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Optimizing equity in intermittent water supply systems: A volume-driven demand and flow control approach

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ABSTRACT

In many developing countries, intermittent water supply (IWS) systems are prevalent, resulting in limited access to water for consumers who do not have continuous 24/7 supply. Consumers are compelled to utilize private storage tanks to adapt to IWS conditions and overcome periods with no water access. While achieving greater water availability, the use of storage tanks exacerbates existing supply inequity. We propose a simulation–optimization approach that models consumers using a volume-driven demand technique to account for IWS consumer behavior, and employs a Bayesian optimization to determine the flow control valve schedule to improve local supply and global equity. The results demonstrate the existence of a hierarchy in supply in which consumers with favorable hydraulic conditions are able to fill their tanks any time supply is available, leaving consumers with less-favorable hydraulic conditions to fill their tanks only when an excess in supply exists. With limited control, only some global disparities can be offset. Additionally, intermittency in supply exacerbates the inequity and limits the efficacy of controls, reinforcing the importance of improving the continuity in supply. The proposed approach provides insights into the mechanisms behind inequitable supply in IWS systems, where further research is needed to maximize consumer welfare.

1. Introduction

Intermittent water supply (IWS) systems are water distribution systems that are characterized by their inability to provide continuous water supply for 24 hours a day (Ghorpade et al., 2021). It is estimated that up to 1.3 billion people worldwide are supplied water through IWS systems, where countries such as India, Nepal, Italy and many low and middle income countries are particularly disposed to conditions that necessitate IWS operation (Laspidou & Spyropoulou, 2017; Vairavamoorthy et al., 2008). The challenges associated with IWS include scarcity and unreliability in water supply, compelling households and communities to implement adaptive strategies (Vairavamoorthy et al., 2007). In many cases, consumers in IWS systems adapt to supply intermittency through the use of private storage tanks in order to cache water and meet demands during periods of non-supply (Ameyaw et al., 2013; Cobacho et al., 2008; Criminisi et al., 2009). While storage tanks provide a local solution for IWS consumers to improve supply reliability, these tanks can exacerbate existing disparities in water supply, which are governed by the hydraulic conditions of each consumer, even in cases in which existing supply is sufficient to meet all demands (Campisano et al., 2023; Mokssit et al., 2018). The resultant IWS system behavior is that consumers with hydraulically favorable conditions, e.g., lower elevations and closer proximity to the sources, have greater access to water supply (De Marchis et al., 2011).

Given the susceptibility of IWS systems to water scarcity, greater access to supply for some often results in a deficiency in supply for others, and *this difference in local supply availability between the consumers coalesces as global inequity in supply*. In this context, we focus on a system-wide model-based approach to (1) explore the mechanisms through which differing hydraulic conditions give rise to disparities in local supply and global equity in order to provide insight and guidance into the behavior of IWS systems, and (2) analyze the improvement in local supply and global equity between different consumers through strategically limiting the amount of flow allocated to different regions of an IWS under different intermittent supply schedules.

In the context of the challenges presented above, two primary considerations are the modeling approach to represent consumer behavior in IWS systems and the choice of the control strategy to implement. In traditional continuous water supply (CWS) systems, consumers are modeled using a demand-driven approach (DDA), which assumes an instantaneous satisfaction of all consumer demands, or with a pressure-driven approach (PDA), in which supply to consumers depends on the pressure at the consumer node and supply deficits occur when the

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pressure falls below a specified threshold (Ciaponi & Creaco, 2018; Tanyimboh & Templeman, 2010). While PDA captures deficiencies in supply for consumers with low pressure, neither approach directly models local storage, and as a result, might incorrectly represent the water supply. In contrast to DDA and PDA, representing consumer behavior with volume-driven demands (VDD) directly includes local storage, where consumer withdrawals from the system are no longer limited to a specified demand flow rate, but rather, the withdrawals are limited by the total volume of the storage tank (Suribabu et al., 2022). Consequently, the VDD approach augments the PDA approach by capturing both pressure-driven and volume-driven conditions. In IWS systems, consumers regularly take advantage of the ability to withdraw water at volume-limited rates to fill their storage tanks with more water than they demand in order to ensure demand can be met during periods of supply interruption (Andey & Kelkar, 2009; De Marchis et al., 2015; Reddy & Elango, 1989).

Previous research has been conducted to augment traditional CWS hydraulic models with volume-driven approaches in order to run extended-period simulations for IWS systems (Sivakumar et al., 2020), simulate aggregated household behavior at each consumer node (Suribabu et al., 2022), compare different storage tank configurations (Abhijith et al., 2023), and develop a parsimonious macroscopic model to characterize high-level IWS performance irrespective of topological details (Taylor et al., 2019). The proposed application of VDD comprises a high-level modeling approach that avoids the need to have detailed information about local tanks, which is typically not available (Ghorpade et al., 2021; McIntosh, 2003). In this approach, insights and high-level system behavior can be gleaned from the model and guide effective management decisions even under substantial uncertainty of the fine-grained details (Lucas & McGunnigle, 2003). Overall, the application of VDD to CWS models allows for a more accurate representation of consumer behavior in IWS systems, leading to improvement in the estimation of system-wide hydraulic conditions and more effective decision-making for IWS managers.

While hydraulic models for IWS systems have seen significant advancement in recent years, a vast majority of the literature on the optimal management of water distribution systems still focuses on continuous water supply (Sarisen et al., 2022). Furthermore, research that focuses on optimizing equity in IWS systems does not tend to directly account for any local storage capabilities of consumers, despite the negative effects that storage tanks have on equitable supply (Ayyash et al., 2024; Gottipati & Nanduri, 2014; Ilaya-Ayza et al., 2017; Nyahora et al., 2020; Solgi et al., 2015). An example of recent efforts to improve the management of IWS systems is the Battle for Intermittent Water Supply, a hydraulic modeling and optimization competition with the goal of optimizing control elements and infrastructure investment decisions for an IWS system subjected to numerous leaks and pressure deficiencies (Marsili et al., 2023; Mottahedin et al., 2023; WDSA CCWI, 2022). Despite the goal of finding control strategies to maximize consumer welfare in a large IWS system, the provided system did not account for local consumer storage. This omission can significantly alter system hydraulics substantially, resulting in the system being essentially modeled as a CWS system.

In extending the management of CWS systems to IWS systems while accounting for consumer storage, this research explores control strategies aimed at overcoming supply inequity. These strategies involve imposing flow limits to certain areas of the IWS system to allow flow to areas in less hydraulically favorable positions. Such flow control strategies can be implemented through the use of flow control valves (FCV) or pressure-reducing valves (PRV) (Mala-Jetmarova et al., 2017). Another common type of control for CWS systems are programmable logic controllers (PLC), which automate valve operation based on sensor input (Puig et al., 2017). This setup requires sensors in local tanks to continuously measure water levels and a central control unit to communicate and update the valve settings. However, since PLCs control flow restrictions, consumers may resist sensor installation, thereby self-imposing flow restrictions. In addition, using a central control unit relies on reliable real-time transmission of tank levels (Creaco et al., 2019), requiring advanced telecommunication capabilities that might be impractical for many IWS systems.

Therefore, in this research we assume that limited FCVs are present in the IWS system and we apply an optimization model that aims to determine the optimal schedule for the settings of each FCV over a given operating horizon. These settings restrict flow for consumers that perpetuate inequity across the system through the unrestricted filling of storage tanks. The resultant schedules can then be reconfigured for each new time horizon based on the known or forecasted intermittent supply schedule. This approach serves the advantage of being relatively easy to implement and does not require advanced telecommunication and sensing capabilities, which are both expected to be limited in the context of IWS systems.

To account for the local storage in IWS systems, the proposed approach directly incorporates volume-driven demands into the hydraulic simulation. However, the addition of VDD combined with controls makes the governing equations in the hydraulic model highly complex, necessitating the use of simulation–optimization approaches such as genetic algorithms, simulated annealing, and particle swarm optimization (Djebedjian et al., 2021). An increase in the model complexity also means an increase in the computational burden of the simulation, which is particularly critical for simulation-based approaches. One such simulation–optimization approach that has been successful in dealing with problems characterized by expensive simulations is Bayesian optimization (BO) (Frazier, 2018). BO is a probabilistic technique, particularly amenable to problems where objective evaluations are costly, and the number of evaluations is therefore limited (Wu et al., 2017). Given the time-consuming and resource-intensive requirements of implementing VDD into a simulation–optimization approach, this research utilizes BO to improve computational tractability.

This research contributes to the current literature by (1) exploring the mechanisms through which this difference in hydraulic conditions manifests as supply inequity, (2) improving the local supply and global equity through the implementation of an optimized FCV setting schedule, and (3) assessing the effects that intermittency in source supply has on the global equity and efficacy of the flow control strategy. Additionally, to validate the optimization approach, the performance of the optimization model is compared to an alternative model that utilizes PRVs for system control and a sensitivity analysis is performed to assess the degree to which uncertainty in consumer tank capacities affects the performance of the optimal flow control decisions. As IWS operation continues to be the reality for supply systems worldwide, the inclusion of more accurate real-world behaviors into advanced management models is needed to identify optimal strategies to maximize consumer welfare.

2. Methodology

In this section we propose a methodology for improving equitable supply in an IWS system with a flow control optimization model. First, we introduce the problem and give an overview of the solution method. Second, the hydraulic model is introduced and details are provided on the augmentation of a CWS model to convert it into an IWS model. Third, the model performance criteria are defined and discussed. Finally, the framework for the simulation–optimization model to maximize equity is provided, where the details on the Bayesian optimization approach are elucidated.

