Demand Satisfaction as a Framework for Understanding Intermittent Water Supply Systems

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Key Points:
- Without topology details, our proposed model of intermittent water supplies (IWS) matches closely with more complete network models
- While inadvisable, IWS provide utilities traditionally ignored, short-term benefits (e.g., supply timing will change less due to drought)
- We propose a new demand satisfaction metric to quantify supply availability and help track Sustainable Development Goal 6.1 in IWS

Supporting Information:
- Supporting Information S1
- Figure S1
- Figure S2
- Figure S3
- Figure S4
- Figure S5
- Figure S6
- Figure S7
- File S1–S16

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Demand Satisfaction as a Framework for Understanding Intermittent Water Supply Systems

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Abstract Nearly one billion people worldwide receive water through piped networks that are not continually pressurized and operate intermittently. The prevalence and persistence of these Intermittent Water Supplies (IWS) is surprising as this mode of operation induces water contamination and customer equity issues. Shortages of source water, customers' water demand, and leaking pipes are frequently cited as necessitating IWS. We propose a framework for understanding the persistence and operation of IWS. The supply system is represented by an average customer and a spatially averaged leakage rate. With this macroscopic hydraulic model, we relate customer demand satisfaction, source water availability, customer demand, and leakage. While this approach ignores the complexities of network topology, we find that the model approximates real systems well (calibrating to four intermittent reference networks achieved $R^2 > 0.87$). The calibrated model is robust to moderate changes in demand and leakage (maintaining $R^2 > 0.81$). Using the model, we show that the tipping point between satisfied demand and unsatisfied demand is a local optimum for utilities, which may explain the persistence of IWS. Beyond this point, the volume received by customers does not increase, but utilities must supply more water to the network. The generality of the proposed model enables its use when regulating and upgrading IWS. We demonstrate the latter by critiquing a performance-based contract that was intended to improve an intermittent supply in India. Demand satisfaction has profound implications for hydraulics and human welfare. We propose the degree of demand satisfaction as a metric for evaluating IWS and for tracking the United Nations Sustainable Development Goal 6.1.

Plain Language Summary While most people get drinking water through underground water pipes, in some areas these pipes only provide water for a few hours each week. Globally, more than one billion people are served by these “intermittent water supply systems”. In severely degraded systems, keeping pipes empty most of the time can reduce leakage and conserve source water, but it can also allow mud or sewage to enter through holes or cracks in the pipes, contaminating the water. This paper presents a simple model (an equation) that approximates how intermittent systems behave. The model suggests why intermittent operation is so common and highlights the challenges of improving such systems. The model relates hours of operation to factors such as source water supply, consumer demand, leakage, and if consumer demand is satisfied. The model implies that once consumer demand is satisfied, a system crosses a threshold and behaves differently: leakage, rather than demand, determines most of a system's water requirements. Measuring this threshold could identify systems that leave people thirsty and prioritize such systems for improvements. The model, therefore, provides new tools to support global commitments outlined in the United Nations' Sustainable Development Goal 6.1 and the Human Right to Water.

1. Introduction

The term intermittent water supplies (IWS) refers to piped water distribution networks that deliver water to customers for less than 24 hr/day. IWS are often used to reduce water consumption in drought stricken areas but are also the standard mode of operation in systems serving approximately one billion people worldwide (Bivins et al., 2017; Laspidou & Spyropoulou, 2017). Water distributed by IWS is inequitably divided between customers (De Marchis et al., 2011; Vairavamoorthy et al., 2007). The water input to IWS is often potable, but its quality degrades substantially during intermittent distribution (Kumpel & Nelson, 2013). Bivins et al.

(2017) have used quantitative microbial risk assessment to estimate that IWS cause 17 million infections annually (including 4.5 million cases of diarrhea).

To improve access to safe water, the United Nations' (UN's) Sustainable Development Goal (SDG) 6.1 targets "universal and equitable access to safe and affordable drinking water for all" (World Health Organization [WHO], 2017b). Under SDG 6.1, a "*safely managed*" water supply must, among other things, be "*available when needed*" (World Health Organization, 2017b). The UN's articulation of the human right to water similarly specifies that water supplies should be "continuous enough to allow for the collection of sufficient amounts to satisfy all needs" (de Albuquerque, 2010). Since IWS range from being pressurized almost all of the time to only being pressurized for a few hours per week (Kumpel & Nelson, 2016), when, if ever, are IWS *"available when needed"* or "*continuous enough*"? Answering such a question requires a framework for understanding the diversity of IWS.

Totsuka et al. (2004) provide one framework, distinguishing between three conditions leading to IWS. In the first instance, cases where customer demand exceeds the available source (untreated) water, IWS are caused by "*absolute scarcity*" (Totsuka et al., 2004). In the second, when it is possible to augment the treatment and/or distributional capacity (e.g., pipe diameters) of networks to allow for continuous water supplies (CWS or "24 × 7"), IWS are caused by *"economic scarcity"* (Totsuka et al., 2004). Third, there are cases where leak repair and/or different network-operating strategies would allow for CWS; such IWS are caused by *technical scarcity*. Unfortunately, for IWS facing technical scarcity, the framework of Totsuka et al. (2004) is not specific enough to predict the outcomes of system management decisions such as "fixing 10% of leaks" or "supplying half as much water."

More specific theories about the causes and effects of IWS abound, overlap, and sometimes conflict, due in part to the diversity of IWS (Galaitsi et al., 2016; Klingel, 2012; Simukonda et al., 2018). Similarly, case studies about IWS find varying and sometimes conflicting results (Erickson et al., 2017; Kumpel & Nelson, 2013). Adjudicating between conflicting theories and credibly generalizing case studies requires a better understanding of the similarities and differences between different IWS and different modes of operating IWS.

To understand IWS, other researchers have turned to increasingly complex hydraulic models of IWS (e.g., including losses induced by float valves in customers' homes; De Marchis et al., 2011). These complex models have two major drawbacks. First, in IWS, information about pipe connectivity, let alone losses on customer premises, is often unreliable (McIntosh, 2014) due to "the chaotic arrangements that actually characterize" many IWS (Sangameswaran, 2014). Recalling Aristotle's recommendation "to look for precision in each class of things just so far as the nature of the subject admits" (Aristotle & Ross, 2000), we argue that less precise models are better suited to understanding and managing IWS. Second, "when important aspects of the truth are simple, simplicity illuminates, and complication obscures" (Box, 1979); complex models of IWS obscure the underlying principles of how IWS operate.

We posit, therefore, that a new type model is required to understand IWS: a *macroscopic hydraulic model*. By definition, *macroscopic models* describe the aggregate behavior of a system without characterizing its individual elements. This reduction in detail gives *macroscopic models* simpler and more easily understood structure, which allows decision makers to more efficiently infer insights from the model's structure and outputs, even amidst substantial uncertainty about the model's inputs (Lucas & McGunnigle, 2003).

From the 1960s to the 1990s, macroscopic or simplified hydraulic models were used to optimize high-level operational decisions for water networks (e.g., pumping schedules; DeMoyer & Horwitz, 1975; Ormsbee & Lansey, 1994). Motivated by computational efficiency, many of these models predicted system behavior based on total customer demand. Some models were calibrated using linear regression, while others used first principles to estimate model coefficients (Ormsbee & Lansey, 1994). These macroscopic models, despite their reduced accuracy, improved the operation and control of real water distribution networks (Ormsbee & Lansey, 1994). Macroscopic models proved useful because their modeling objective (to optimize high-level operational decisions) matched their level of detail (high-level system variables). Yet, computational efficiency is not the motivation of this paper. Instead, we hypothesize that a macroscopic model of IWS would be useful because it would not require difficult-to-acquire network details and its simpler structure would provide a framework to understand the diversity of IWS.

In this paper, we aim to demonstrate that a simple approximation of IWS can provide generalized insights into IWS and can substantially improve our ability to understand, classify, and manage IWS. As "all models are wrong but some are useful" (Box, 1979), we demonstrate the value of this macroscopic model by contrasting its reduced accuracy with its increased utility. In this paper, we propose a macroscopic model of the average behavior of IWS (section 2); next, we validate the model against detailed hydraulic simulations of four reference networks (section 3). We then demonstrate two uses of the macroscopic model: analytically comparing the causes and effects of IWS (section 4) and designing more feasible improvement projects for IWS (section 5). Given the prevalence of IWS (21% of all water pipe networks; Bivins et al., 2017; World Health Organization, 2017a), creating frameworks for understanding and defining water availability and sufficiency in IWS will be key to meeting the human right to water and SDG 6.1.

2. Model Construction

Detailed models and simulations of IWS are usually compromised by the lack of data on the initial conditions in the pipes and by incomplete or inaccurate information on pipe network connections, which are particularly chaotic in large urban centers (e.g., McIntosh, 2014). We circumvent the need for specific and accurate pipe network information by constructing an analytical model for the average behavior of an intermittent network. We outline a series of simplifying assumptions that are used to construct the macroscopic model. The accuracy of these simplifications is quantified in aggregate in section 3. To construct the model, first, the behavior of a single leak is generalized to represent leakage across the whole network. Second, flow to all customers in the network is modeled by the behavior of the network's average customer. Finally, the total water required by a network is considered to be the superposition of the water required by leaks and customers.

