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Practical real-time optimization for energy efficient water distribution systems operation

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ABSTRACT

The production, treatment and delivery systems of drinking water and wastewater is one of the largest energy consumers in the US with about 4% of the nation's power consumption. Roughly 80% of the water treatment and distribution costs are associated with electricity, mainly for pumping. Increasing the efficiency of drinking water pumping systems could benefit both the energy- and water-sectors. Despite the advancement of optimal pump scheduling technology, most water utilities are relatively small, and thus lack the funds, hardware and technical personal to support the use of sophisticated and computer intensive pump optimization programs. This study presents a simple and practical model predictive control methodology for real-time pump scheduling. This methodology can be deployed on a standard hardware (e.g., PLCs in pumping stations), which is currently in use by most water utilities. As such, it provides optimal pump scheduling benefits without necessitating large investment in new computational hardware (e.g., advanced controllers). The proposed methodology reduces both the energy consumption (by selecting the most efficient pumps' combinations) and the operation cost (by optimizing the pumps' operation according to electricity tariff periods). The results show that our practical methodology, which could be implemented in simple controllers, can provide near optimal decisions comparable with sophisticated optimization methods that require advanced hardware. To the best of our knowledge, there is no available methodology with such capabilities which is specifically designed for local control schemes. Thus, the novelty of this study is the utilization of this optimization methodology on a simple PLC hardware. Our results are of high importance for both academic and practical reasons, as it shows that the proposed methodology could be a kernel for a low-cost pumps' optimization technology.

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1. Introduction

The operation of Water Distribution Systems (WDSs) is energy intensive. In 2010, the energy consumed by treating and pumping of water and wastewater in the United States (US) is estimated as 4% of the total energy consumption (Copeland and Carter, 2017; Sanders and Webber, 2012). The US is not a special case, energy consumption of water systems is significant in other regions on the globe. Lam et al. (2017) surveyed the energy use for water provision in 30 cities over 15 years. They report energy intensity, in most cities, of up to 1 kWh per m^3 of supplied water. This intensity is lumped to an annual energy use of 100 kWh per-capita. There are many factors that influence the energy use of water systems such as climate, topography, water use pattern, and operation efficiency (Lam et al., 2017). The latter is the focus of the current study. Optimal pumps' operation in WDSs has both economic and environmental benefits (Bunn and Reynolds, 2009). The economic benefits are achieved mainly by shifting the pumping times from periods of higher electricity cost to cheaper ones. Whilst the environmental benefits are achieved by choosing the most efficient pumps combination, which reduces the energy consumption. Thus, reducing the greenhouse gas (GHG) footprint of the water utility (Blinco et al., 2016; Torregrossa and Capitanescu, 2019). We note that shifting pumping times from periods of peak energy costs to non-peak hours require water storage facilities (water tanks),

Abbreviations: FAA Flow Allocation Algorithm, GHG Greenhouse Gas; HPZ Hydraulic Pressure Zone, LP Linear Programming; MAE Mean Absolute Error, MILP Mixed-Integer Linear Programming; MPC Model Predictive Control, NDF Naïve Demand Forecasting; PLC Programmable Logic Controller, SCADA Supervisory Control and Data Acquisition; SST Sorted States Table, TMC Theoretical Minimum Cost; US United States, WDS Water Distribution Systems.

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which have capital cost and water quality implications. Several studies (Edwards and Maher, 2008; Farmani et al., 2006; Slavik et al., 2020) discuss the tradeoff between positive and negative implications of water storage in WDSs.

Optimal pumps' scheduling seeks the optimal pumps operation in space (which pumps combination?) and time (when to turn-On/Off the pumps?) that minimizes the energy cost subject to hydraulic and water supply reliability constraints. Because of hydraulic requirements, WDSs are usually comprised of one or more Hydraulic Pressure Zones (HPZs). An HPZ is a defined area of a WDS which receives water from a given hydraulic grade line. Thus, it is supplied by at least one pressure control device such as a water tank, pumping station or a pressure reducing\sustaining valve. The boundaries of an HPZ can include a closed pipe or valve (i.e., confined HPZ), single or multiple inlets and outlets. HPZs are widely used in practice due to their benefits in avoiding high pressure in the WDS, reducing leakage by pressure control, and the ability to isolate specific zones in the WDS during emergencies and more. Large networks may be divided to many HPZs, for example, the Barcelona (Spain) network is comprised of over 60 HPZs (Ocampo-Martinez et al., 2013) and the network of Haifa (Israel) have over 100 small HPZs due to its sloped topography. Nonetheless, many water utilities manage small networks. For example, 95% of the 52,000 community water systems in the US are small-scale systems serving 3300 persons or fewer (Copeland and Carter, 2017). For most of these small systems, it is impractical to be divided into many HPZs and thus usually consist of limited number of HPZs. Mei-Carmel (2020) states that the vast majority of WDSs in Israel consist of two or three HPZs. In terms of operation, the division of the network into zones helps to focus the control actions on limited number of devices and thus simplifying the optimal operation task. Generally, an HPZ can be operated without a storage tank by supplying water via a pressure reducing valve or a variable speed pumping station (Nowak et al., 2018). However, having a tank within the zone provides a more reliable water supply as well as the ability to reduce the energy cost of the pumped water by shifting pumping times between different electricity tariff periods. As such, including tanks within HPZs is a desirable property for better WDSs operation. Herein, we consider HPZs that include storage tanks. Under this setting, there is a need for a control system to optimally operate the pumps and the trajectories in the tanks. For these purposes, Supervisory Control and Data Acquisition (SCADA) systems became popular in the past decades as their installation and maintenance costs decreased. Installing a SCADA system, allows for centralized control scheme that utilizes sophisticated and resource intensive operating methodologies (Predescu et al., 2020). These systems are often installed in a central location, such as a control room, that oversees the entire water network operation (Cembrano et al., 2000). A recent application of the centralized management system is the Digital Twin WDS presented by Conejos Fuertes et al. (2020). This Digital Twin resides in the control room and communicates with the SCADA system while aiming at providing a holistic overview of the system for improved operational decisions. Mala-Jetmarova et al. (2017) and previously Ormsbee and Lansey (1994), presented a detailed literature review of central operation control schemes. The centralized control schemes can be used to derive operational decisions that account for both water quantity and water quality aspects. For example, Abdallah and Kapelan (2019) suggested a pump scheduling method, based on an Evolutionary Algorithm, for optimum energy cost while accounting for water quality consideration in the WDS. Khatavkar and Mays (2018) used Genetic Algorithms for real-time control of WDSs while considering both water quality and limited electrical power availability. These centralized control schemes benefit from powerful computation resources which are installed in the control room, as such this allows for using classical optimization methodologies such as Linear Programming (LP) (Jowitt and Germanopoulos, 1992), Non-Linear Programming (Candelieri et al., 2018; Yu et al., 1994), Mixed-Integer Linear Programming (MILP) (Salomons and Housh, 2020), Mixed-Integer Non-Linear Programming, Dynamic Programing (Carpentiert and Cohen, 1993) and Evolutionary Algorithms (Cimorelli et al., 2020; Luna et al., 2019; Odan et al., 2015; Torregrossa and Capitanescu, 2019; Vieira et al., 2018). Typically, centralized control schemes that rely on classical optimization methods use dedicated software and hardware installed in the control room, thus requiring high level of technical personnel to operate and maintain them.

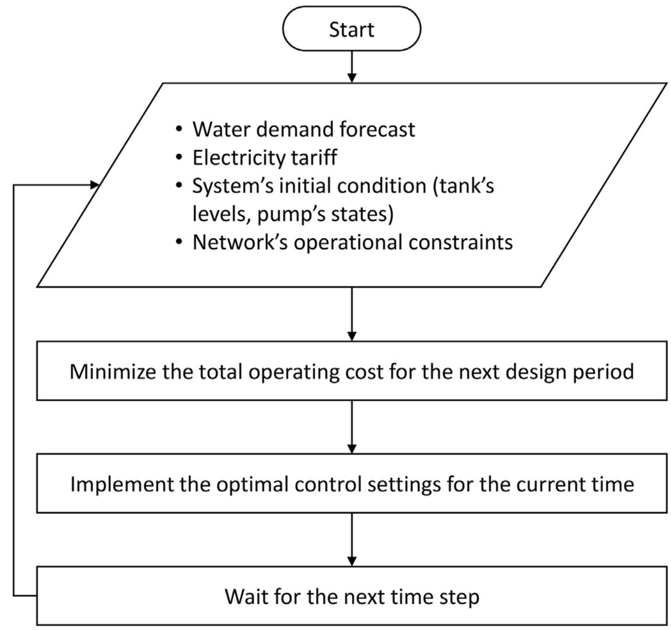

Fig. 1. Control loop for Water Distribution System (WDS) operation.

A simpler control, which is more widely used in practice, is the local control scheme in which the control logic is decentralized and embedded in local controllers installed in the pumping stations or water tanks. A comprehensive review of real-time local control schemes is presented in Creaco et al. (2019). Usually, local controllers are based on simple control rule. For example, in many practical applications, fixed speed pumping stations relay on tank trigger levels. These triggers invoke pump turn-on command when the tank level is low and pump turn-off command when the level is high. Optimized trigger levels can be computed off-line and then embedded in the local Programmable Logic Controller (PLC) for implementation (Alvisi and Franchini, 2017; Housh and Salomons, 2019; Paschke et al., 2001). The pumping station's PLC communicates with the PLC located at the water tank to receive its water level and determine the pump state based on the embedded logic.