2.1. Problem statement

The unique hydraulics of IWS systems allow some consumers to make unrestricted withdrawals from the system, thereby decreasing water access for others during periods of supply and inhibiting their ability

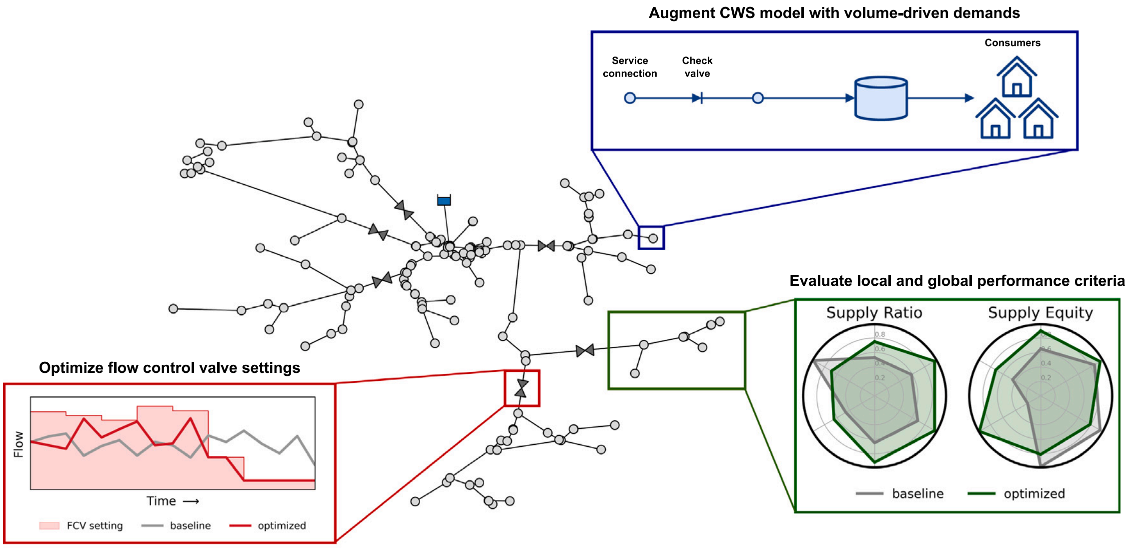

Fig. 1. Overview of the simulation–optimization approach.

to store sufficient water for non-supply period. As such, a simulation–optimization model is proposed that accounts for this unique behavior of IWS systems and tailors a control strategy to override the inequitable distribution of water among IWS consumers. The overall approach is shown in Fig. 1, in which a standard CWS model is converted into an IWS model through the adoption of consumer tanks, local and global performance metrics are defined to capture the system behavior, and an FCV control optimization model is applied to the IWS system to maximize the supply equity. The approach is tested for two different configurations of IWS systems. In the first, water is supplied from a source tank with limited water volume and the supply period is equal to the time it takes for the tank to empty (Vairavamoorthy et al., 2007). In the second, a water rationing scheme is applied to supply from a reservoir in which the extent of supply period restricted to a limited number of hours a day, representing a management strategy employed in many IWS systems (Randeniya et al., 2022). For the second configuration, the supply schedule is varied to assess how distributing supply throughout the day affects system equity and the ability to overcome inequity.

2.2. IWS system model

The objective behind developing the IWS system model is to account for inequity in supply to IWS consumers, and achieved through integrating VDD into a pressure-driven hydraulic model. Traditional CWS demand models, such as DDA and PDA, only account for the immediate water use, neglecting the discharge or withdraw into the local storage tanks that offsets the actual timing and volume of consumers' demand Boulos et al. (2006). DDA and PDA models can be considered *flow-restricted*, as they limit the flow rate from the system to the consumer node in any given time step to match the immediate demand flow rate. To overcome these limitations, VDD is introduced as a *volume-restricted* demand model in which flow from the system to the consumer node is only limited by the local tank volume (Abdelazeem & Meyer, 2024). To implement VDD, a CWS model is converted to a IWS model by augmenting each consumer node with the artificial elements illustrated in Fig. 1. The VDD approach (Taylor et al., 2019) was implemented with two primary modifications. First, a demand node is introduced downstream of the storage tank to represent consumer withdrawals from the tank. Demands at the consumer nodes downstream of the tank are modeled using the PDA approach, in which p_{min} and p_{req} are the minimum and the required pressure to supply partial and full demand, respectively. The pressure settings are selected such that consumers are able to withdraw water anytime there is available water in the storage tank. Second, model aggregation is performed at the node level, i.e., local aggregation, as opposed to the system level in the macroscopic VDD approach, where all nodes are reduced down to a single representative node (Ormsbee & Lansey, 1994). Local aggregation is utilized to reduce model complexity in large networks by combining groups of households into individual nodes.

The result is a system-level analysis where the effect of household plumbing configurations are not explicitly included, but rather, a focus is placed on the effects that the system topology, elevations, and local storage have on the hydraulic behavior of the system. The modeling approach assumes that the tank storage capacity of consumers equals their total daily demand. The optimization model is initially solved under this assumption and its sensitivity to the uncertain tank capacities is explored. Having reconfigured each consumer using the VDD approach, the IWS model is simulated by solving the governing hydraulic equations (mass and energy conservation) over a given time horizon (Boulos et al., 2006). The inclusion of a large number of consumer tanks in the VDD approach can introduce instabilities in the hydraulic model, where the tank inlet and outlet pipes cyclically turn on and off in time steps smaller than the hydraulic time step. To mitigate this behavior, control rules were applied to each tank where the inlet pipe is closed once the tank level reaches 99% capacity and re-opens when the tank level falls to 95% capacity, thereby improving the stability of the simulation. The IWS hydraulic models utilized in this research are provided in the Supplementary Material (SM).

2.3. Performance criteria

To measure the extent and distribution of the water shortage across consumers, different equity metrics were explored (Ameyaw et al., 2013; Gullotta et al., 2021; Guragai et al., 2017). In this approach, we evaluate the performance of the IWS model with two performance metrics derived from the uniformity coefficient (Ilaya-Ayza et al., 2018): (1) the *supply ratio* which captures the *local* demand satisfaction of each individual consumer and (2) the *supply equity* which distills the supply ratios of all consumers into one *global* metric representing the disparity among consumers. To capture the deficiency, the supply ratio measures the fraction of demand that is satisfied in each time step t:

$$SR_n^t = \frac{q_n^t}{d_n^t} \tag{1}$$

where SR_n^t is the supply ratio at a given consumer node n, q_n^t is the tank discharge flow rate, which represents withdrawals from the tank by the consumer, and d_n^t is the consumer demand. A supply ratio equal to 1 in all time steps indicates a consumer that has their demand fully satisfied. To analyze the supply ratio across different scales, SR_n represents the temporal averaging of SR_n^t across all t time steps, SR^t represents the spatial averaging of SR_n^t across all n consumers, and SR represents the temporal and spatial averaging of SR_n^t across all n consumers and all t time steps.

To quantify the disparity in supply across the system, the supply ratios of each consumer are compared with one another to form the supply equity:

$$SE^t = 1 - \frac{1}{N}\sum_{n=1}^{N}\frac{\left|SR^t - SR_n^t\right|}{SR^t} \tag{2}$$

where SE^t is the global supply equity at time t, SR^t is the average supply ratio among all consumers at time t, and N is total number of consumers in the network. The final equity metric is a single index that represents the temporal averaging of the global supply equity:

$$SE = \frac{1}{T}\sum_{t=1}^{T} SE^t \tag{3}$$

where SE represents the total equity across the network and T represents the total number of time steps in the model. In this formulation, a value of 0 represents no equity and a value of 1 represents absolute equity, i.e., uniform SR_n across all consumers. We note that the two metrics, SE and SR, are complimentary and should be used in conjunction when assessing the performance of IWS systems.

2.4. System control model

The primary component of the proposed approach is the system control model, which consists of a simulation–optimization model to determine the optimal FCV setting schedules that maximize the global supply equity between consumers. FCVs are valves used to regulate flow in water systems, where the FCV setting determines the maximum-allowable flow rate through the valve and the setting schedule defines the FCV settings for specified time periods. We assume that the management of the FCVs does not require water level information from the local tanks, but instead, the setting schedule for each FCV is determined by the control model for a given operating horizon and forecasted intermittent supply schedule. The overall strategy employed by the optimization approach is to impose spatiotemporal flow limits in the system in order to prevent over-consumption by consumers with more favorable hydraulic conditions, thereby granting increased water access to consumers with less favorable conditions and increasing the global supply equity.

In the proposed optimization approach, the objective function is the global supply equity (Eq. (3)) which integrates the local supply ratios. The decision variables are the values of the FCV settings that comprise the setting schedules for each valve in the system. The decision variables are continuous and bounded between q_{min} and q_{max}. The variable bounds were determined through a trial-and-error process to ensure the bounds were non-binding constraints, i.e., the flow rate into any zone will not be limited by the variable upper bounds in any iteration of the BO model. The timing of the FCV setting schedules, i.e., the times in which the FCV settings are implemented, are provided as model inputs, which align with the intermittent supply schedule.

