Tracing the Dependency of Water and Energy in Smart and Connected Communities Through a Multi-Domain Modeling Framework

Saranya Anbarasu
University of Colorado Boulder

Kathryn Hinkelman
Pennsylvania State University

Wangda Zuo
Pennsylvania State University

Topic: Urban Microclimate and Energy, Smart Buildings and Smart Cities (ML, AI, IoT)

Tracing the Dependency of Water and Energy in Smart and Connected Communities through a Multi-Domain Modeling Framework

Saranya Anbarasu[1], Kathryn Hinkelman[2], Wangda Zuo[2]

[1]Civil, Environmental and Architectural Engineering, University of Colorado Boulder, USA
[2]Architectural Engineering, Pennsylvania State University, USA

[*]*Corresponding email: wangda.zuo@psu.edu*

Keywords: Smart and connected communities, Critical infrastructure system, Water distribution network, Integrated modeling, Modelica

SUMMARY

Essential needs such as electricity generation, water distribution, and water treatment account for 12.6% of US energy consumption, of which water distribution (3.15%) is highly energy-intensive with the average energy use of 1300 kilowatt-hours per million gallons (kWh/MG). Water Distribution Networks (WDNs) are promising candidates for providing demand response due to the large fluid inertias, pressurized piping networks, and high energy intensity associated with pumping. However, to take advantage of the demand response potential of WDNs, we need to better understand the operation of community-level water networks and ways of energy optimization in connection with electricity operation. In this paper, we develop component and system models of community-level WDN using equation-based object-oriented Modelica language. Further, we exhibit the water-energy interdependencies through demand response (DR) pump controls based on time-of-use and critical-peak energy pricing as well as the commonly used tank level-based pump control using the developed modeling package. The DR pump controls exhibit a 25-29% energy savings and 17-27% cost savings compared to the commonly used pump control. This research has the potential to support dynamic modeling and optimization, demand response, resiliency analysis, and integrated decision-making in future smart and connected communities.

INTRODUCTION

Water distribution networks (WDN) are a critical infrastructure system in communities and consume about 3-5% of the total electricity across the world [1, 2, 3]. A typical WDN consists of a source/reservoir, pumping station, storage tank/water tower, pressurized pipe network, and demand nodes. As pressurized networks, WDNs consume an enormous amount of energy to maintain the pressure as well as balance the demand. Optimization in the design of WDN is a well-established field since the 1980s [4]. Few earlier studies examined the design of WDNs with an objective of flexible design [5], hydraulic balance, cost minimization [6], contaminant control [7], and energy recovery [8]. Mala-Jetmarova et al. [9] present a comprehensive review of 120 publications with various optimization objectives, optimization methods, and applications related to WDN. Of these works, only 16% focus on optimized operation, while 41% focus on optimized design and the rest on expansion and rehabilitation of WDNs. With the rising energy prices and operational sustainably, optimized operation of WDNs has become a prime emphasis in the current decade. The fundamental decision-making problem of WDN is pressure management by modulating storage and pumping. The hydraulic dynamics of head, pressure, and water flow across pumps and water demand is nonlinear and nonconvex [10]. Likewise, real-world WDNs normally involve large networks with complex topologies, comprising of varied types of elements, such as reservoir, pumping stations, booster pumps, control valves, pipe networks, demand nodes or buildings, fire hydrants, and water towers. To evaluate both hydraulics and energy, these complex systems often require a sophisticated simulation model [11]. Although studies exist that report on successful solutions to such problems [9], they are limited due to the complexity associated with the mathematical formulation and availability of computation tools [12]. Commercially available tools such as EPANET can accommodate hydraulic modeling of WDNs, yet they lack precision in computing the energy performance [13]. Further, viewing WDNs as a part of critical infrastructure systems (CIS) in communities with interdependencies with other systems initiates a need for a simplified, integrated, and multi-domain modeling approach, yet complies with the hydraulic performance. Thus, to explore interdependent CIS, we have developed physics-based models for the community-level WDNs in this paper. The proposed WDN models are implemented using the equation-based object-oriented modelling language Modelica [14]. These models will be integrated into our existing open-source Smart and Connected Communities (SCC) Modelica library [15], consisting of component and coupled models of energy, transportation, and communication systems. The prime contributions of this paper are:

1. Validated WDN models with controls: Using hydraulic component models from the Modelica Standard Library (MSL) and Modelica Buildings Library (MBL) [16], two complete networks are implemented with increasing levels of complexity and are validated against EPANET [17].

