MODELING IN THE COVID-19 PANDEMIC: OVERCOMING THE WATER SECTOR'S DATA STRUGGLES TO REALIZE THE POTENTIAL OF HYDRAULIC MODELS

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ABSTRACT

Hydraulic models can provide efficient and cost-effective ways for water utilities to evaluate changes in operating conditions (e.g., population dynamics, disasters), thereby increasing system resiliency during crises. Unfortunately, model development remains out of reach for many utilities due to high software costs, data needs, or personnel requirements. This study seeks to classify hydraulic modeling data needs, identify success factors and challenges associated with model development, and determine whether modeling a sub-zone of a larger water distribution network can provide useful insight during a crisis, specifically, the coronavirus disease 2019 (COVID-19) pandemic. At the pandemic onset, we began developing a hydraulic model of the water distribution systems of The University of Texas at Austin campus—a subsystem of the water distribution network of Austin, Texas—to understand how

spatiotemporal changes in water demands impacted system performance. We found that the completed model can offer useful insight into the impacts of demand changes within the modeled subsystem (e.g., potential locations of water stagnation). However, the data collection and processing challenges encountered (e.g., siloed collection efforts, lack of standardization, lengthy processing) reflect barriers to model development and use. The amount of time required to gather and process the necessary data shows that model development cannot occur during a time-sensitive crisis, likely rendering any insight too late for use. Here, we make recommendations to address data-related challenges and support utilities in incorporating hydraulic modeling into emergency planning.

INTRODUCTION

When communities experience changes, whether acute (e.g., hurricanes) or protracted (e.g., public health emergencies, population shifts), water infrastructure systems might no longer operate under the conditions for which they were designed. Hydraulic models—mathematical descriptions of real-world water distribution systems (Walski et al. 2003)—can provide utilities with critical information to understand how such changes impact their water systems (e.g., increasing stagnation, altering pressures), enabling rapid and effective responses and thereby building resiliency. However, fully developed and calibrated hydraulic models are typically accessible only to relatively wealthier or urban utilities. Smaller, rural, or resource-constrained water utilities often do not possess hydraulic models—some might not even have digitized maps or records of their infrastructure. Other utilities often have only limited access to models prepared by outside consultants for design purposes, which may be based on unclear assumptions or represent only a portion of their distribution system (Atkinson 2014), thereby making the model of limited use for long-range planning or crisis response purposes. For managers to take advantage of the potential benefits that models can offer in planning (e.g., forecasting population dynamics, development) and crisis management (e.g., identifying stagnation, low pressure), utilities must build, calibrate, and maintain their own hydraulic models. A complicating factor in model development—one that is frequently overlooked in hydraulic modeling literature and technical resources—is the data requirements and sheer amount of data processing needed to build models. Often, instructional modeling literature (e.g., textbooks, industry guides, software documentation) relies on the assumption that the modeler is in possession of all necessary data in the appropriate format; in practice, this is rarely the case. The result of these extensive data and processing needs is that model development is a lengthy, time-consuming process that cannot be completed in the midst of a crisis. At the onset of the recent coronavirus disease 2019 (COVID-19) pandemic, our research team began development of a hydraulic model of a real-world distribution system with the goal of better understanding the impact of pandemic-related policies on system performance. As this study shows, if a hydraulic model does not already exist when a crisis occurs and model development begins at the onset of the event, the crisis will likely be nearly over by the time the model is ready for use.

While researchers have reviewed the many recent advances in the development and application of hydraulic models (Bach et al. 2014; Campisano & Creaco 2020), actual adoption by water utilities can be hindered by underlying data problems. Data issues impacting hydraulic modeling include the lack of standardization in water data (e.g., format, timescales, type of data collected), siloed institutional expertise and data collection efforts (e.g., multiple disjointed collection efforts occurring across departments), and the underuse of collected data. Notably, the water sector lags behind other industries (e.g., transportation, energy, telecommunications) in the application of data science and analytics (Kadiyala & Macintosh 2018; Neemann et al. 2013). For instance, a 2018 Water Research Foundation study found that only 10% of data collected by water utilities was analyzed and used (Kadiyala & Macintosh 2018). Others have identified the lack of uniformity in collecting, analyzing, and applying water data as a longstanding challenge in the industry (Deloitte 2016; Kiefer & Krentz 2018). However, progress is underway as the industry gradually begins to capitalize on existing data and embrace data analytics (Deloitte 2016). Previous work has summarized the trends towards data driven urban water management (Eggimann et al. 2017; Neemann et al. 2013) and hydroinformatics (Makropoulos & Savić 2019), though all acknowledge challenges remain to transform digital data and institutional knowledge into actionable information. Researchers have worked towards addressing data issues by outlining steps to embrace data analytics for broader utility management (Keck & Lee 2021) and demonstrating new data management systems and technologies (Carriço et al. 2020; Flint et al. 2017; Kawasaki et al. 2018). For instance, Keck & Lee (2021) offered recommendations for wider implementation of data analytics in the water industry, such as developing a culture around analytics by educating all levels of an organization's workforce on the value of data and data integrity, building an organizational "toolbox" of core tools and technology, and providing professional development and collaborative research opportunities. Others demonstrated the application of new water data integration technologies for asset management (Carriço et al. 2020) and flood control modeling (Kawasaki et al. 2018). In the hydrology space, researchers developed a data management and classification system for integrating social science data (e.g., census data, social vulnerability index) and biophysical water data (e.g., storm event data, land use changes) to advance interdisciplinary social water science (Flint et al. 2017).

Despite these advances, a gap remains in defining and developing a data classification system for hydraulic modeling as well as providing an in-depth discussion of the specific modeling-related data challenges facing utilities. Previous work has emphasized the importance of data management for overall utility management and for specific applications (e.g., asset management, flood control, hydrology). However, the pathway for efficient data collection, curation, and management needed for hydraulic modeling has not been mapped. Further, technical documentation rarely mentions data needs or processing requirements, instead jumping directly into the model building process. To address this gap, in this study we developed a hydraulic model of a subsystem of a large municipal water utility. In doing so, we seek to (1) classify hydraulic modeling data needs and document the data collection and processing stages, (2) identify success factors and challenges associated with model development, and (3) determine whether focusing on a smaller subsystem can provide useful insights to management during a protracted crisis while alleviating some data-related challenges. Such developments can promote and facilitate the adoption of hydraulic modeling tools to support decision making and improve resiliency, measures that are urgently needed as highlighted during the COVID-19 pandemic.

While the state of data management in hydraulic modeling and the broader water sector lags, the emphasis on infrastructure resiliency is greater than ever (Brears 2018; Florin & Linkov 2016). Resiliency—defined by the National Academy of Sciences as "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (NAS 2012)—is widely discussed in policy and literature (Brears 2018; Florin & Linkov 2016; Horn 2020; Shin et al. 2018; US EPA 2019b). The America's Water Infrastructure Act (AWIA) of 2018 "requires community water systems serving more than 3,300 persons to develop or update risk and resilience assessments and emergency response plans" (US EPA 2019b). The AWIA mandates utilities "conduct an assessment and reduce risk, plan for and practice responding to emergencies, and monitor systems for contaminants" (US EPA 2020a) as well as develop an Emergency Response Plan (ERP) (US EPA 2019a). However, ERPs lack standardization, and the ERP mandate does not specifically require utilities to develop or maintain hydraulic models. This study seeks to show how, despite challenges in development, hydraulic models can be an important tool for improving resiliency and emergency planning—and therefore belong in a utility's ERP.

Researchers have demonstrated the effectiveness of hydraulic modeling in studying protracted changes in operating conditions (e.g., shrinking urban populations, Faust & Abraham 2014; gentrification of urban neighborhoods, Faure & Faust 2020; water conservation measures, Abokifa et al. 2020; Zhuang & Sela 2020) as well as acute or sudden disasters (Mentes et al. 2020). Models developed in these studies assessed the impacts of the examined changes on pressures and fire flow capacities (Faure & Faust 2020; Faust & Abraham 2014), water quality (Abokifa et al. 2020), network performance (Zhuang & Sela 2020), and the ability to meet demands with rapidly reduced supply (Mentes et al. 2020). Recently, with the proliferation of Advanced Metering Infrastructure (AMI) systems, researchers have advanced the application of digital twins in the water sector (Conejos Fuertes et al. 2020), enabling real-time dynamic demand assignment in hydraulic simulations (Shafiee et al. 2020). These modeling studies demonstrate how hydraulic models can be used to study uncertain operating contexts. One such context is the COVID-19 pandemic. Beginning in March 2020, the COVID-19 pandemic developed into a significant protracted crises facing the water sector, with utilities worldwide experiencing widespread operational and financial challenges (Spearing et al. 2020; Berglund et al. 2021). Increased digitalization of the water sector, data management improvements, and hydraulic modeling played a key role in responding to the COVID-19 pandemic and are expected to continue to be critical in future crises (Neal 2020; Poch et al. 2020). For example, a challenge that could be addressed with modeling is understanding potential impacts of changing demands resulting from the implementation of social distancing policies (SDPs) and shifts in occupancy from commercial, industrial, and academic spaces to residential spaces. Such population shifts can alter water usage patterns (Spearing et al. 2021), thereby increasing water age in areas with reduced occupancy and potentially promoting the growth of harmful microorganisms such as *Legionella* (Wang et al. 2012). These water quality concerns require operational and management adjustments such as increased system monitoring and flushing (Deem 2020; Faust et al. 2021). Hydraulic modeling can be used to better understand the impact of changes in demand due to SDPs and identify areas vulnerable to water quality degradation within a water distribution system (Pesantez et al. 2022). Having this knowledge during an ongoing crisis can help utilities make targeted operational changes, contributing to a more efficient and cost-effective management response.