In the simulation–optimization approach, the objective and the constraints are evaluated through a hydraulic simulation of the IWS system (Amaran et al., 2016). This approach involves the search for the specific FCV settings that are provided as inputs to each hydraulic simulation such that the objective function, i.e., the global supply equity calculated based on the simulation outputs, is optimized. The hydraulic simulation of the IWS system is computationally intensive due to the added complexity from the inclusion of local storage tanks and control valves. In order to increase the computational tractability, BO is used to optimize the objective while limiting the number of simulations and thus, limiting the total computational burden (Wu et al., 2017). The BO method involves learning the input–output relationships by constructing a surrogate model that approximates the underlying simulation model. The BO method consists of two primary components: a probabilistic surrogate model that is iteratively updated to represent the objective function, and an acquisition function that determines the next point where the objective should be evaluated, i.e., new FCV settings (Frazier, 2018). In this approach, the surrogate model employed is Gaussian process regression (GPR). Gaussian processes define a multivariate Gaussian distribution over functions and are specified by a mean function and a covariance kernel. The selected kernel is the Materń kernel, which determines how function values at different inputs relate to each other (Archetti & Candelieri, 2019). As new data points are acquired, the Gaussian process updates its beliefs about the objective function, yielding a posterior probability distribution. At a given point, the posterior provides both a mean prediction and associated variance which represents the uncertainty of the prediction. For the acquisition function, we chose to utilize the Expected Improvement (EI) function, which estimates the potential improvement over the current best-known value of the objective function (Archetti & Candelieri, 2019). It achieves an effective balance between exploring regions of high uncertainty, where the surrogate model is less confident about its predictions, and exploiting areas of predicted favorable objective values. This mechanism ensures that the optimization process continually refines its approximation of the objective function, focusing on regions that are most promising or necessitate further exploration. The BO method has several parameters determined using sensitivity analyses, including the number of iterations and initial points, as well as the hyperparameter ξ that controls the exploration-exploitation trade-off (Candelieri et al., 2018). Additional information about BO is provided in the SM.

In the proposed simulation–optimization model, the added complexity from the inclusion of check valves, tanks, and FCVs in the hydraulic model can result in hydraulically unstable or infeasible solutions. If the FCV settings that result in the highest-scoring objective value also result in an unstable solution, a second iteration of the BO model is implemented to find stable optimal solutions. This is accomplished by first initializing the second BO model with the optimal FCV setting schedule achieved in the previous BO model, i.e., $x_{0,II} \leftarrow x_I^*$. The variable bounds are then tightened to limit the variable search space within a specified range above and below the initial point, i.e., between $(1+\alpha)x_{0,II}$ and $(1-\alpha)x_{0,II}$, where α determines the range. In tightening the variable bounds and exploring the local solution space, the second iteration of the BO model leverages the high objective score of the original unstable solution. At the conclusion of the second BO model, the stable solution with the highest objective value is selected as the final FCV setting schedule. Through this process, the high objective score from the first BO model is maintained or improved, and the stability of the final solution is guaranteed. The choice of surrogate model, acquisition function, kernel, and number of iterations in the second BO model are the same as the first implementation of the BO model. The only changes between the two models are the initial points and variable bounds.

3. Results

The proposed methodology is applied to two systems to (1) demonstrate the effects of modeling consumer behavior through the VDD method and explore the mechanisms that drive inequitable supply, (2) analyze the result of applying optimized flow controls to maximize local supply ratios and global equity, and (3) explore the effects of intermittent source supply on the system performance. Both systems have a branched topology and were selected to resemble IWS systems segmented into district metered areas. The first system, S-1, is an idealized system that is used to examine the changes in system

Table 1
Parameters for Bayesian optimization model.

Parameter description	Value
Surrogate model	Gaussian process regression
Acquisition function	Expecteed improvement
Covariance kernel	Matérn
Number of iterations	100
Number of initial points	5
ξ (Exploration vs. exploitation)	0.01
α (size of variable restriction)	0.1

hydraulics when accounting for consumer storage tanks and display the effects of optimizing a fully-controlled system, i.e., a system with an FCV connecting each individual consumer to the transmission main. The second system, S-2, is a medium-sized system where multiple consumers are grouped together into zones, which are connected to the transmission main through an FCV. S-2 is used to demonstrate the results of optimizing granular controls in which the FCVs control the flow rate entering each zone but the inter-zone distribution of water to consumers remains enforced by hydraulics. Following the application of the simulation–optimization model on S-2, further analyses are conducted to examine the affect of the source supply schedule on system performance. To validate the optimization approach, we compare the utilization of FCVs with a control scheme that employs PRVs and test the sensitivity of the optimization model performance to uncertainty in consumer tank capacities.

We used the open source Python library, `scikit-optimize` (`skopt`), to implement the BO model, where the GPR surrogate model was executed using the built-in method `gp_minimize` (Head et al., 2020). The selection of parameters for the BO model listed in Table 1 was guided by a sensitivity analysis and relevant literature (Moeini et al., 2023). The results of the BO model represent the best solution found for each application. The IWS system model was constructed using the Water Network Tool for Resilience (WNTR) (Klise et al., 2017) and the hydraulic simulation was conducted using the EPANET 2.2 solver (Rossman et al., 2020). The minimum and the required pressure to supply partial and full demand, are set to $p_{min} = 0$ and $p_{req} = 0.1$, respectively. The pressure settings are selected such that consumers are able to withdraw water anytime there is available water in the storage tank and are able to satisfy their full demand whenever their storage tanks are at least 10% full. The selected value for p_{req} is the minimum allowable value in EPANET. Each simulation is conducted for 24 h with a hydraulic time step of 5 min. The small time step is selected to in order to more accurately capture the tank dynamics, which is essential given the large number of tanks in the VDD approach. All remaining details for the hydraulic simulations can be accessed through the standard hydraulic model .INP files provided in the SM. The runtime for the BO model with 100 iterations is about ten minutes on a Windows machine with Intel(R) Core(TM) i7-8700 CPU@3.60 GHz.

3.1. Small system

S-1 is a small branched system where water is supplied from a single source tank. The network has a total of six consumer nodes, where each node is modeled using the VDD approach, as detailed in Section 2.2. Each individual consumer node is connected to the transmission main through an FCV, a setup representing an idealized scenario of complete system control. The IWS condition is imposed through the source tank in which the volume of supply is limited and is equal to the total daily demand of all consumers. A schematic of S-1, including the elevations of each consumer and details of the control period, is provided in Fig. 2. The optimization problem involves deciding on the flow settings for each of the six FCVs during the six control periods in the 24-h simulation, resulting in 36 total decision variables.

3.1.1. Analysis of overall system performance

The performance of three hydraulic models with respect to the local supply ratio, SR^t, and global supply equity, SE^t, are compared with one another to reveal the supply inequity that CWS modeling approaches are unable to capture and examine the ability of the optimized flow controls to overcome inequity in a fully-controlled system. The three modeling approaches are the (1) *CWS model*, which represents a traditional approach for modeling consumer demands using PDA, (2) *baseline model*, which represents the implementation of the IWS system without any controls, and (3) *optimized model*, which represents the implementation of the IWS system control model with optimized FCV settings. Fig. 3(a) displays the time series data for the supply ratio (top) and supply equity (bottom) and Fig. 3(b) displays bar charts for the temporally-averaged performance metrics SR (top) and SE (bottom) for all three models. In Fig. 3(a), the CWS model is represented with a black solid line, the baseline model is represented by a blue dashed line, and the optimized model is represented by the blue solid line. The associated SR and SE values for the three models are represented by the gray, striped blue, and solid blue boxes in Fig. 3(b). Any value of SE^t or SR^t below 1 indicates that one of the six consumer nodes has unsatisfied demand at time t.

With no consideration of local storage at the consumer nodes, the CWS model does not capture the inequity in supply that the baseline model displays in Fig. 3. While the CWS model uses PDA, allowing for supply deficits when the local pressure is beneath the required pressure, the resultant supply ratio $SR = 1$ for the CWS model indicates that the pressure conditions are not low enough to induce diminished supply, i.e., the pressure is adequate for a CWS system with no local storage. However, the baseline model reveals that the difference in pressure conditions at the consumer nodes, as evidenced by the difference in elevation, leads to inequitable supply even when there is sufficient pressure in the system. The inequitable supply in the baseline model occurs primarily at the beginning of the simulation and after hour 6, resulting in $SE = 0.72$. With the introduction of flow controls in the optimized model, SR^t reaches a value of 1 more quickly and extends the period in which all consumer demands are met until hour 22, after which both SR and SE taper off once more. Fig. 3(b) summarizes the temporal performance metrics, where the application of flow controls almost completely overcomes inequitable supply in the baseline model, where SR increases from 0.85 to 0.96 and SE increases from 0.72 to 0.98.

3.1.2. Analysis of individual consumer tanks

This section analyzes the dynamics of the consumer storage tanks in the baseline model and the optimized model in order to explore the mechanisms underlying inequity in S-1. Fig. 4 plots the temporal tank levels, L_n^t, for each consumer in both the baseline model and the optimized model during the control period. The plot backgrounds are shaded to represent the FCV settings applied in each control period in the optimized model where the periods shaded blue represent no flow restrictions. In the baseline model, consumers 1 and 2 (see Fig. 4 top row, dashed lines) take precedence over the others and fill their tanks to the maximum levels while the remaining consumers are subjected to lesser tank inflow rates. Once the maximum level is reached for consumers 1 and 2, consumers 3–5 are able to increase their tank inflow rates until they also reach the maximum storage capacity, the order of which occurs commensurately with their respective elevations. Thus, a water supply hierarchy is established that corresponds to the consumer elevations (Fig. 2), where lower elevations translate to higher pressures and vice versa. In the subsequent periods after the storage tanks for consumers 1 and 2 reach capacity, the tanks are repeatedly filled as long as there is available supply from the source, further demonstrating their place on top of the supply hierarchy as dictated by their hydraulically favorable pressure conditions. On the opposite end of the spectrum lies consumer 6, who is unable to receive supply until the other consumers have all reached capacity. In the subsequent

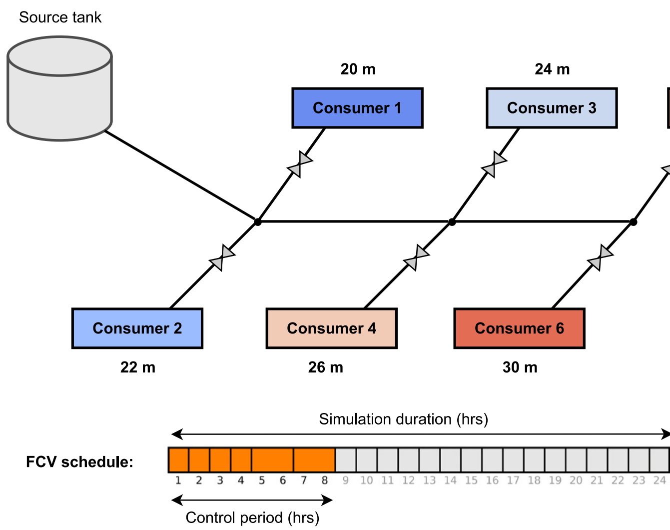

Fig. 2. Schematic of S-1 with the FCV schedule. Consumers are colored by elevation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

