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COUPLING AGENT-BASED MODELING WITH WATER DISTRIBUTION SYSTEM MODELS TO SIMULATE SOCIAL DISTANCING AND WATER INFRASTRUCTURE PERFORMANCE DURING COVID-19

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Abstract

Beside the immense impacts on public health, the COVID-19 pandemic also disrupted daily routines for people around the globe due to the adoption of social distancing measures, such as working from home and restricted travel in order to minimize viral exposure and transmission. Changes in daily routines created new water demand patterns, and the spatial redistribution of water demands in urban water distribution system networks affects water age, nodal pressures, and energy consumption. A range of factors influence individuals' social distancing decisions including demographics, risk perceptions, and prior experience with infectious disease. This presentation reports a comprehensive modeling framework to capture decisions to social distance, the effect of social distancing on water demands, and the effects on the performance of water infrastructure. First, new Bayesian Belief Network (BBN) models are developed to simulate social distancing decision-making based on publicly available survey data describing COVID-19 risk perception, social distancing behaviors, and demographics. Data were collected in March and April of 2020 and included over N=6,991 participants from 11 countries in North America, Europe, and Asia. Feature sets are developed from participant characteristics using forward selection and Naïve Bayes classifiers to predict behaviors, including working from home. BBN model output is used within an agent-based modeling (ABM) framework to simulate how individuals interact within a community and dynamically adopt social distancing behaviors based on communication and transmission of infection. Agents represent individuals who transmit COVID-19, communicate with each other, decide to social distance, and exert water demands at residential and non-residential locations. COVID-19 transmission among agents is modelled using a susceptible-exposed-infected-removed (SEIR) model. Finally, the ABM is coupled with a water distribution model to simulate how changes in the location of demands affect water distribution metrics. The model is applied for a virtual city, Micropolis, to explore how varying population characteristics can affect water infrastructure. This research provides a new framework to develop and evaluate water infrastructure management strategies during pandemics.

Keywords
Bayesian Network, Water Distribution System, Modelling, COVID-19, Agent-based Modelling.

1 INTRODUCTION

The COVID-19 pandemic, caused by the novel coronavirus (SARS-CoV-2), has caused immense public health concerns and impacted communities around the world. Governmental mitigation efforts including lockdowns and mask mandates have been widely instituted, and one third of the global population lived under some form of restriction in April 2020 [1]. By January 1, 2021, more than 80% of countries had a mask mandate in effect, and approximately 50% had mandated one or more social distancing measures, such as working from home, workplace closures, school closures, or international travel controls [2]. These social and economic restrictions were implemented to mitigate the transmission of the coronavirus but also had profound impacts on the daily lives of the people living with restrictions [3]. Many individuals adapted their daily routines of commuting to work and visiting places of interest to shop, dine out, or socialize. As a result, communities changed their interactions with infrastructure and their consumption of resources and services provided by infrastructure. One impact of these behavioral changes is the spatial and temporal change to domestic water demand, with an overall increase in residential water demand, reduction in the overall demand, and shifting of the common bimodal daily pattern [4]. Changes in demand subsequently impact the operation and management of the water distribution systems (WDSs), which are designed to deliver water to meet demands and expectations around the levels of service, including pressure. Water utilities reported a range of operational and management challenges due to changes in customer behaviours and observed noticeable differences in water demands during the COVID-19 pandemic [5].

To address water management challenges that arise during pandemics, water utilities need comprehensive modelling tools for demand, pipe flow, and pressure prediction that account for consumer behaviors, pandemic coping strategies, mobility, and changes in demands. Integrated modelling frameworks have been developed to simulate consumer behaviors to estimate changes in water demands and the associated effect on network performance. Modelling frameworks were developed to simulate demand changes and changes in infrastructure performance based on consumer decisions to adopt water reuse technology and alternative water sources [6-8] and consumer responses to contamination of drinking water [9-11]. The tool developed in this research builds on these previously developed frameworks, listed above, that couple agent-based models (ABMs) with hydraulic modeling. Agents represent individual water consumers that exert demands at nodes in a water distribution system and travel among nodes using diurnal patterns. As agents become aware of disease transmission, they make decisions to social distance, including working from home and cooking meals at home. A Bayesian Belief Network (BBN) modeling approach is used to represent agent decision-making around social distancing behaviors. The BBN model was developed using survey data that was collected to explore psychological predictors, risk perception, and coping strategies during the COVID-19 pandemic (N=6,991). A susceptible-exposed-infected-removed (SEIR) model is integrated to simulate COVID-19 transmission, using parameter settings that are specific to the transmission of COVID-19 [12]. The ABM framework is applied to simulate coping strategies that are taken by consumer agents to avoid exposure to COVID-19 and the emergent shifts in water distribution system performance metrics, including pipe flows and nodal pressures.