To address the gaps outlined in hydraulic modeling data classification and management and demonstrate how a model can improve management response and resiliency, we developed a hydraulic model of the real-world water distribution network serving The University of Texas at Austin (UT Austin), a subsystem of the water distribution system of the City of Austin, Texas. With the goal of supporting utilities who seek to develop their own hydraulic models, this paper classifies modeling data needs and provides documentation of the collection and processing stages before discussing the success factors and challenges associated with model development. Finally, we perform a hydraulic analysis with the completed model simulating changes in water demands on campus due to SDPs to determine if we can learn information that can support decision-making in a crisis by isolating a portion of a larger water distribution network.

METHODS

Developing a hydraulic model of a water distribution system involves (1) obtaining and processing the required data, (2) building the model with modeling software, (3) calibrating and testing the model, and finally, (4) conducting analyses. As noted, there are many existing technical resources for model building, calibration, and hydraulic analysis (e.g., textbooks, Boulos et al. 2006, Houghtalen et al. 2016, Walski et al. 2003; industry guides, American Water Works Association [AWWA] 2013, Edwards 2008, Walski

2000, 2017; Bentley 2021a; Klise et al. 2017; US EPA 2020). These resources typically omit the first steps of modeling—obtaining and processing the required data—and proceed directly to building the model in a software program. As such, to address our first research objective, we emphasize the initial stages of model development, with the goal of improving modeling processes by providing a classification system for hydraulic modeling data needs. Figure 1 shows the resulting footprint of data collection and hydraulic model development processes and summarizes the data sources and types, processing stages, and timeline associated with each stage.

Study Area

UT Austin is a large, urban, public university in the United States serving approximately 70,000 people (UT Austin, 2021). The water distribution system serving the 400-acre campus is independently maintained and operated by university utilities but is supplied by the surrounding municipal distribution system via more than two dozen metered connections. The water distribution system serving the campus forms a closed system, in which water entering and leaving the system is metered (Morrison 2004; Sela Perelman et al. 2015). The water entering the system is metered via city metered connections and water only exits the system via consumption by on-campus users. As a controlled system with independently managed water infrastructure, based on the number of customers served, the campus provides a comparable proxy for a small municipal utility or a sub-zone of a larger utility (e.g., a pressure zone or a district metered area). By isolating and modeling only the campus distribution system, we seek to understand if university utility managers could gain useful information about potential vulnerabilities in their subsystem.

The main campus system supplies drinking water to approximately 80% of the campus; buildings not supplied by this closed system have individual direct connections to the city supply and were not included in the model. The campus includes diverse water users, including buildings (e.g., classrooms, labs, offices, athletic facilities, and dormitories), a power plant, and chilling stations. There is no water storage or pumping within the campus network; however, the university distribution system is subject to the pumping and water quality conditions of the surrounding city pressure zone. Notably, other campus infrastructure exists to supply irrigation and reclaimed water to parts of campus. Because these additional systems do not supply drinking water, they were not modeled in this study.

Data Sources and Types

Developing a hydraulic model that can be useful to a utility during a time of crisis requires: (1) the physical system characteristics (e.g., pipe material, age, size, elevation), (2) network layout (e.g., pipe locations and connections), (3) user characteristics (e.g., locations, elevations, diurnal demands), (4) information about the sources feeding the system (e.g., location, volume supplied), and (5) measured system parameters that can be used to calibrate the model (e.g., pressure measurements). To meet these data needs, thirteen datasets were obtained from ten unique sources (Figure 1). Online publicly available resources (Google Earth and USGS) provided geospatial data for the user locations and elevation data. The remaining datasets were provided by university-affiliated departments and technical personnel with knowledge of the system and access to proprietary digital information. The mechanical distribution group, which oversees the operation and maintenance of the water distribution system, provided data directly to the research team and coordinated on the team's behalf to obtain geospatial data from the university GIS office and billing data maintained by the municipal utility that supplies the university system. This group provided the physical infrastructure and network layout information needed to build the actual hydraulic model. The energy management group maintains internal billing data for both water and energy and provided water billing data for the system users, which was needed to estimate users' water demands. The power plant and six chilling stations are managed by the power plant operations group, who provided additional data for these specific users so that their demands could be estimated and incorporated into the model. The energy management group, together with the control systems group, manages an online portal for water and energy data collected from digital meters throughout the university campus. Finally, a university researcher who maintains pressure monitoring sensors throughout the distribution system provided pressure data that could be used to calibrate the model. These 13 data components are grouped into three broad categories based on the data format and type of information included—geospatial data, sensor data, and institutional knowledge—each of which is described in further detail as follows.

Geospatial Data

The geospatial information required for hydraulic model development includes the layout of pipes in the network, water source locations (e.g., meter connections to the city infrastructure in this case), user locations, hydrant locations, and elevation. Pipes, sources, users, and hydrant locations are all required to build the actual network model. Elevation data are required for each point in the network (e.g., pipe junction, user, source) to perform a hydraulic analysis. In this instance, the geospatial data were obtained from three sources in different formats. The pipe network, hydrant locations, supply meter locations, and elevations (10-ft contour lines) were received as shapefiles. The pipe network shapefile contained diameter, material, and status (e.g., abandoned or in service) for most pipes. Had the physical network data not been available in shapefile format, digitizing and georeferencing of existing physical infrastructure maps would have first been required. User locations were obtained manually via Google Earth as latitude and longitude coordinates as this information was unavailable as a shapefile.

Sensor Data

Sensor data refers to information gathered from water meters or other types of sensors installed throughout the system. In this study, sensor data were obtained from six sources. To characterize users' water demands and diurnal distribution, water consumption data are needed. Hourly-resolution consumption data were obtained from digital meters installed in approximately 60% of buildings throughout campus. The digital meter data were validated and supplemented by monthly-resolution data from manually recorded meters on 85% of buildings. To characterize the water supplied to the campus system from the city sources, flow information at each source connection (city meter) was needed. Supply volumes were obtained from monthly billing data maintained by the city and validated using the monthly building meter data maintained by the energy management group for billing purposes. Supply volume data also were used in model validation to calibrate flows through each supply meter. For further model validation, pressure data are needed and were obtained from five sensors located across the campus collecting pressure over a nine-month period with a sub-minute resolution. Notably, lower resolution (e.g., hourly, sub-hourly) pressure measurements would likely be sufficient for calibration purposes. While high-resolution data provided a greater level of accuracy, it also added to the challenges of reconciling many different temporal resolutions in the data processing stages.

Institutional Knowledge

The model building process requires knowledge that is often not formally documented about water sources, users, and general system characteristics and functionality, beyond what is conveyed in the geospatial and sensor data. Several utility managers across three campus utility groups—mechanical distribution, power plant operations, and energy management—shared such institutional knowledge throughout the data collection, data processing, and model building stages via email, virtual meetings, and phone calls. This information included, but was not limited to: descriptions of the system and its interaction with the surrounding municipal infrastructure; lists and descriptions of the connection points that supply the system; lists and clarification of which users are served by the water distribution system of interest (e.g., the domestic potable system vs. reclaimed or irrigation); clarifications regarding missing information in the pipe network layout, meter locations, and hydrant locations (e.g., newly installed pipes not included in the GIS files, missing pipe diameters); characteristics of the energy facilities located on the system (e.g., composition of water supply at each facility); and explanations of the metering systems used throughout the distribution network. Our partners in utility management were consulted repeatedly throughout the project to gain a better understanding of system operations, clarify missing or unclear information, or to request additional data. Without these consultations, the research team would have been forced to rely solely on the geospatial and sensor data, the result of which would have been incorrect pipe layouts (e.g., a newly built section of the campus excluded from the model), delineated system boundaries, and calculated user demands (e.g., data from the wrong meters used to calculate demands).

Data Processing

Given the amount of data obtained and the wide variety of data formats and sources, three stages of processing were undertaken, as shown in Figure 1: (1) performing a system-level analysis (i.e., a mass balance analysis of inputs and outputs), (2) preparing the physical infrastructure data, and (3) preparing the data used in calibration and analysis.

System-Level Analysis

Creating a hydraulic model requires an understanding of the real-world water distribution system under consideration (e.g., the water sources, system boundaries, and largest water consumers). To better understand system-wide trends in consumption, identify dominant users, and carry out quality assurance and control (QA/QC) with the received data, a mass balance analysis was performed to account for all inputs and outputs to the system. Because the provided demand data included meters for all university-owned buildings—not only those served by the distribution system under consideration—non-system meters were manually filtered out using lists supplied by the mechanical distribution group. Unlike a typical municipal system, approximately 60% of water users were outfitted with high-resolution digital water meters, providing a high level of data coverage across the network. Had the system not been metered to this extent (i.e., many buildings with only monthly billing meters or no meter at all), we would have made assumptions about user demand patterns based on the monthly billing usage (if available), building type, and size. To calculate the demands of the power plant and five chilling stations—which receive a combination of municipal reclaimed, onsite recovered, irrigation, and domestic drinking water—the domestic drinking water component of the supply was separated for each facility. The approximate inputs to the system (flow volume through meters connecting to city mains) were calculated to determine monthly system supply.