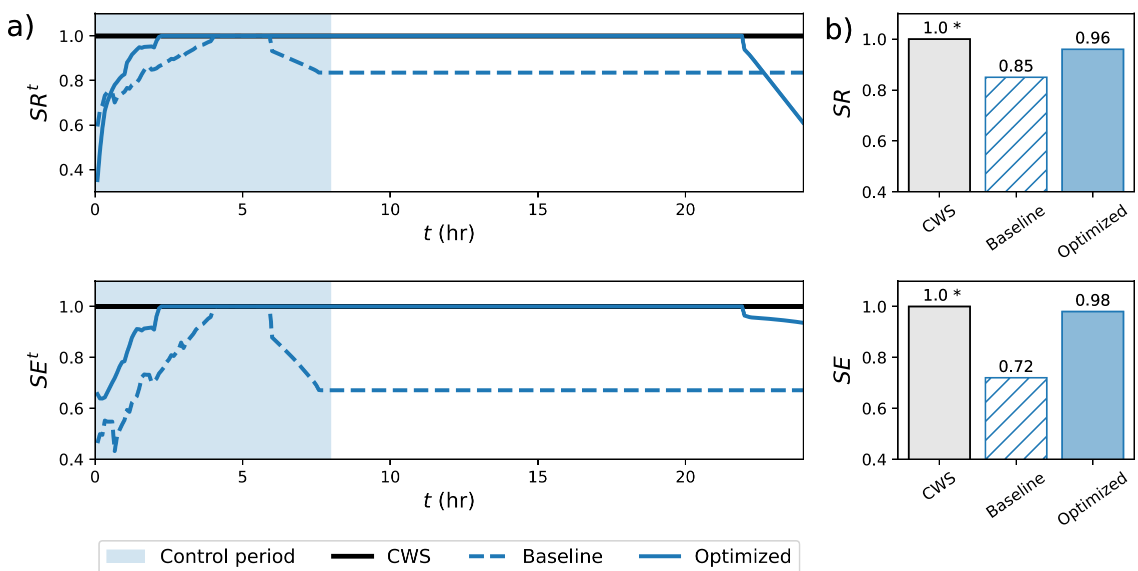

Fig. 3. (a) Supply ratio (top) and supply equity (bottom) time series for CWS, baseline, and optimized models, and (b) bar plots for total average supply ratio and global supply equity for CWS, baseline, and optimized models. *The SR and SE values for the CWS model highlight an artificially equitable supply amongst the consumers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

periods of supply, the flow rate for consumer 6 is limited by the other consumers refilling their tanks and as a result, the former is unable to incur enough storage to continue to meet demands beyond the control period (see Fig. 4 bottom right, dashed line). As a result of the poor pressure conditions, consumer 6 only meets about a sixth of the daily demand with $SR_6 = 0.17$. The application of optimized FCV settings alters the distribution of supply by limiting flow to consumers 1–5 during the first 6 h, allowing the storage tank for consumer 6 to both fill up earlier in the control period and continue to meet demand for a longer duration. The result is a slight decrease in the ability of consumers 1–4 to meet all demands, with each SR_z value decreasing from an average of 1.0 to 0.96, while SR_6 increases by a factor of 5.8 from 0.17 to 0.98.

3.2. Medium system

S-2 is a modified version of KY24 from the University of Kentucky Water Distribution System Research Database (Jolly et al., 2014). S-2 is a branched network with 161 consumers that are supplied through pumping from a single reservoir located in the center of the network. The network was partitioned into six zones designated 1–6, each connected via FCV to the transmission main which is designated as Z-0. The network topology, node elevations, and zone assignments are displayed in Fig. 5. The intermittent supply condition is represented through a supply schedule in which the source pumps are active for the first 8 h of the 24 h time horizon, and are inactive for the remainder of the time horizon. The decision variables for the optimization model are the same as the model applied to S-1, in which each of the six FCV has six different settings that constitute the control period.

3.2.1. Optimal flow control strategy

The optimal FCV setting schedule is analyzed in order to assess the emergent flow control strategy applied to S-2, and compare that strategy with the one applied to S-1. Fig. 6 displays the FCV flow rate time series, q_z^t, and FCV settings for each zone z during the supply

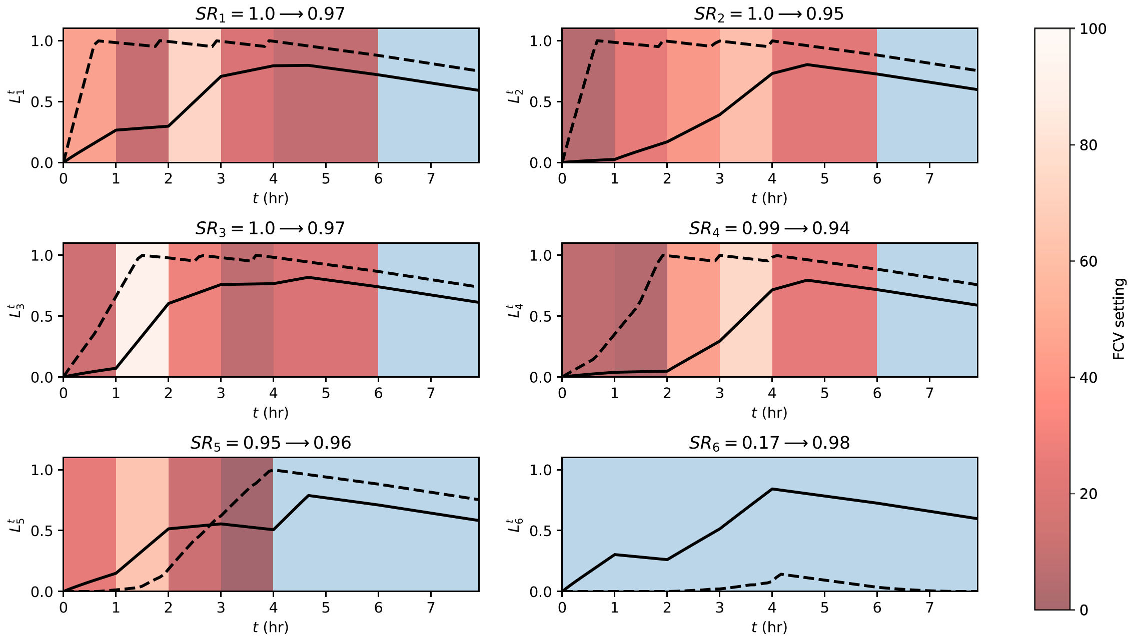

Fig. 4. Consumer tank levels L_n^t for baseline (dashed) and optimized (solid) models. Changes in supply ratios are provided for each consumer, displayed as SR_z = baseline supply ratio $\longrightarrow$ optimized supply ratio. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

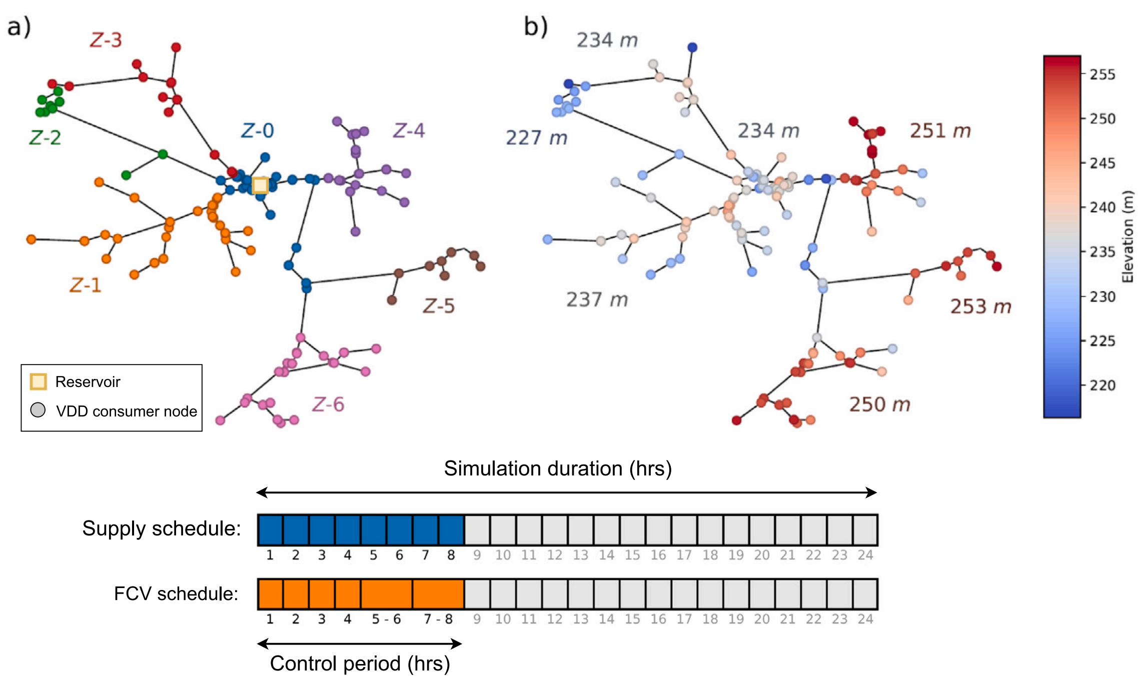

Fig. 5. Schematic of S-2. Consumer nodes are colored with respect to (a) zone and (b) node elevation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

period in the baseline and optimized models. The FCV settings are represented by the blue shaded area in each plot, which reveal the maximum allowable flow for each zone in the optimized model, and the actual FCV flow rates for the baseline and optimized models are represented by the gray and orange lines, respectively. In the baseline model, the zones with lower average elevations, i.e., Z-1, Z-2, and Z-3, see greater flow rates relative to the zones with higher average elevations, Z-4, Z-5, and Z-6. Furthermore, the zone with the lowest average flow rate, Z-2, shows intermittent flows after hour 3 which can be interpreted as the cyclical re-filling of tanks once the tank levels have dropped slightly after reaching capacity. In the optimized model, the FCV flow rates into zones Z-1, Z-2, and Z-3 face minimal limits from the FCV settings at the beginning of the supply period, however, the settings for all three FCVs are set at 0 later in the supply period, which effectively disconnects the zones from the rest of the system. When all three zones are disconnected in last two hours of the supply period, zones Z-4 and Z-6 experience increased flow rates relative to the baseline model. The general strategy imposed through the FCV settings in the optimized model is to allow zones with more favorable pressure conditions to fill tanks early in the supply period before imposing flow restrictions, allowing greater flow to the remaining zones. The flow control strategy contrasts with the strategy imposed for S-1 (Fig. 4),

