteration, the so-called lbest (for local best), $\lambda_i = (\lambda_{i1}, \lambda_{i2}, ..., \lambda_{iD})$.

The gbest and lbest vectors are used to update the velocity of the particle from an iteration t to the next $t + 1$, taking into account the current velocity of the particle $\mathbf{v}_i^t$. Equations 13 and 14 represent the updating process of PSO.

$$v_i^{t+1} = \mathbf{w}v_i^t + c_1 r_1 \frac{\zeta_i^t - \lambda_i^t}{\Delta t} + c_2 r_2 \frac{\zeta_i^t - \mathbf{\Gamma}^t}{\Delta t} \tag{13}$$

$$\zeta_i^{t+1} = \zeta_i^t + v_i^{t+1} \Delta t \tag{14}$$

Here $i = 1, 2, \cdots, M$ are the particles, w is the inertia weight, $c_1 = 1.5$ and $c_2 = 1.5$ are cognitive and social learning coefficients, respectively, and r_1 and r_2 are random numbers responsible for introducing diversity into the optimization process, thus avoiding local optima. The inertia weight is calculated at each time step, varying from 1.2 to 0.4, and decreasing linearly. The values of c_1 and c_2 are selected according to the convergence criteria presented by (Eberhart and Shi, 2001). There are other approaches in the literature, for example, Montalvo et al. (2010), using self-adaptive values for c_1 and c_2. However, in this paper the authors show that the self-adaptive values, in general, approximately converge to the values considered in our paper. Two alternative termination criteria are used to stop the PSO algorithm: the number of iterations without improvements (50 iterations); or the total number of iterations (5000 iterations).

CASE STUDY - D-TOWN WATER NETWORK

The case study presented in this work is the network known as D-town in the literature (Marchi et al., 2013), with the topological solution presented by Stokes et al. (2012). The network is composed of 388 nodes, 429 pipes, 13 pumps, 4 PRVs, 1 reservoir, and 7 tanks, and is divided into 5 DMAs. In this work, pumps with VSD with a minimum speed of 70% of the nominal speed, and undergoing a maximum of four switches per day, together with modulated PRVs, are considered to generate the optimal management of the system. The minimum pressure at the demand nodes is 25m, and 0m for non-demand nodes. Figure 3a presents the D-town topology and figure 3b presents the DMA configuration and the monitoring nodes. The nodes are located exactly in their corresponding physical coordinates (latitude and longitude).

The D-town network was selected as a case study considering the complexity to determine optimal operations due to the number of control elements, namely 13 pumps and 4 PRVs. Furthermore, the solution presented by Stokes et al. (2012) contains a control scheme for the pumps that enables a comparison of results. The electrical tariff varies during a day as presented by Marchi et al. (2013).

The benchmark networks found in the literature generally enable comparisons with other works and guarantee manageable scenarios. In these cases, the oscillation of the water demand during a day is typically approximated by a quasi-periodical function, mainly in the case of residential consumers. However, using these quasi-periodical functions precludes any on-line approach due to the absence of real consumer data in the literature networks. Still, it is well known that the random feature of some consumers directly affects the water demand pattern. To synthesize the real behavior of water demand, the methodology proposed by Brentan et al. (2017b) is applied. This methodology takes into account the mean behavior of the water demand and the allocated nodal base demand to generate a random noise signal that is summed on top of the standardized average demand. The noise is obtained by an analysis of real demand data for a number of DMAs. This procedure enables following the original demand trends of a literature hydraulic network, while adding the random behavior of consumers, which for near real-time forecasting and optimal control is paramount. In our case, the study is based on real data from Franca, a Brazilian city, and considers five of its DMAs to evaluate the mean behavior of water demand.

A two-year water demand dataset was generated for each DMA of D-town. We followed the procedure described by considering the mean value of the original pattern of the network and the noise created within the normalized range obtained by the analysis of Franca's DMAs. This dataset was complemented with environmental data (temperature, air humidity, presence of rain, and wind velocity) from Franca, to build a 1.5-year dataset for training purposes, while another 0.5-year dataset was considered to test the NARX ANN.