The mass balance analysis proved to be a fruitful, but time-intensive, exercise. Numerous errors were discovered in the data involving individual meter readings, meter classification (e.g., building feed vs. submeter), or data recording. Potential data errors (e.g., readings of 0, abnormally high values, missing values) were forwarded to the energy management or power plant operations groups for confirmation and correction. Ultimately, this process resulted in more accurate data and the correction of previously unknown reporting errors in multiple departments. Had this mass balance exercise not been completed, incorrect demand data for multiple users, including some of the largest consumers, would have been used for the hydraulic model, leading to a less accurate understanding of the system and its vulnerabilities.

Physical Network Infrastructure Data Preparation

Processing of the physical infrastructure data was required to ensure all data were in shapefile format and contained only the physical infrastructure of interest. Geospatial data were compiled and prepared as shapefiles in ArcMap (Esri 2020) before being exported to the model building software. For geospatial data received from the university GIS office, required processing involved selecting the features to be included in the model based on specific attributes (e.g., ownership, operation status), creating new layers from these selections, and exporting the layers as new shapefiles. Because geospatial data were not readily available in shapefile format for the buildings on campus (water users), the building names and coordinates (obtained via Google Earth) were compiled into a table, converted to a layer, and then exported as a shapefile.

Calibration and Analysis Data Preparation

Simulating system behavior and user demands requires real-world data from the study area to compare against model results. Preparation of the data that would eventually be used in model calibration and the hydraulic analysis took place before and congruently with the model building phase. To prepare the pressure data for use in calibration, files for each of the five sensors were compiled and reformatted to the appropriate time scale. Daily profiles for each sensor were plotted, against which simulated pressures could be compared. To confirm relative accuracy of the pressure and elevation data, pressures and elevations at each sensor were compared and validated (i.e., higher pressures occurred at low elevations, lower pressures at high elevations). To prepare the demand data for use in analysis, after thorough QA/QC, correction of discovered meter errors, and resolution of differing temporal scales, base demands were determined for each user based on meter data for a representative pre-pandemic month that showed average consumption behavior.

Hydraulic Model and Software Requirements

Model Building

Highlighting a challenge for resource-constrained utilities with limited technical knowledge and software access, model development and analysis in this study occurred across multiple software platforms, because no one program contained all the preferred tools. Importantly, several software options are available for each of the tasks described. As such, in Figure 1 and below we identify the programs applied in this study, with the acknowledgement that other programs may be utilized based on availability. After obtaining, processing, synthesizing, and cleaning all data, the resulting final dataset contained GIS shapefiles (physical system infrastructure) and time series data (supply, demand, and pressure). To build a hydraulic model, this GIS and times series data needs to be translated in an accepted format for hydraulic modeling software. There are numerous hydraulic modeling software programs in existence, with EPANET (US EPA 2020b) being a popular and commonly used publicly available option. However, EPANET does not have GIS integration capabilities and requires data in .INP file format with a specific structure categorizing pipe connectivity and demand and source node coordinates. Further, EPANET offers limited model building functionality compared to commercial hydraulic modeling software programs (e.g., automated model-building tools, easy system modifications) and after initial testing proved to be an inefficient modeling software option for the task of building the model. As such, model development was completed in Bentley OpenFlows WaterGEMS (Bentley 2021b), a commercial software capable of reading GIS shapefiles. Using Bentley's ModelBuilder tool, the physical infrastructure shapefiles previously cleaned in ArcMap were imported for the pipe network, hydrants, users, and source meters to create a hydraulic model. To do so, the ModelBuilder tool (and similar tools offered in other GIS-compatible modeling programs) converts GIS data consisting of lines (e.g., pipes) and points (e.g., users, meters, hydrants, pumps) into a network of edges and nodes, establishing connectivity between the elements. Once the network model is created, skeletonization—the process of removing the parts of the hydraulic network that do not significantly impact the behavior of the system—is required to simplify the model and reduce unnecessary amounts of data and time-consuming troubleshooting (Walski et al. 2003). In this study, skeletonization was completed manually and with the automated Skelebrator tool to remove abandoned pipes, orphan nodes/pipes, dead-end pipes with a diameter less than or equal to 4 inches, and nodes not located at pipe junctions. Once model construction and skeletonization was completed, previously calculated base demands were assigned to all water users. Using the TRexWizard tool, elevations were assigned to all junctions from the imported USGS elevation contours shapefile. A skeletonized network of municipal piping surrounding the university was added, with connection points between the city and the university distribution network at each of the supply meter locations. A reservoir, pump and tank were added to the external city network to simulate pumping conditions in the surrounding city pressure zone.

Calibration and Analysis

While Bentley offers numerous tools for model development, to integrate the model with automated analysis the completed network model was exported as an .INP file to be used in publicly available software including EPANET and the Water Network Tool for Resiliency (WNTR) (Klise et al. 2018). WNTR, an open-source Python package that integrates hydraulic and water quality simulation and offers advanced resiliency analysis options, was utilized so that the modeling analysis could be available and completed with a publicly available, free software. As many utilities, including the university utility in this study, do not have access to commercial modeling software, it was desirable to have the final model in EPANET .INP file format so that our utility partners could freely use the model in EPANET or WNTR in the future.

Once imported to WNTR, to calibrate the model the following parameters were adjusted manually until simulated pressures at each of the five sensors matched the measured daily pressure profiles in both pattern and magnitude: pump curve, pump control rules, tank levels, and tank dimensions. Monthly flow data was used to validate the magnitude of simulated flows through the connection points (supply meters) between the university system and city water mains. Water user demands and relative changes in demand during the COVID-19 pandemic provide the foundation of the hydraulic analysis in this study. Two demand scenarios—base demand (pre-SDP implementation) and low demand (during SDP implementation)—were simulated using the EPANETSimulator (Klise et al. 2017) to measure water pressure, flow velocity, and relative water age across the system. Simulation results for the base and low demand scenarios were then compared to assess the impact of changes in demand on system performance.

Timeline

The project schedule (Figure 1) shows the time requirements of each process component. Despite the urgency to employ a completed model for use in response to the pandemic, the estimated total project length was approximately eight months. While challenges were encountered, particularly around data processing and cleaning, our utility partners were accessible and cooperative and much of the data needed already existed, *making this timeframe of about eight months the best-case scenario given our circumstances*. Without this level of cooperation, or if critical data had not existed, project completion would have been significantly delayed or impossible. For instance, had a GIS shapefile of the pipe network not existed, the research team likely would have needed to digitize and georeference paper maps. Had pressure sensor data not been available, field tests and measurements from across the system would have been required. Notably, project length for other researchers or utilities will vary greatly based on access to resources such as trained available staff, software, data, and—above all else—funding.

Among the project components, there was overlap between the data collection, processing and modeling phases, reflecting congruent iterative processes over the course of these eight months. Due to the rapidly evolving nature of the COVID-19 pandemic and data quality issues encountered, supply and demand datasets were updated frequently as new information became available. Given the amount of new sensor data and institutional knowledge that was needed throughout the entire project, gathering, processing, and interpreting these types of data continued in tandem with other project tasks until near-project completion. Once a skeletonized, fully labeled model had been created with the physical infrastructure data, calibration and analysis could occur.

Limitations

This study is not without limitations, the primary one being that the study area is a university campus. While the campus distribution system is managed independently and therefore operates in many ways like its own utility, it is impacted by the larger municipal distribution system. Further, given the distinction between the university utility and a traditional municipal utility, there may be differences in organizational structure, data policies, and technology access between university utilities and other public or private utilities. Additionally, as university researchers, our team had access to resources (e.g., technology, personnel, scheduling) not typically available to some utilities (the issue of academic resources is addressed further in the Results and Discussion). Despite these differences, as an independently managed subsystem of a larger network, hydraulically the campus still serves as a useful study area representative of a pressure zone or district metered area. Because the data related challenges we experienced reflect many of the sector-wide problems discussed in the literature, we believe insights gained are transferrable to the broader water sector. For instance, the underuse of collected water data encountered here is a common theme in the water sector in general (Kadiyala & Macintosh 2018). While every utility—whether public, private, or university-owned—will have unique management frameworks and challenges, the data requirements in hydraulic modeling remain similar.

Further, it should be noted that this study does not detail the stages and data needs for calibrating water quality models. The development and calibration of a hydraulic model is a critical first step towards calibrating water quality models, as water quality models rely heavily on the transport of constituents (i.e., velocities and travel times). Once a hydraulic model has been developed and calibrated, additional resources, samples, and data are required to characterize the specific local water quality conditions.

RESULTS AND DISCUSSION

Here, we address the second research objective by identifying the success factors and challenges associated with the hydraulic modeling process, summarized in Table 1.