2. Demonstration of the developed models to evaluate two WDN control approaches: commonly used tank level-based pump control and demand response pump control actions based on time-of-use (TOU) and critical peak (CP) electricity pricing scheme.

In the following sections of the paper, we present the methodology, followed by validation of WDNs. Further, we evaluate the WDN pump controls with the results, discussions, and conclusions.

METHODOLOGY

Modeling framework

The WDN models follow a novel multi-level, multi-layer, multi-agent approach to enable flexible modeling of the interconnected CIS, which was first introduced with our SCC Modelica library [18]. We developed the WDN networks models using the complex hydraulic component models from the MBL [16] and MSL. Since the objective of these models is to demonstrate the integrated CIS modeling in smart communities, considerable simplifications are made without sacrificing the basic hydraulic balance of the network, such as (a) pressure reducing valves which are commonly found in high-pressure areas of the network has been removed, since the network implemented has only eight demand nodes (b) demand nodes are implemented as ideal pumps that draw mass flow rate which is different from the typical control valve action (This could result in variations on node pressure measurements).

The WDN Modelica package consists of two network models: a simple WDN in which the consumer demands and network pipe lengths can be scaled (Figure 1a); and a commonly used eight-node WDN model [17] that allows variable demand at each node, and pipe inputs based on the topographical needs. The demand nodes are implemented as negative mass flow rate pumps to draw the demand; the pipe networks are modeled using a hydraulic pipe component from MSL, which calculates the pressure drop across the pipe segment using the length, diameter, elevation difference between the ends of the pipe and the roughness index of the pipe. Both models consider network leakage in calculating the hourly mass flow rates. The commonly used WDN controls are implemented using State Graphs from the MSL (Figure 1b) and the optimization-based control is implemented using the Optimization library v2.2.4 [19]. Overall, this package allows users to model both generic WDN and custom design WDN based on a real-world network.