Using the trained network made of 30 hidden neurons and trained with a delay of 24 hours, it is possible to find the optimal operation for any day, using the estimated demand to surrogate the mean demand presented to the model. The time needed to forecast each time step demand is

0.085s. Figure 4 presents a comparison between the real (generated) and the forecasted demands. The average value of the root mean squared error (RMSE), taking the RMSE for the five DMAs, is $1.80m^3/h$ and the correlation coefficient is 0.998, showing the high quality of the demand forecasting model. The algorithms are run in a computer running an Intel inside core i7 2.7Ghz.

To find the optimal solution and to compare the classical approach for the optimal operation, the optimal control for pumps and PRVs was found using the PSO algorithm applied to the model with the mean demand. In this case, considering the horizon of one day with a time-step of an hour, the number of decision variables is 408. Following the literature recommendations, a swarm with three times the number of variables was used in the optimization process. The comparison of this approach with the scenario without optimized control, that is to say, with all pumps working at nominal speed and with all valves open, shows that it is possible to obtain a reduction of 42.55% of energy consumption. In terms of pressure management, Figure 5 compares the scenarios for minimum and maximum demands. It is possible to note some regions where the operational pressure reaches the minimum values, as expected from the optimal pressure management viewpoint. The optimization process to find pump speeds and PRV settings took approximately 18 hours.

Using the solution of the mean demand to initialize the near real-time optimal control process, the optimal point changed from the mean scenario to the real-time scenario, and the energy saving increased to 50%, when compared with the uncontrolled scenario. The total energy cost for one optimally operated day is 8163 monetary units. To compare with a more realistic scenario, the near real-time methodology presented in this work is compared with the control proposed by the original network (Stokes et al., 2012), evaluated in the new demand scenario. The proposed methodology saves 17% more energy than the original control presented by the authors. Furthermore, the near real-time control of the pumps with VSD is compared with the usual approach for pump operations (ON/OFF). In terms of energy gains, the use of VSD saves 23% more energy when compared with the binary control of pumps.

In terms of pressure management, Figure 7 shows the comparison between the mean demand control applied to the new demand and the near real-time control for the minimum and maximum demands. It is possible to observe the improvement of pressure when near real-time control is used. For each time-step, the optimal solution is reached in approximately 15 minutes.

For the monitoring nodes and tanks considered, Figure 7 presents pressure and fluctuation levels during a day, respectively. The tank levels oscillate to reduce the energy consumption as expected for an optimization process. During the period when the energy price is lower, the tanks are filled, enabling the pumps to be turned off when the energy price is higher. In terms of pressure, two main behaviors of pressure variation during a day can be observed. The nodes with the highest elevation (critical nodes for the minimal pressure) have a controlled pressure, with flat oscillation during a day. In contrast, nodes near the PRVs exhibit larger pressure oscillations as a response to the control on the respective PRV.

CONCLUSIONS

Managing WDNs for maximum efficiency of the system requires special attention not only because a WDN is an important infrastructure for the city, but also because WDNs are responsible for a large consumption of electrical energy, and because of the new environmental challenges, for which a reduction of energy consumption is fully required.

The use of near real-time optimal control in water distribution systems can be a powerful tool for operating the systems with maximum efficiency, as observed in the results presented in this work. The improvement in energy savings is linked to the possibility of finding the maximum efficiency point of the pumps, which is correlated with the hydraulic features of the system, among them, the water demand.

Several methods to forecast water demand can be found in the literature. ANNs as forecasters can treat the non-linearity of the demand problem with great accuracy. However, these tools can become obsolete because of changing urban conditions. An online forecaster model can be an interesting solution to update in real-time the modification of the demand consumption pattern, thus increasing the accuracy of the model. Post-processing of errors can significantly improve the quality of water forecasting. The UKF has been shown to be powerful for this task and should be strongly recommended for real-time water demand forecasting.