Success Factors

Several success factors ultimately contributed to the model's completion. Use of all five software programs (Figure 1) was aided by extensive open-source online resources offering technical support in the form of forums, blogs, and videos (e.g., WNTR Read the Docs, EPANET Read the Docs, Bentley Communities, YouTube, Stack Overflow). Further, our partners in utility management were generous with their time, knowledge, data, and networking connections. The utility saw a clear need for a functional hydraulic model and had specific applications in mind for deploying the model during extreme events and in future planning and management decisions. The success of this cooperation highlights the significant existing opportunities identified by other researchers in academic-utility partnerships for sharing resources and expertise to advance the field of hydraulic modeling and water resource management (Keck & Lee 2015).

Working in an academic-utility partnership provided clear technology and personnel advantages. Importantly, the research team had academic licenses to commercial software—Bentley and ArcGIS—that allowed us to rely heavily on geospatial data and advanced automated modeling tools (e.g., Bentley's Skelebrator and TRexWizard tools) in the model building process. While open source technologies (EPANET, Python, WNTR) also were used extensively, the core of model building was completed in these GIS-based commercial software programs. Further, we were able to leverage available personnel, hydraulic modeling expertise, and professional networks to determine what data were required, synthesize the data, and apply it to the modeling process. The length of time required to complete a modeling project, while it will vary at every utility, poses a major challenge for using modeling in a disaster response setting; operating in a research environment provided the time, funding, and human resources needed to complete the project.

Importantly, the technology and personnel advantages experienced in this study are unique to research settings and relatively wealthier, urban water utilities. For smaller, rural, or resource-constrained utilities, technology and personnel are significant barriers to embracing modeling technology. The high cost of commercial modeling software (most licenses cost thousands of dollars per year) creates further inequities between resource-constrained utilities and those that can afford modeling programs. Beyond cost-prohibitive software, hydraulic modeling requires trained technical staff. The scheduling needs around hydraulic modeling would require a traditional utility to employ at least one part-time modeler to not only build the model but continually update data and recalibrate the model as needed. Attracting and retaining talent is one of many critical issues facing the water sector; however, for most utilities the urgent challenges of replacing aging infrastructure and financing improvement projects necessarily take higher priority (AWWA 2020). Without additional support, many utilities will not have the software, technical expertise, or personnel resources needed to complete the lengthy data collection, processing, and modeling stages undertaken in this study.

Challenges

Despite the benefits associated with operating in a research environment, several challenges more indicative of the broader water sector were encountered (Table 1). Notably, such challenges will likely be intensified for modelers attempting to represent an entire distribution network. The number of sources involved in the data acquisition phase (Figure 1) created difficulties in the initial project stages. Collecting the required data was more time-intensive than anticipated because information needed to be requested from many individuals and offices. For example, high-resolution digital meter data were obtained from the university's "Energy Portal" (which contains both water and energy digital meter data) via the energy management and control systems groups, while monthly resolution building meter data were provided by a different source in energy management. A third source—the mechanical distribution group—provided system supply data. As a result, some supply and demand data were provided in spreadsheets used for accounting and billing purposes and required sorting and cleaning before analyzing. Determining which offices had the required information and the authority to share it led to delays.

While every utility is unique, siloed departmental organization—like the structure encountered here—is the norm in water and wastewater management, with utilities divided into departments such as engineering, operations, customer service, and finance (Dell 2005). While these departments work well at managing their specific responsibilities, weaknesses emerge (e.g., duplicate efforts, inefficiencies, hampered decision making) when tasks cross multiple departments (Dell 2005). Data collection and management is one such process requiring careful coordination and communication across departments. In this case, there was not a standardized format for water data among different departments, meaning each dataset was received in a different format (e.g., timescale, file type), nor was there one centralized location for all water-related data. The number of sources and lack of cohesion among the various departments consulted therefore led to increased processing needs.

While the specific division of data management responsibilities between utility management groups seen here may be unique to UT Austin, lack of standardized or centralized data management is typical across the water industry (Deloitte 2016; Kiefer & Krentz 2018). As such, modelers at traditional water utilities that lack coordinated data collection and management processes will face problems similar to those discussed above. These challenges point to the need for dedicated personnel, departments, or sub-committees within utilities to coordinate data curation, standardization, and maintenance, as well as inter-departmental communication. As noted, water utilities are collecting increasing amounts of data but only putting a small amount to use (Kadiyala & Macintosh 2018). Having dedicated data management personnel can improve data accessibly, consistency, and ease of use, thereby increasing overall data utilization and improving data quality. In this study, errors discovered in the mass-balance analysis had gone previously undetected because such analysis had not been performed on this part of the system before. The analysis process itself led to improved data quality outcomes. Without coordinated data management efforts, the barriers around acquiring, processing, cleaning, and synthesizing the data needed for a hydraulic model may be insurmountable at some utilities. Modelers will have to consult multiple disparate departments (e.g., finance, operations, customer service) to gather the required information and devote additional time to data processing. These tasks, already difficult under normal operating conditions, cannot be completed in tandem if a utility is also actively responding to a crisis.

Coordinated data collection and management will not only improve efficiency but also better ensure that the appropriate data are being collected. In this study, datasets that would have been useful in the analysis (e.g., supply data on a smaller time scale, flow velocity meter data) were unavailable. Without these data, modeling assumptions about the temporal distribution in demands were made. Conversely, while pressure data at a sub-minute resolution improved the overall quality of analysis, lower resolution data would have been acceptable if that were the only available option. Simply put, hydraulic modelers at most utilities will use the best data available to them and make assumptions when there are gaps. Having coordinated and standardized data management efforts can help utilities better understand what data exist, what data are missing, and where data collection efforts should be focused to reduce these gaps and assumptions.

Despite the potential benefits, industry-wide improvements in data management will occur only if made a priority. In their 2020 State of the Water Industry Report, the AWWA found that of the top 20 issues facing the water industry, data management ranked 19th among surveyed utilities (AWWA 2020). Many of the issues that survey respondents ranked higher than data management—such as emergency preparedness, compliance with regulations, cybersecurity, asset management (AWWA 2020)—can be enabled and improved upon by advancing data management and analytics. Unfortunately, many utilities simply do not have the resources to address anything other than the most pressing needs and without additional support will be unable to make data management a higher priority.

In addition to difficulties stemming from siloed data collection efforts, certain network characteristics can cause further complications. Complex or high-demand water users (e.g., manufacturing, energy facilities) can pose additional data collection challenges because they frequently have irregular metering systems, and the associated data might be managed by yet another department. Furthermore, these types of users often have multiple water supplies (e.g., a combination of domestic potable, reclaimed, and/or onsite reuse), and each supply component will have its own meter(s). For example, UT Austin maintains a power plant and five chilling stations, each with a unique water supply composition and system of meters and submeters. Because each water type is supplied by a different system, modeling the demands of such users required first meeting with the facilities' manager (the power plant operations group) to understand the metering system for each individual facility and then separating the various supply streams.

Throughout the modeling process institutional knowledge emerged as a critical source of information. For instance, the mechanical distribution group verbally described the system boundaries and clarified pipes alignments when this information was missing or unclear in the data. However, siloed expertise—meaning each utility group has detailed knowledge of the system component they manage (e.g., energy facilities, accounting, distribution) but not the rest of the system—made transferring this institutional knowledge difficult. This points to broader challenges surrounding the sharing of knowledge within organizations in the engineering industry (Javernick-Will 2012; Sanaei et al. 2013). This pattern manifested itself in our needing clarification on specific data points and having to consult multiple sources to get an answer. For example, concerns about usage values for the power plant and chilling stations could not be answered by the energy management group who provided the data. Rather, the question needed to be directed to the power plant operations group. Similarly, while the mechanical distribution group was able to share large quantities of data and knowledge related to the physical infrastructure and water supply and serve as a liaison between other departments, they did not manage or maintain the campus wide user demand data. This type of siloed expertise can not only reduce efficiency, but it risks the loss of valuable information when utility managers leave or age out of the workforce (retirement has been a growing concern for the water industry, AWWA 2020; Kane & Tomer 2018).

To avoid potential knowledge loss, models (and the associated data) must be documented and understood by others in the future. Documenting assumptions, key steps taken, and decisions made is essential throughout the entire process for clarity, quality, and reproducibility (Ayllón et al. 2021; Grimm et al. 2014). Clear documentation of the modeling process is especially critical when hydraulic models are prepared by a third party, such as an outside engineering firm. For instance, water utility managers for Moore Country, NC, discussed the difficulty of using models prepared by outside contractors due to the number of assumptions, high cost, and fact that outsourced models often only represented part the system (Atkinson 2014). Further, our research team has worked with utilities throughout the United States with a wide range of modeling capabilities, from not possessing hydraulic models or even digitized records to having fully staffed modeling departments. Utilities with limited in-house engineering expertise often turn to outside firms and outsource the model development process. However, a common result of outsourcing is that utilities never use—and might not even own—the completed model. Without clear documentation, access, or ownership, it impossible for utility managers to maintain the model and use modeling tools to make planning decisions or model changes in operating conditions during a crisis. In this instance, the utility had previously contracted out model development to a consulting firm several years prior. However, the resulting model was incomplete, provided no information or documentation about assumptions made, calibration procedures, or other modeling decisions, and was thereby rendered useless. To our team's knowledge, the model had never been used by utility managers. Given the incompleteness of the previously commissioned model and lack of accompanying documentation, an entirely new model was required so that all assumptions and procedures could be documented, with the goal of providing both the model and full documentation to future users.