2 MATERIALS AND METHODS

An ABM framework is developed to integrate three modules, including a BBN model for agent decision making, a SEIR model for COVID-19 transmission, and a hydraulic model for simulation of the water distribution system flows and pressures (*Figure 1*). Individual water consumers are represented as agents that move between work and home nodes based on predetermined patterns. Agents make decisions to work from home based on the posterior probability of the BBN based on their individual state and parameters at each time step (*Table 1* lists agent parameters).

COVID-19 is transmitted between agents when a healthy agent occupies the same node as an infected agent and a threshold exposure probability is attained. Information about other infected agents is used to update an agent's understanding of the environment and inform its decision at the next time step. Once agent mobility and COVID-19 transmission are complete, the demand at each water network node is calculated based on the number of individual agents at each node compared the node capacity. This framework is shown in *Figure 1*, and the modules of the framework are described in the following sections.

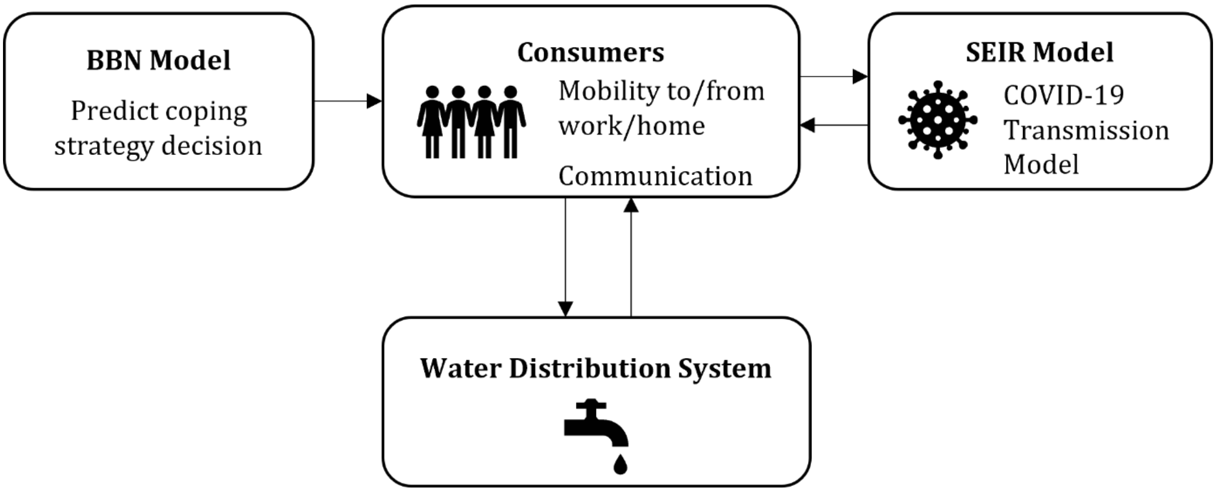

Figure 1. Agent-based modelling framework including BBN model for agent coping strategy decision making, SEIR model for COVID-19 transmission dynamics, and a hydraulic model for water distribution simulation.

2.1 COVID-19 Risk Perception Dataset

A new dataset was collected and made publicly available to explore how individuals around the world responded to the coronavirus and perceived information about protective behaviors [12]. Responses were collected from N=6,991 participants in 11 countries (Australia, Canada, Germany, Italy, Japan, Mexico, Spain, Sweden, South Korea, United Kingdom, and United States), between mid-March and mid-April, 2020. The timing was specifically chosen to capture a subset of countries before governmental mandates and others after mandates were put into place. This also induced differences in the number of infected individuals in each country, increasing the complexity of the survey cross-section. Participants were selected as representative based on age, gender, and ethnicity with approximately 700 participants selected from each country. The dataset was used to train the BBN model, which predicts agent decisions on coping strategy based on interactions with other agents and the environment. Development of the BBN using this dataset is described below.