The coupled model (forecaster-optimizer) can produce better system management, when compared with the classical approach using the mean demand, because updating demands bring the most real field conditions to the model, thus reducing the uncertainty linked to water demand.

The computational efforts can be reduced by the use of meta-models that surrogate the hydraulic simulator, as presented by other authors in the literature. However, the use of warm solutions brings significant improvements to the computational problem by reducing the computational time in the search process. Nevertheless, a deeper study is recommended into the effect of warm solutions on the optimization process, focusing on the possibility of conditioning the optimization process at some local optimal points.

The single-objective approach is interesting for the specific case of near real-time optimization, since the optimal solution found can be implemented by the controllers of the systems. However, the need to handle the constraints makes optimization harder and convergence slower. The use of a multi-objective approach can be an interesting option if an automatic methodology to select the optimal solution from the Pareto front is implemented.

The oscillation of the tank levels is an important issue in near real-time operation since it can bring substantial gains from the operational and quality point of view, thus guaranteeing better water quality and the avoidance of unneeded water storage. In terms of pressure control and, consequently, tank level management, the use of VSDs enables a better control of tank oscillations. This occurs thanks to the possibility of controlling the system in a continuous region, thus making pressure management smoother. As a result, the control of the tanks is more flexible and can guarantee oscillations within the operational limits.

The near real-time operation of WDNs can bring significant gains to the water industry since systems can be made highly efficient permanently by means of an optimized operation. However, the computational approach, and the real-time process bottleneck, should be further studied to guarantee good results independently of the size of the network.

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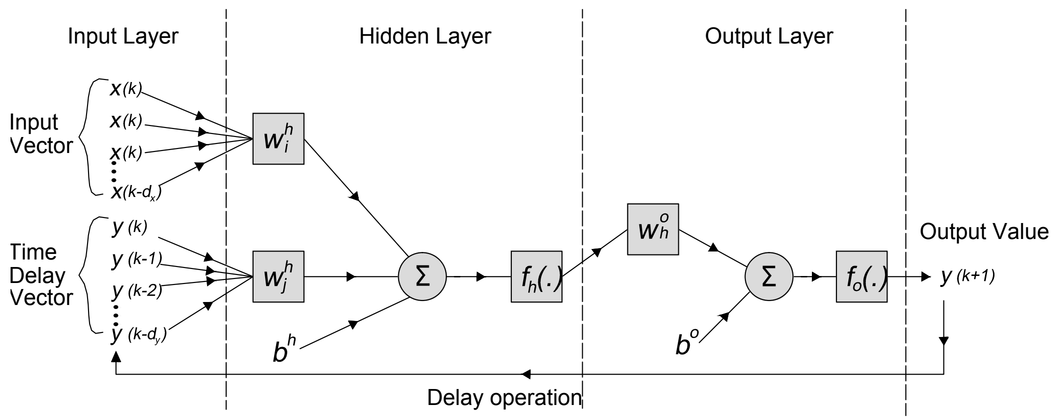


Fig. 1. Typical architecture of a NARX (Brentan et al., 2017a)