The completed hydraulic model was developed over the course of eight months. As shown in the project schedule (Figure 1), the first three months were devoted exclusively to data collection and processing. While model building began in month four as soon as the physical infrastructure data were processed, further data collection and processing continued in tandem with modeling, calibration, and analysis until the penultimate month. These time requirements are the culmination of all previous discussed challenges and create a resiliency gap in crisis response. A hydraulic model will be of little use in responding to a crisis if it does not already exist, because development time is simply too long. Though project timelines will vary depending on a utility's specific circumstances (e.g., available trained personnel, data availability, funding), traditional utilities will likely experience similar challenges. Importantly, focusing on a single sub-zone of the water network reduced data needs and challenges, implying that modelers attempting to represent an entire system will likely face even greater difficulties than those encountered here.

While the original intention of this project was to create a model to understand if vulnerabilities in the network could be predicted in the context of the COVID-19 pandemic, by project completion the pandemic was assumed to be in its final stages and utility management had developed other systems for monitoring and responding to water quality issues. In short, by project completion, the key window when a hydraulic model would have been the most useful in this specific crisis had passed. Had the model existed in April 2020, utility managers could have simulated the demand changes taking place to understand how water quality might be impacted throughout the system and directed resources (e.g., targeted water quality sampling and flushing operations) to specific areas of concern. Without a hydraulic model, mangers relied on institutional knowledge of the system and widespread manual monitoring and flushing, actions that required increased financial and human resources in a time of extreme risk and uncertainty. Fortunately, by making these operational adjustments, utility managers avoided adverse water quality and public health impacts. However, the use of additional resources during a crisis to avoid negative outcomes when more efficient alternatives are available constitutes a gap in resiliency and indicates an area where improvements can be made. Now that the model exists, with regular data updates and maintenance it can be used for routine planning and management and will be ready for future crisis response.

Modeling During a Crisis

Here we address the third research objective to determine how a hydraulic model can be useful to identify the potential vulnerabilities (e.g., areas of high stagnation) during a crisis (the COVID-19 pandemic). The final hydraulic model (Figure 2) is comprised of 565 pipes and 503 nodes that deliver water to 107 users including buildings, the power plant, and chilling stations. The total daily demand supplied is estimated at 2,436 m^3 (643,520 gallons) through a total pipe length of 31,170 meters (102,264 feet). To understand the potential impact of SDP-related changes in demand on the campus system, two hypothetical demand scenarios were tested. The standard base demand pattern was developed to represent conditions over a typical 24-hr period (beginning at 12:00 am) prior to the onset of COVID-19 and SDP implementation, with the average daily demand per building estimated at 19.5 m^3 (5150 gallons). The low-demand scenario, a 50% reduction from base demand, represents an approximate overall decrease in water demands on the university campus after SDP implementation, when most faculty and students were working and learning remotely but certain other essential operations (e.g., power generation, building cooling, maintenance, research, administrative work) continued. This assumption was based on a review of building water consumption meter data and the characterization of UT buildings' demand patterns before and during the COVID-19 pandemic by Spearing et al. (2021). Figure S1 in the Supplemental Material (SM) illustrates the base and low demand patterns applied in this case study. While outside the scope of this study, further analysis of the digital meter data would allow for the development of building-specific demand patterns. The three performance indicators chosen—pressure, velocity, and water age—represent a sample of hydraulic and water quality initial indicators that can be used to assess system performance and reveal deviation from the baseline or from set performance standards (Abokifa et al. 2020; Zhuang & Sela 2020). Importantly, there are numerous applications and analyses possible using the completed model. As such, the following analysis provides only a small subset of potential uses in the context of crisis response.

Results

The completed model was manually calibrated using measured pressure data from five sensors located throughout the study area (Figure 3a). Resulting simulated pressures for the base demand scenario and low demand scenario (Figure 3b and 3c, respectively), show simulated pressures matched the measured pressures in magnitude and rank (i.e., the order of sensors from highest to lowest in measured data and all simulation results is the same). Further, the differences between the measured and modeled pressures are within the typical accuracy range of pressure sensor elevations (Walski 2021) and the elevation model used (USGS 2021), indicating sufficient model calibration for this context. Summary statistics, measured across the entire network over the full 24-hr simulation, are presented in Table 2 for the two scenarios. Results for all three parameters exclude the reservoir, pump, and tank as well as their immediately adjacent pipes and nodes, as these elements were added to replicate the pumping conditions of the surrounding municipal system and do not represent actual existing infrastructure in the campus distribution system. Age results exclude dead end nodes that do not supply water users (i.e., where node degree = 1 and user demand = 0) such as fire hydrants or other types of dead ends.

Pressure results for the two simulated scenarios show that a 50% reduction in demand led to an increase in pressures throughout the system. Figure 4 illustrates the pressure for the two scenarios at a location in the center of the study area, where lower demands (dotted line) produced higher average pressures compared to the base demand scenario (solid line). Because of the more gradual increase in demands, the drop in pressure between the morning (hour 8) and midday (hour 12) was less steep in the low demand scenario, with the minimum pressure occurring 3 hours later than in the base demand scenario. Figure S2 in the SM shows the pressure results for additional selected locations in the network demonstrating similar trends. Figure 5a summarizes the change in pressure ($pressure_{low} - pressure_{base}$) across all nodes in the system at each hour. The distribution of the change in pressure at all nodes is shown, with the greatest increases in pressure between the two scenarios occurring between hours 12-16, when difference in the demands is greatest (see Figure S1 in the SM). Across all nodes over the simulation, the overall increase in pressure was modest, with a change in mean pressure of +2.1 m (an increase of 4.5% from the base scenario). In both scenarios, all pressures were above the state-mandated minimum of 24.6 m (35 PSI) (Texas Commission on Environmental Quality 2019). In terms of maximum pressures, the City of Austin requires new buildings with pressures above 47.7 m (65 PSI) to install pressure reducing valves (PRVs) (Austin Water 2021). Therefore, any pressure increases resulting in pressures above 47.7 m (65

PSI) at buildings that do not already have PRVs installed would potentially be of concern. However, in this analysis, there was almost no change in the maximum pressure, revealing that in terms of pressure, the system is relatively resilient to a 50% reduction in demand. Such results are in line with research examining shrinking cities that found reduced demands typically did not drastically alter system pressures (Faust & Abraham 2014).

As expected and consistent with other studies (Abokifa et al. 2020; Zhuang & Sela 2020), flow velocity and water age results indicate that lowering demand does reduce flow velocity and increase water age. Figure 5b summarizes the change in velocity ($velocity_{low} - velocity_{base}$) across all pipes in the system at each hour, showing a decrease in velocity across the system from the base case scenario to the low demand scenario. The distribution of the change in velocities reflect the respective demand patterns, with the greatest decrease in velocity occurring in the hours when the differences between the demand patterns were greatest. Overall, the 50% reduction in demand resulted in 0.021 m/s decrease in the mean velocity (measured across all pipes over the full simulation period), which represents a 50% decrease from the base scenario.

The change in water age between the two scenarios ($age_{low} - age_{base}$) is shown for all nodes (excluding dead-ends without demands) in Figure 5c, with an overall increase in water age from the base case to the low demand scenario. Similar to pressure and flow velocity results, the difference in water age between the two scenarios becomes more pronounced as the difference in demand patterns increases after hour 12. Importantly, the water age results do not consider the age of water entering the distribution system at each of the supply points from the surrounding city distribution system. Therefore, the minimum, maximum, and mean age results shown in Table 2 are relative age measurements and do not represent the actual age of water in the system. Across all nodes over the full simulation period, mean water age increased by 2.9 hours, or 39.1%. While a full water quality simulation would typically evaluate performance on a multiday or weekly basis, 24 hours was found to be sufficient here as the difference in water age begins to stabilize after approximately hour 18 (Figure 5c). When considering a longer timeframe, such as 72 hours, results similarly show stabilized water age differences after hour 18 and display a cyclical trend reflecting the 24-hour demand pattern and pumping rules in place. In terms of macroscopic water quality parameters such as residual chlorine, this level of change in water age would not have a significant impact on chlorine residuals due to the slow rate of monochloramine decay within the Austin system (relatively high pH of 9.6 and monochloramine disinfection) (Vikesland et al. 2001). However, in all simulation scenarios, utility managers may wish to further examine outlier nodes with the highest change in water age, and these locations may require additional targeted flushing.

Management Implications

By modeling the university subsystem, we can gain insight into the impacts of changes occurring within the subsystem on performance indicators such as water pressure, flow velocity, and water age. In this analysis over a simulation period of 24 hours, results showed that the system did respond to changes in demand, though impacts were likely not significant enough to warrant specific management response without further analysis (e.g., additional scenarios, longer simulation). Due to the specific network topology and pipe diameters, changes in demands caused smaller magnitude velocity changes, which in turn produced only limited increases in water age. Importantly, these results are network specific, and other systems (e.g., those with less looping or fewer redundancies) could exhibit greater changes. In bounding the model at the border between city and university infrastructure, we can not only reduce some of the data-related challenges associated with model development, but also ensure that any changes observed in performance indicators output by the model are the result of changes occurring *only within the university system*. However, despite the benefits of modeling the university subsystem in this way, when delineating one system or subsystem from another, information will always be lost at the boundaries. In this instance, changes that occur outside the modeled subsystem in the wider distribution network would not be reflected. For example, the university system is subject to the water quality conditions (e.g., monochloramine levels, pH) of the city water treatment plants and surrounding distribution system. Changes in water quality at the city level will not be captured in the model without more information or model adjustments, but as shown here, the model can capture changes in water quality occurring within the university system.