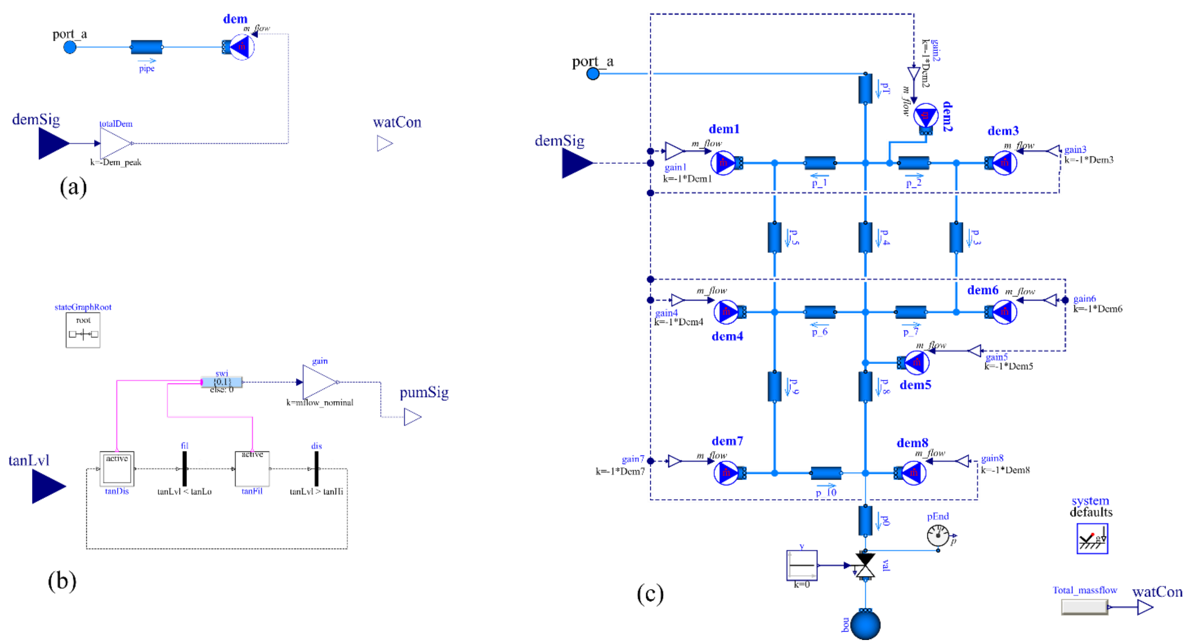

Figure 1. (a) Simple WDN implementation; (b) Tank-level based control implementation; (c) Eight-node WDN implementation in Modelica.

WDN Controls

Pumps are the critical control elements in water networks. Most networks either use traditional constant mass flow rate pumps or variable speed pumps for efficient operation. The decision to either turn ON/OFF or modify the speed of the pumps are the typical control actions considered in WDNs. Valves are another control elements that safeguards the pipes from excessive pressure buildup in the network and direct flow. To optimize the operation of pumps, appropriate decision variables and criteria must first be identified. In this work, we use the water levels in the tank (threshold levels without tank overflow), the demand profile, and the electricity price as decision variables. The decision criteria are set based on the decision variables. The water tanks in WDNs are designed for the 24-hour demand of the community with the flexibility to support additional demand during emergency fires, network bursts, or power outages. These tanks are typically filled during the night when the demand and the electricity prices are low. In this work, to evaluate the pump controls, we undersize the water tank to have two filling periods in a day (diameter = 4m, height = 5m, and elevation = 30m). A hypothetical single-family residential community in California with 160 residential units, each with a per capita demand of 946 l/day [20], is considered as the test case. Each node of the WDN represents 20 residential units with a peak demand of 1kg/s and a consumption profile per the 24-hour single-family residential demand from CALMAC Study ID CPU0052.01 [21] (Figure 2). Specific control details for each of the approaches are as follows:

Tank level-based control is a commonly used control action in community WDN (Figure 3). The level of water in the tank changes with the demand requirement of the network, i.e., the profile of the tank levels closely match the inverse profile of the demand. Therefore, we used the level of water in the tank T_l, as the decision variable to ON/OFF the pumps. In real cases, pressure sensors are mounted in the tanks, which constantly measure the pressure of the water column. The level of water is determined using this measured pressure. To test this control action, we used the eight-node WDN, which is connected to a tank and is filled by a constant mass flow rate pump (nominal flow rate = 15 kg/s, nominal pressure drop = 5.5bar). The controller switches the pump ON when $T_l \leq 0.3m$ and switches OFF when $T_l \geq 4.7m$.

Demand responsive pump control can save energy (and energy costs) while also providing balancing services for the electric grid. The key operational cost of WDNs is energy at the pumping stations, which is dependent on the mass flow rate of water, duration of pumping, and electricity tariffs. Instead of shaping the demand in individual residences, we kept the community demand unmodified in this study and engaged the community-level pumps and storage tank as demand response functions. In this study, we are optimizing the pumping operations over 24 hours as the day ahead pricing scheme is a growing trend in electricity pricing programs. We used the PG&E commercial time of use (TOU) and critical peak (CP) electricity pricing to understand how the demand response actions vary with different pricing schemes [22] (Figure 2). Our objective is to evaluate the two demand response actions (a) load shedding and (b) load shifting. To realize load shedding, we implemented a simple configuration (Figure 4) with a variable mass flow rate pump, water tank, and check valves to prevent backflow. The optimization is performed in Dymola using the Optimization Library v2.2.4. We used the simplex method (well-known downhill simplex) with continuous tuners and inequality constraints. The minimization problem is defined by the objective function of operation cost:

$$\min_{x\in[0,1]} \sum_{i=0}^{24} C_{p_i} \int_{t_i}^{t_{i+1}} P_{pump,i}(x,s)ds \qquad (1)$$