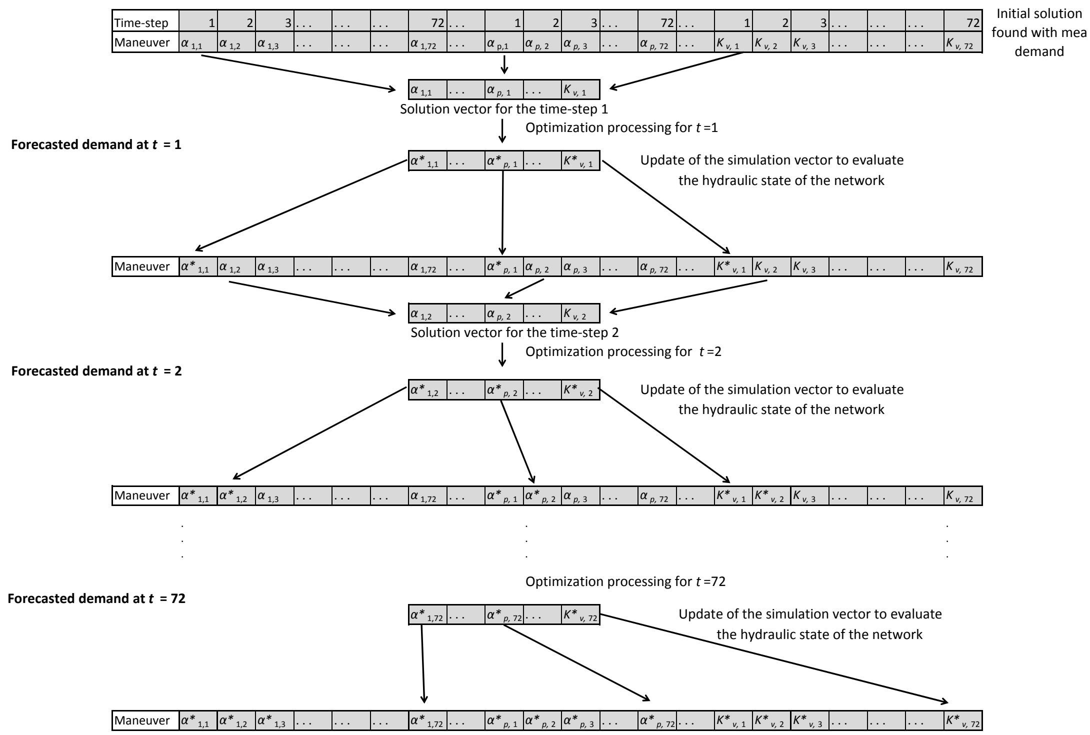
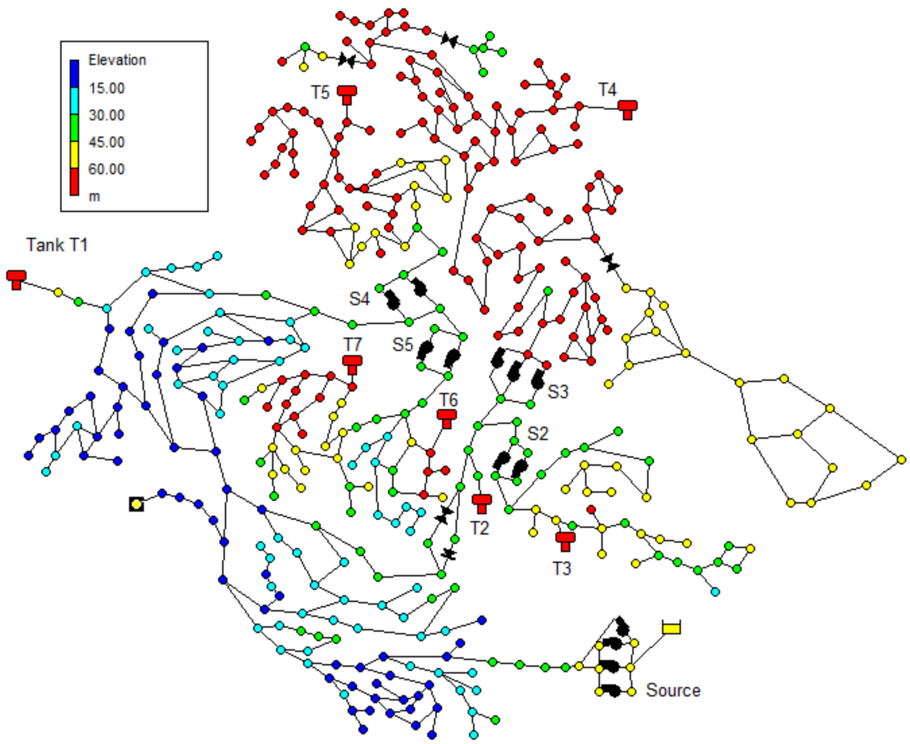