In hydraulic simulations of CWS, customers are assumed to receive the flow of water that they demand, which varies over time (Tanyimboh & Templeman, 2010). When pressure is low, flow to customers depends on the pressure in the system, which is captured in hydraulic simulations that use *pressure-dependent demand* (PDD; Ciaponi & Creaco, 2018; Tanyimboh & Templeman, 2010). In the simplest models of intermittent supply situations, each customer is assumed to leave their tap(s) open, and hence, the flow rate increases with pressure (flow through an orifice; e.g., Mohapatra et al., 2014; Reddy & Elango, 1989). The effects of customers storing water can be modeled by including customer tanks in the hydraulic simulation (Macke & Batterman, 2001). Such tanks fill at a pressure-dependent rate (i.e., behave like PDD), and flow ceases when tanks are filled. In this paper, this type of demand (i.e., PDD until a demand volume is delivered, after which demand is zero) is defined as *volume-dependent demand* (VDD). In simulations of networks with VDD, the volume of demand, which may be modeled as a tank, is not related to the volume of a customer's physical tank but only to the volume of their demand (Appendix A). Some VDD models assume that the pipe network is initially full of water (e.g., Macke & Batterman, 2001), while other simulations include some of the pipe filling process by assuming that any pipe cross section is either completely full or completely empty (resulting in a 1-D filling process; e.g., De Marchis et al., 2010; Fontanazza et al., 2007; De Marchis et al., 2016). In this paper, VDD will refer exclusively to simulation methods that begin with full pipes.

2.1. Notation

Most utility managers discuss average flow rates as if they were volumes (e.g., 50×10^6L/day). The model that follows matches their vocabulary; V represents a volume per day (i.e., average flow rate) and Q represents an instantaneous flow rate.

IWS vary in how frequently they deliver water and the duration of their average delivery cycle (Guragai et al., 2017). In this paper, the *supply period*, T, denotes the elapsed time between the start of two consecutive supplies, equivalent to 1 over frequency. The *supply duration*, τ, denotes the average duration of water delivery in a single supply. To account for varying supply periods and supply durations, we propose the metric of *duty cycle*, $t \in [0, 1]$, to represent the fraction of time that a system is pressurized ($t = \tau/T$; e.g., $t = 0.125$ for both a system supplying water for 6 hr every other day and a system supplying water for 3 hr daily). The model that follows assumes that customers have enough water storage capacity, which depends on their demand, the supply period, and their consumption during the supply period. Appendix A explores the interactions of each of these terms.

Water distribution networks typically operate within regulatory or contractual frameworks that specify targets, for example, a minimum pressure head (H_t) and a maximum daily volume of leakage (V_{LC}). It is

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convenient to use these targeted values to normalize the equations that follow. The total daily volume of water available as input into a network, V_T, will be used to normalize daily volumes.

2.2. Leakage

The leakage rate (Q_L) of a single leak can be modeled by the orifice equation (American Water Works Association, 2009; Colombo & Karney, 2002)

$$Q_L = C_d A[2gH]^\alpha \left(\frac{86,400\text{ s}}{1\text{ day}}\right) \tag{1}$$

where C_d accounts for the orifice's shape, A is the orifice's cross-sectional area, g is gravitational acceleration, H is the pressure head (denoted hereafter as "pressure"), and α accounts for the flow rate's pressure dependency.

Equation (1) can be extended to approximate many leaks aggregated together using an equivalent orifice area (EOA, of size A), whose Q_L matches the sum of all leaks in the system (e.g., Lambert, 2001; van Zyl & Cassa, 2014). Taking the average system pressure, H, to be constant (i.e., exogenous), averaging by the duty cycle, t, and combining constants into K_L, the daily leakage volume for the network is

$$V_L = tQ_L = K_L A t H^\alpha \tag{2}$$

where α depends on the pipe material, the shape of individual leaks, and elevation changes in the network. The value of α ranges from 0.5 to 2.5 (Lambert, 2002). In the absence of specific data for IWS, we assume that $\alpha = 1.0$, as is common practice for CWS (American Water Works Association, 2009).

The orifice equation does not account for the more frequent pipe bursts that higher pressures can induce (Thornton & Lambert, 2005). Moreover, modeling pressure as constant neglects its dependence on other system parameters (e.g., duty cycle affects the rate at which water flows to customers, which thereby affects pressure losses and the average system pressure). Indeed, these couplings represent an opportunity to refine the current model formulation.

For a water utility with a targeted supply pressure (H_t) and a targeted duty cycle (assumed to be continuous supply, $t = 1$), the utility will be able to stay below its targeted daily volume of leakage (i.e., V_{LC}) if its EOA (A) stays below some maximum EOA, which we define as A_t. With $A > A_t$, a utility cannot meet its pressure, duty cycle, and leakage targets simultaneously. It is therefore convenient to use H_t, A_t, and V_{LC} to normalize equation (2)

$$V_L = V_{LC} a t h^\alpha = Q_L t \tag{3}$$

$$\therefore v_L = v_{LC} a t h^\alpha \tag{4}$$

where $h \equiv H/H_t$, where $a \equiv A/A_t$, and where v_L and v_{LC} are the current and targeted leakage rates, as a percentage of the total available water supply, V_T. As the leaked volume (V_L) increases substantially with pressure and duty cycle, the current EOA of most IWS is much larger than A_t (i.e., $a \gg 1$).

2.3. Behavior of a Single Customer

Fan et al. (2014) found that customer consumption changes more slowly with respect to duty cycle when $t \in [0.25, 1]$. Similarly, Hamilton and Charalambous (2015) report that the total customer consumption reduced by only 15% when the duty cycle was reduced from $t = 1 \rightarrow 0.25$ in Limassol, Cyprus. Therefore, in this simple model, daily customer demand (which is not always met) will be considered independent of duty cycle.

A *satisfied* customer receives a daily volume of water (V_R) equal to their demand (V_D), while an *unsatisfied* customer receives less than they demand (i.e., $V_R < V_D$). Unsatisfied customers are assumed to keep their taps open and therefore exhibit behavior that can be characterized by the orifice equation. Combining these two possibilities for a customer,

$$V_R = \begin{cases} V_D & : \text{Satisfied} \\ K_D t h^\phi & : \text{Unsatisfied} \end{cases} \tag{5}$$

where K_D is a combined constant that accounts for topography and pipe characteristics. Physically, K_D is the daily volume of water that a customer could receive with a fully open connection to an ideally pressurized

CWS (i.e., a system in which $t = h = 1$). ϕ is the pressure exponent of customer demand and is not necessarily the same as α. V_D denotes the volume of demand and not the volume of a customer's storage tank (the distinction is explored in Appendix A). Accordingly, this model also captures the behavior of customers who consume water during the supply cycle by assuming that their consumption is distributed in proportion to the rate at which they receive water. This model does not capture components of customer demand that are dependent on pressure or duty cycle (e.g., internal leakage).

2.4. Aggregate Customer Demand

When scaling from the demand of a single, residential customer (i.e., equation (5)) to the network level, one can consider two extremes of systems: *Satisfied IWS* in which every customer receives as much water as they demand and *Unsatisfied IWS* in which no customer receives as much water as they demand. While a network may be fully satisfied or fully unsatisfied, most large IWS are a combination of the two; advantaged customers are easily satisfied, while tail-end customers struggle to get enough water. As a first-order model, the transition of IWS between unsatisfied and satisfied is considered instantaneous.

Pipe pressure can vary significantly throughout a network. However, detailed network connectivity information is needed to establish these pressure fluctuations, which this model attempts to avoid. Instead, we assume that the average daily volume of water received by customers (V_R) in a network can be modeled as in equation (5), except where h and t now correspond to the characteristic pressure and duty cycle for the whole network.

Nondimensionalizing each daily volume in equation (5) by the system's total available daily volume of water (V_T) yields

$$v_R = \begin{cases} v_D & : \text{Satisfied IWS} \\ k_D t h^{\phi} & : \text{Unsatisfied IWS} \end{cases} \tag{6}$$

where $k_D \equiv K_D / V_T$ and is the percent of a system's total daily volume that customers could receive if they left their taps fully open while the system was operated at its targeted pressure and duty cycle (i.e., operated at $t = h = 1$).

According to equation (6), the transition between satisfied and unsatisfied regimes occurs at $v_D = k_D t h^{\phi}$. To simplify notation, consider γ_S to be the value of th^{ϕ} at which this transition occurs

$$\gamma_S \equiv \frac{v_D}{k_D} = \frac{V_D}{K_D} \tag{7}$$

Similarly, for a given, normalized pressure (h), the minimum duty cycle required for a system to be satisfied (t_S) is

$$t_S \equiv \frac{\gamma_S}{h^{\phi}} \tag{8}$$

Combining equations (5)–(7),

$$V_R = V_D \min(1, \frac{th^{\phi}}{\gamma_S}) \tag{9}$$

$$v_R = v_D \min(1, \frac{th^{\phi}}{\gamma_S}) \tag{10}$$

From the available data on IWS, residential demand comprises a median of 78% of total demand (data from van den Berg & Danilenko, 2011). Accordingly, our model of residential demand (equations (9) and (10)) is equated with the total customer demand in IWS. This aggregate demand is comparable to other macroscopic hydraulic models where a lumped demand parameter is common (Ormsbee & Lansey, 1994). More recently, Ilaya-Ayza et al. (2016) used a model with lumped demand to explore the connection between hydraulic capacity and intermittent operations.