PLCs are industrial rugged computers, usually with tailored operating systems, which have limitations on the programs and control logic they can run. Thus, in practice, water utilities tend to have simple control logic in PLCs. Although modern and advanced PLCs may run almost any program, many water utilities are not upgrading their control systems due to high costs and broader effects such changes have on the organization (Water-and-Sewer, 2014; Water-Technology, 2013). In many cases, local control by PLCs, which is currently in use in many water utilities, is not suitable to run real-time pump scheduling programs that rely on the aforementioned classical optimization methods. Thus, the potential of achieving efficient energy and cost savings are not fully utilized when local control scheme is adapted.

In control theory, the real-time control of WDSs can be addressed using a Model Predictive Control (MPC) framework. MPC is a framework for controlling dynamic processes under a set of constraints that utilizes three modules: (a) a simulation model to simulate the control of the dynamics of the system over a finite future time horizon; (b) a prediction model for predicting the unknown future conditions; and (c) an optimization procedure, that decides on the optimal decisions to optimize a pre-defined objective using the predicted conditions and the simulated dynamics. In MPC, the process (i.e., using the three modules a-c) is repeated for each time-step, where the state of the system is updated with a receding horizon strategy. The MPC framework is widely used in many applications, including centralized control of WDSs (Ocampo-Martinez et al., 2012; Wang et al., 2017) as well as traffic control (Jamshidnejad et al., 2016), energy management (Wytock et al., 2017) and many more applications. Fig. 1 shows the real-time MPC loop of a WDS operation. When started, and at every time-step, a water demand forecast is made for the next operation horizon and the electricity tariff for the same period is obtained. The current system conditions are read from the control system and are used as initial conditions for the next time-step. Finally, user defined operational constraints such as time-based minimum and maximum tanks levels, minimum and maximum pressures at the demand nodes, physical constraints on power limitations and water quality considerations (Darweesh, 2020; Khatavkar and Mays, 2019) are formulated. Next, an optimization procedure is carried out to generate the system's operation decisions for the next operation horizon (e.g., the next 24, 48 h) that yield minimum cost subject to the formulated constraints. Once the future operation decisions are obtained, the first time-step (i.e., the next hour) decision is implemented. At this stage, the procedure waits for the next time-step to repeat the same control loop again with a receding horizon strategy.

Within this control loop, the most computationally intensive tasks are the demand forecasting and the minimization of the energy cost. Demand forecasting is a basic element in all WDS design and operation problems, where different forecasting horizons are used according to the problem at hand. Typically, demand forecasting for operational purposes (unlike strategic and tactical planning) uses a short-term forecast of a few days with hourly periodicity (Donkor et al., 2014). Many methods have been proposed for short-term demand forecasts. Some methods use long data series (years) for seasonal demand variations (Alvisi et al., 2007; Zhou et al., 2002). Other methods use explanatory climate variables such as temperature and rain (Herrera et al., 2010). Herrera et al. (2010) considered demand forecasting using data driven models such as Projection Pursuit Regression, Support Vector Regression and Artificial Neural Networks which require both long demand datasets and computationally intensive tuning and learning stage. Thus, the aforementioned forecasting methods require large datasets and computational resources. While these requirements may be suitable for centralized control scheme (where dedicated software and hardware are available), using such demand forecasting methods in local control PLC may be impractical or impossible. To cope with this, Pacchin et al. (2017) suggested a simpler short-term demand forecast method in which the total daily demand is first estimated based on the previous day, and then, the hourly pattern is derived from a weighted average hourly patterns in previous weeks. In a recent study, Salomons and Housh (2020), further simplified this forecasting method and introduced the Naïve Demand Forecasting (NDF) method, which uses the arithmetic average of hourly demands in previous weeks as a prediction for future hourly demands. The NDF method requires only a few weeks of historic demand data and uses simple mathematical expressions (e.g., summation and divisions) for deriving the prediction. These characteristics make the NDF demand forecasting method practical for implementation on PLCs. Owed to its simplicity and suitability to local control schemes, this method is adopted in this paper and will be further explained in Section 2.1.

The second challenge of optimizing the energy cost is even more computationally demanding. As detailed above, the central control scheme uses computation intensive solvers for optimization. Among these tools one can find commercial solvers such as CPLEX (IBM Corp, 2009), open-source tools such as CBC (Forrest and Lougee-Heimer, 2005), and tailored simulation-optimization software which uses hydraulic solvers (e.g., EPANET (Rossman, 2000)). Without heavy modifications, none of these tools can run on a typical PLC and thus are unsuitable for local control scheme. While these tools may appear essential for handling the nonlinear nature (e.g., nonlinear hydraulics) of the problem, in many situation the nonlinearity could be relaxed. Jowitt and Germanopoulos (1992) suggested that the explicit hydraulics (which is the source of nonlinearity) of the system may be relaxed and thus the optimal pump scheduling problem could be formulated as an LP problem. This relaxation assumes that any pump scheduling plan which satisfies the minimum and maximum water level constraints at the tanks will also satisfies the required nodal pressure constraints in the network. This assumption is valid when a well-designed WDS is considered. That is, when the water demand can be delivered in an appropriate pressure from the tanks even when pumps are not operating (Ormsbee and Lansey, 1994). Moreover, this assumption implies that flow and power consumption of the pumps are relatively not affected by other elements in the network. For example, this is satisfied when the magnitude of the static head is large compared to the dynamic head (Housh and Salomons, 2019), i.e. when a pump operates against relatively constant head that dictates the pump's operation point on the characteristic curve. This is a typical situation in HPZs, in which the pump stations work against relatively constant pressure in the zone. Salomons and Housh (2020) utilized the relaxation above to solve the real-time centralized control of WDSs by formulating the optimization problem as MILP problem. Nonetheless, the suggested approach is designed for centralized control scheme, since it requires off-the-shelf MILP optimization packages, which, as discussed previously, are incompatible with local PLCs.

This study presents a simple and practical MPC methodology which is specifically designed for local control schemes. This method could be deployed on local PLCs, which are currently in use by most water utilities. As such, it provides optimal pumps scheduling benefits without necessitating large investment in new computational hardware (e.g., advanced controllers or centralized control scheme). The core of the proposed framework is an efficient optimization procedure, the Flow Allocation Algorithm (FAA), which could be easily implemented in local PLCs, since it only requires a few basic operators that are available in standard PLCs, such as loops and if conditions.

With simplicity and practicality in mind, we designed an efficient local control framework, which achieves near optimal decisions comparable with sophisticated optimization methods that are exclusive to centralized control schemes. The proposed methodology reduces both the energy consumption (and as a result the GHG footprint of the water utility) and the utility's operation cost. The former is achieved by selecting the most efficient pumps' combinations, while the latter is achieved by optimizing the pumps' operation in accordance with electricity tariff periods.

The reminder of this paper is organized as follows: Section 2 details the proposed methodology. In Section 3 we present the test case and in Section 4 the results of the test case are discussed.

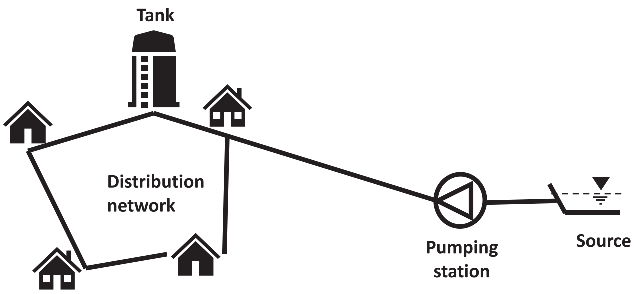

Fig. 2. Simple illustration of Hydraulic Pressure Zone (HPZ).

Table 1
Sorted States Table (SST) of the pumping states in the illustrative network.

State	Q (m^3/hr)	E (kWh)
1	40	4
2	75	11.25
3	100	22

Finally, in Section 5 we conclude the study results and propose future research directions.

2. Methodology

We consider an HPZ (Fig. 2) for which we need to develop an MPC framework, compatible with local control scheme deployment. The HPZ includes pump stations with multiple fixed speed pumps and storage tanks. The task is to select the best combinations of the pumps and the best time-steps for operating them subject to water supply constraints and the system dynamics. For this MPC framework, Section 2.1 presents a practical demand forecasting methodology while Section 2.2 presents an efficient optimization procedure which is tailored for the system dynamics of HPZs in water distribution systems.