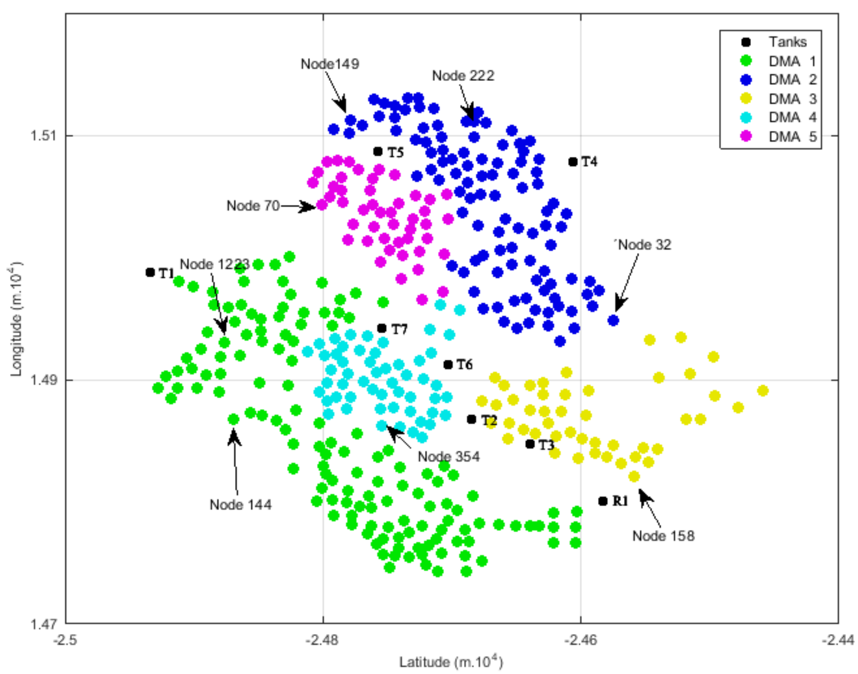