With this understanding of the limitations of modeling a subsystem, utility managers can use the model to compare the impacts of specific changes in operating conditions within their subsystem (e.g., SDP-related changes in demands on campus) and test management responses that are within their control. For instance, in the context of the COVID-19 pandemic, campus utilities increased flushing and water sampling after SPDs were implemented due to concerns about stagnation in empty or reduced-occupancy university buildings. Such management practices have been broadly recommended by water professionals nationwide throughout the pandemic (Deem 2020; Faust et al. 2021; Spearing et al. 2020), because stagnation and growth of potential human pathogens are of concern in areas with vacant buildings. The modeling tool demonstrated here could assist in these efforts by showing what the relative water age is at each user in the system and where water age is particularly high (i.e., pinpointing areas of concern for stagnation). Being able to use a model to identify system vulnerabilities is especially important during a public health emergency like the COVID-19 pandemic, when the water sector workforce itself risk. If an individual with advanced, but undocumented, knowledge of the system's vulnerabilities is incapacitated, a model can help fill in some of this critical information gap. While not shown here, extensions of the simulation could also test the impacts of increased flushing to help managers efficiently rollout intensified flushing protocols.

While demand increases were not a concern in this specific context and study area, such a model can also be useful in areas where SDP implementation results in higher water use (e.g., residential areas where more people are working from home and avoiding non-essential outings). As increased demand has potential to cause issues of low pressure, particularly during peak use hours (Faure & Faust 2020), utilities concerned with system performance could carry out similar analyses with higher demands. Results could inform whether pressure drops during peak demand hours are reaching concerning lows (e.g., compromising service to customers or fire flow capabilities), and, if so, where problem areas exist. Similarly, other systems may experience simultaneous decreases and increases in demand in different parts of the system. During the COVID-19 pandemic, spatial redistributions of water demands were observed in residential and nonresidential areas (Bakchan et al. 2021). For instance, a pressure zone containing both a business district and residential neighborhood could see demand decreases in the business district and increases in the neighborhood. To model such changes, distinct demand patterns would need to be established for each user type based on historical data and observed demands during the pandemic (i.e., different demand patterns for business users and residential users). The analysis could then be repeated with these distinct demand patterns imposed to identify changes in system performance. Management strategies to address low pressure in some areas (e.g., pumping changes) and stagnation in others (e.g., flushing), can then be simulated to assess the effectiveness of operational changes before implementation.

RECOMMENDATIONS

The process described in this work illustrates that while hydraulic models are useful tools in crisis response, model construction cannot be completed in the midst of an emergency or sudden event, even when focusing on a sub-zone of a network. As such, we recommend that utilities of all sizes make hydraulic modeling a part of their planning procedures (e.g., ERPs) so that functional, calibrated models will be ready for use for immediate assessment of vulnerabilities when operating conditions change. In turn, future infrastructure legislation should make financial support available to utilities to undertake this task and support personnel, software, and data management efforts. To ensure that models are actually used in planning and emergency response, it is highly preferable to provide utilities with the tools to develop and maintain their own models or actively collaborate with partners, rather than simply outsourcing.

Over the last two decades, GIS integration has rapidly increased in popularity among utilities using hydraulic models (AWWA 2014). GIS makes both the modeling process and future updates faster and easier and gives utilities greater control over their models (Atkinson 2014). Therefore, it is imperative that utilities have access to GIS-based modeling software, which can be cost-prohibitive (notably, EPANET, a widely used open-source modeling software developed by the US EPA is not GIS-compatible). However, to take advantage of GIS integration, utilities need high-quality GIS data. While many utilities or municipalities have designated GIS departments similar to the university studied here, access to high-quality, current GIS data is far from universal. A potential solution to address this lack of GIS data might lie in state-wide programs like the Kentucky Infrastructure Authority’s Water Resource Info System. The program, which provides water and wastewater GIS to support modeling and planning efforts, “allows for cost-effective analysis of engineering alternatives, and facilitates the efficiencies needed to meet the needs of Kentucky's infrastructure development.” (Kentucky Infrastructure Authority 2017). Such initiatives could take the burden off resource-constrained utilities while fulfilling a critical data need.

Regarding the current state of information gathering for hydraulic modeling, there is much work to be done. Centralized, standardized, and coordinated data collection efforts need to be put in place to improve data collection, processing, and overall quality. Utilities can reduce barriers caused by siloed departmental structures by establishing designated, inter-departmental data collection initiatives that focus on clear processes and specific, measurable, achievable, realistic, and time-based (SMART) goals (Dell 2005). Other authors (Chastain-Howley 2014; Keck & Lee 2021; Makropoulos & Savić 2019; Neemann et al. 2013) have put forth recommendations to create conditions conducive to increased analytics in the water industry such as increased professional development and research opportunities. Data quality can be improved by conducting regular water accounting (particularly with high-demand users) and instrument testing, leading to increased data analysis and improved operations (Simpson & Van Arsdel 2020). To implement these improvements, water data management must be seen as a key component of infrastructure and funded as such. The gap in water infrastructure funding has led to underinvestment in both built and technology systems at utilities. When funding for water infrastructure is implemented, it is imperative that provisions are made for hydraulic model creation as this can improve water system resiliency and reduce detrimental outcomes (e.g., areas of low pressure or stagnation).

The amount of institutional knowledge, from many sources, required to complete this study points to a crucial need to improve the transfer of knowledge in the water industry, especially as experienced members of the workforce prepare for retirement or leave the sector (almost 3 million vacancies are expected in the next decade, Kane & Tomer 2018). Practices and techniques for improving the knowledge sharing between utility managers and across generations (Javernick-Will 2012; Sanaei et al. 2013) could help the water industry retain this valuable information. Documenting and sharing information about a water distribution system and incorporating it into a hydraulic model builds resiliency by creating redundancies in knowledge, which are particularly critical during public health emergencies when the utility workforce is also at risk. Finally, academic-utility collaboration can help address issues within the water sector by working to close gaps in the knowledge base between utility and research communities (Keck & Lee 2015). Partnerships like the one developed in this study can offer many opportunities to advance the field of water research while supporting utilities in their efforts to improve or develop modeling capacities and protocols for data management that can be shared among utilities.

CONCLUSION

Following the onset of the COVID-19 pandemic, we began developing a hydraulic model the UT Austin water distribution system to understand the impacts of changes in demand induced by SDPs on system performance. Results indicate that such a model can provide useful insights into the impacts of changes in operating conditions on campus and system performance, in turn contributing to overall system resiliency. However, the current lack of attention to the data needs and processing requirements in model development threatens utilities' ability to build their own hydraulic models. To address this gap, we documented the data requirements, collection and processing stages involved with hydraulic modeling and categorized the central challenges and success factors encountered. Notably, the challenges identified would likely apply even more dramatically to an entire network with more data and complexity. Utilities are therefore encouraged to prioritize organizing the data needed to construct a hydraulic model and to begin this effort before the next disaster occurs. Further, it is essential that future infrastructure spending support water utilities to develop hydraulic models and incorporate them into their planning through efforts focusing on data collection (including access to high quality GIS data), data management and analytics, and GIS-based modeling software. Finally, to promote the development and use of hydraulic models and reduce the risk of valuable institutional knowledge being lost, academic-utility partnerships and the implementation of organizational knowledge sharing initiatives are recommended. While the potential utility for hydraulic model use is great, real management support will only occur if hydraulic models are developed, calibrated, and ready for use well before a crisis occurs.

DATA AVALIABILITY STATEMENT

The following data, models, or code used during the study were provided by a third party: water distribution system GIS data, water supply data, water demand data. Direct requests for these materials may be made to the provider as indicated in the "Acknowledgments."