2.1. Demand forecast

Following the goal of utilizing simple and practical algorithms, we adopt the NDF method presented by Salomons and Housh (2020). For the completeness of this paper we briefly describe the NDF method. For the prediction of an hourly demand value, the NDF method averages the demand in the same hour in previous weeks. Denoting the current absolute time in hours passed from a predetermined time reference (e.g., the beginning of the year), h, the demand forecast for the next hour is given by Eq. (1).

$$\tilde{d}_h = \frac{1}{w}\sum_{i=1}^{w} d_{h-168\cdot i} \tag{1}$$

where w is the number of previous weeks considered, d is the historic demand, 168 is the number of hours in a week and $\tilde{d}$ is the forecasted demand. For implementing the MPC, there is a need to predict the demands for a future operation horizon T (e.g., optimization horizon of 48 h). That is, for each time instant t in the set $\tau_h \equiv \left\{h,\ h+\Delta t,\ \ldots\ h+\frac{T}{\Delta t}-1\right\}$ where Δt is the time-step (e.g., 1 h). Eq. (1) could be used for all elements in the set τ_h to create an extended

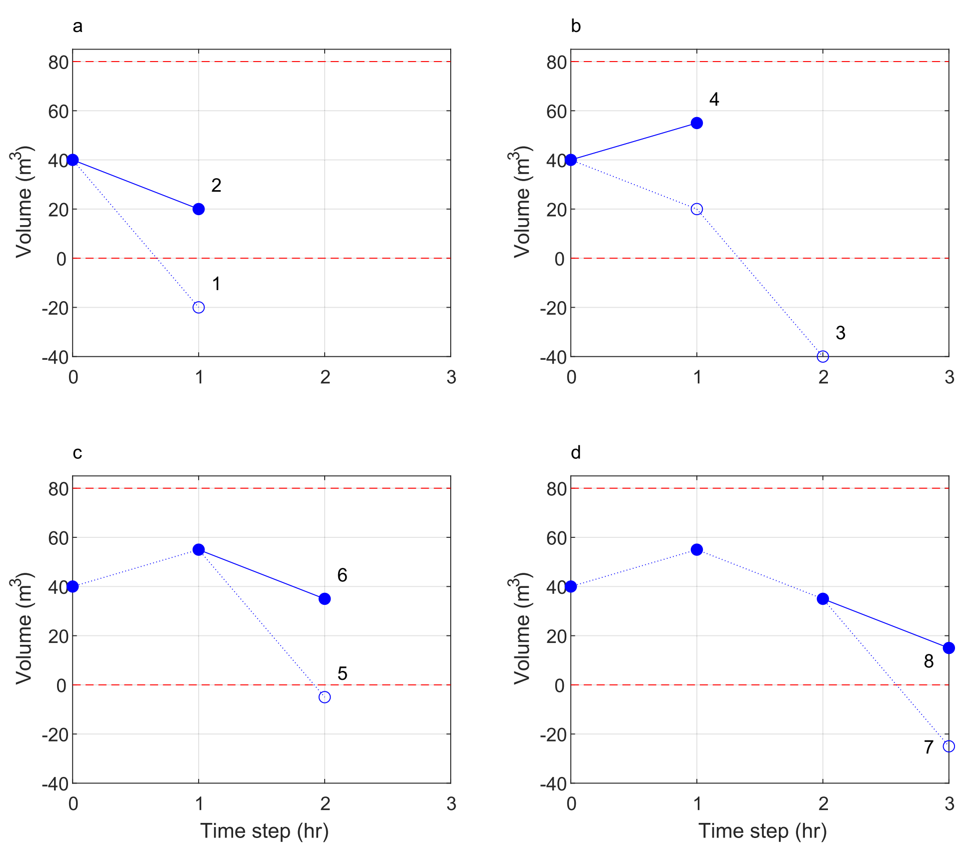

Fig. 3. Demonstration of the FAA steps, water trajectories: (a) first iteration, (b) second iteration, (c) third iteration and (d) fourth iteration. Dotted line: water trajectories before adding pumping in the current iteration. Solid line: water trajectories after adding pumping in the current iteration. Dashed lines: minimum and maximum tank's volume.

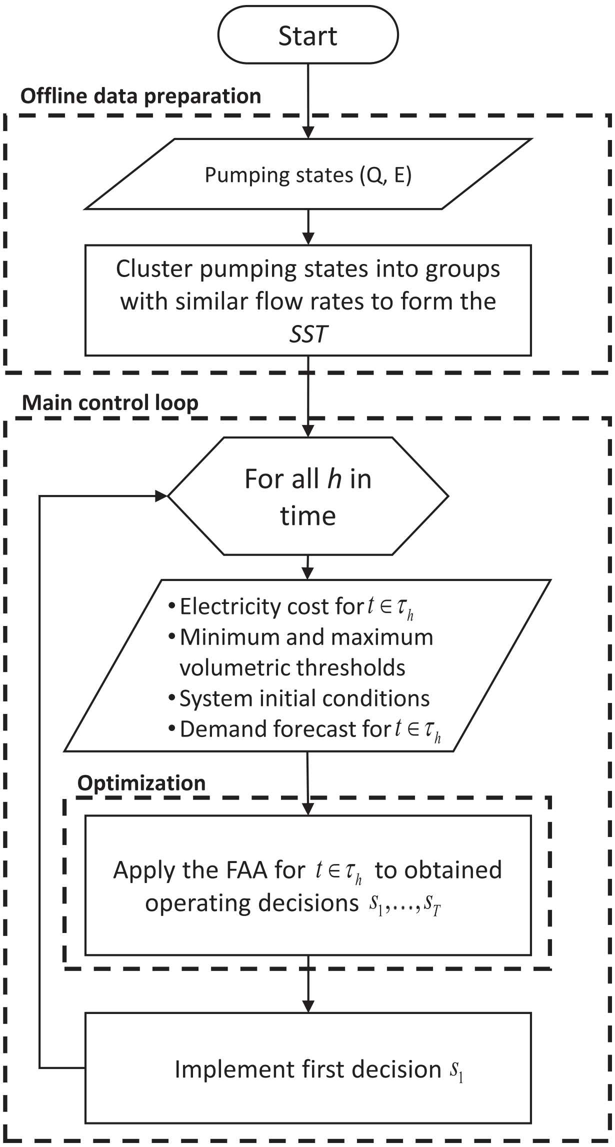

Fig. 4. Flowchart of the proposed methodology.

demand forecast as shown in Eq. (2).

$$\tilde{d}_t = \frac{1}{w}\sum_{i=1}^{w} d_{t-168\cdot i} \quad \forall t \in \tau_h \tag{2}$$

2.2. Flow allocation algorithm

There are two main roles for any optimization procedure, optimizing the objective and satisfying the constraints. The FAA builds on a very basic property of the problem, which indicates that a decision of "do nothing" (i.e., no pumping at all) is the lowest possible cost, which obviously infeasible for the system dynamics. Then, the FAA iteratively looks for infeasibility in the system and tries to resolve it by incrementally allocating additional flow. Accounting for the system dynamics, the added flow must be allocated at time-steps before the infeasibility occurs in order to reduce it. While accounting for the minimum cost objective, indicates that we must add the flow with minimum additional cost.

To illustrate the FAA, we first consider a simple WDS in Fig. 2, which consists of one pumping station and one tank. There are three pumping states in the pumping station as detailed in Table 1. A pumping state represents a combination of pumps within the station. For example, the three pumping states in Table 1 represent three combinations of two pumps. The first pump working alone in the first state, the second pump working alone in the second state, and the two pumps working together in the third state. In addition to these three states, there is a fourth state representing the case when the two pumps are off. Each pumping state in the table is characterized by its flow (Q) and its hourly energy consumption (E). The states table is sorted according to flow and hence we denote it as Sorted States Table (SST). For simplicity, we consider a tank with a minimum and maximum volumes of $V_{MIN} = 0\ m^3$ and $V_{MAX} = 100\ m^3$, respectively and initial tank volume of $V_0 = 40\ m^3$. For demonstration purposes, we limit the operation horizon, T, to 3 h in which the electricity tariff, ET, is 1 $\$/kWh$ for the first and third hours and 2 $\$/kWh$ for the second hour. The water demand, d, is constant for the 3 h at the rate of 60 m^3/hr. The task is to select which pumping state, s, to operate at each time-step to minimize energy costs while maintaining the tank volume within the minimum and maximum constraints.