$s.t.$:

$$0.3 \leq L_{t,i} \leq 4.7 \qquad (2)$$

$$\dot{m}_{dem_i} + \dot{m}_{lek_i} = \dot{m}_{tank_{out,i}} \qquad (3)$$

$$0 \leq \dot{m}_{pump_i} \leq 15 \qquad (4)$$

where, $P_{pump,i}$ is the pump energy integrated over $t_i \rightarrow t_{i+1}$ and C_{p_i} is the electricity tariff ($/kWh). The constraints are enforced for every time step $i = 1\ hour$, which includes the tank filling and discharging limit $L_{t,i}$, maintaining the adequate demand $\dot{m}_{dem_i}$ accounting for the network leakage $\dot{m}_{lek_i}$, and operating the pumps within their operational limits $\dot{m}_{pump_i}$(min – 0kg/s and max- 15kg/s). To realize load shifting, we tested the same optimization case (Equation 1-4) with discrete tuning of a constant mass flow rate pump (0 kg/s or 15 kg/s). Because genetic algorithm and pure random search are the only available options for discrete tuning with the Optimization Library v2.2.4, we used the genetic algorithm (population size =10 and generations = 100), which had better success at finding a global optimum. We tested this DR action for the two electricity pricing schemes considered.

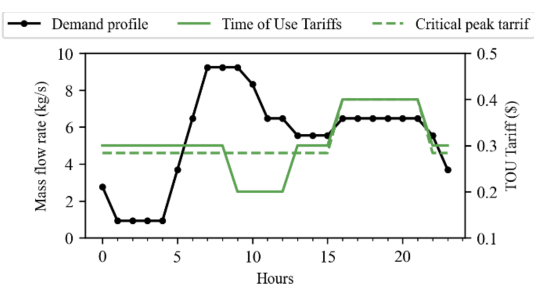

Figure 2. Single-family residential water demand profile and PG&E commercial time of use and critical peak pricing tariffs.

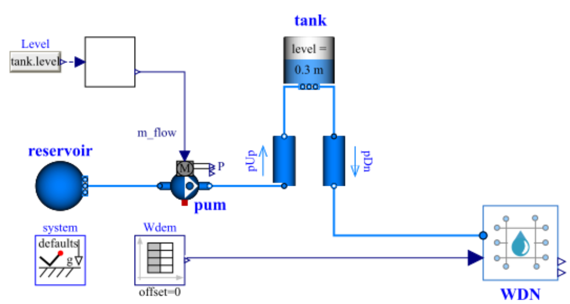

Figure 3. Modelica diagram for the tank level-based control.

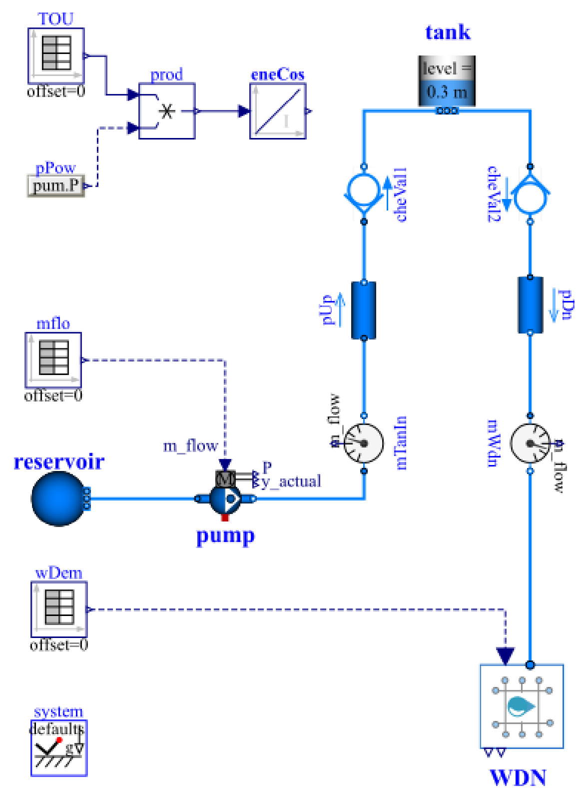

Figure 4. Modelica diagram for demand response pump control based on TOU/CP pricing.