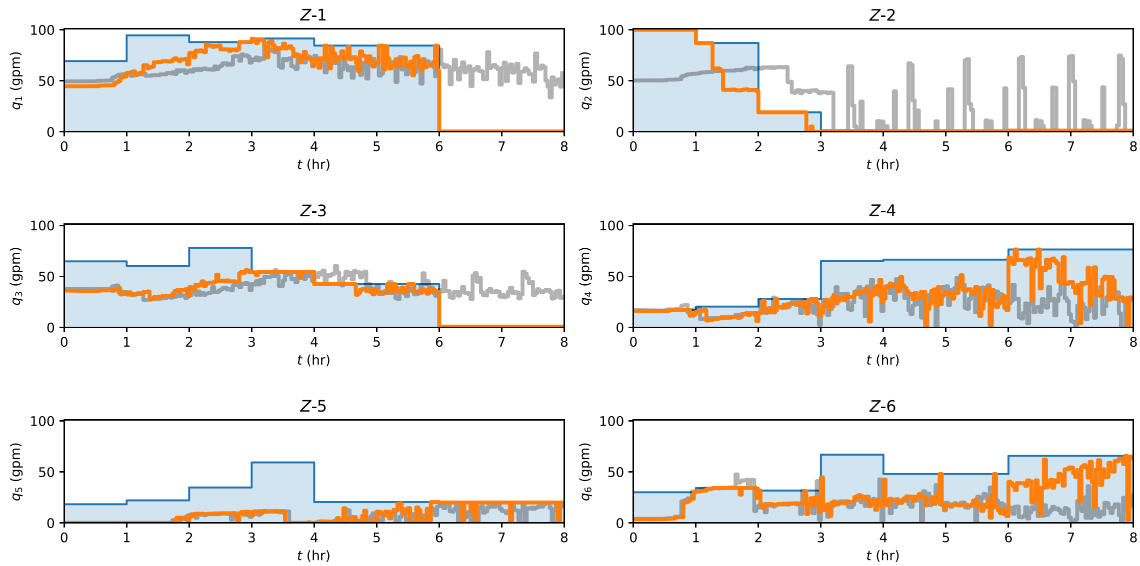

Fig. 6. FCV flow rates into each zone during supply period for baseline (gray) and optimized (orange) models, along with optimal FCV settings (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in which S-1 consumers with favorable pressure conditions (consumers 1–5) faced early flow restrictions to allow the consumer with the least-favorable pressure conditions (consumer 6) to receive flow throughout the entire time horizon.

3.2.2. Analysis of zone-specific performance

This section examines the performance improvement for the optimized model with respect to the baseline model, focusing on the global equity and average supply ratios across the zones. The local supply ratio, SR_z, and global supply equity, SE_z, are displayed for each zone z in Fig. 7, where the blue lines represent the baseline model and the orange lines represent the optimized model. The radial axes in the two plots each represent the range of SR_z (or SE_z) for each zone, where 1 indicates perfect performance and 0 represents otherwise. Fig. 7 (left) shows an increase in SR_z for zones Z-4, Z-5, and Z-6, while zone Z-3 decreases slightly and zones Z-1 and Z-2 register no change. The supply equity, SE_z, in each zone display similar behavior between the two models as the supply ratio, however, Z-5 shows a slight decrease despite the increase in SR_z. As expected, the performance of the group of consumers along the transmission main (zone Z-0) remains unchanged, as they are directly connected to the source without an FCV in between. The overall performance of the baseline and optimized models show an increase in SR from 0.79 to 0.87 and an increase in SE from 0.61 to 0.78, thus improving both the local and global metrics. Despite the flow restrictions applied to zones Z-1, Z-2, and Z-3 in Fig. 6, the result is a minimal deficit in supply directly to consumers, whereas the increased flow rates to zones Z-4, Z-5, and Z-6 at the end of the control period result in an average increase in SR_z of 43% from 0.42 to 0.6. Comparing SR_z for the two models with the average zone elevation in Fig. 5, the general behavior exhibited in Fig. 7 is an increase in supply to the zones with less favorable hydraulic conditions as a result of the implementation of flow controls.

Since the improvement in global supply equity, SE_z, for zones Z-4 Z-5, and Z-6 was achieved at minimal decrease in local supply ratio, SR_z, to the other zones, the apparent surplus of water in the optimized model is explored by analyzing the total water volumes supplied to each of the zones. Fig. 8 displays the volume of water supplied to the consumers in each of the zones for both the baseline and optimized models, where (a) displays the total supplied volume (b) displays the water volume that is leftover in the consumer tanks at the end of the time horizon, and (c) displays the water volume that consumers withdrawal from the tank throughout the time horizon to meet demands. The blue lines in each plot represent the baseline model values, the orange lines represent the optimized model values, and the radial axes represent the water volumes (m^3). Together, the plots show that in the baseline model without FCV controls, consumers in zones benefiting from favorable hydraulic conditions store excess water in their local storage tanks, thereby restricting the supply to consumers with in zones with less favorable hydraulic conditions. In the optimized scenario, the increase in supply ratio of in zones with less favorable hydraulic conditions (Z-4, Z-5, and Z-6) essentially represents a transfer of water that would otherwise be stored in excess by consumers in zones with more favorable hydraulic conditions.

3.2.3. Analysis of emergent consumer groups

Following the assessment of the system control model at the zone level, where the granularity of the performance evaluation matches the granularity of the optimized controls, this section analyzes the effects of optimization on consumer-specific outcomes and inter-zone distribution of supply. To begin, emergent groups of consumers with similar supply ratios in the baseline model were identified: Group 1 for consumers with near-perfect supply, $SR_n \geq 0.99$, Group 2 for consumers in the upper quartile range for supply, $0.75 \leq S_n < 0.99$, Group 3 for consumers in the interquartile range for supply, $0.25 \leq S_n < 0.75$, and Group 4 for consumers in the lower quartile range for supply, $SR_n < 0.25$. The number of consumers contained in each group are 37%, 44%, 4%, and 16%, respectively. Fig. 9 displays the average tank level time series L^t_{avg} for the consumers in each of the groups, where the faded dashed lines represent the baseline model and the solid lines represent the optimized model. While the supply ratios for individual consumers may change between the baseline and optimized models, the constituents of each group are the same for both models and are only based on the baseline supply ratios of each consumer. Comparing the baseline and optimized models, Groups 3 and 4 experience a significant increase in SR, from 0.38 to 0.79 and 0.08 to 0.46, while Group 1 maintains the baseline $SR = 1$ value and Group 2 decreases only slightly from 0.9 to 0.88. Furthermore, in the optimized model, the average tank levels for Groups 3 and 4 are able to store enough water during the supply period (first 8 h) to last until the end of the day, whereas in the baseline model, the average Group 3 tank emptied by hour 21 and the average Group 4 never reached 5% capacity and emptied by hour 10.

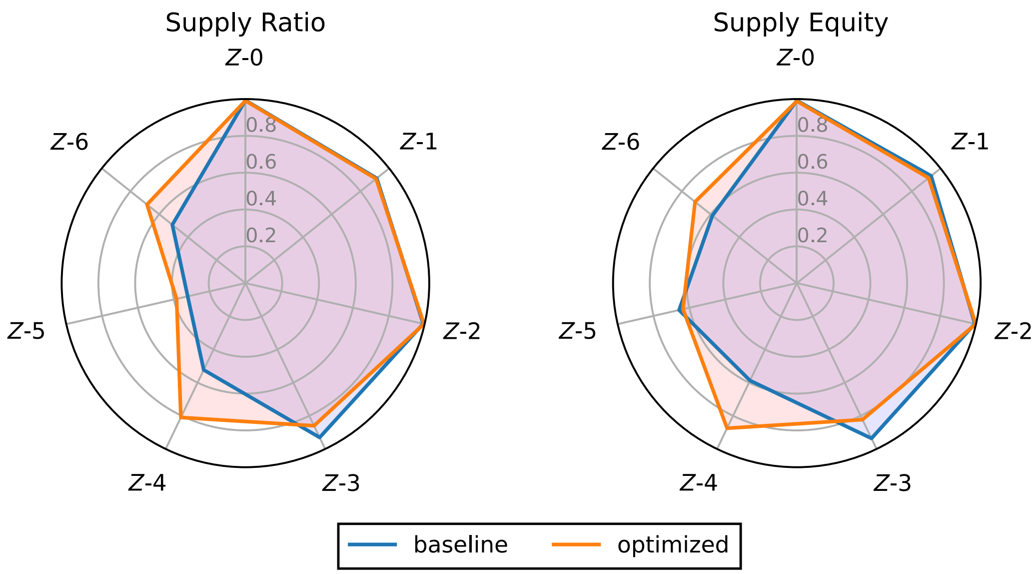

Fig. 7. SR_z (left) and SE_z (right) values for each zone. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