To solve this optimization problem using the FAA, we initialize the algorithm in the first iteration by assuming that the pumps are off during all time-steps, thus, starting with the initial volume of 40 m^3 and with a demand of 60 m^3/hr, the tank volume is expected to reach a value of $-20\ m^3$ at $t = 1$ which is infeasible (point 1 in Fig. 3a). As such, in the next iteration some flow must be allocated in the first time-step (in which the infeasibility is encountered). Considering the available pumping states from Table 1, we allocate the first pumping state which is the most efficient one with the smallest energy consumption. With a flow rate of 40 m^3/hr for this pumping state, the tank volume is expected to reach a value of 20 m^3 at $t = 1$ (point 2 in Fig. 3a) which is within the feasible range of the tank's volume. However, the tank's volume at $t = 2$ is expect to be $-40\ m^3$ (point 3 in Fig. 3b) which is again not within the feasible range and thus additional flow must be allocated before $t = 2$. Now, we have two options: (1) increase the flow at $t = 1$ to the second state, i.e. from 40 to 75 m^3/hr or (2) increase the flow at $t = 2$ to the first state, i.e. from 0 to 40 m^3/hr. In the first option, the additional cost is $(11.25kWh - 4kWh) \times 1\$/kWh = \$7.25$ (i.e., replacing the first state with the second) while the additional cost in the second option is $4kWh/m^3 \times 2\$/kWh = \$8$. Note that despite the lower energy consumption of the first state, 4 kWh, compared to the additional energy consumption of the second state $11.25kWh - 4kWh = 7.25kWh$, moving to the second state at $t = 1$ is favorable due to the higher energy price at $t = 2$ (2 $\$/kWh$ vs. 1 $\$/kWh$). To this end, for the second iteration the algorithm allocates the second pumping state at $t = 1$ with a flow rate of $70m^3/hr$ bringing the tank volume at $t = 1$ to 55 m^3 (point 4 in Fig. 3b). The process is repeated for the third iteration, in which the tank's volume will be $-5\ m^3$ at time $t = 2$ (point 5 in Fig. 3c) which is outside the feasible range of the tank volume. As such, additional flow must be allocated in the first or second time-steps. Again, we have two options: (1) allocate the third pumping state in the first time-step or (2) allocate the first pumping state in the second time-step. Comparing the additional cost of the third pumping state in the first time-step, $(22kWh - 11.25kWh) \times 1\$/kWh = \$10.75$, to the first pumping state in the second time-step, $4kWh/m^3 \times 2\$/kWh = \$8$, reveals that the second option is preferable. Utilizing this selection, with a flow rate of 40 m^3/hr, will bring the tank volume at $t = 2$ to 35 m^3 which is within the feasible range (point 6 in Fig. 3c). In the fourth iteration, considering again the demand, the tank's volume in $t = 3$ is expected to be $-25\ m^3$ (point 7 in Fig. 3d) which is not feasible and requires additional flow to be allocated. In this

Table 2
The flow allocation algorithm (FAA).

Algorithm: Flow Allocation

Input: $\tilde{d}$, V_0, V_{MIN}, V_{MAX}, T, ET, Sorted States Table with columns $SST = \{s, G, E, Q\}$ and n_{states} rows
Output: Selected operation states for each time-step s_t
Initialize: $s_t = 0 \ \forall t = 1 \ldots T$
Simulate $V_{i+1} = V_0 + \sum_{j=1}^{i} Q(s_j) - \sum_{j=1}^{i} d_j \quad \forall i = 1 \ldots T$
Check for infeasibility in V_{MIN}, return the infeasibility time, t_{viol}; if none $t_{viol} = \infty$
Execute: While $t_{viol} \le T$ do:
    Set $\Delta C_{\min} = \infty$
    For $t = t_{viol}$ to 1 do
        For $s_{tmp} = s_t + 1$ to $n_{states} - 1$ do
            If $G(s_{tmp}) > G(s_t)$ then
                Set $\Delta C = (E(s_{tmp}) - E(s_t)) \cdot ET_t$
                If $\Delta C < \Delta C_{\min}$ then
                    Simulate $V_{i+1} = V_0 + \sum_{\substack{j=1 \\ j \ne t}}^{i} Q(s_j) + Q(s_{tmp}) - \sum_{j=1}^{i} d_j \quad \forall i = 1 \ldots T$
                    If $V \le V_{MAX}$ for all times, then
                        Set $\Delta C_{\min} = \Delta C$
                        Set $t^* = t$, $s^* = s_{tmp}$
                        Break s_{tmp} loop
                    End if
                End if
            End if
        End s_{tmp} loop
    End t loop
    $s_{t^*} = s^*$
    Simulate $V_{i+1} = V_0 + \sum_{j=1}^{i} Q(s_j) - \sum_{j=1}^{i} d_j \quad \forall i = 1 \ldots T$
    Check for infeasibility in V_{MIN}, return the infeasibility time, t_{viol}; if none $t_{viol} = \infty$
End while loop
Return: $s_t \ \forall t = 1 \ldots T$

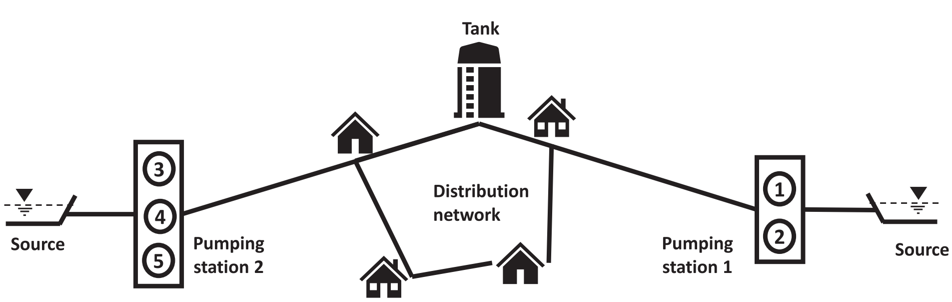

Fig. 5. Case study network layout.

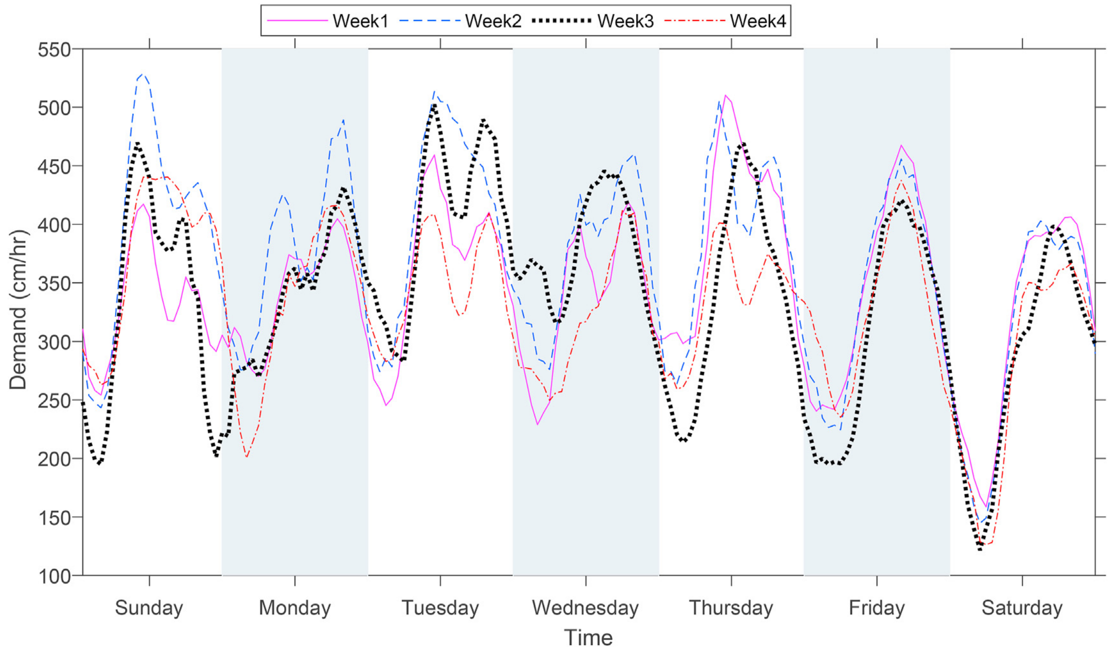

Fig. 6. Hourly demand profile during four weeks in the case study.

case we have three options: (1) the third pumping state in the first time-step; (2) the second pumping state in the second time-step or (3) the first pumping state in the third time-step. These options have additional costs of \$10.75, \$14.5 and \$4 respectively, making the third option the preferable one. Utilizing this option, with a flow rate of $40m^3/hr$, will bring the tank volume at $t = 3$ to 15 m^3 which is within the feasible range (point 8 in Fig. 3d). After the fourth iteration we end up with a feasible solution for all the time-steps and the optimization procedure is terminated.

Next, we present a detailed explanation of the methodology which consists of three main stages as outlined in Fig. 4. The first stage is an offline data preparation process in which the pumps' characteristics are analyzed. The pumps data may be obtained from SCADA system records, field measurements, pump tests or the original pump's manufacturer data sheets. The required data is a list of operational states with their flow and hourly energy consumption. If there are n pumps in the pumping station, the number of pumping states (i.e., pumps combinations), n_{states}, is 2^n including the "do-nothing" state in which no pumps are working. In practice, not all theoretical states are feasible due to different constraints such as pressure restrictions in the system and/or limitation on the power connection to the pumping station. The final list of the states should include only the feasible states. Next, the list of feasible states is clustered into groups of states with similar flow values. This is done since the FAA is designed to add flow in each iteration to reduce the infeasibility of the system by selecting the best state from a higher flow group. For example, if there are two similar pumps in a pumping station, there are three distinct groups of states: (1) one state with no pump is working (2) two states in which only one pump is working, and (3) one state with the two pumps are working. In the illustrative example, presented in Table 1, which also includes two pumps, four groups could be identified because the two pumps are not similar and each one of them, when working alone, could be a separate group. Noteworthy that the groups' id ranges from 0 to N_G from the lowest flow group to the highest flow group.

To summarize, the off-line first stage, produces the states table which is sorted first by flow group (G) and then by the energy (E) to form theSST. This table also holds the states index (S) and the states flow (Q).