Validation

As an initial step to check the correctness of WDN model implementation, we compared the energy consumption and hydraulic analysis of the WDN Modelica models with the commercially accepted tool EPANET. The results exhibit an accuracy of 94% and 86% for eight-node and simple WDN.

RESULTS AND DISCUSSION

Figure 5 depicts the energy performance and tank level variations due to the commonly used tank-level based control (baseline) and the DR pump controls. The TOU pricing scheme has off-peak (lowest $/kWh), part peak (low $/kWh), and on-peak (high $/kWh) pricing (Figure 5b). The DR actions take advantage of the pricing structure and shape the loads by shifting and shedding the peaks away from the on-peak TOU periods (16:00 – 21:00) (Figure 5a). The DR with a constant mass flow rate pump case completely shifts the load before 16:00 into the off-peak TOU period (9:00 – 13:00). The DR with a variable mass flow rate pump exhibits both shifting and shedding. As the pump energy varies with the pressure head, pumping water into the tank more than halfway will consume more power (kW) compared to an empty or less than a half-filled tank. Thus, the pump modifies its mass flow rate to maintain the tank levels less than 2.5m, so that the water can be delivered to consumers per the aggregate demand with lower pump power demand. In addition, this DR action also shifts the loads before 16:00, taking advantage of the off-peak TOU period.

The CP pricing scheme has off-peak (low $/kWh) and on-peak (high $/kWh) pricing (Figure 5d). The CP-based DR action (Figure 5c) follows a similar trend as the TOU-based DR action. For DR with a constant mass flow rate pump, the loads are shifted to off-peak periods (before 16:00), while DR with a variable mass flow rate pump exhibits both shifting (0:00-5:00) and shedding (6:00-10:00). The baseline tank level-based control is not impacted by the pricing variation; in this baseline case, the pump switches ON/OFF based on the tank level thresholds only.

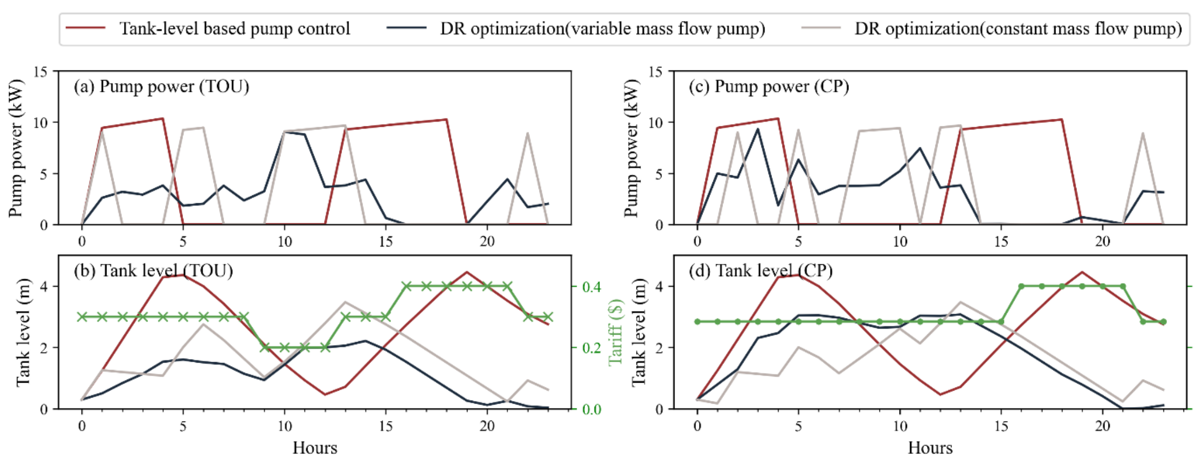

Figure 5. Energy performance of different pump controls with (a) TOU and (c) CP pricing; Tank levels due to different pump controls with (b) TOU and (d) CP pricing.