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AUTHOR STATEMENT

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FIGURES

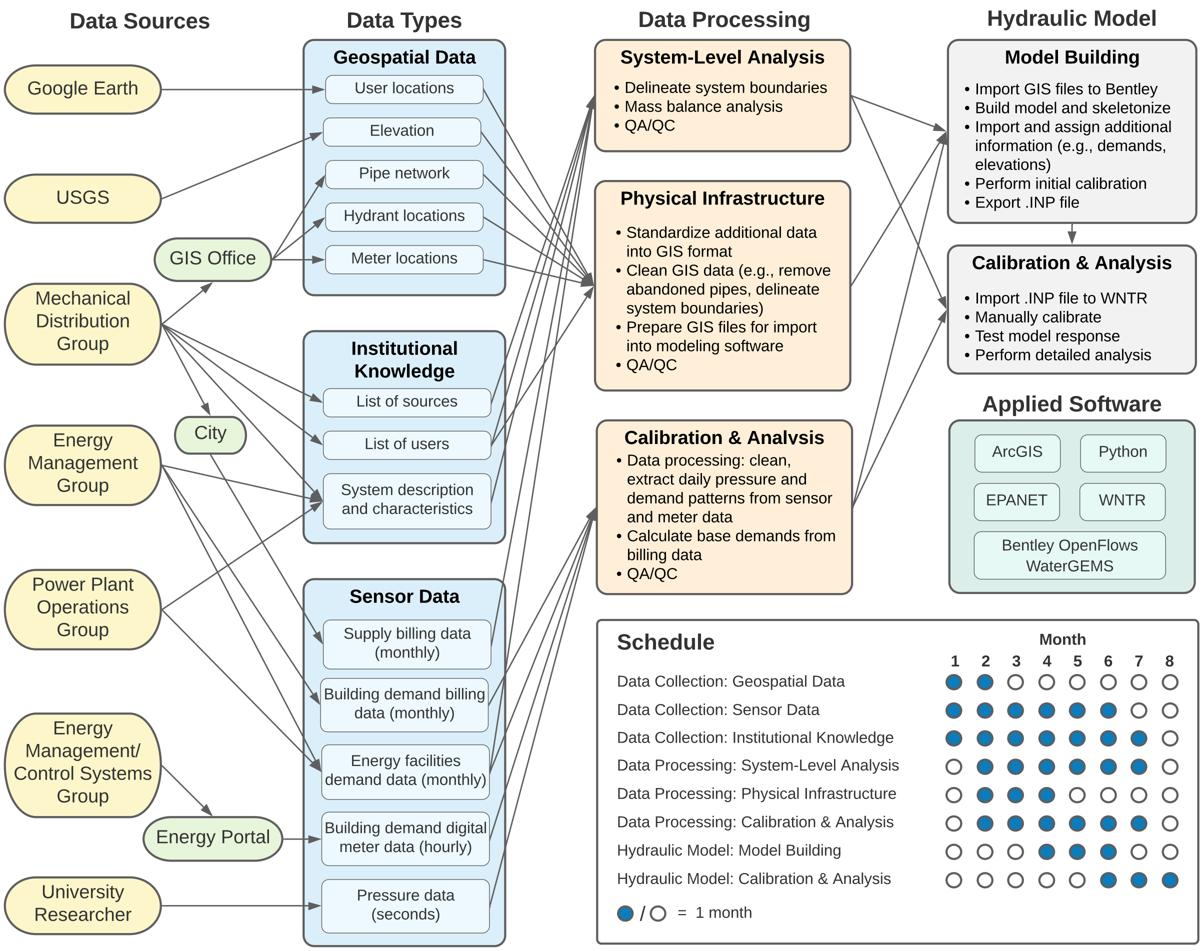
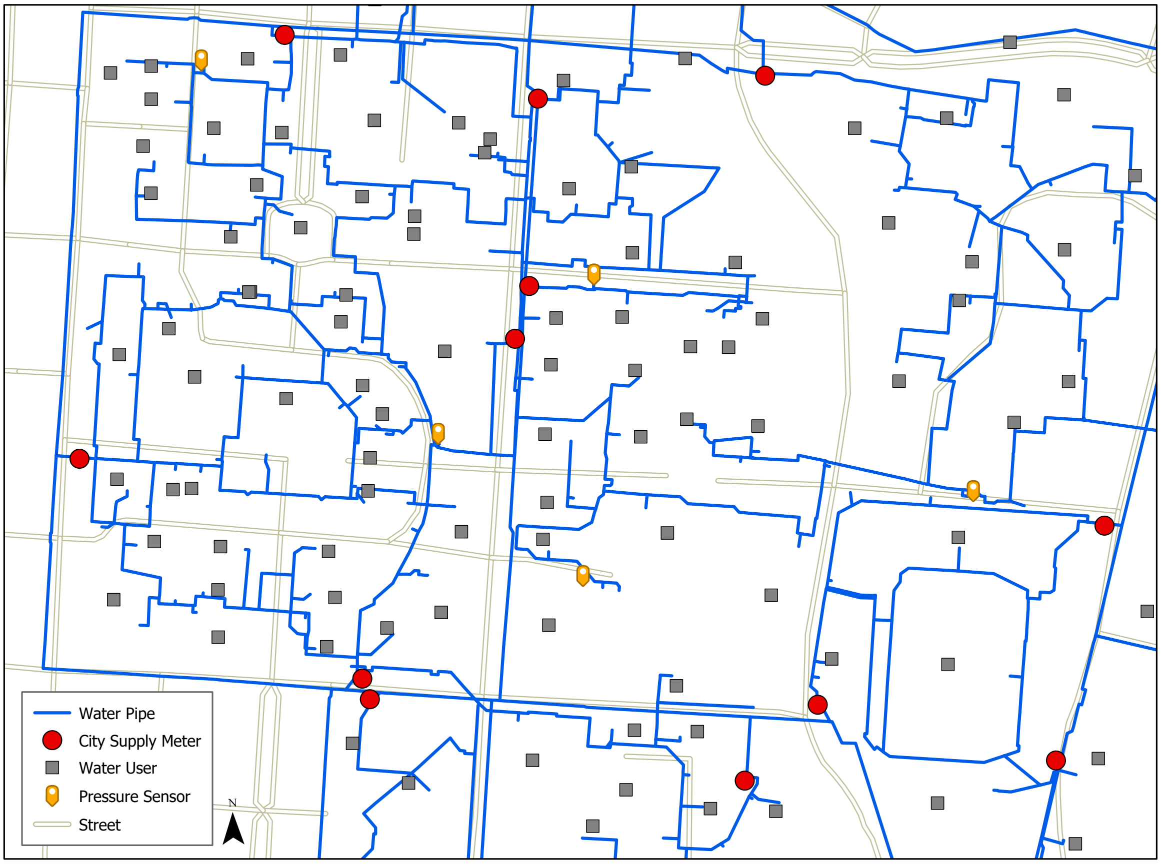


Fig. 1. Footprint and timeline of data collection and hydraulic model development processes.



1024

1025 **Fig. 2.** A portion of the completed hydraulic model of the university water distribution network.

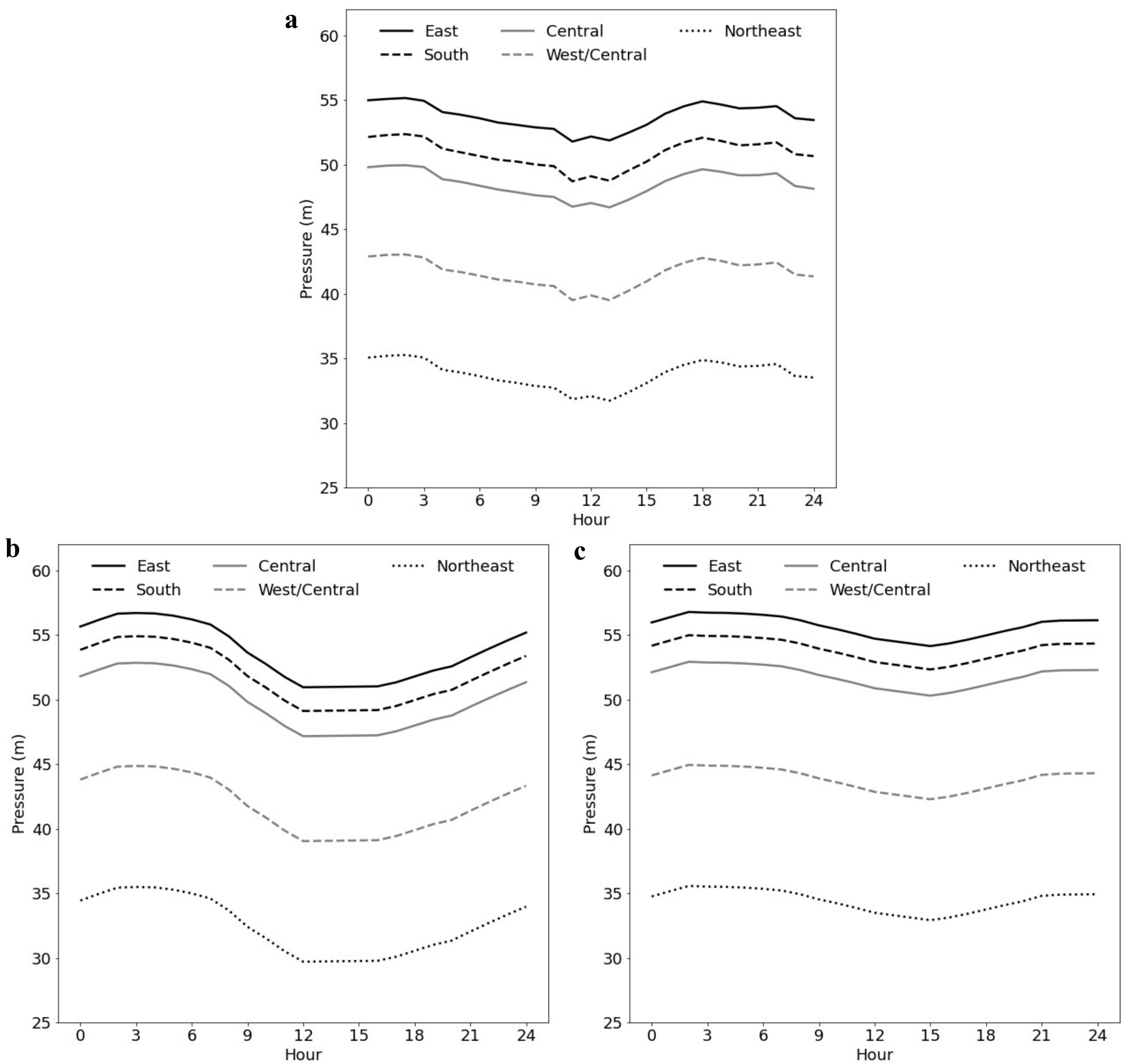


Fig. 3. Pressures at five locations in the study area: measured pressures (a); simulated pressures, base demand scenario (b); simulated pressures, low demand scenario (c).