Fig. 2. Warm solution construction and initialization of real-time optimization



(a) Topology of D-Town network with the solution proposed by (Stokes et al., 2012)



(b) DMAs of the D-town network highlighting the monitored nodes

Fig. 3. Presentation of the case study topology, the monitoring nodes and the DMAs

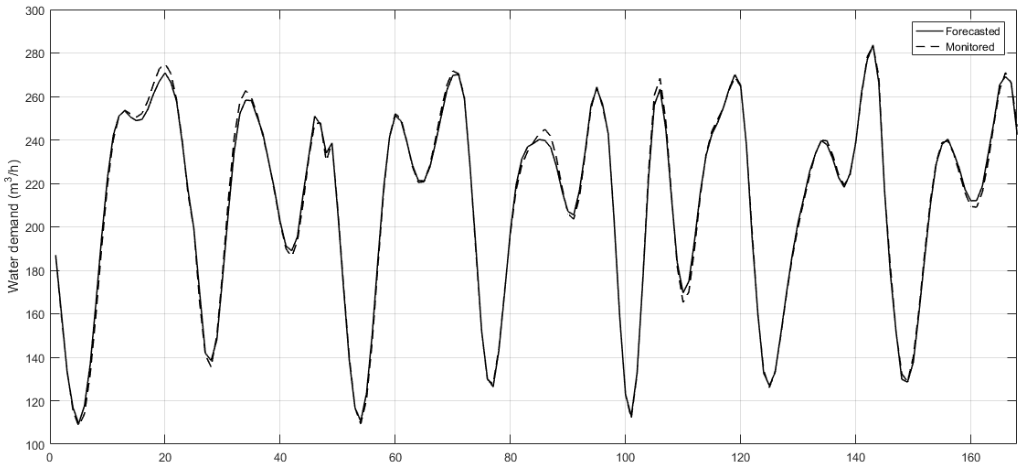
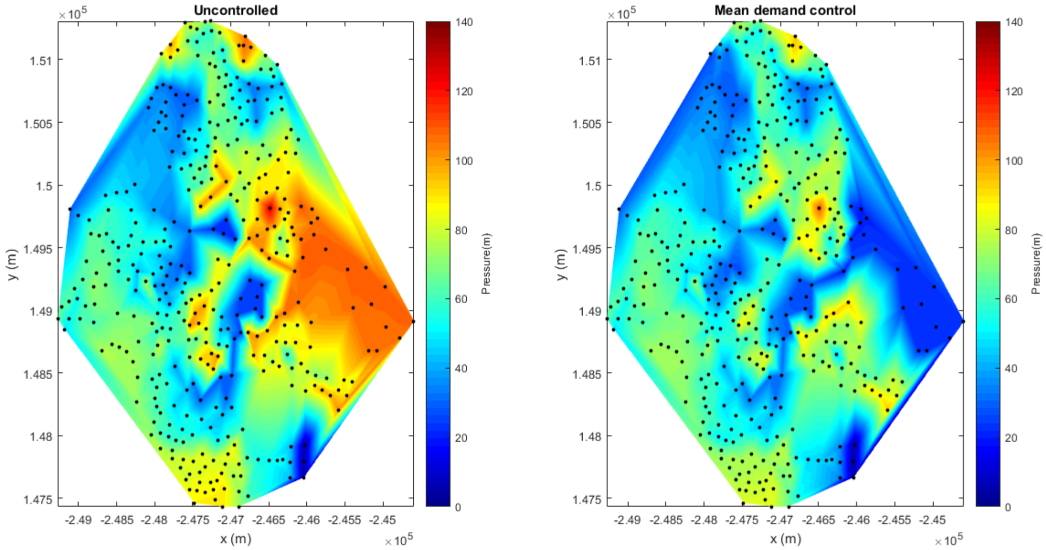
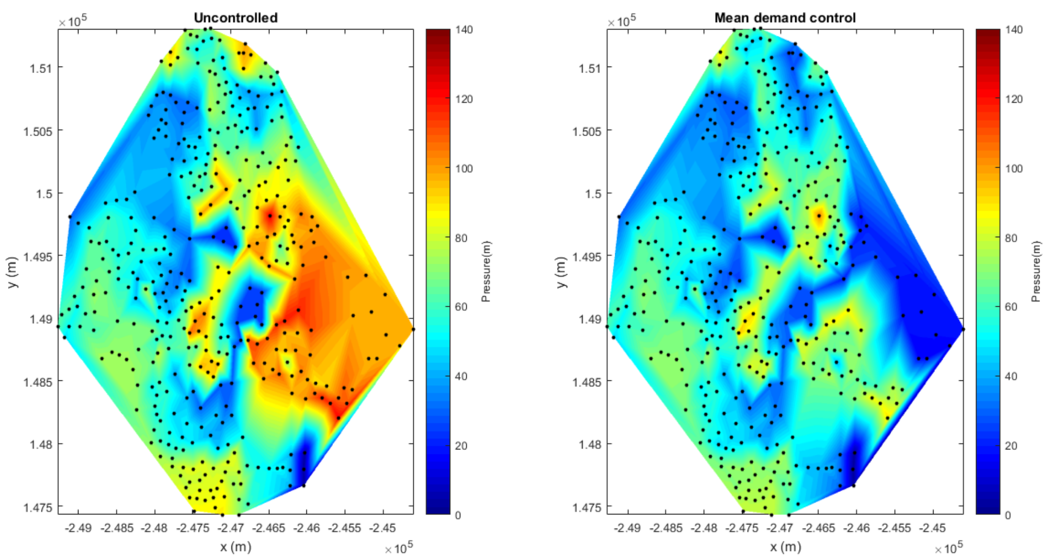


Fig. 4. Forecasted and synthetically generated water demand in the D-town network