The second stage is the main control loop which continuously runs in the PLC. The loop is repeated for every time-step (e.g., every hour) for any given time h with the following input: the electricity tariff (ET), the minimum and maximum tank's volumetric constraints (V_{MIN} and V_{MAX} respectively), the demand forecast ($\tilde{d}$) for

Table 3
Sorted States Table (SST) of the pumping states in the case study.

State	Group G	Flow Q (m^3/hr)	Energy E (kWh)
0	0	0	0
1	1	215	75.25
2		220	75.90
3		215	77.83
4		250	110.00
5		250	115.00
6	2	420	151.20
7		430	151.79
8		430	153.94
9		465	186.00
10		470	187.06
11		465	188.33
12		460	188.60
13		470	190.82
14		460	190.90
15		410	221.40
16	3	625	228.13
17		680	261.80
18		675	263.25
19		680	264.52
20		675	264.60
21		670	265.99
22		675	266.63
23		620	293.26
24		620	294.50
25		630	297.36
26	4	875	338.63
27		870	341.04
28		835	371.58
29		835	372.41
30		830	390.10
31	5	1030	448.05

the next operation horizon (T), and the initial conditions of the system (e.g., the current tank level). Usually the pumping station's PLC can communicate directly with the tank's PLC without the need for a centralized system. With the availability of tanks' water level records and flow records in the pump station PLC, it can construct demand records through simple water mass balance. These demand records are used for demand prediction within the PLC using the NDF method. Next, the control loop invokes the optimization stage (i.e., FAA). The output of the optimization stage is the pumps schedule for the next operation horizon, that is, the list of pumping states to be operated at the next T time-steps. Once the list is obtained, only the decision of the current time-step is implemented and then the control loop waits for the next time-step and the process is repeated in a receding horizon manner. The FAA which is used as the optimization procedure in the third stage is the main novelty of the proposed framework, the details of the FAA are presented in Table 2.

The algorithm is invoked with the input parameters detailed in line L1 of Table 2. The output is the selected operation states for each time-step, s_t (L2). The decision variables are initialized with the do-nothing state (L3) and the tank's volume is simulated for all times (L4). Then, an initial feasibility test is conducted (L5) and the time of the violation (t_{viol}) of the minimum volume is returned. The main loop of the FAA is initiated (L6) and will continue until no tank volume violation is observed. The FAA allocates flow with the minimum added cost so we initialize (L7) a local variable to hold the current minimum additional cost ($\Delta C_{\min}$). In order to reduce the infeasibility at time t_{viol} it is evident that the additional flow must be allocated at a time not exceeding t_{viol}. To this end, we search to add flow between t_{viol} and the first time-step (L8). The reasoning for searching from t_{viol} backwards in time is that we prefer delaying our pumping decisions, such that we will have the option for recourse actions when time progresses. At each time t we loop through the SST, starting with states above the existing state of time t (L9), while limiting our search to states in a higher group (L10). During the search, we calculate (L11) the additional cost incurred (ΔC) which is the difference between the energy consumption of the examined state (s_{tmp}) and the existing state, multiplied by the electricity tariff (ET_t). If this additional cost is less than the current minimum additional cost ($\Delta C_{\min}$) (L12), we simulate the tank's expected volume with the proposed state (L13) and check for infeasibility in the tank's upper limit (L14). If this proposed state (s_{tmp}) causes infeasibility in the upper limit, we move on to check the next state (L21). However, if there are no violation of the upper volume constraint, we update $\Delta C_{\min}$ with the new additional cost (L15) and record the selected state and time (L16). Now we break the states' loop (L16) and move to examine the possibility to add flow in earlier time-steps (L22). Once we cover all the optional time-steps we update the new selected state and time (L23) which completes one iteration of the FAA. Next, we simulate the tank's volume trajectories (L24) and check for infeasibility (L25). If there is an infeasibility, t_{viol} is updated and the loop continues (L6). If no infeasibility is found, the algorithm returns the set of the selected operational states (L27). An important observation is that the FAA described above, can be computed easily with the use of common operators "For\While" loops, "If" statements and basic mathematical operations. Hence, as described previously, it is compatible with local control scheme and it could be implemented

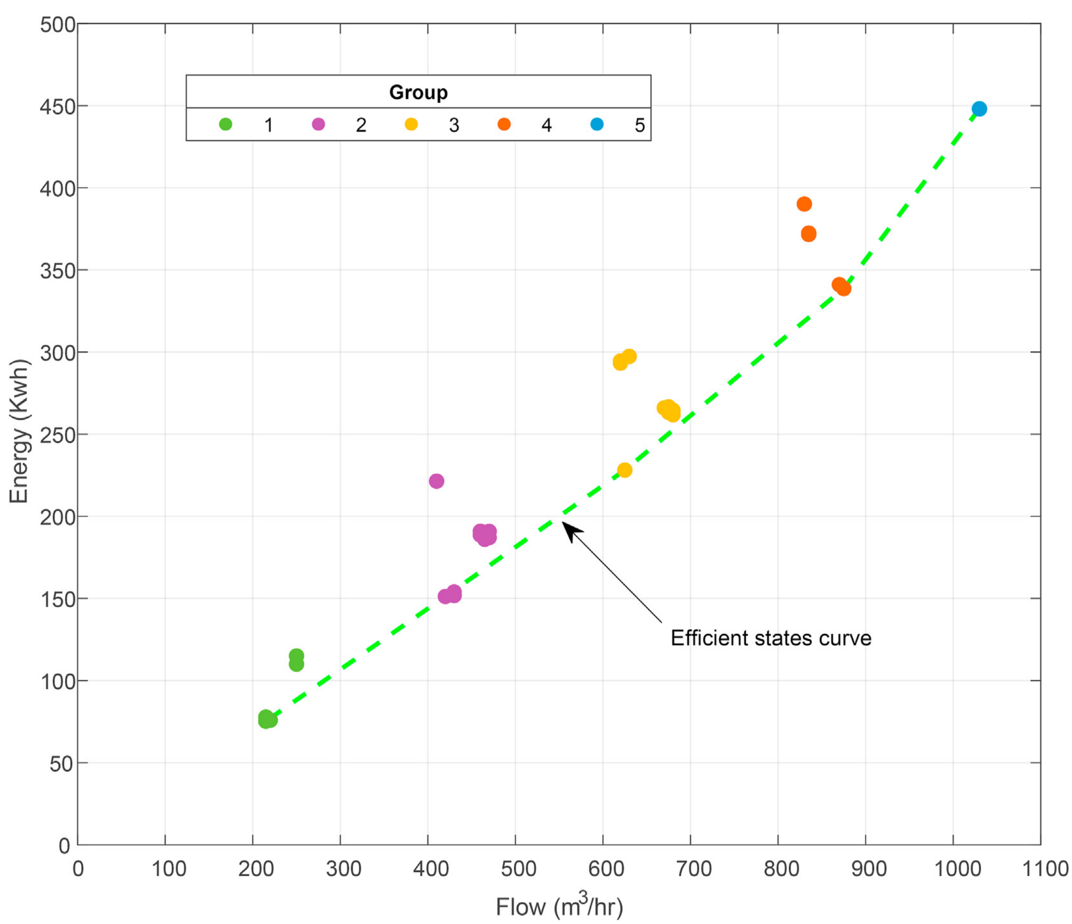

Fig. 7. Pumping states energy consumption vs. flow in the case study.

Table 4
Electricity tariff structure.

Day	Off-peak hours	Mid-peak hours	Peak hours
Sun − Thu	00–05 22–23	20–21	06–19
Fri	00–05 20–23	06–19	–
Sat	00–16 20–23	17–20	–
Electricity price ($/ kWh)	0.0842	0.1066	0.1339

on a standard PLC.

3. Case study

To demonstrate the suggested methodology we consider an HPZ (Fig. 5), which is supplied by two pumping stations, one with two pumps and the second with three pumps. The zone is served by one elevated tank with an operational minimum and maximum volume constraints of 1500 m^3 and 6000 m^3 respectively. The data of this case study are based on real-life measurements of pump flows, consumed power (i.e., pump states) and demand time series. Fig. 6 shows four weeks of demand data. Each series in Fig. 6 is an hourly demand profile for one week. The origin of this case study's data is an Israeli city with a mixed Muslim and Jewish population; thus, Friday and Saturday are holydays. For the weekdays (i.e., Sunday to Thursday), a typical two demand peaks can be observed. The weekend days have a different pattern in which the demand decreases in Friday afternoon.

In our case study, the operation of any pump in one pumping station would not significantly affect the operation of the pumps in the other, thus, pumping states in each station can work at the same time. This is because the two pumping stations work (almost) directly against an elevated tank. In this situation, the two pumping stations work against the topographic difference independently. Noteworthy that, in this real example, the change in the tank level is negligible compared to the high topographic difference. These conditions are also satisfied in other networks. Jowitt and Germanopoulos (1992) provide a thorough explanation on the validity of this assumption. They argue that in some practical networks, despite that the flow pattern in the network may change significantly as a result of pump switching, the magnitude of the nodal heads will not change significantly, and thus, the pumping stations will operate near the same operating point.