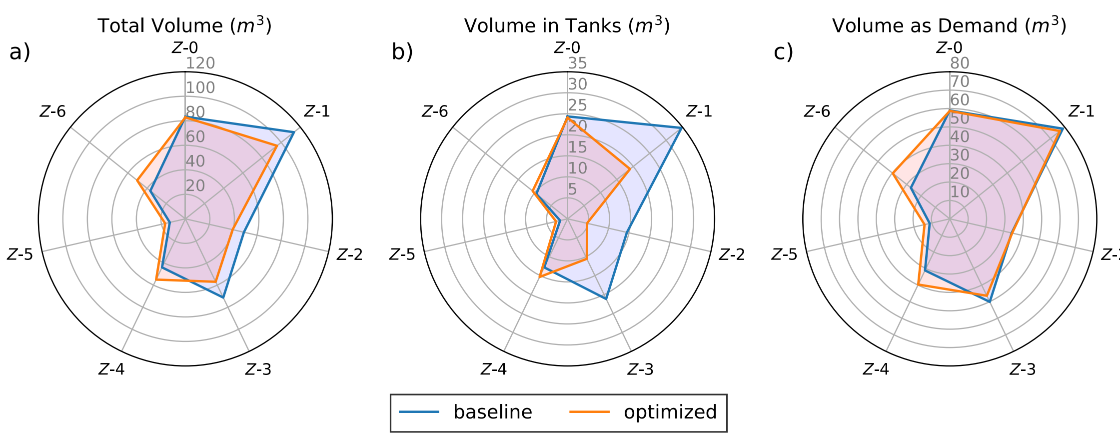

Fig. 8. (a) Total volume supplied to each zone, divided into (b) volume as leftover storage in consumer tanks, and (c) volume used to meet consumer demands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

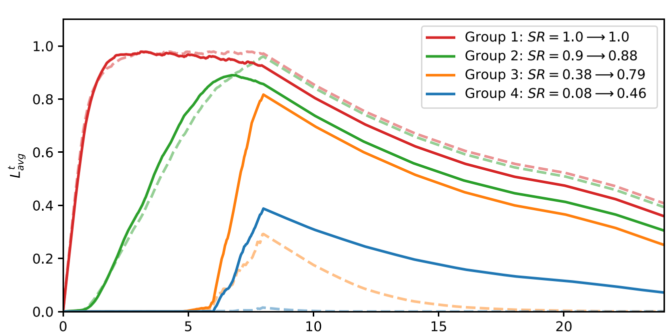

Fig. 9. Average tank levels, L^t_{avg} for consumer supply ratio groups for baseline (faded dashed lines) and optimized models (solid lines). SR values for each group provided in legend as $SR_{\text{baseline}} \rightarrow SR_{\text{optimized}}$.

As indicated by the analysis of S-1, the value of the baseline supply ratio for a consumer is indicative of how favorable the local hydraulic conditions are. Therefore, the four groups also represent the spectrum between consumers with the most-favorable hydraulic conditions to those with the least-favorable conditions. In this system, the tank behavior follows a similar trend observed in the individual consumer tanks in S-1, wherein the tanks fill in the order of the hydraulic favorability spectrum. The application of controls in the optimized model induce an increase in tank filling for Groups 1 and 2 in the beginning of the supply period, which allows those consumers to reach tank capacity more quickly. Once Groups 1 and 2 have reached tank capacity, consumers in Groups 3 and 4 start filling at increased flow rates, thereby reaching maximum tank capacities earlier and extending the duration of consumer demand satisfaction. When the flow restrictions are applied at the end of the control period, tanks in Groups 1 and 2 begin to decrease, displaying the transition from excess water in the storage tanks for consumers with hydraulically favorable conditions to direct water supply for consumers at the opposite end of the spectrum, as discussed in Section 3.2.2.

3.2.4. Supply schedule comparison

In this section, we examine how the system behavior in both the baseline and optimized models is affected by changes in the supply schedule. This application expands on the IWS supply configuration in S-2, which represents a water rationing scheme in which water is provided to the system for the first 8 h before being disconnected

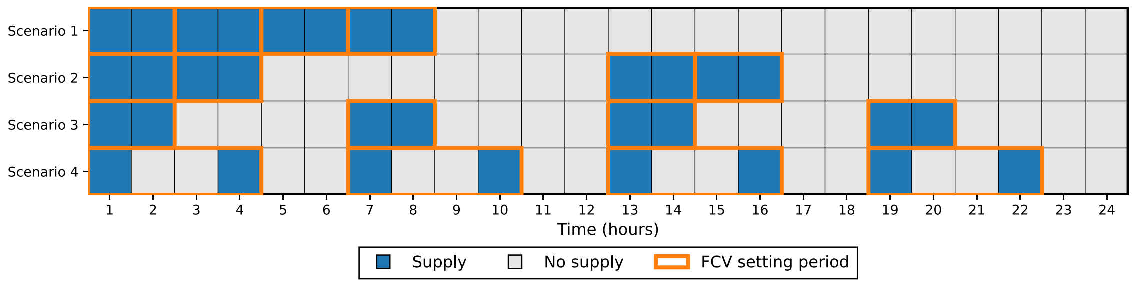

Fig. 10. Supply schedule scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

for the remainder of the day. The analysis consists of four different supply scenarios, in which each scenario has a total of 8 h of supply from the reservoir. However, there are variations in the intermittency of the supply among these scenarios, which is characteristic of IWS systems (Totsuka et al., 2004). Fig. 10 displays the supply hours for each of the four scenarios, where the blue blocks represent periods of supply, gray boxes represent periods with no supply, and the orange boxes represent the periods over which each of the FCV settings are applied. For each scenario, the optimization model is applied 10 times in order to examine the general performance trends of the optimized models.

The first aspect of the system behavior being explored is the high-level distribution of water in the system, which is characterized by the system-wide performance metrics (SR and SE), the total volume of water supplied from the source (V_{source}), and the division of supply water between consumer storage tanks and direct consumption by the consumers (v_T). The variable v_T represents the ratio between the total volume of water remaining in the consumer tanks at the end of the time horizon and the total volume of water discharged from the consumer tanks to the consumer nodes throughout the time horizon. Fig. 11 displays the results, where the x-axes represent the different supply scenarios and the y-axes represent (a) SE and SR, (b) V_{source}, and (c) v_T. In each plot, the data collected from the 10 optimization model outputs are displayed as box plots where the extent of the boxes represent the interquartile range of the data, and the whiskers cover the full range of the data. Likewise, the results of the baseline model are plotted as individual points.

In Fig. 11(a), a monotonic decrease is observed for both SR and SE for the baseline and optimized models as the supply schedule becomes more distributed. Furthermore, a comparison of the baseline and optimized models for each scenario shows that the performance of the optimized model relative to the baseline model decreases, i.e., applying flow controls to the system becomes increasingly less effective from Scenario 1 to 4. In Fig. 11(b) and (c), V_R and v_T for both models increase from Scenarios 1 to 4, and the values in the optimized models are consistently less than those in the baseline models. This result underscores the observations that, in the optimized model, less water is being withdrawn from the source and water is being utilized more for direct supply rather than being stored in local tanks. Overall, Fig. 11 shows that despite the increases in volume that are supplied to the system with a distributed supply schedule, the SR and SE values show that consumers are receiving less water to meet their demands while the v_T values show that consumer storage tanks are receiving more water. As shown in Section 3.2.2, the increase in tank storage only occurs for hydraulically-advantaged consumers at the expense of a decrease in direct consumption for disadvantaged consumers.

The second aspect of system behavior being explored is the consumer-level distribution of water in the system, represented by the average tank behavior across the consumer groups defined in Section 3.2.3. Given the high-level system behavior in response to the supply scenarios, the average tank levels L^t_{avg} for each of the consumer groups are examined to explore why distributing the supply schedule throughout the day both increases v_T and decreases SR and SE, and how the phenomena relate to the supply hierarchy. Fig. 12 displays the average tank levels L^t_{avg} for each consumer group for the baseline and optimized models in Scenarios 1 and 4, where the optimized model is represented by the model with the median SE score between the 10 runs for each scenario. For both plots, the tank levels for baseline models are represented by the faded dashed lines and the tank levels for the optimized models are represented by the solid lines. The legend displays the percentage of consumers that constitute each group for the two scenarios, e.g., 16% of consumers in Scenario 1 belong to Group 4 (baseline supply ratio <0.25) as compared to 23% in Scenario 4.

When comparing the emergent consumer groups between the two scenarios, we observe a notable shift in the distribution of supply ratios. In Scenario 1, 80% of the consumers benefit from $SR_n \geq 0.75$, however in Scenario 4, only 52% of consumers exhibit $SR_n \geq 0.75$. In the baseline model in Scenario 4, Groups 1–3 all approach tank capacity by the end of the time horizon while Group 4 only reaches 10% capacity by hour 22. While the optimization model in Scenario 4 is able to increase the average tank levels and the number of hours the consumers in Group 4 have water access, the overall effect on SR and SE is limited, as shown in Fig. 11(a). Overall, Fig. 12 reveals how a distributed supply schedule exacerbates the effects of the supply hierarchy on the supply equity amongst consumers. In Scenario 1, consumers with more favorable hydraulic conditions (Group 1) reach tank capacity sooner than the same consumers in Scenario 4, thereby effectively limiting their ability to extract more supply while their tanks are full. Due to the intermittent periods of non-supply (extended periods of tank withdrawal) in Scenario 4, Group 1 experiences more supply hours in which their tanks are not at capacity. The consequences of the supply hierarchy are such that consumers in hydraulically-unfavorable conditions are only granted water access once consumers in hydraulically-favorable positions cannot extract anymore water due to capacity limits on their storage. Therefore, increasing the number of supply hours in which the tank levels in Group 1 are not at capacity decreases the number of hours in which Groups 3 and 4 have access to supply. Scenarios 2 and 3 display comparable, but less pronounced, behavior.