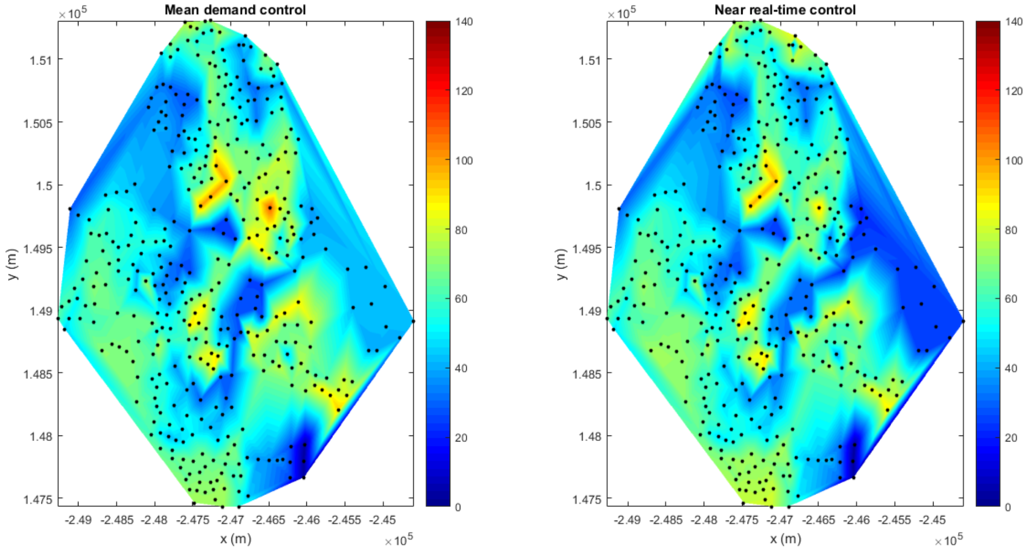


(a) Pressure surface comparison between the uncontrolled and mean demand controlled cases for the minimum demand

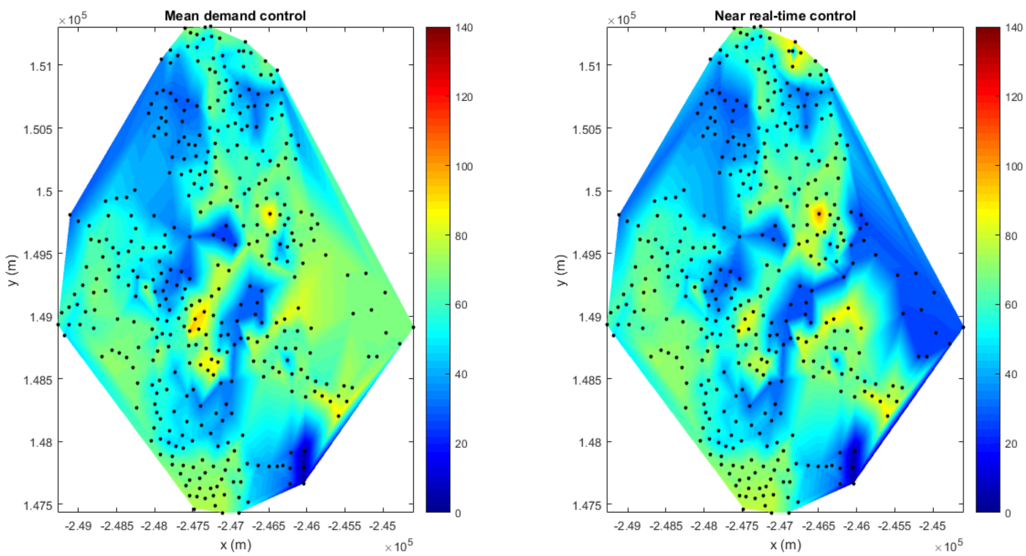


(b) Pressure surface comparison between the uncontrolled and mean demand controlled cases for the maximum demand

Fig. 5. Comparison of pressure management between the uncontrolled and mean demand controlled cases for the minimum and maximum demands