2.5. Combining Customers and Leaks

Most utilities have an operational choice about how much of their available total water supply (V_T) to input into the network (V_P). V_P is the superposition of the volume received by customers, V_R (equation (9)), and

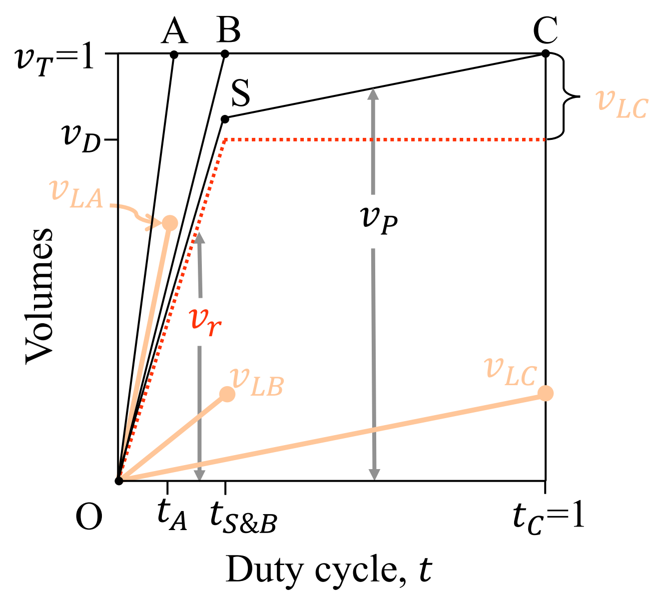

Figure 1. The combined demand and leak model. For three systems OA, OB, and OSC, the input daily volume (v_P; thin black lines) is the superposition of the daily volume received by customers (v_R; dotted red line of medium weight) and the leaked volume (v_L; thick orange lines). The maximum duty cycle of each system is t_A, t_B, and t_C, respectively. The system is satisfied at $t_S = t_{S\&B}$ and has a total water availability of $v_T \equiv 1$.

the volume leaked, V_L (equation (3))

$$\therefore V_P = V_D \min(1, \frac{th^{\phi}}{\gamma_S}) + V_{LC}ath^{\alpha} \tag{11}$$

$$\therefore v_P = v_D \min(1, \frac{th^{\phi}}{\gamma_S}) + v_{LC}ath^{\alpha} \tag{12}$$

where $v_P = V_P/V_T$.

To graphically display equation (12), assumptions are required about demand and how quickly it can be satisfied. The results that follow are not sensitive to these assumptions. Many contracts to improve IWS require that after all system improvements have been made (i.e., when $t = h = 1$), the leakage rate should be less than some maximum (defined as v_{LC}). This leakage rate is often lumped into the broader category of nonrevenue water (NRW, which includes leakage, theft, meter inaccuracies, and nonpayment). As an example, we considered NRW targets from four contracts in India, which ranged from 15% to 30% (Table S1 in Supporting Information; Delhi Jal Board, 2012a, 2012b, 2012c; Dinesh Rathi & Associates, 2008). As a major system improvement project is likely to reduce unauthorized consumption and metering inaccuracies, much of the improved system's NRW would be physical leakage. The authors therefore suggest that $v_{LC} = 0.2$ and $v_D = 1 - v_{LC} = 0.8$ are reasonable approximations for a system without *economic* or *absolute scarcity*.

Figure 1 illustrates the relationship between the volume supplied (v_P) and the duty cycle (t), assuming that demand is 80% of the water available to the system (i.e., $v_D = 0.8$). For the reference/base case (line OSC), $t_S = 0.25$, implying that the customers' demand can be satisfied provided $t \geq t_S$. For duty cycles $t > t_S$, the additional input volume (line SC) is controlled by the leakage rate (equation (4)). The figure shows two other scenarios (at the same characteristic pressure) in which the EOA is higher than in the base case. Lines OA and OB correspond to systems in which EOAs are 30 times and 5 times higher, respectively, than in the base case (line OSC). For each system, the daily volume received by customers v_R and the volume leaked v_L are shown separately. v_L can also be seen as the difference between v_P and v_R. To visually emphasize that each of these systems (OA, OB, and OSC) has the same customer response ($v_R(t)$), they are plotted on the same figure.

States A, B, and C in Figure 1 correspond to conditions where all available water has been input to the system (i.e., $v_P = v_T = 1$) and it is not possible to input any more water (e.g., because the supply reservoir is empty). Accordingly, system OA has a maximum duty cycle of $t_A < t_S$ and its customers are always unsatisfied. Along line OB, the system is unsatisfied, unless the system is operated exactly at state B, which sits at the transition between unsatisfied and satisfied; as such, system OB's maximum duty cycle is $t_B = t_S$ (denoted $t_{S\&B}$ in Figure 1). For system OSC, state C corresponds to a continuous system ($t_C \equiv 1$) in which customers are satisfied ($t_C > t_S$). Going forward, the system represented by line OB will be denoted as unsatisfied because everywhere along the line OB the system is unsatisfied (except exactly at state B).

It is important to emphasize that t represents the duty cycle not the accumulated time. For example, a system operating at state C does not necessarily satisfy all of its customers first (in $t_S \times \tau$) and then spend the remainder of its supply leaking water. In *predictable IWS* (Galaitsi et al., 2016), customers know when the supply will arrive and satisfied customers in such systems may spread out their demand (Abu-Madi & Trifunovic, 2013; Batish, 2003). Figure 1, therefore, does not depict the system's evolution with time but instead shows how the average behavior of the system depends on its duty cycle. Similarly, after a change in duty cycle, the system (including its customers) takes time to adjust. The constructed model does not predict system behavior during this transient adjustment period but instead predicts behavior once the system has reequilibrated (e.g., after the first five supply periods with a new duty cycle).

3. Model Validation

The proposed model's parsimony arises because it does not consider network topology (comprising hundreds or thousands of interconnected pipes), the spatial variation of pressure, the dependence of pressure

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on other system parameters, the heterogeneity of customers and their demand, the gradual transition from unsatisfied to satisfied, or the pipe filling process. The most rigorous validation would test the proposed model against several physical IWS. Unfortunately, such a validation is not feasible because information about customer demand and leakage in IWS is notoriously poor (e.g., Anand, 2015; McIntosh, 2003), and changing the duty cycle in physical networks substantially changes the water requirements and can change customer satisfaction. Nevertheless, suggestions for how the proposed model could be validated against physical IWS are included in our recommendations for future work (section 6).

The major assumptions used to construct the model can, however, be tested against simulations of IWS. The method of modeling VDD proposed by Macke and Batterman (2001) makes only one of the major simplifying assumptions used in constructing our proposed model (pipes begin full). We therefore use VDD simulations to quantify the loss of accuracy caused by most of the simplifications we assumed. To maximize the transparency of our validation, more complex, custom-built simulations with pipe filling (e.g., De Marchis et al., 2010) were not used; supplementing our validation with such simulations is recommended as future work.

3.1. Reference Networks

Reference networks are hydraulic models of water pipe networks that are publicly available and are often based on physical water pipe networks. Unfortunately, the only available reference networks we found were based on leak-free CWS. To validate the proposed model, we modified four of these reference networks to behave as IWS using the VDD methodology of Macke and Batterman (2001). The demand at each node in each network was segmented into 15% pressure-dependent leakage and 85% VDD (the sensitivity of our validation to this assumption is described below). Full conversion details are in Text S1.

The four reference networks ranged in complexity from 23 to 447 nodes (Table S2). The simplest, the GoYang network, features 23 nodes, is supplied with a 4.5-kW pump, and its elevation varies by less than 10 m (Table S2; Kim et al., 1994). The Pescara and Modena networks are skeletonized versions of two Italian cities and are both gravity fed from several reservoirs (Table S2; Bragalli et al., 2012). The Balerma Irrigation Network (BIN) was adapted from an irrigation network in Spain, and its elevation varies by over 100 m (Table S2; Reca & Martínez, 2006). Access to the original network files is described in Wang et al. (2014); the original files are hosted by the University of Exeter. The intermittent versions of each network (EPANET2 input files) are included as Files S1–S4.

The conversion process from models of CWS to IWS introduces two check valves for each node with demand in a network and therefore makes the hydraulic solution more complicated. BIN was the most complicated network included in the current validation; its simulations converged in more than 80% of scenarios. Our studies have found that it is difficult to apply the VDD method for larger networks due to problems of numerical convergence.

The intermittent versions of each reference network were simulated using an extended period simulation with the EPANET2 solver (Rossman, 2000), implemented in Python 2.7.14 using the "epamodule.py" wrapper (Open Water Analytics, 2018). Simulations used 10-minute simulation (and reporting) timesteps and a simulation period of 24 hours. The results were converted back to duty cycle by dividing the simulated time by the simulation period (i.e., dividing by 24 hr). This conversion is a conservative test case for the proposed model (see Text S2). The maximum number of iterations at each time step was limited to 40 (numerical convergence was not observed to be sensitive to this choice).