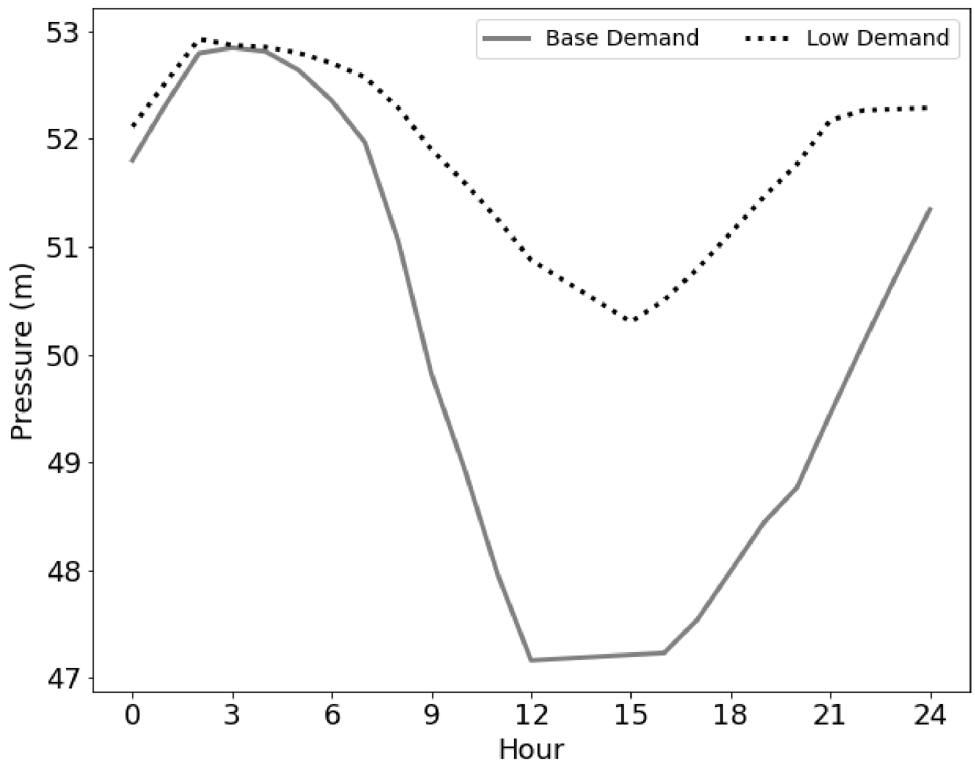


Fig. 4. Simulated pressure results for the base demand scenario (solid) and low demand scenario (dotted) at a location in the central region of the study area (hour 0 = 12:00 am). (See S2 in SM for results at additional locations).

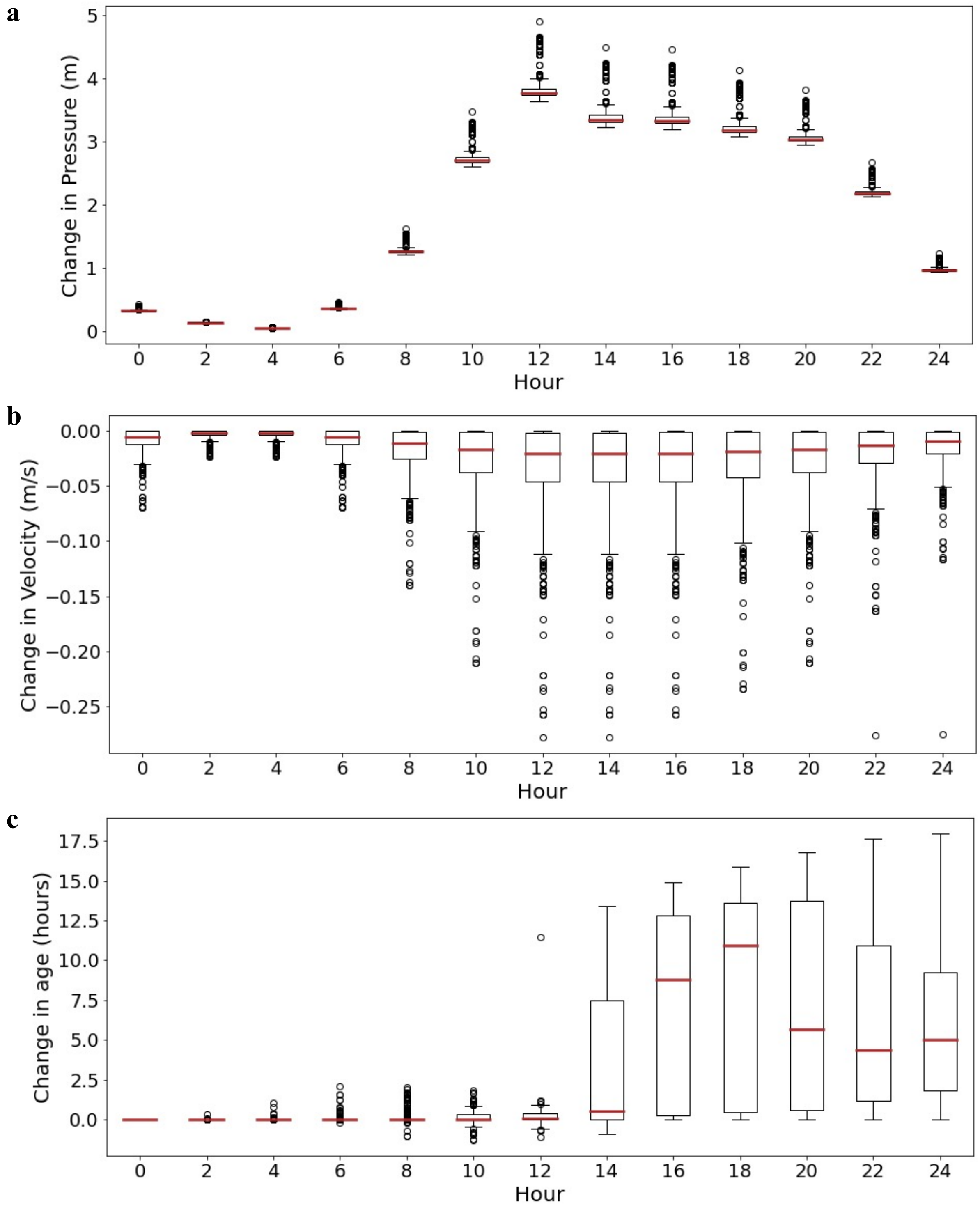


Fig. 5. Distribution (with median line) of differences between the base demand and low demand scenarios ($low - base$) for three performance indicators: pressure (a), flow velocity (b), and water age (c).

TABLES

Table 1. Success factors and challenges for hydraulic model development

	Category	Examples
Success Factors	Open-Source Technical Support	Online technical support resources in modeling, coding, analytics (blogs, videos, forums)
	Academic-Utility Partnership	Willingness among utility managers to share data, knowledge, other resources
	Software*	Access to ArcGIS, Bentley OpenFlows WaterGEMS via academic licenses
	Personnel*	Available personnel with expertise to complete modeling process
Challenges	Data Collection and Siloed Sources	Data must be acquired from many different sources; little coordination between departments
	Data Integration	Various data are in different formats, extensive processing required
	Data Quantity	Overwhelming amounts of data that are unused; conversely, certain required data might not exist
	Data Quality	Outdated data; human, meter, or recording errors
	Complex Customer Types	High-demand water users have separate and irregular datasets
	Knowledge Transfer	Individuals have specialized knowledge of parts of system; knowledge is not shared across areas of specialization
	Accessibility & Documentation	Model assumptions and procedures not documented; practitioners might not own model
	Scheduling	Entire modeling process is lengthy, cannot be completed under crisis conditions

* Factor could be a barrier rather than an advantage for a traditional water utility lacking financial or technical resources

Table 2. Hydraulic analysis summary statistics: water pressure, flow velocity, and water age*

	Pressure (m)			**Velocity (m/s)**			**Age (hr)**		
Demand Scenario	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Base	29.5	69.9	46.4	0	0.51	0.042	0	24	7.4
Low	32.6	70.0	48.5	0	0.28	0.021	0	24	10.3
Change: Base to Low	+ 3.1 (10.5%)	+ 0.1 (0.001%)	+ 2.1 (4.4%)	0	- 0.23 (45.1%)	- 0.021 (50.0%)	0	0	+ 2.9 (39.1%)

* Water age entering university distribution system is assumed to be 0.