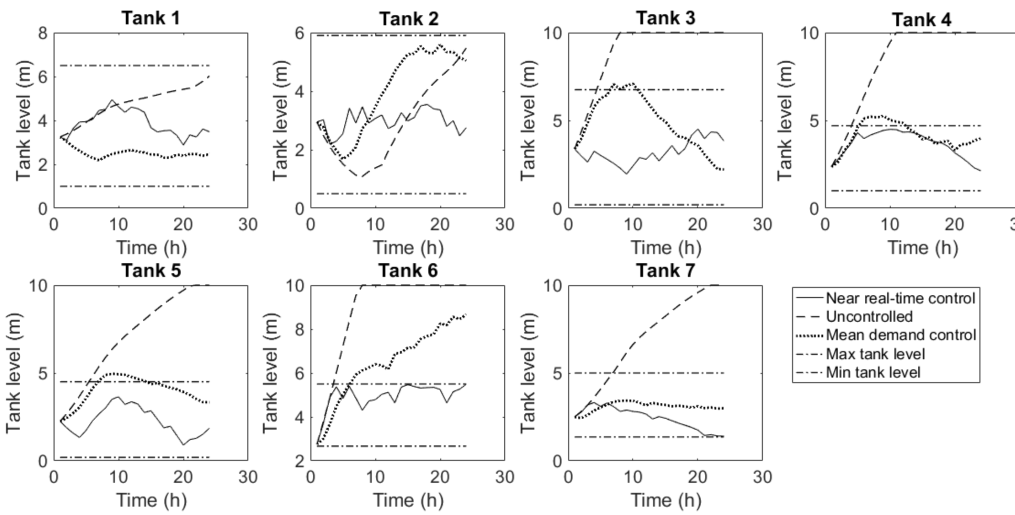


(a) Pressure surface comparison between the mean demand and the near real-time control cases for the minimum new demand

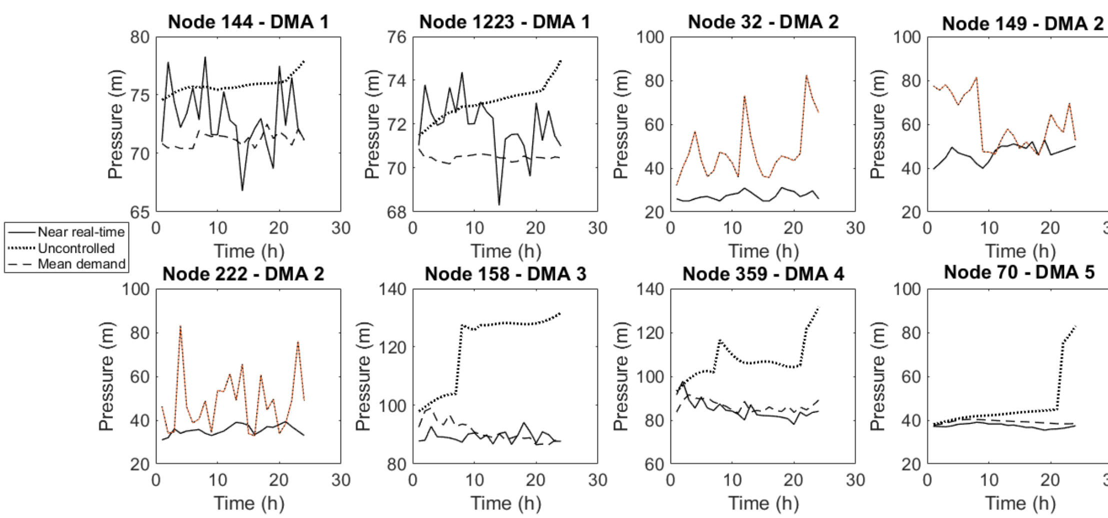


(b) Pressure surface comparison between the mean demand and the near real-time control cases for the maximum new demand

Fig. 6. Comparison of pressure management between the mean demand and the near real-time control cases for the new forecasted demand



(a) Comparison of tank level oscillation for the uncontrolled, mean demand, and near real-time control cases for the new demand scenario



(b) Comparison of pressure fluctuation for the uncontrolled, mean demand control, and near real-time control cases for the new demand scenario

Fig. 7. Comparison of pressure management between the mean demand and the near real-time control cases for the new forecasted demand