2.2 Agent-based Model Framework

The ABM implements consumer agents that communicate with each other, exert water demands at their current location, transmit COVID-19, and employ personal social distancing measures. The ABM was developed using Mesa, a Python package specifically designed for ABM creation and data collection. Agents are instantiated as objects using the Mesa framework and assigned parameters to describe specific attributes of interest (*Table 1*). Agents then move between home and work nodes according to predetermined patterns and spread COVID-19 through contact with other agents. Each agent's decision to work from home is updated each time they are potentially exposed. The coupling of the ABM with the hydraulic simulation is based on frameworks that were developed in previous research [13, 14].

Each simulation was run with an hourly time-step and continued for a total of 90 days. The model reports agent location, disease state, and work-from-home status and nodal demand and pressure at each hourly time-step.

Table 1. Agent parameters and state variables. All COVID-19 related time data are reported by Kerr et al. [12].

Attribute	Value
Work node	All work nodes
Home node	All residential nodes
Age	[0-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80-89, 90+]
COVID-19 status	[Susceptible, exposed, infected, removed]
Time in exposed compartment	~ log-normal(4.5, 1.5)
Time in infectious compartment	All time spent in symptomatic, severe, critical states
Time in symptomatic state	~ log-normal(1.1, 0.9) (to severe state) ~ log-normal(8.0, 2.0) (to removed compartment)
Time in severe state	~ log-normal(1.5, 2.0) (to critical state) ~ log-normal(18.1, 6.3) (to removed compartment)
Time in critical state	~ log-normal(10.7, 4.8) (to dead state) ~ log-normal(18.1, 6.3) (to removed compartment)
Symptomatic	[Symptomatic, asymptomatic]
WFH decision	[Not WFH, WFH]
Predictors*	All predictors in *Table 2*

2.2.1 Coping Strategy Decision Model

Each agent uses a Bayesian Belief Network (BBN) model to select work-from-home (WFH) decisions, expressed as WFH and Not WFH in *Table 1*. BBN models were constructed using forward selection and the Naive Baye's classifier. Previous work showed little difference between forward selection and backward elimination, and forward selection is a more efficient model-building approach [15]. Models were evaluated and selected using accuracy and F_1. Accuracy is defined as the ratio of the number of true predictions made to the total number of predictions:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

The F_1 metric is the harmonic mean of the recall and precision metrics. Recall and precision are defined as the proportion of true positives to the total correct values and the total true values, respectively.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + TN} \tag{3}$$

$$F_1 = \frac{2 \cdot Recall \cdot Precision}{Recall + Precision} \tag{4}$$

A series of cross-validation steps were performed to reduce systematic error in the selection of responses used for the training and validation datasets. Cross-validation was completed with 10 runs of 10 folds with each run, using nine folds for training and one fold for validation. Each run used a different fold for validation.

2.2.2 COVID-19 Transmission Model

Disease transmission of COVID-19 is modeled using a SEIR model called Covasim, which was developed by Kerr et al. [11]. At the beginning of each simulation, 5% of the population was assumed as infected, while the remaining agents were susceptible. As agents move between nodes, susceptible agents have an age-progressive (increasing with age) probability of becoming exposed when an infected agent occupies the same node. For nodes with capacities greater than 10 agents, the maximum number of agents that was potentially exposed was restricted to 10 to reflect realistic contact dynamics. Once an agent is flagged as exposed, they can become exposed and then pre-symptomatic or asymptomatic, based on an age-progressive probability. Time spent in each stage is log-normally distributed with mean and variance calculated using a range of sources, as reported by Kerr et al. [12]. If an agent is asymptomatic, they progress to the removed stage where they stay until the end of the simulation. If an agent is symptomatic, they progress through increasing stages of disease severity from mild to severe to critical, based on age-progressive probabilities. Agents in the mild and severe stage move to the removed stage after a recovery period, and agents in the critical state have an age-progressive probability of entering a death state. Agents that are in the removed stage no longer contract or transmit the disease.

2.2.3 Hydraulic Model

Hydraulic simulation is modeled using the Python package Water Network Tool for Resilience (WNTR) which utilizes EPANET, version 2.2 [16, 17]. Each agent exerts water demand at the node they occupy at each hourly time step, and demands are aggregated at each node and passed to the EPANET simulation using WNTR. The WNTR package is built in Python, which allows for direct communication between the agents in the ABM and the hydraulic simulation. Results from the hydraulic simulation for each node and for each hourly time step were recorded.