3.2.5. Comparison with PRV control scheme

In this section, we compare the performance of the flow control scheme with a control scheme that utilizes PRVs in place of the FCVs. In the new PRV model, the PRVs are installed in the same location as the FCVs and the timing of the PRV setting schedule matches the timing of the FCV setting schedule. The PRV optimization model was solved 10 times. The performance of the optimized PRV and FCV models in terms of SR and SE are displayed in Fig. 13(a), where the baseline values are represented in blue, the optimized FCV values are represented in orange, and the PRV values are represented by the red box plots. Overall, the performance of the optimized PRV model falls short of the optimized FCV model in both SR and SE. To explore the suboptimal performance of the optimized PRV model, the flow rate into the hydraulically-favorable subzone Z-1 is plotted for the baseline model, optimized FCV model, and the best solution of the optimized PRV model in Fig. 13(b). This example highlights the

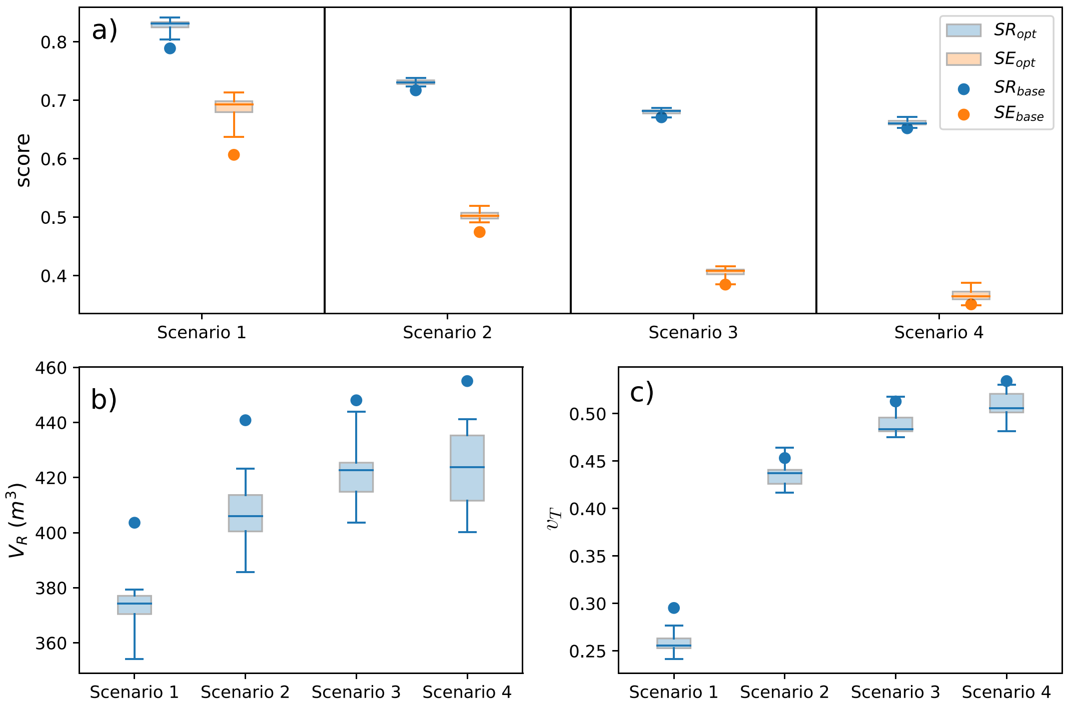

Fig. 11. Results for baseline and optimized models for each supply schedule scenario: (a) SE and SR, (b) V_R, and (c) v_T.

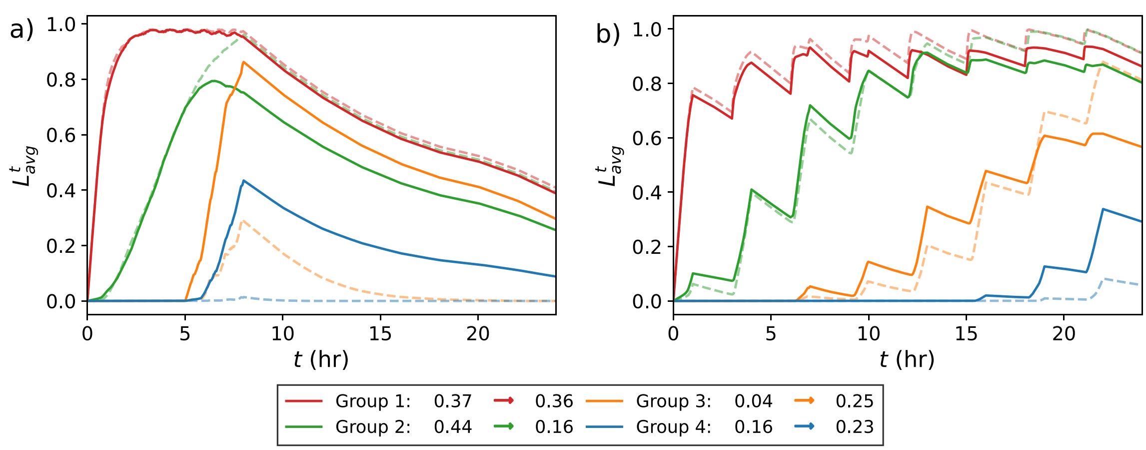

Fig. 12. Average tank levels for consumer supply ratio groups for baseline (dashed lines) and optimized models (solid lines): (a) Scenario 1 and (b) Scenario 4.

strategies of the two optimization models to limit flow into a subzone with hydraulically-favorable conditions. Compared to the optimized FCV model, the optimized PRV model shows a similar control strategy in which the advantaged subzones receive increased flows early in the control period before the PRV settings decrease to reduce flow later in the control period. However, unlike the FCVs, the PRVs are not able to fully limit flow into the subzones during such periods, as lower elevations downstream of the valves still ensure a pressure gradient that drives flow. While the supply hierarchy overall is a pressure-driven phenomenon, the utilization of PRVs show to be a suboptimal control strategy relative to flow control through FCVs.

3.2.6. Assessing performance sensitivity to uncertainty in tank sizes

Consumer tank configuration and sizes are a source of uncertainty in the IWS model. To represent this uncertainty on the aggregate level of consumers in the model, a sensitivity analysis is conducted by ranging tank sizes from a 50% decrease to a 50% increase in capacity. The analysis is performed by iterating over different randomized combinations of tank volumes, applying the same optimal flow control scheme presented in Section 3.2.1, and calculating the global metrics SR and SE for each simulation. The results of the sensitivity analysis are presented in Fig. 14, where the horizontal axis represents the new average tank capacity compared to the original average and the vertical axis represents the global metric score for SR (left) and SE (right). In both plots, each point represents the result of an individual model run, where the blue points represent the performance of the new baseline models, the orange lines represent the new optimized models, and the green points represent the original baseline and optimized models. In both plots, the new baseline values form a neighborhood around the values of the original baseline model, where a general trend is observed in which SR and SE decrease as the average tank size increases. This relationship matches the intuition of advantaged consumers with greater capacity for storage exacerbating the supply

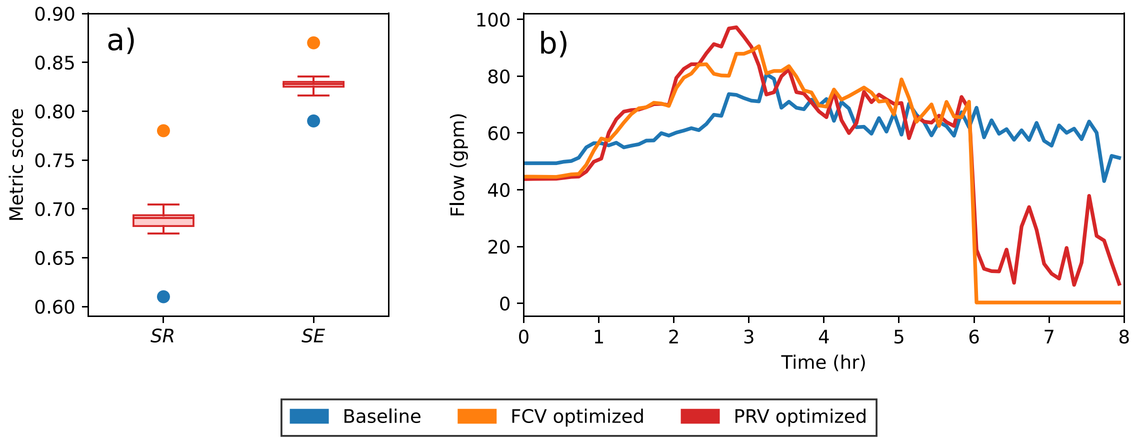

Fig. 13. (a) SR and SE comparison between optimized FCV and PRV models, and (b) example of flow control strategies applied by each model for Z-1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