The states from the two stations could be combined to construct the *SST*. With five pumps feeding the HPZ, there are a total of $n_{states} = 32$ pumping states, including the "do-nothing" state, as shown in the *SST* (Table 3). The pumping states in Table 3 are grouped by flow similarity which coincide with the number of pumps included in each state (e.g., in states 1–5 of group 1, only 1 pump is operated). The coefficient of variation (i.e., standard deviation divided by the average) of the flow in each group ranges between 0% (group 5) to 8% (group 1) as can be seen in Fig. 7.

Fig. 7 shows the hourly energy consumption of the pumping states as a function of their flow. The energy consumption raises with the flow between the pumping groups while the flow and

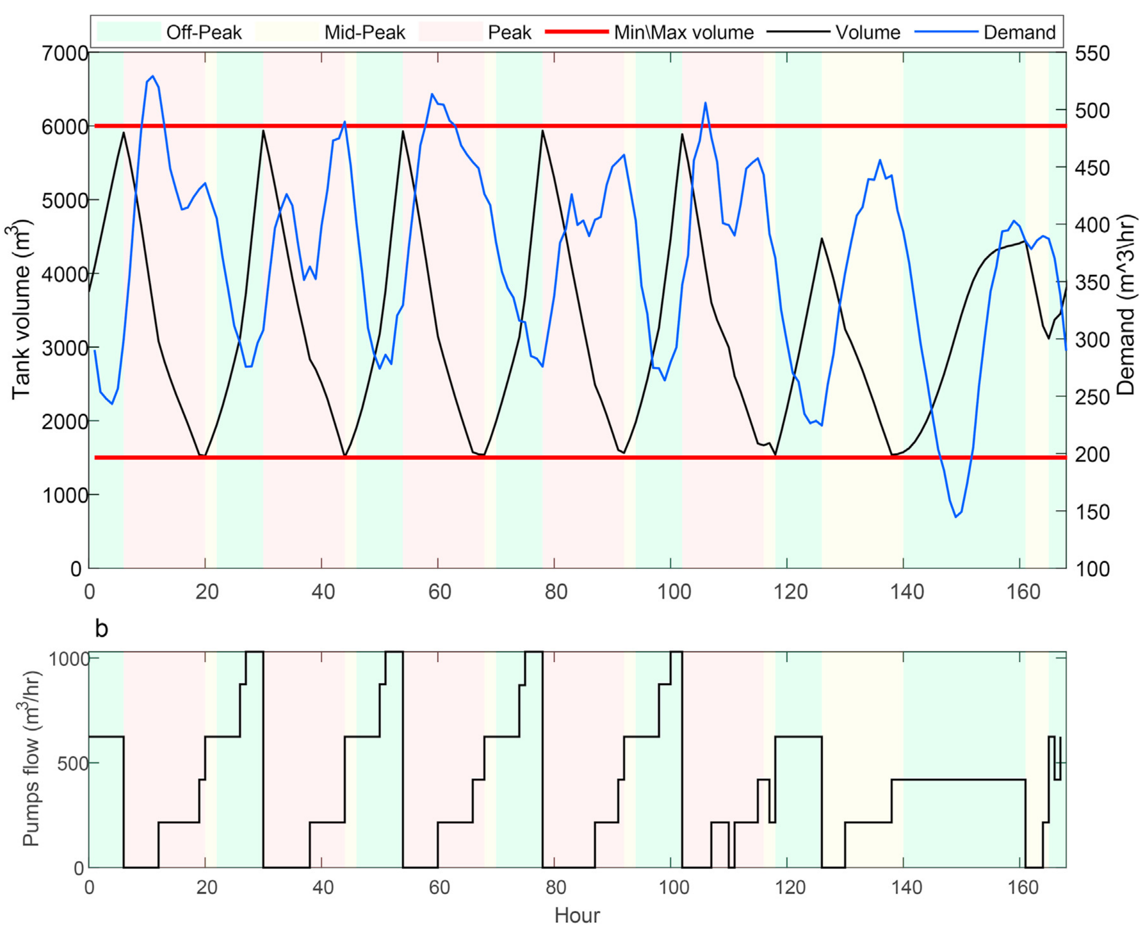

Fig. 8. Tank's volume (a) and pumps flows (b) results for one week.

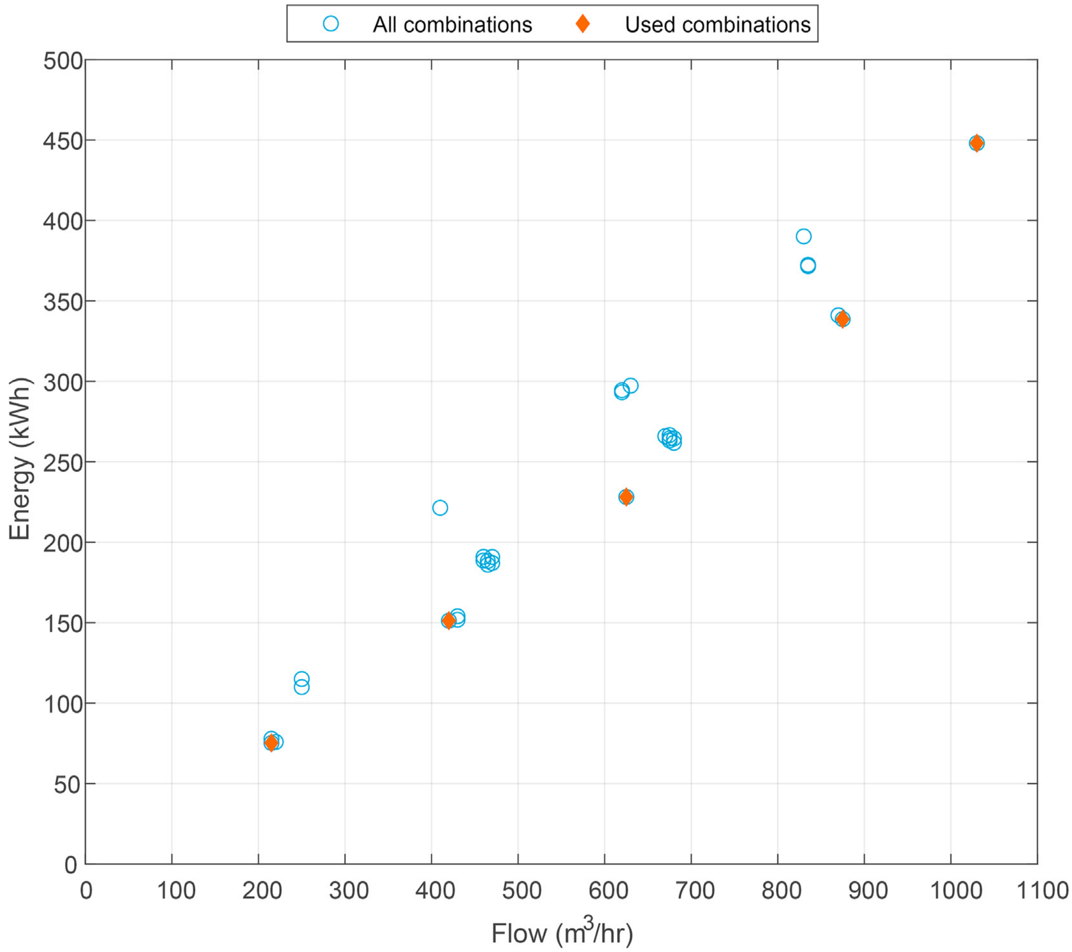

Fig. 9. Selected pumping states during one month operation of the test case.

energy vary within each group. The most efficient pumping state in each group is the one with the smallest energy consumption. This set of pumping states comprises the efficient states curve as marked in Fig. 7. These states correspond to the first state for each group in Table 3 (i.e., states 1, 6, 16, 26 and 31).

The electricity tariff is outlined in Table 4. The tariff has three cost levels: off-peak, mid-peak and peak which vary during the hours of the day and the days of the week. Sundays through Thursday have the same tariff structure while Fridays and Saturdays have a different structure each. These tariffs are based on the Israeli electricity tariff structure.

As the electricity tariff structure has a weekly cycle and the demand profile of this HPZ also vary in a weekly manner, the operation horizon is set to one week, $T = 168$ hours, with a time-step of 1 h. The time step of 1 h is usually selected for practical reasons mainly to reduce frequent pump switches, which can cause mechanical damage, water hammer and water quality issues (Alvisi and Franchini, 2017; Housh and Salomons, 2019; Lansey and Awumah, 1994; Wood, 2005).

4. Results

The abovementioned test case was run hour by hour in a receding horizon mode for a full month with a total of 720 runs according the methodology outlined in Fig. 4. The process started with a tank volume of $V_0 = 3750\,m^3$ which is the middle of the operational volume of the tank. The results of one-week, out of the full month, are shown in Fig. 8. The tank volume for the week (Fig. 8a) fluctuates between the minimum and maximum allowed volumes, where, in general, the tank fills during the off-peak electricity tariff periods and empties during the peak periods. Fig. 8a also shows the hourly water demand for the week which exhibits decreasing demands during the weekend (Friday and Saturday). Fig. 8b shows the pumps flow over time. The results show that most of the pumping is done during the off-peak periods, where the high flows are always postponed to the end of the off-peak period. This property of delaying high flow, is due to the backward in time flow allocation strategy (L8 in Table 2) which we discussed earlier. During the weekend (the last 48 h) the tank does not totally fill since there are enough off-peak and mid-peak hours to allow more modest pumping rates (which are more energy efficient) over longer time as can be noticed in Fig. 8b. Additionally, the pumps operation is smooth and the changes in the flow rate is gradual. This is a desirable property in pumps operation, since frequent on/off operation of pumps may affect the WDS functionality as discussed in many studies (Lansey and Awumah, 1994). All the results in this paper were built using MATLAB version R2018b, the YALMIIP toolbox (Lofberg, 2004) on a 64-bit Lenovo X1 ThinkPad with an Intel i7-7600U CPU @ 2.8 GHz and 16 GB of RAM.