3.2. Calibration Method

VDD simulations of each reference network resulted in $V_L(t)$ and $V_R(t)$ with $t \in [0, 1]$ in increments of approximately 0.007. The proposed model of $V_R(t)$ (equation (9)) depends on two parameters, the total customer demand (V_D) and the rate at which demand can be satisfied ($Q_R = K_D h^{\phi}$). $\hat{Q}_R$ was estimated using a least squares fit of the simulation results. The proposed model for $V_L(t)$ (equation (2)) depends only on $Q_L = V_{LC} a h^{\alpha}$; $\hat{Q}_L$ was also estimated using a least squares fit. To allow for testing against networks in which customers are never satisfied, V_D was not calibrated; the true value from the reference network was used in the proposed model. These models are combined such that $V_P(t) = V_L(t) + V_R(t)$. All comparisons of the proposed model and VDD simulations used pressure exponents $\phi = 0.5$ and $\alpha = 1.0$. A flow chart of the calibration method is included as Figure S1a.

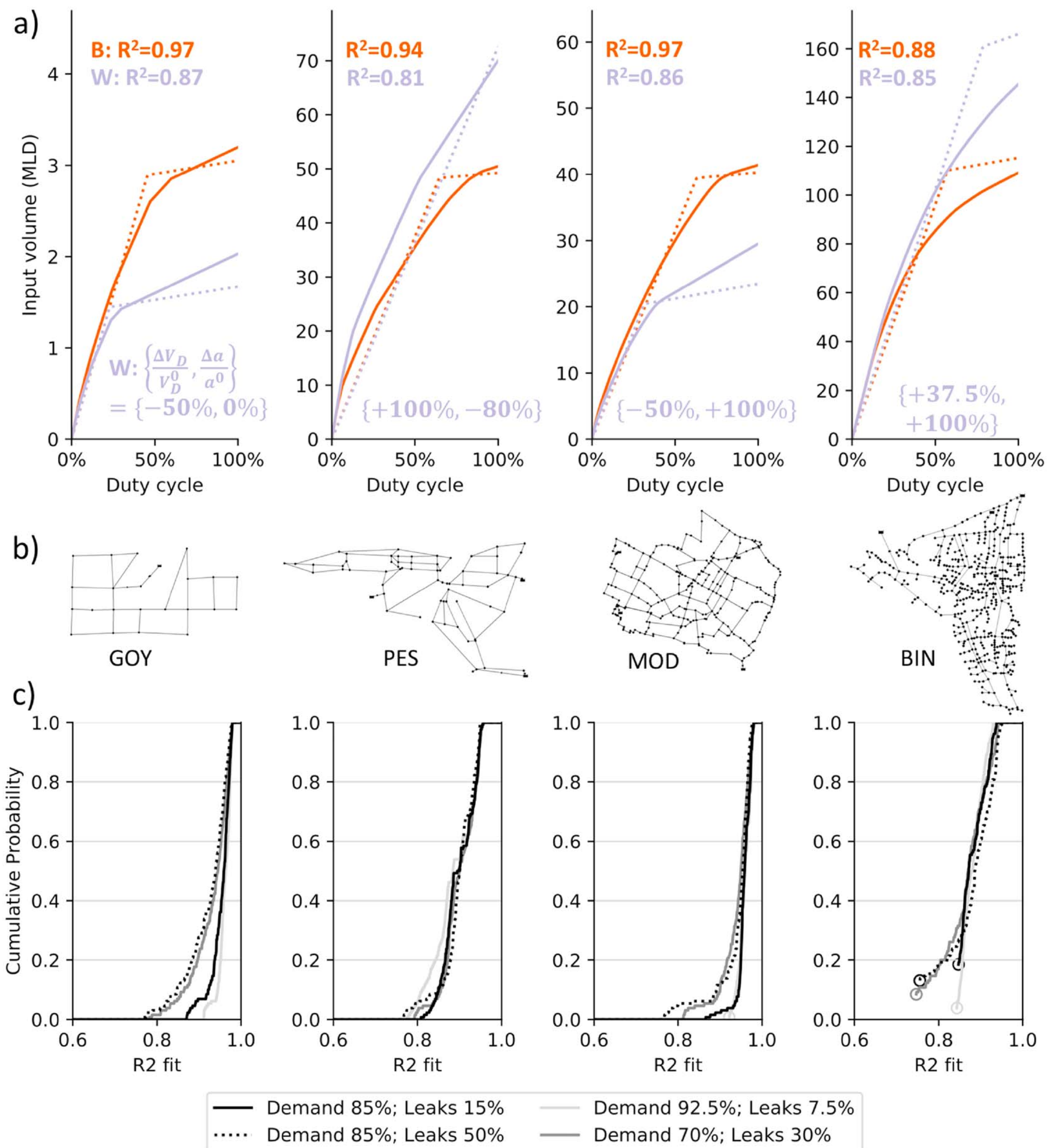

Figure 2. Model's fit with volume-dependent demand simulations. (a) Proposed model predictions (dotted lines) for $V_P(t)$ are compared to volume-dependent demand simulations (solid lines) for two scenarios: B (dark orange, at model calibration) and W (light purple, worst-case fit for $\Delta V_D/V_D^0 \in [-50\%, +100\%]$ and $\Delta a/a^0 \in [-80\%, +100\%]$). The $\{\Delta V_D/V_D^0, \Delta a/a^0\}$ with the worst R^2 fit is different for each network and is shown in the bottom of each subfigure of (a). (c) The cumulative distribution of all validation tests within this range is shown for each network. The conversion of continuous, leakless reference newtorks to intermittent systems assumed that demand comprised 85% of the leakless demand, while leakage comprised 15% (black line). Alternate assumptions about demand:leakage fractions are compared as follows: 92.5%:7.5% (light gray), 70%:30% (gray), and 85%:50%(black dotted line). Cumulative distributions that include scenarios where some simulations did not converge are conservatively truncated (open circle). (b) Networks are shown, not to scale. MLD = Millions of liters per day. GOY = GoYang; PES = Pescara; MOD = Modena; BIN = Balerma Irrigation Network.

3.3. Validation Method

After calibration at each network's initial values of demand and EOA (i.e., $\{V_D^0, a^0\}$), the proposed model of $V_P(t)$ was compared to simulation results across a range of values for V_D and a (i.e., $\Delta V_D/V_D^0 \in [-50\%, 400\%]$ in increments of 12.5% and $\Delta a/a^0 \in [-80\%, 700\%]$ in increments of 20%). The goodness of fit between the model and simulation was quantified by the R-squared (R^2) value for each pair $\{V_D, a\}$. Details of this method are in Text S3 and Figure S1b.

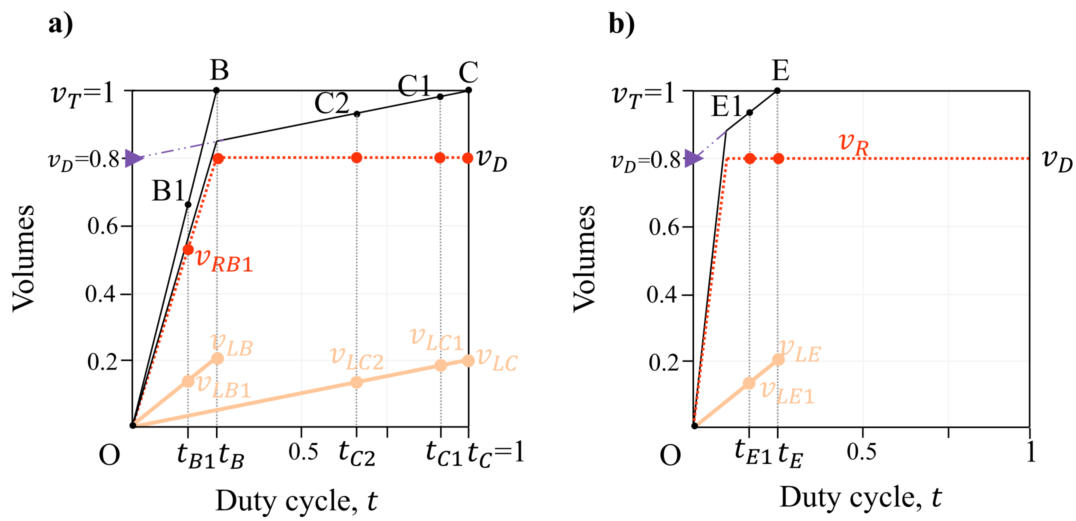

Figure 3. The effects of shorter duty cycles. The effects of reduced duty cycle on the volume input into the system (v_P, thin black lines OB, OC, OE), the volume received by customers (v_R, red dotted lines of medium weight), and the volume lost to physical leaks (v_L, thick orange lines). (a) Customers in systems OB and OC are satisfied at $t_S = 0.25$. (b) Customers in system OE are satisfied at $t_S < 0.25$. Where the slope/gradient of $v_P(t)$ (purple dashed and dotted line) intersects the y axis (purple triangle) at v_D, the system is satisfied.

3.4. Validation Results

After calibration, the model matched the behavior of the four reference networks (Figure 2a) with goodness of fit values $R^2 = 0.97, 0.94, 0.97, 0.88$ for GoYang, Pescara, Modena, and BIN networks, respectively (B in Figure 2a). For variations of $\Delta V_D/V_D^0 \in [-50\%, +100\%]$ and $\Delta a/a^0 \in [-80\%, +100\%]$, the model's prediction of $V_P(t)$ always matched with simulations such that $R^2 > 0.81$ (W in Figure 2a). Unfortunately, 18% of simulations of BIN in this range did not converge (Figure 2c); accordingly, the fit $R^2 > 0.81$ is not strictly a lower bound. Nevertheless, the R^2 fit varies smoothly with respect to V_D and a (Figure S5) and so we argue that $R^2 > 0.81$ is a representative accuracy bound.