While both TOU and CP-based DR control saved energy relative to the tank level-based control, energy, and energy costs between the two DR pricing schemes did not vary significantly (Table 1). The TOU-based DR control resulted in a 3% less energy cost compared to CP-based DR control. Since we ran our simulations only for 24 hours, TOU and CP-based DR control may exhibit larger differences for longer time frames. This will be evaluated in the future. Looking into the types of pumps, the variable mass flow rate pump cases consumed 6% less energy than the constant mass flow rate pump cases. Hence, DR actions such as load shifting and shedding are primarily responsible for the large savings in the energy (kWh) and the cost ($) from the baseline case (Table 1). The load shifting DR action by the constant mass flow rate pump saved 25% energy (kWh) and 20% cost from the baseline. Meanwhile, the load shifting and shedding DR action by the variable mass flow rate pump saved 29% energy and 27% cost from the baseline. Also, as our current test case is a small community with down-sized water tanks, the magnitude of savings in the real-world application could vary. Yet, this evaluation shows a promising opportunity for energy savings, energy cost savings, and DR services for community-level WDNs. Moreover, even with downsized infrastructure (pumps and tanks), these results still achieve cost and energy savings compared to the baseline; while outside of the scope of this study, the potential to downsize infrastructure can also lower investment costs for the future and retrofitted WDNs.

Table 1. Energy and cost savings of the DR control.

	Tank level based		TOU-based DR control		CP-based DR control	
	TOU	CP	Constant mass flow pump	Variable mass flow pump	Constant mass flow pump	Variable mass flow pump
Energy (kWh)	98.15	98.15	74.07	69.49	74.03	70.18
% Energy savings		0%	25%	29%	25%	28%
Cost ($)	30.46	29.5	24.46	22.13	25.2	23.55
% Cost savings		3%	20%	27%	17%	23%

CONCLUSION

In this paper, a Modelica-based modeling approach for community-level WDNs is developed and is added into our existing open-source multi-domain modeling framework for smart and connected communities, the SCC Modelica library. We demonstrated the application of the WDN models through DR pump controls based on two different electricity pricing schemes (TOU and CP). We then determined the energy and cost savings relative to the commonly used tank level-based pump controls. The DR actions resulted in 29% energy and 27% energy cost savings from the baseline. From the results, we also observed water-energy interdependencies at the distribution network level that can be extended to realistic communities for evaluation of several co-operational benefits.

Typical water consumption demand profile varies for different building types, such as multi-family residential, commercial, institutions, hotels, etc. Most larger communities have mixed building types while smaller communities more frequently contain a single building type. Further, the structure and components of the water network vary with the type and location of the community. Thus, an extended exploration into various types of community WDNs can lead to various DR control actions based on different decision variables and thresholds.

ACKNOWLEDGEMENT

This research was supported by the National Science Foundation under Awards No. IIS-1802017 and IIS-1633363. BIGDATA: Collaborative Research: IA: Big Data Analytics for Optimized Planning of Smart, Sustainable, and Connected Communities. This work also emerged from the IBPSA Project 1, an inter- nationally collaborative project conducted under the umbrella of the International Building Performance Simulation Association (IBPSA). Project 1 aims to develop

and demonstrate a BIM/GIS and Modelica Framework for building and community energy system design and operation.

REFERENCES

[1] K. T. Sanders and M. E. Webber, "Evaluating the energy consumed for water use in the United States," *Environmental Research Letters*, vol. 7, 2012.

[2] V. C. Tidwell, B. Moreland, and K. Zemlick, "Geographic footprint of electricity use for water services in the western U.S.," *Environmental Science and Technology*, vol. 48, pp. 8897–8904, 2014.