It should be noted that the tank volume is not enough to supply the water during the entire peak period. Thus, some pumping must be made during the peak hours (e.g., hours 12–20 in Fig. 7b), but this is mostly done with the small flow rate of pumping state 1, i.e. 215 m^3/hr (Table 3). Another nice property of the FAA algorithm, is

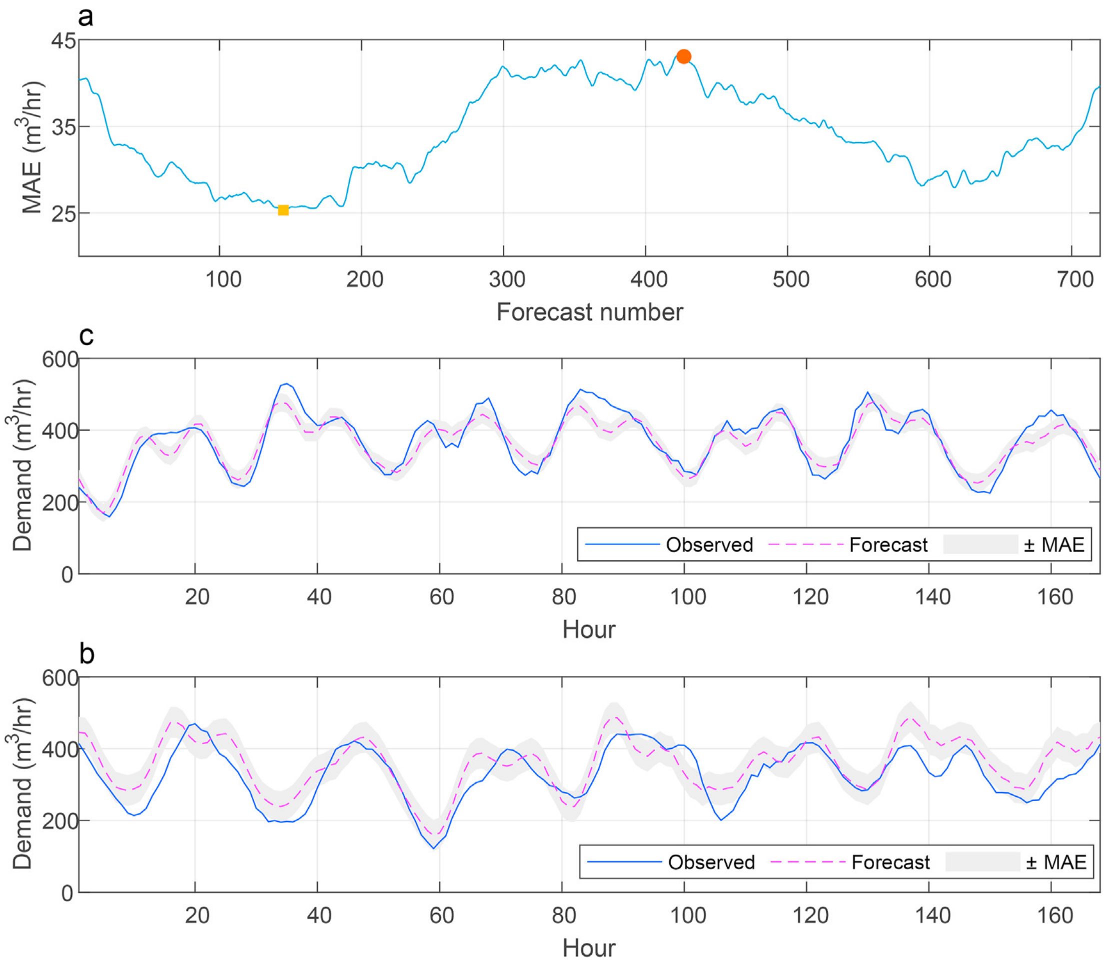

Fig. 10. NDF method performance: (a) MAE for all forecasts; and (b and c) observed and forecast demands for the minimum and maximum MAE, respectively.

Table 5
Comparison of optimization methods.

Run	Optimization procedure	Strategy	Demand	Total cost ($)
FAA(RH-FD)	FAA	Receding horizon	Forecasted	29,911
MILP(RH-FD)	MILP (CBC)	Receding horizon	Forecasted	29,248
TMC_{FAA}	FAA	Full month	True	29,753
TMC_{MILP}	MILP (CPLEX)	Full month	True	29,032

that all the selected pumping states during one month of operation belong to the efficient states set, as can be seen in Fig. 9. This indicates an efficient use of energy for pumping purposes, which also contributes to reducing the GHG footprint of the water utility, in addition to reducing the operation cost.

The results above are based on the framework presented in Fig. 4, which requires weekly demand forecasts for each of the 720 runs. To evaluate the accuracy of the NDF demand forecast, which is adapted in this study, we compare the forecasts with the real demand values by calculating the Mean Absolute Error (MAE) in Eq. (3).

$$MAE = \frac{1}{|\tau_h|}\sum_{t\in\tau_h}|d_{obs,\ t} - \tilde{d}_t| \tag{3}$$

where $d_{obs,\ t}$ is the observed demand at time t and $|\tau_h|$ is the number of time-steps in the forecasting horizon, T. The MAE for all 720 forecasts is shown in Fig. 10a with a minimum (best) and maximum (worst) values of 25.3 m^3/hr and 43.1 m^3/hr respectively. The observed and forecasted weekly demand pattern for the best and the worst forecasts are shown in Fig. 10b and c, respectively. These results demonstrate the good performance of the NDF method despite its simplicity.

The total cost for the entire month of the Receding Horizon strategy with Forecasted Demands (RH-FD), as obtained by the FAA, is $29,911. To evaluate the optimality of this solution, we compare it with other optimization methods (Table 5). First, using the receding horizon strategy and the NDF forecasted demands, we formulate the optimization problem as a MILP problem and solve it using the CBC solver (Forrest and Lougee-Heimer, 2005) and obtain a total cost of $29,248 which is only 2.3% less than the FAA. The daily costs obtained by the FAA and the MILP solver are shown in Fig. 11a.

Next, we use the FAA and the MILP formulation and solve the full month with the true demands, here we solve the entire month as one problem without a receding horizon strategy. This is done to estimate the Theoretical Minimum Cost (TMC) of the WDS operation, when unrealistically assuming that the demand can be perfectly predicted for the entire month. Thus, this filters out the effect of the NDF method and focuses the comparison on the

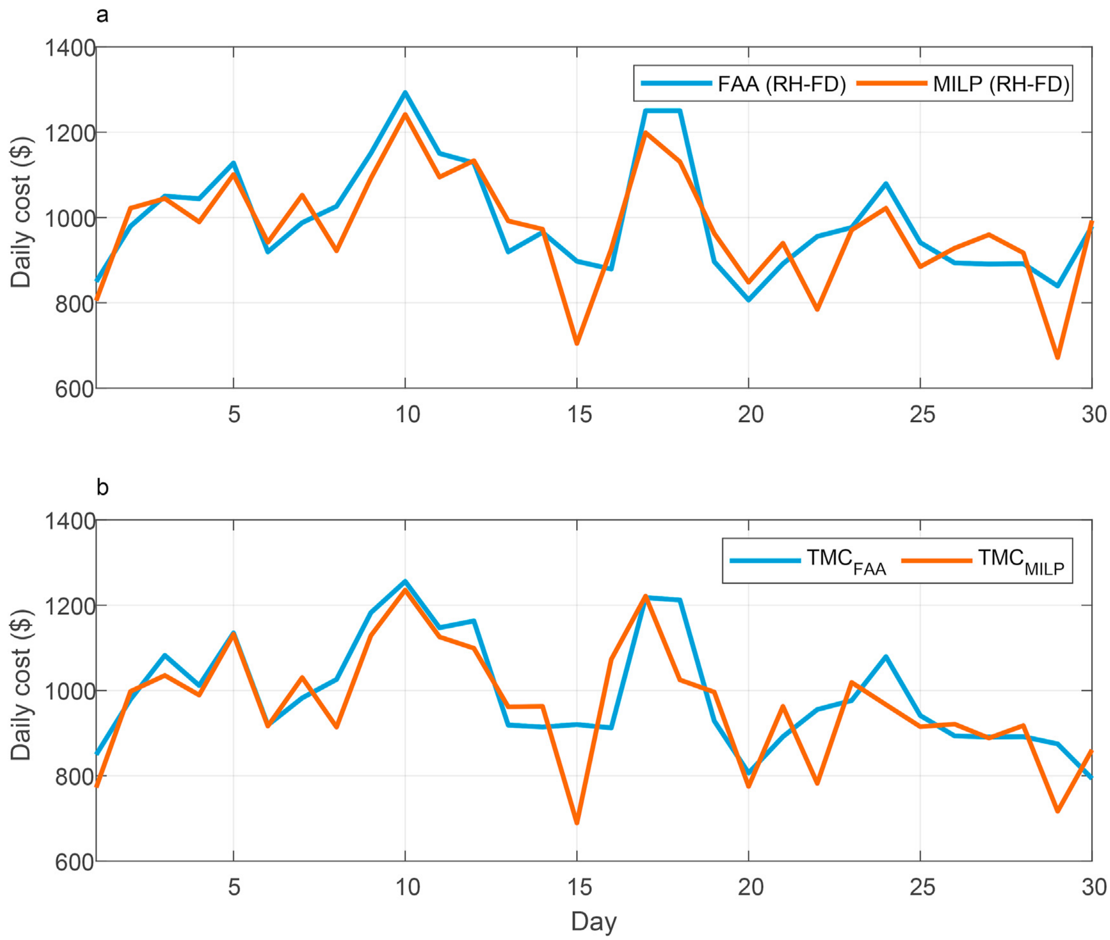

Fig. 11. Daily operation costs for FAA and MILP solvers.