To demonstrate the limits of the proposed model, V_D and a were varied much more than would be expected in the normal aging and growth of a water distribution network (i.e., up to +400% and +700%, respectively). The model's performance at these extremes is discussed in detail in Text S4.

The accuracy of the customer model ($V_R(t)$) is relatively unaffected by changes in EOA but decreases with large increases in demand (Figure S2). The customer model assumed that Q_R was unaffected by changes in V_D. In reality, as demand (V_D) increases, the supplied demand concentrates near the network's water sources (thereby increasing Q_R). This limitation was most evident in PES (see Text S4) and matches with the limitations found in previous macroscopic hydraulic models. When such models are based on the aggregated demand, they assume (implicitly or explicitly) that the relative spatial distribution of demand and leaks will not change as the network changes (Ormsbee & Lansey, 1994).

The proposed leakage model ($V_L(t)$) is less robust to changes in demand and leakage than the model of $V_R(t)$ (Figure S3). In simulated networks, changes in demand affect how quickly customers become satisfied. Once customers become satisfied, the network pressure builds (Figure S4d). This endogenous pressure variation substantially affects leakage but is not captured by the proposed model.

When demand and EOA both increase, the current customer model underpredicts the water required by customers while overpredicting the leaked water. When networks grow in demand and EOA, which is likely as they age, the combined model of a network's input volume (i.e., $V_P(t) = V_L(t) + V_R(t)$) is more robust to such changes than either of its components (Figure S5).

3.5. Validation Sensitivity

As reference networks based on real IWS were unavailable, we needed to convert models of leak-free CWS to be representative of IWS. In doing so, we assumed that leakage comprised 15% of demand in the leak-free networks. Similarly, we assumed that customer demand comprised 85% of demand in the leak-free networks. This assumption was tested by halving and doubling the assumed fraction of leakage (to 7.5% and 30%)

Table 1
Effects of Shortened Duty Cycles in the Example Systems of Figure 3

Effect on	Metric	OB Unsatisfied Intermittent (B→B1)	OE Satisfied Intermittent (E→E1)	OC Satisfied Initially continuous (C→C2)	(C→ C1)
Duty cycle	Δt	−0.083	−0.083	−0.333	−0.083
Duty cycle	$\Delta t/t$	−33%	−33%	−33%	−8.3%
Leakage	$\Delta V_L/V_L$	−33%	−33%	−33%	−8.3%
Consumption	$\Delta V_R/V_R$	−33%	0	0	0
Water required	$\Delta V_P/V_P$	−33%	−6.7%	−6.7%	−1.7%

Note. Four system transitions in Figure 3 are considered: (B→B1), (E→E1), (C→C2), and (C→C1). These occur in an unsatisfied intermittent supply (OB), a satisfied intermittent supply (OE), and a satisfied, initially-continuous supply (OC). Initially, each system delivers 80% of its water to customers, while 20% goes to physical leakage.

while maintaining the same total demand (customer demand was concomitantly changed to 92.5% and 70%, respectively). Finally, in an extreme case, demand was assumed to be 85% of the leak-free demand, while leakage was increased to 50% of the leak-free demand (which increased the total water requirements by 35%). These alternate versions of Files S1–S4 are included as Files S5–S16 (see also Taylor et al., 2019).

The goodness of fit between the model and the simulations does degrade modestly as the baseline rate of leakage increases (Figure 2c). However, across all four assumptions about leakage and demand, the calibration $R^2 > 0.86$ (drop of 0.02) and the validation $R^2 > 0.74$ (drop of 0.07), suggesting that our model's validity is not substantially dependent on this initial assumption about leakage and demand in the reference networks (Figures 2c and S6).

4. Model Application

Having demonstrated that much of the average behavior of IWS can be approximated by the proposed model, this section uses the model to assess the effects and causes of duty cycle changes and thereby demonstrates the value of the model for research and regulatory purposes.

4.1. Effects of a Reduced Duty Cycle

Consider the effects of reducing the duty cycle in three systems: an unsatisfied system (OB, Figure 3a) that begins at state B, which is the only state in OB at which customers are satisfied (i.e., along OB, $t \leq t_B = t_S = 0.25$); a satisfied system (OE, Figure 3b), which begins at $t_E = 0.25 > t_S$; and a satisfied, initially continuous system (OC, Figure 3a; $t_C = 1 > t_S$). In each system, customer demand is assumed to be 80% of the available water. The remaining 20% of available water is assumed to be leaked from each system in its initial state. Because it is assumed that $t_S = 0.25$ in both systems OB and OC, they are plotted on the same subfigure.

The effects of reducing the duty cycle by one third are shown in Figure 3. For the unsatisfied intermittent system (line OB in Figure 3a), reducing the duty cycle by one third ($t_B \rightarrow t_{B1}$) causes a one-third reduction in customer consumption ($v_D \rightarrow v_{RB1}$), in leakage ($v_{LB} \rightarrow v_{LB1}$), and in the total water required to be input ($B \rightarrow B1$).

In the cases of the initially continuous system (OC in Figure 3a) and of the satisfied intermittent system (OE in Figure 3b), reducing the duty cycle by one third does not affect customer consumption but does reduce leakage by one third in both systems ($v_{LE} \rightarrow v_{LE1}$ and $v_{LC} \rightarrow v_{LC2}$; Table 1). Since leakage was assumed to be 20% of the total input volume in both satisfied systems, reducing it by one third only reduces the total water requirements by 6.7% (Table 1). In this example, therefore, reducing the duty cycle by a fixed percentage affected a satisfied intermittent system and a satisfied, initially continuous system equally.

For the satisfied, initially continuous system (state C in Figure 3a), if the duty cycle is instead reduced by one third of $t = 0.25$ (i.e., by 0.083 as it was in systems OB and OE), then leakage in system OC is only reduced by 8.3% (4 times less than in the case of the intermittent systems OB and OE). This reduction in leakage corresponds to reducing the total water required for the continuous system by 1.7% (Table 1).

Table 2
Formulas to Quantify Three Effects of Shorter Duty Cycles in Unsatisfied and Satisfied IWS

Effect	Gradient	Unsatisfied IWS	Satisfied IWS
Reduced leakage	$-\frac{\partial V_L}{\partial t}$	$\frac{-V_L^0}{t^0}$	$\frac{-V_L^0}{t^0}$
Suppressed consumption	$-\frac{\partial V_R}{\partial t}$	$\frac{-V_R^0}{t^0}$	0
Reduced water requirements	$-\frac{\partial V_P}{\partial t}$	$\frac{-V_P^0}{t^0}$	$\frac{-V_L^0}{t^0}$

Note. The degree to which shorter duty cycles (t) reduce leakage (V_L), suppress the water received/consumed by customers (V_R), and reduce the total water required by a network (V_P) is analytically represented by the partial derivatives (gradients) shown. Each is evaluated for unsatisfied and satisfied IWS; the gradients are piecewise constant. Superscript ^{0} indicates a variable evaluated at its initial value. Derivations are in Text S5. IWS = intermittent water supplies.

These examples are generalized by the partial derivatives of leakage, volume received by customers, and total input water with respect to the duty cycle (Table 2; derivations in Text S5). These gradients provide a unifying framework to understand, compare, manage, and regulate IWS. Much of the recent literature on IWS has tried to reassure utilities that (i) converting to CWS does not require extra water and that (ii) intermittent supply does not reduce leakage (e.g., Charalambous & Laspidou, 2017; The World Bank, 2013). Table 2 qualifies such claims.

Changing the duty cycle by a certain percentage will affect the total water needed in unsatisfied IWS by V_P^0/V_L^0 times more than in satisfied IWS ($\approx 1/v_L^0$ times more; Table 2; e.g., 5 times more in state B than E in Figure 3). Moreover, a certain absolute change in duty cycle will affect the total water needed in unsatisfied IWS by $V_P^0/(V_L^0 t^0)$ times more than in satisfied CWS (e.g., 20 times more in state B than C in Figure 3a). From the perspective of satisfied IWS (let alone CWS), therefore, reducing the duty cycle may not save very much water. However, from the perspective of unsatisfied IWS, the idea of increasing the duty cycle is untenable. Even though real IWS are unlikely to be fully satisfied or fully unsatisfied, the differences observed in these extremes highlight that the degree of demand satisfaction is one likely source of the conflicting perspectives on how much additional water is required to convert IWS to CWS.

In both unsatisfied and satisfied IWS, reducing the duty cycle by a given percentage had an equal effect in reducing leakage (i.e., $\Delta V_L/V_L^0 = \Delta t/t^0$; Table 2). Therefore, in systems with initially short duty cycles (t^0), a given absolute reduction in duty cycle (Δt) equates to a larger percent change and has a magnified effect on leakage. More generally, each effect of changing the duty cycle is magnified at shorter initial duty cycles (except demand suppression in unsatisfied IWS; Table 2). This again explains how conflicting perspectives can arise.