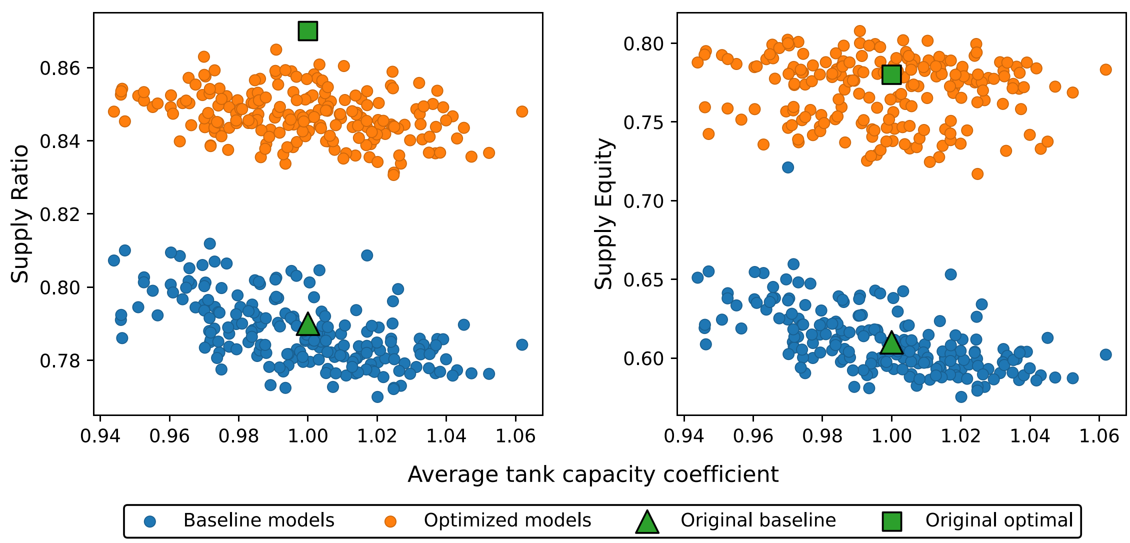

Fig. 14. SR (left) and SE (right) for each randomized tank size test case. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

inequity. In Fig. 14(a), changes to the consumer tank capacity decrease SR since the optimized model was tailored to specific tank capacities, however, the new results still show consistent improvement over the baseline models, whereas SE actually improved in many cases relative to the original optimized model. Overall, the optimal flow control schedule shows consistent improvement in SR and SE relative to the baseline values even with uncertainty in tank sizes.

4. Discussion

Our results underscore several insights into the mechanisms behind inequitable supply in IWS systems. Below we outline how these insights might be generalized to other studies highlighting further investment needed in research to improve equitable supply.

4.1. Supply hierarchy as driver of inequity

The simulation–optimization approach applied to the IWS systems reveals a hierarchy in supply between consumers based on local hydraulic conditions. In S-1, the supply hierarchy is most closely connected with elevation, as shown in the individual tank behavior in Fig. 4. However, S-2 also shows that proximity to the source plays an important role, as displayed in Fig. 7 where the consumers in the transmission main (Z-0) all registered $SR_n = 1$ despite having the fourth-lowest average zone elevation. The proximity to the source is essentially a proxy for head loss incurred along the path from source to demand, where increased peak flows particularly decrease the pressure for consumers far from the source. Thus, the supply hierarchy is both engendered by the utilization of private storage tanks and exacerbated by head loss from peak flows, both of which are characteristics of IWS systems. At a higher level of abstraction, the supply hierarchy does not emerge from the use of private storage tanks by consumers, but rather, the misalignment of local incentives and global control objectives. Since IWS systems are often associated with unreliable supply (as explored in Section 3.2.4), it is in consumers' best interests to fill their tanks whenever possible in order to secure continuous personal supply during periods of indefinite non-supply. In such periods of unreliable supply, the incentive to secure one's own supply significantly diminishes equity amongst fellow consumers, limits the ability to overcome inequity through optimized system controls, and enhances the effects of the supply hierarchy (Figs. 11 and 12).

4.2. Control strategies to overcome supply hierarchy

Different flow control strategies were implemented for S-1 and S-2 to disrupt the supply hierarchy and increase global equity. Following the application of the IWS model to S-1, the global equity was evaluated at 0.72, revealing inequities that are otherwise overlooked by the CWS model. Through the inclusion of VDD in the IWS model, the optimization model is able to account for the consumer behavior, restrict flow to the appropriate consumers, and increase SE back to 0.98. Likewise in S-2, the application of the IWS model reveals $SE = 0.61$, and the application of optimized control rules were able to increase SE by 28% to 0.78. However, further increases were limited by the granularity of the controls which were unable to account for the inter-zone supply hierarchy. The limitations are made apparent by the difference in control strategies implemented by the optimization model in S-1 and S-2. In the idealized system (S-1), consumers in hydraulically favorable positions had flow restrictions imposed at the beginning of the supply period in order to allow for simultaneous flow to the rest of the network, while no such flow restrictions were applied to the more complex system (S-2). Instead, the optimal control strategy was to allow unrestricted flow to the hydraulically favorable zones flow at the beginning of the control period in order to decrease the time for tanks in Groups 1 and 2 to reach capacity.

In summary, the control strategies are case specific and vary based on the underlying conditions and level of control. Based on the systems explored in this work, for systems in which the granularity of control does not match the granularity of the consumers, the optimal strategy is to let the supply hierarchy run its course until those on the upper end of the spectrum have reached tank capacity. At that point, flow restrictions are imposed to prevent refilling and allow the remaining consumers further down in the supply hierarchy to fill their tanks. This same strategy was employed for S-2 when utilizing PRVs, although less effectively since the valves were not able to fully limit flow when necessary. When the flow control strategy was tested against uncertainty in tank capacity, it still proved to consistently increase equity in the system. Although the control model was applied to two branched systems, the simulation–optimization model can be seamlessly implemented to looped networks, thus allowing for the exploration of the effect of network topology on control efficacy. Overall, given the limitations imposed by the supply hierarchy and macro-level controls that are incapable of fully addressing inequities realized at the consumer-level, IWS managers should place a premium on addressing supply irregularities in order mitigate the effects of the supply hierarchy and aid the control strategy.

4.3. Limitations and future work

The primary limitations of the presented research stem from simplifications in the hydraulic model, VDD approach, and simulation time horizon. In this approach, we use a hydraulic model that assumes pipes that are initially full of water, thus overlooking the filling and draining process of pipes during intermittent supply. Other studies have explored the implications of these process (De Marchis et al., 2016; Mohan & Abhijith, 2020), and while we do not consider these phases in the high-level model, they are important to include for a comprehensive model of IWS hydraulics. Another limitation of this research is the simplifications made in the VDD approach for modeling consumer storage tanks and consumer behavior. In focusing on the demand-side details of IWS modeling, other researchers have sought to explore how system hydraulics and consumer welfare is affected by different detailed tank configurations (Abhijith et al., 2023) and household water decisions (Wunderlich et al., 2021). Integrating these consumer-focused facets into a hydraulic model can further increase the accuracy of IWS simulations for the purposes of optimizing water management decisions. The final limitation is the 24 h time horizon. Although increasing the time horizon increases the computational burden associated with the simulation, long-term planning and management of IWS systems will require such extended-period analysis. Along with increasing the model resolution and time horizon, additional model extensions should seek to add other facets of IWS systems, such as public taps and water tankers, which alter water withdrawal from the supply system (Galaitsi et al., 2016; Klassert et al., 2023).

The presented work highlights the limitations of applying macro-level controls to IWS systems to overcome the supply hierarchy. Given this result, two alternative pathways should be considered that focus on local solutions to achieving supply equity. The first pathway focuses on consumer behavior, where the supply hierarchy is perpetuated by consumers incentivized to always fill their tanks when supply is available. A focus should be placed on studying consumer behavior and consumer engagement to tailor demand management strategies (Huerta-Vergara & Escolero, 2024; Tiedmann et al., 2024). Suggested demand strategies to explore include incentives to limit local tank storage, e.g., decreasing tank storage volumes to lower water age and increase overall water quality as a result (Kumpel & Nelson, 2013). The second pathway focuses on smart water system and infrastructure advancements to improve supply equity. While IWS systems often lack the economic resources for advanced technological improvements, sensors are becoming more economically viable and low-cost solutions for water metering are continually being developed (Oberascher et al., 2021). Management strategies to explore include local technological improvements such as smart meters to implement local controls (Creaco et al., 2019; Jones & Leibowicz, 2021). For larger-scale, more economically-feasible approaches, the management of decentralized or satellite water tanks can yield a compromise between local and global controls (Kalbar & Gokhale, 2019; Shrestha & Buchberger, 0000). In all applications and future work, it is paramount that the real-world complexities and intricacies of IWS systems are thoroughly captured in order to address the challenges that IWS systems impose on consumer welfare.

5. Conclusions

In this study, a simulation–optimization framework incorporating volume-driven demands into the hydraulic simulation has been proposed as a tool to enhance equity in intermittent water supply systems. The framework is applied to two networks, a small-idealized network and a larger more complex network, where flow control valve settings are optimized to impose flow restrictions with the goal of alleviating disparities in supply. The application of the VDD approach revealed inequity in both networks that is not registered using traditional modeling approaches for CWS systems, where the inclusion of private storage tanks are shown to induce a hierarchy of supply amongst consumers. This work illuminates the challenges in reversing the supply hierarchy to ensure equitable delivery of supply to all consumers, where macro-level controls have a limited capability in overriding a consumer-level phenomenon. In addition, achieving reliability in source supply should be paramount for IWS managers, as inconsistency in supply reinforces the supply hierarchy and encumbers the efficacy of flow control strategies to increase equity.

In conclusion, the presented work highlights the ability of the simulation–optimization model to find equitable control schemes for IWS systems, identifies the mechanisms through which inequity emerges, and elucidates the salient factors that worsen inequity. While effectively managing IWS systems is a multi-faceted problem that requires solutions across the sociopolitical, economic, and engineering domains, accurate management models are essential tools to inform decision-making. Therefore, these models must move beyond assumptions related to traditional CWS systems and must be continually improved in order to make effective decisions for enhancing consumer welfare in IWS systems.

CRediT authorship contribution statement

Greg Hendrickson: Writing – original draft, Software, Methodology, Formal analysis. **Lina Sela:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

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.

Data availability

The data was provided in the Supplementary Materials.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.scs.2024.105615.

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