[3] S. Pabi, A. Amarnath, R. Goldstein, and L. Reekie, "Electricity use and management in the municipal water supply and wastewater industries," *Electric Power Research Institute, Palo Alto*, vol. 194, 2013.

[4] H. Nasrollahi *et al.*, "Optimization of water pressure of a distribution network within the water–energy Nexus," *Applied Sciences (Switzerland)*, vol. 11, 2021.

[5] J. Marques, M. Cunha, and D. Savić, "Many-objective optimization model for the flexible design of water distribution networks," *Journal of Environmental Management*, vol. 226, pp. 308–319, 2018.

[6] D. Jung and J. H. Kim, "Water Distribution System Design to Minimize Costs and Maximize Topological and Hydraulic Reliability," *Journal of Water Resources Planning and Management*, vol. 144, p. 06018005, 2018.

[7] X. Y. Fan, J. J. Klemeš, X. Jia, and Z. Y. Liu, "An iterative method for design of total water networks with multiple contaminants," *Journal of Cleaner Production*, vol. 240, 2019.

[8] G. Meirelles Lima, B. M. Brentan, and E. Luvizotto, "Optimal design of water supply networks using an energy recovery approach," *Renewable Energy*, vol. 117, pp. 404–413, 2018.

[9] H. Mala-Jetmarova, N. Sultanova, and D. Savic, "Lost in optimisation of water distribution systems? A literature review of system design," *Water (Switzerland)*, vol. 10, 2018.

[10] J. Xu, H. Wang, J. Rao, and J. Wang, "Zone scheduling optimization of pumps in water distribution networks with deep reinforcement learning and knowledge-assisted learning," *Soft Computing*, vol. 25, pp. 14757–14767, 2021.

[11] L. A. House-Peters and H. Chang, "Urban water demand modeling: Review of concepts, methods, and organizing principles," *Water Resources Research*, vol. 47, 2011.

[12] O. M. Awe, S. T. A. Okolie, and O. S. I. Fayomi, "Review of Water Distribution Systems Modelling and Performance Analysis Softwares," *Journal of Physics: Conference Series*, vol. 1378, 2019.

[13] E. Gómez, E. Cabrera, J. Soriano, and M. Balaguer, "On the weaknesses and limitations of epanet as regards energy," *Water Science \& Technology: Water Supply*, vol. 16, pp. 369–377, 2016.

[14] P. Fritzson, *Modelica 2.1*.

[15] SBS lab, "Smart and Connected Community (SCC) Library." https://www.colorado.edu/lab/sbs/scc-library (accessed Feb. 14, 2022).

[16] M. Wetter, W. Zuo, T. S. Nouidui, and X. Pang, "Modelica Buildings library," *Journal of Building Performance Simulation*, vol. 7, pp. 253–270, 2014.

[17] L. Rossman, H. Woo, M. Tryby, F. Shang, R. Janke, and T. Haxton., "EPANET 2.2 User Manual," *U.S. Environmental Protection Agency Cincinnati*, 2020.

[18] X. Lu *et al.*, "An Open Source Modeling Framework for Interdependent Energy-Transportation-Communication Infrastructure in Smart and Connected Communities," *IEEE Access*, vol. 7, pp. 55458–55476, 2019.

[19] DLR Institute of System Dynamics and Control, "Optimization Library for Dymola," pp. 1–89, 2012.

[20] United States Census Bureau, "U.S. Census 2010," *Social Explorer Version*, 2010. [Online]. Available: http://www.socialexplorer.com

[21] C. P. U. Commission, "CALMAC Study ID CPU0052 Main Report Embedded Energy in Water

Studies Study 3 : End-use Water Demand Profiles Prepared by Prepared for the California Public Utilities Commission Energy Division Managed by California Institute for Energy and Environment," 2011.
[22] Pacific Gas & Energy, "PG&E business energy accounts." https://www.pge.com/en_US/large-business/large-business.page (accessed Feb. 14, 2022).