Where customer demand is known or estimated, IWS can be classified as satisfied or unsatisfied by observing how the input water requirements change as a function of small changes in duty cycle. Specifically, if we define V_S (purple triangle in Figure 3) as the y intercept of the slope (i.e., gradient) $\left.\frac{\partial V_P}{\partial t}\right|_{t^0}$,

$$V_S \equiv V_P^0 - t^0 \left.\frac{\partial V_P}{\partial t}\right|_{t^0}$$
$$\therefore V_S = \begin{cases} V_P^0 - t^0 \frac{V_P^0}{t^0} = 0 & : th^\phi < \gamma_S \text{ (Unsatisfied)} \\ V_P^0 - t^0 \frac{V_L^0}{t^0} \equiv V_D & : th^\phi > \gamma_S \text{ (Satisfied)} \\ \text{undefined} & : th^\phi = \gamma_S \end{cases} \quad (13)$$

Therefore, where $V_S < V_D$, customers (collectively) are unsatisfied and such systems are *unsatisfied IWS*.

While real IWS do not instantaneously transition from fully unsatisfied to fully satisfied (e.g., the gradual transition can be seen in Figure 2a), during the transition, V_S transitions between the extremes predicted by equation (13). In real IWS, therefore, where the transition is gradual, V_S can quantify the degree of system

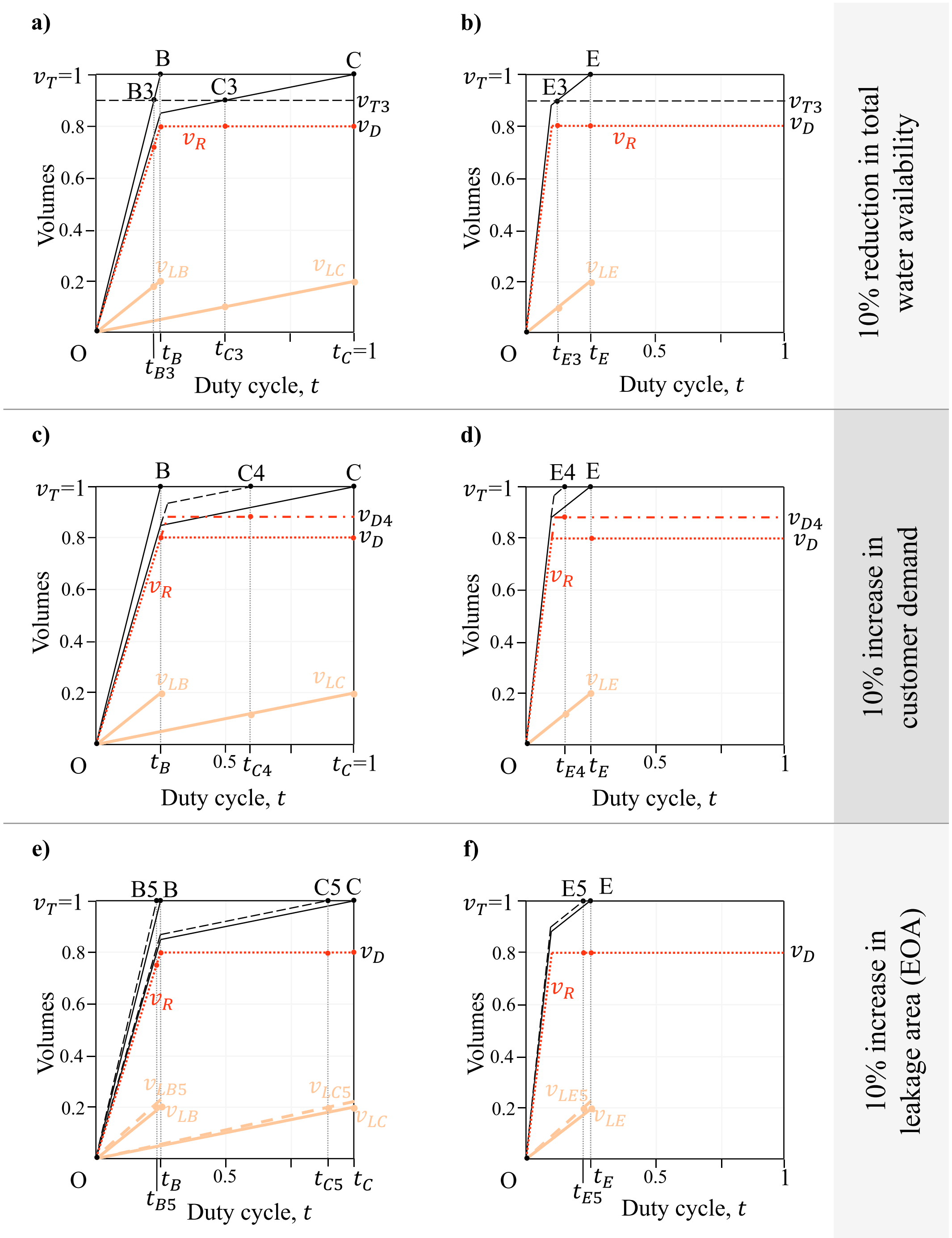

Figure 4. The causes of shorter duty cycles. The reduction in duty cycle induced by system changes for three systems (OB, OC, and OE). The systems' new configurations are shown with dashed lines in each subfigure. (a, b) A reduction in the available water by 10%. (c, d) A proportional increase in demand by 10%. (e, f) A proportional increase in EOA by 10%. The initial lines of v_R are shown as a dotted lines; the new configurations for v_R in (c) and (d) are shown as dash dotted lines. EOA = equivalent orifice area.

Table 3
Relative Importance of Three Potential Causes of Reduced Duty Cycles in the Example Systems of Figure 4

Potential cause	OB Unsatisfied Intermittent $\Delta t\,(\Delta t/t)$	OE Satisfied Intermittent $\Delta t\,(\Delta t/t)$	OC Satisfied Initially continuous $\Delta t\,(\Delta t/t)$
10% water shortage	−0.025 (−10%)	−0.125 (−50%)	−0.5 (−50%)
10% demand increase	0 (0%)	−0.1 (−40%)	−0.4 (−40%)
10% EOA increase	−0.0049 (−1.96%)	−0.023 (−9%)	−0.091 (−9%)

Note. The reduction in duty cycle (absolute (Δt) and relative ($\Delta t/t$)) caused by reduced water availability, increased customer demand, and pipe degradation (i.e., increased EOA) is considered for three systems in Figure 4: an unsatisfied intermittent supply (OB), a satisfied intermittent supply (OE), and a satisfied, initially-continuous supply (OC). Initially, each system delivers 80% of its water to customers, while 20% goes to physical leakage. EOA = equivalent orifice area.

satisfaction, S

$$S \equiv \frac{V_S}{V_D} = \frac{V_P^0 - t^0 \left.\frac{\partial V_P}{\partial t}\right|_{t^0}}{V_D} \tag{14}$$

where $S = 0$ indicates a system that is fully unsatisfied and $S = 1$ a system that is fully satisfied.

SDG 6.1 and the UN's articulation of the human right to water target water supplies are *available when needed* and *continuous enough*. While SDG 6.1's documentation suggests that "a minimum of 12 hr/day will be used as the global benchmark for available when needed" (i.e., $t \geq 0.5$), this benchmark has not been justified (World Health Organization, 2017b, p.33). Equation (14), in contrast, provides the first theoretically founded metric for quantifying the level of satisfaction in an IWS.

4.2. Causes of a Reduced Duty Cycle

The three causes of IWS proposed by Totsuka et al. (2004; absolute, economic, and technical scarcity) map onto our model: when $\nu_D > 1$, IWS suffer from economic and/or absolute scarcity. When $\gamma_S > 1$, the networks' distributional capacities are limiting and IWS suffer from economic scarcity. Finally, when $\nu_D < 1$ and $\gamma_S < 1$, IWS suffer from technical scarcity.

To supplement the framework of Totsuka et al. (2004), this section considers the relative importance of three potential causes of IWS: reduced water availability, increased customer demand, and increased leakage. We begin by reconsidering the three systems depicted in Figure 3 and the change in duty cycle that would be caused by (i) a 10% reduction in the available total water, (ii) a 10% increase in the volume demanded by customers, and (iii) a 10% increase in the EOA of each system (Figure 4). Changes in demand and EOA

Table 4
Formulas to Quantify Three Causes of Reduced Duty Cycles in Unsatisfied and Satisfied IWS

Cause	Gradient	Unsatisfied IWS	Satisfied IWS
Supply shortfall	$-\frac{\partial t}{\partial V_T}$	$-\frac{t^0}{V_T^0}$	$-\frac{t^0}{V_L^0}$
Demand increase	$\frac{\partial t}{\partial V_D}$	0	$-\frac{t^0}{V_L^0}$
EOA increase	$\frac{\partial t}{\partial a}$	$-\frac{t}{a}\nu_L$ ‡	$-\frac{t}{a}$ ‡

Note. The duty cycle (t) reduction required by a water supply (V_T) shortfall, demand (V_D) increase, or pipe degradation (i.e., EOA increase, normalized to a) is analytically represented by the partial derivatives (gradients) shown. Each is evaluated for unsatisfied and satisfied IWS. Superscript ^{0} indicates a variable evaluated at its initial value. Derivations are in Text S5. IWS = intermittent water supplies; EOA = equivalent orifice area.
‡Unlike other gradients shown, these are not constant.