optimality of the obtained schedule. When solving the TMC with the FAA we obtain a solution of $29,753 while solving the TMC with the MILP solver we obtain a solution of $29,032 which is only 2.5% cheaper than the FAA solution. Solving the large-scale MILP of one month required the use of the advanced commercial CPLEX solver (IBM Corp, 2009). Noteworthy that the deference between FAA(RH-FD) and TMC_{FAA} is only 0.5% indicating the good performance of the NDF despite its simplicity. The daily costs of the TMC as obtained by the FAA and CPLEX solver are shown in Fig. 11b. These results highlight the optimality of the FAA, as it can reach near optimal solutions in all days.

The near optimal solution of the FAA highlights its applicability to the real-time MPC framework in local control scheme. This is because, firstly, it solves the optimization problem three orders of magnitude faster than the MILP formulation. The cumulative probability distributions of the run time for the FAA and the MILP solvers are shown in Fig. 12 (note the horizontal log axis). As the optimization procedure is intended for real-time control scheme, a practical time limit for each optimization run is set at 5 min (Salomons and Housh, 2020). Despite that the time step is 1 h, a new operating plan for the next time step must be obtained much faster (e.g. 5 min). Allowing the optimization to run for 1 h, and only then deploying the plan, is not advisable since after 1 h the system state may be changed significantly. In such case the obtained results are not relevant anymore. The results show that the FAA solves the optimization problem in less than one tenth of a second in all cases! Whilst the MILP solver exceeds this threshold in 13% of the cases (in 4% of the cases the run time is above 1000 s which is the defined maximum run time for the CBC MILP solver). Secondly, and this is the most important advantage of the FAA, the execution of the algorithm can be performed in a simple PLC with simple operators such as loops and conditional statements, as opposed to heavy software dependencies and heavy computational demand of the MILP solver.

5. Conclusions

Pump scheduling methods which utilize computation intensive optimization algorithms may be suitable for implementation as a centralized solution in dedicated control rooms where advanced software and hardware are available. However, these methods cannot be installed in local PLCs of pumping stations or water tanks sites. Typically, the control logic which runs on the local PLC should be simple and with less computational requirements. As such, in many water utilities which use local control schemes, the potential benefits of optimal pumps' scheduling are unexploited. This study presents a practical optimization methodology for real-time control which is compatible with local control schemes. Hence, it leverages optimization methods in simple PLCs without the need for large investments in centralized control infrastructure.

The core of the proposed framework is the practical optimization procedure depicted in the FAA. The algorithm iteratively allocates additional flow to the water network to reduce infeasibilities while balancing the optimality of the solution over the operation horizon. The pumping states are allocated according to the SST which ensures efficient pumps' states selection. The most reliable data for the pumps' combinations characteristics, which is used to

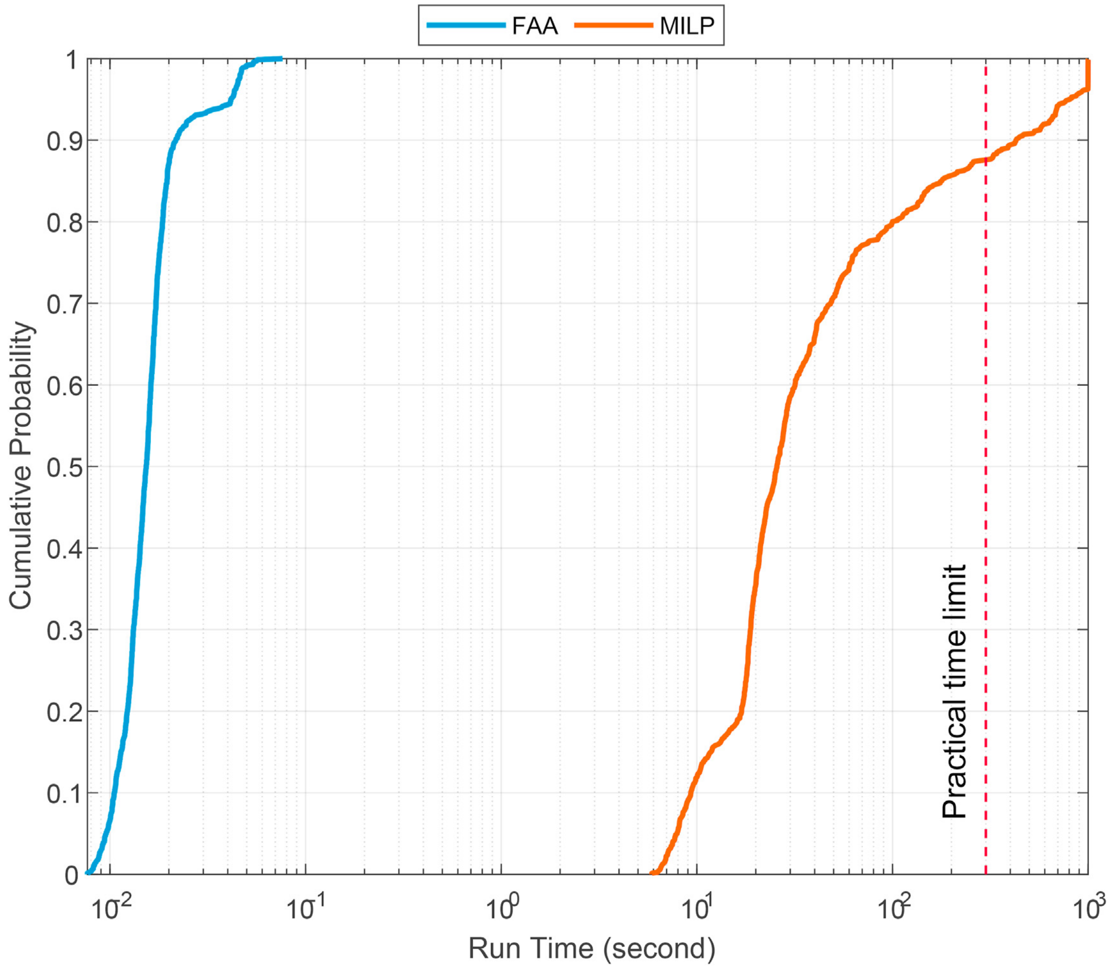

Fig. 12. Cumulative probability distributions of run time for FAA and MILP solver.

build the SST, can be obtained by analyzing SCADA data. This process is done offline and depends on both the specific pumps and the network characteristics. Our results indicate that the suggested framework not only reduces the operation costs, but also saves energy by utilizing the most efficient pumps. Thus, it can help the utility in reducing its GHG footprint. The proposed optimization procedure is compared to MILP solvers (which are typically used in centralized control schemes). The results show that it can provide near-optimal solutions, comparable with the obtained from MILP solvers, in a fraction of the time required by the solvers. In fact, the MILP implementation does not always run within a practical time limit suitable for real-time implementation, while the FAA runs in less than one tenth of a second.

The suggested framework is simple, practical, and applicable to local control schemes. This is achieved by its modest software computational requirements of loops, simple conditional statements, and basic mathematical operators. The proposed algorithm is designed for fixed speed pumps; however, variable speed pumps are also common. This is especially true in HPZs without storage in which the variable demand is supplied directly by the pumps and the pump's speed is dynamically adjusted to meet the demand. One way to incorporate variable speed pumps in the proposed method is to discretize the range of possible speeds into a set of states. Future work should examine the applicability of the proposed method for variable speed pumps. Other directions for future research may include better simulation of the water system with a hydraulic simulator acting as the real system, the inclusion of user defined constraints such as mid-day tank volume targets and more complex electricity tariffs (e.g., power spot markets).

CRediT authorship contribution statement

Elad Salomons: Conceptualization, Methodology, Software, Data curation, Writing - original draft, preparation, Visualization, Investigation. **Mashor Housh:** Supervision, Software, Validation, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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