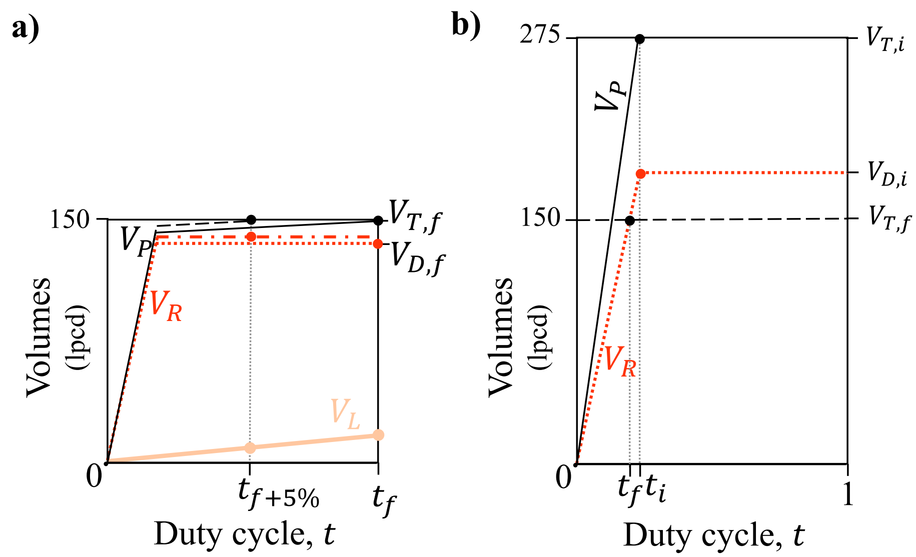

Figure 5. Target robustness and feasibility. (a) Target robustness. The contracted ideal is depicted (black solid line and red dotted line) with the contracted duty cycle shown as $t_f = 1$. A customer demand increase of 5% (red dash-dotted line), causes the total water required to increase (black dashed line) and reduces duty cycle to t_{f+5}%. (b) Target feasibility. If every leak were fixed, without demand reduction, when the total water available reduces to 150 lpcd (black dashed, horizontal line), the duty cycle will reduce from t_i to t_f (vertical dotted lines). Variable subscripts i and f indicate initial and final values.

are assumed to be proportional across the whole network (e.g., each customer's demand increases by 10% instead of having 10% of customers double their demand).

Reducing the available water by 10% causes the unsatisfied intermittent system (OB in Figure 4a) to move from state B to state B3, reducing its duty cycle by 10%. For both satisfied systems (OC and OE in Figures 4a and 4b), customer demand is inelastic; the water supply deficit, therefore, must be compensated with reduced leakage. Accordingly, the leakage rate (initially 20%) needs to reduce by 10 percentage points (i.e., half), which requires halving both duty cycles (C to C3 and E to E3 in Figures 4a and 4b).

Proportional increases in customer demand (i.e., where customers all increase their demand, V_D, by the same proportion) do not change duty cycles in unsatisfied IWS (e.g., OB in Figure 4c) but do decrease the fraction of demand that is met. For both satisfied systems (OC and OE in Figures 4c and 4d), a proportional increase in demand by 10% increases demand from 80% of the available water supply to 88%. Therefore, leakage, which starts at 20%, must be reduced by 8 percentage points. To accomplish this, the duty cycle must decrease by 40% (8/20) in both satisfied systems (C to C4 and E to E4 in Figures 4c and 4d; Table 3).

Finally, if the EOA of each system proportionally increased by 10%, leakage would, unchecked, increase to 22% of the total supply. Accordingly, the unsatisfied intermittent system must reduce its duty cycle by 1.96% (2/102; B to B5 in Figure 4e; Table 3). Both satisfied systems again have to make up the difference with leakage alone, requiring a 9% (2/22) reduction in duty cycle in each case (C to C5 and E to E5 in Figures 4e and 4f; Table 3).

The gradients of duty cycle with respect to water availability, demand, and EOA generalize the above examples (Table 4; derived in Text S5). We believe that this is the first model to articulate the link between customer satisfaction in IWS and factors that can affect duty cycle.

While narratives about IWS often suggest that the water demand of customers and growing populations necessitate low duty cycles (Coelho, 2004; Galaitsi et al., 2016; Simukonda et al., 2018), our model suggests that changes in total water availability have a larger effect on duty cycle than proportional changes in customer demand or EOA, assuming that each was changed by the same percent (e.g., 10% as in Figure 4; Table 4). In unsatisfied IWS, proportionally increased demand has the smallest (i.e., no) effect on duty cycle. In satisfied IWS, proportionally increased EOA has the smallest effect on duty cycle, provided $v_L^0 < 0.5$ and assuming small changes in each factor (Table 4). While this strongly suggests that proportional increases in customer demand are not the most important causal factor of IWS, our model does not capture the effects of increasing demands at the extremities of a network.

Under our assumption of an instantaneous transition between satisfied and unsatisfied, our results suggest that operating intermittent supplies at the tipping point between satisfied and unsatisfied is optimal (in the short term) for utilities for four reasons:

1. All gradients are either constant (including zero) or increase (in magnitude) with respect to duty cycle (Table 4). As IWS have lower and lower duty cycles, therefore, they will change more slowly in response to equal percent changes in water availability, demand, and EOA (Table 4). From the utility's perspective, therefore, operating at a lower duty cycle increases the robustness of their duty cycle to system changes.
2. The influence of total water availability and EOA on duty cycles is approximately $1/v_L$ times less in unsatisfied IWS than in satisfied IWS (Table 4). Moreover, unsatisfied IWS are unaffected by proportional changes in customer demand. From the utility's perspective, therefore, unsatisfied IWS are more robust (with respect to t) to system changes than satisfied IWS.
3. While duty cycle is more robust in unsatisfied IWS, this comes at the cost of customer satisfaction. In satisfied IWS, changes in duty cycle do not affect the volume received by customers (Table 2). From the perspective of the customer, therefore, unsatisfied IWS are the least robust (with respect to V_R).
4. Managers of IWS constantly make "adjustments until people stop shouting" (Anand, 2011). Since satisfied IWS in which $t > t_S$ supply more water than required to satisfy their customers (e.g., E in Figure 3b), their duty cycle is likely to reduce, either passively (through increased EOA or growth in consumption) or actively (diverting water elsewhere). Once such systems become unsatisfied, customers will undoubtedly complain.

While real IWS are expected to exhibit a more gradual transition from unsatisfied to satisfied states, the preceding arguments suggest that there is an optimal state of demand satisfaction (within this transition) from the perspective of the water utility. For both public and private utilities, the existence of a local optimum other than continuous supply suggests that careful regulation of IWS is required (Dasgupta & Dasgupta, 2004; Sangameswaran, 2014).

5. Case Study: A Performance-Based Contract in India

As the proposed model does not use detailed pipe network information, it can be useful in evaluating project robustness and feasibility before expensive contracts are signed. Consider a $25 million, 10-year, performance-based contract awarded in India, supplying 250,000 people (project details are intentionally generalized). Project targets were to increase the duty cycle from 5.5 to 24 hr/day (i.e., $t = 0.23 \rightarrow 1$) and also to reduce the total water input from $V_P = 275$ to 150 liters per capita per day (lpcd). Performance penalties were waived only if the project received $V_T < 150$ lpcd and so V_T was outside of the project's control and was quickly reduced to 150 lpcd. Of the 150 lpcd of input water, 135 lpcd needed to flow to customers to meet Indian city standards (CPHEEO, 1999), allowing only 15 lpcd (10%) for physical leaks.

To consider project robustness, assume that the project achieved its targets, providing continuous supply with $V_T = 150$ lpcd while supplying the regulated minimum to customers (i.e., $V_R = 135$ lpcd, implying $v_L = 10\%$). In this ideal case, a 5% increase in demand would require cutting the duty cycle by 45% (Figure 5a; shown as an example calculation in Text S6). It is difficult to predict either per capita demand or population growth to within ±5% in a growing city and substantially more difficult to estimate their product. Even if the project successfully provided residents with "24×7" water, a 6% error in the predicted demand would require returning to less than 12 hr/day of supply (i.e., $t < 0.5$).

Consider also the feasibility of the project. At its outset, 70% of the input water was NRW and the fraction of this due to physical leakage was unclear. Assuming half of the 70% was due to physical leakage (an approximation McIntosh (2014) suggests for "developing countries"), initial customer demand would have been about 180 lpcd, which is greater than the targeted total input water (V_T). Demand management, therefore, would be essential for the project's success. Yet to avoid criticism of private sector involvement, the price charged to customers is not usually under a water supply project's control (van den Berg et al., 2008); this project was no exception. With no control of either the water price or V_T, the means by which this project could achieve continuous supply should have been questioned at its outset.

If the project fixed every single leak, customer demand, unchecked, would still be larger than the total water input. In fact, to suppress demand to 150 lpcd, the duty cycle must be reduced by at least 17% (Figure 5b). If demand must be suppressed enough to allow for 10% physical leakage, then the duty cycle must be reduced by at least 25% ((180–135)/180).

As should have been predicted before the project's debut, the proposed "continuous" water supply project has resulted in a shorter duty cycle rather than continuous operation. This case study is a clear demonstration of the benefits of the proposed model in evaluating the design of performance-based contracts, enabling regulators and funding agencies to structure more robust and feasible projects.

6. Future Work

Based on the model development, validation, and application, described in this paper, we propose five areas where additional refinements could improve the model's validation, quantitative predictions, and potentially increase its efficiency

1. Further validation of the proposed model would require comparisons with pipe network simulations that include an initial pipe filling phase. This could be achieved by modifications of the current EPANET models of IWS.
2. Comparing the model's predictions to the behavior of real IWS would further validate the model. This might be done by instrumenting a system that was undergoing a major shift in its characteristics. For example, a drought would change V_T and allow $\partial V_T/\partial t$ to be observed.
3. Including endogenous pressure effects would improve the accuracy of the leakage model.
4. Considering variations in customer satisfaction within a network could quantify some of the equity effects of IWS. This is especially important at the extremities of the network, where customers are notoriously underserved (Vairavamoorthy et al., 2007), and for customers who share a connection and therefore receive only a fraction of the "average" (Kumpel et al., 2017).
5. Accounting for the longer-term effects of the pressure and duty cycle (e.g., potentially accelerated pipe degradation) would create a more holistic model of IWS.

A further extension of the proposed model would consider the water quality effects of intermittent operations. The two largest studies of water quality in IWS have found very different results (Erickson et al., 2017; Kumpel & Nelson, 2013). A water quality model might unify these seemingly conflicting results. Such a model might combine the proposed model with the model presented by Taylor et al. (2018).

7. Conclusions

This paper demonstrates the utility of demand satisfaction as a framework for understanding and managing IWS.

We proposed a parsimonious macroscopic model which ignores details of the distribution network's topology and approximates the supply system by the behavior of an average customer and a spatially averaged leakage rate. Intermittent supply was characterized by a duty cycle, t, corresponding to the fraction of time during which a network makes water available to customers. We presented a novel validation of the macroscopic model by comparison with numerical simulations of intermittent operations of four reference pipe networks. This was achieved by converting existing reference networks that normally provide continuous supply to networks that provide intermittent supply using an assumption that customers are satisfied with a fixed volume of supply (i.e., VDD). The close agreement between the macroscopic model and more detailed numerical simulations suggests that much of the underlying behavior of IWS is simple and the behavior relates to the degree of demand satisfaction in a network (S; equation (14)). If customers' demand is fully satisfied ($S = 1$), then a water supply is *available when needed*, which is necessary for it to be considered *safely managed* under SDG 6.1. Hence, the metric S can be used to track progress toward SDG 6.1.

Key Implications

1. There are many apparent contradictions in the literature relating to IWS (e.g., do IWS save water?) that can be harmonized by accounting for demand satisfaction. Hence, researchers, regulators, and policy makers should more carefully distinguish between satisfied and unsatisfied IWS.

2. In contrast to narratives that suggest that converting from intermittent to continuous supply does not require additional water, we demonstrated that without repair or replacement of pipes (and holding pressure constant), the volume of leakage will increase by $1/t^{0}$. Where IWS are initially unsatisfied, the water requirements to operate continuously will be even higher.
3. While some utilities blame customer demand for IWS, proportional increases in demand do not affect the duty cycle in already unsatisfied IWS. Moreover, changes in total water availability have a larger effect on duty cycle than equal percent changes in pipe quality or customer demand.
4. Operating conditions that are ideal for utilities (unsatisfied IWS) differ from those that are best for customers (satisfied IWS); hence, IWS require careful regulatory oversight.
5. The proposed macroscopic model functions when information is sparse. As such, the model can be used to improve the regulation and operation of IWS. We demonstrated this by critiquing the robustness and feasibility of a performance-based contract awarded in India, using only information that was available at the project's outset.

Appendix A: Minimum Supply Period for Customer Satisfaction

Customers' storage capacity ($\forall_S$; an absolute volume, not a daily volume) can change their access to water in IWS (Kumpel et al., 2017; Rosenberg et al., 2007); longer supply periods require customers to have more storage capacity. To model this, customer consumption during the supply cycle is conservatively neglected (even though it can be substantial; Kumpel et al., 2017).

Figure A1 depicts the minimum supply period ($T = 1$ over frequency) required to satisfy customers with a given daily demand (V_D) and total storage capacity ($\forall_S$). The vertical axis represents the supply duration (τ), and the horizontal axis represents the supply period. If $t = 1$, a system provides water continuously; if $t < 1$, a system is intermittent. The minimum duty cycle required to satisfy customers (i.e., $V_R = V_D$) is shown as t_S (equation (8)), the angled bottom of the Satisfied IWS zone.

If the duty cycle is too short (i.e., $t < t_S$), customers are unsatisfied because they are hydraulically limited by the flow out of their tap; they are *orifice limited*. But even when $t \geq t_S$, if customers are to be satisfied, they must have enough storage capacity to store their daily volume of demand for each day until the next supply cycle (i.e., $\forall_S \geq TV_D$). In order to satisfy customers, therefore, IWS must provide water with a period of $T \leq \forall_S/V_D$, where $\forall_S$ should be taken as the storage capacity of the poorest customer in the network. When $T > \forall_S/V_D$, IWS are *storage limited* and not all customers are satisfied. The degree of system satisfaction,

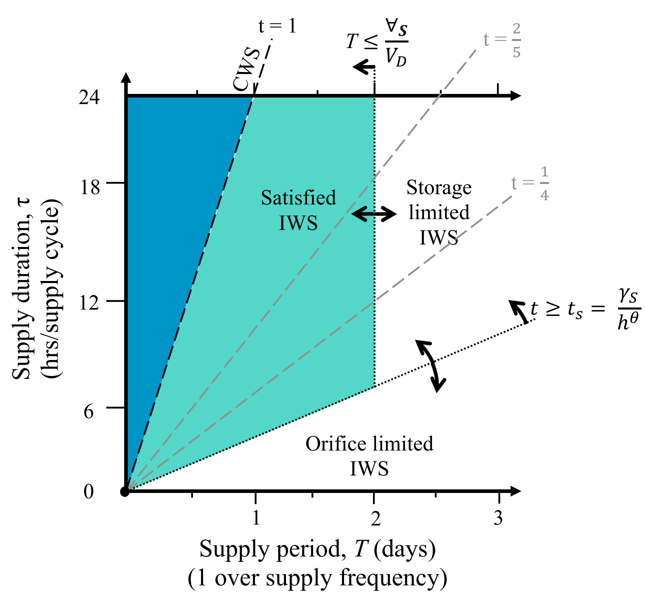

Figure A1. Minimum supply period. The implications of the supply period ($T = 1$ over frequency), duty cycle (t), supply duration (τ), and customer storage capacity ($\forall_S$) on customer satisfaction. CWS = continuous water supplies; IWS = intermittent water supplies.

S (equation (14)), captures the degree to which customers are orifice limited but not the extent to which customers are storage limited.

Nomenclature

Symbol	Units	Description
A	m^2	Cross-sectional area of a leak or equivalent orifice area (EOA) of several leaks
A_t	m^2	EOA required to achieve a project or system's targets
a	—	EOA normalized by A_t
a^0	—	Initial, normalized EOA
C_d	$(ms^{-1})^{2\alpha-1}$	Orifice coefficient
g	m/s^2	Gravitational acceleration
H	m	Average pressure head
H_t	m	Targeted pressure head
h	—	Average pressure head, normalized by H_t
K_D	m^3/day	Pipe and topography constant
k_D	—	Normalized pipe and topography constant; K_D/V_T
Q_L	m^3/day	Instantaneous flow rate of leaks in a system
$\hat{Q}_L$	m^3/day	Least squares estimate of Q_L
Q_R	m^3/day	Flow rate received by unsatisfied customers during supply
$\hat{Q}_R$	m^3/day	Least squares estimate of Q_R
S	—	Degree to which an intermittent system is satisfied; $S \in [0, 1]$
T	day	Period of supply, 1 over frequency of supply
t	—	Duty cycle; fraction of time a system is pressurized
t^0	—	Initial duty cycle
t_S	—	Minimum duty cycle required to satisfy customers
V_D	m^3/day	Daily volume of water demanded by customers
V_D^0	m^3/day	Initial daily volume of water demanded by customers
V_L	m^3/day	Daily volume of leaked water
V_L^0	m^3/day	Initial daily volume of leaked water
V_{LC}	m^3/day	Daily volume of leaked water in the targeted scenario
V_P	m^3/day	Daily volume input (e.g., pumped) to a network
V_P^0	m^3/day	Initial daily volume of input water
V_R	m^3/day	Daily volume of water received by customers
V_T	m^3/day	Daily volume of water available for a network
V_S	m^3/day	y-axis intercept of the input water gradient ($\partial V_P/\partial t$)
$\forall_S$	m^3	Absolute volume of customer's storage capacity
v_D	—	Normalized daily volume demanded by customers
v_L	—	Daily volume of leaked water, normalized by V_T
v_L^0	—	Initial, normalized daily volume of leaked water
v_{LC}	—	Normalized daily volume of leaks in the targeted scenario
v_P	—	Normalized daily volume of water input into a network
v_R	—	Normalized daily volume received by customers
v_T	—	Normalized daily volume available for a network
α	—	Pressure coefficient governing flow to leaks
γ_S	—	Minimum th^{ϕ} required to satisfy customers
τ	day	Duration of an intermittent system's supply cycle
ϕ	—	Pressure coefficient governing flow to customers

Abbreviation	Definition
CWS	Continuous water supplies
EOA	Equivalent orifice area

IWS Intermittent water supplies
lpcd liters per capita per day
MLD Millions of liters per day
PDD Pressure-dependent demand
SDG Sustainable Development Goal
UN United Nations
VDD Volume-dependent demand

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