3 CASE STUDY

The ABM framework was developed and applied for Micropolis, a virtual city developed by Brumbelow et al. [13] for the purpose of modelling a small, realistic city for water distribution system security research. The network consists of 458 terminal nodes (434 residential, 15 industrial, and nine commercial nodes), which represent 4,606 residents and a daily demand of 4.54 ML/day. Diurnal demand patterns are defined for each node type to simulate hourly changes in demand throughout the network. Each node is initialized with a base demand that is updated by the ABM based on node capacities and the number of agents at each node.

4 RESULTS

4.1 BBN Model Performance

A naïve model was constructed using work-from-home (WFH) as the predictant. The predictors were added using forward selection. The model with the largest accuracy was chosen, and included the predictors shown in *Table 2*. The model is defined as a naïve Bayes model, where the predictant is the only parent node, and all selected predictors are children nodes. The percentage of 'yes' responses in the dataset used for this model was 39%, and a WFH decision of 'yes' is labeled true, and 'no' is considered false. The accuracy and F_1 of this model were 63% and 51%, respectively.

Table 2. Predictors selected for inclusion in the BBN model for agent WFH decision making.

Predictor Selected	Question
Prosociality	To what extent do you think it's important to do things for the benefit of others and society even if they have some costs to you personally?
Anticipating personal financial problems	How likely do you think it is that you will be directly and personally affected by the following in the next 6 months: Financial problems?
Exposure to COVID-19 media through place of work of education.	Have you come across information about coronavirus/COVID-19 from: Official messages from your place of work or education?
Exposure to COVID-19 media from the World Health Organization	Have you come across information about coronavirus/COVID-19 from: World Health Organization?
COVID-19 worry, 2 months ago	Thinking back, how worried were you about coronavirus/COVID-19: 2 months ago?
Personal worry about terrorism	How worried are you personally about the following issues at present: Terrorism?
Healthcare worker	Are you a healthcare provider (e.g. doctor, nurse, paramedic, pharmacist, carer)?
Trust in immigrants	How much do you trust each of the following: Immigrants?
Trust in neighbors	How much do you trust each of the following: People in your neighborhood?
Ethnic Minority	Do you consider yourself to be part of a minority group within the country you are currently living in?
Previously affected by SARS epidemic	Have you personally been affected by a previous similar epidemic such as SARS (Severe Acute Respiratory Syndrome), MERS (Middle East Respiratory Syndrome) or Ebola?
COVID-19 worry: 1 month ago	Thinking back, how worried were you about coronavirus/COVID-19: 1 month ago?
Effect of COVID-19 pandemic	To what extent have you been affected by the coronavirus/COVID-19 in the following ways: I have experienced social difficulties as a result of the pandemic?
Sought information about COVID-19	Have you sought out information specifically about coronavirus/COVID-19?
Education qualification	Highest educational qualification
General trust in society	Generally speaking, would you say most people can be trusted, or that you can't be too careful in dealing with people?
Exposure to COVID-19 through media mass media	Have you come across information about coronavirus/COVID-19 from: Journalists and commentators in the media (TV, radio, newspapers)?

4.2 Agent-based Modelling Results

Two scenarios were tested. In the base case, agents visit nodes using their mobility patterns and become infected through disease transmission. In the second case, WFH, agents are mobile, become infected, and decide to work from home. The SEIR model and hydraulic model were used for both scenarios, and the WFH scenario include an active BBN model. In the base scenario, agents followed mobility patterns throughout the 90-day simulation and do not work from home, and they spread COVID-19 and progress through disease severity states. In the WFH scenario, agents follow the established mobility patterns unless they had previously decided to work from home based on the BBN model, in which case, that agent would stay at their residential node and not travel to work for the remainder of the simulation.

The daily maximum and mean system water demand for both scenarios are shown in *Figure 2*.Also demonstrated in *Figure 2* is the increase in max water demand as more agents work from home but shows an overall drop in water demand across the system, corroborating previous work showing decreasing water demand as a result of social distancing [4]. The cumulative number of infected agents and the current number of agents working from home is shown in *Figure 3*. The disease dynamics are shown in *Figure 3* where early decisions to work from home prevented wide-spread transmission of COVID-19. To understand the impact of working from home on the hydraulic system, the system-wide pressure was compared for both scenarios at hour 12 during day 45 (near the peak number of agents working from home from *Figure 3*). These plots are shown in *Figure 4*, which exhibits the differences in system-wide pressure when agents are working from home and exerting demand at their residential node rather than their work node. No pressures changed alarmingly, but the main trunk leading from the reservoir at the north end of the system saw a 50% reduction in demand at this time point. This could lead to changes in water delivery stability or flow changes, causing downstream disruptions.

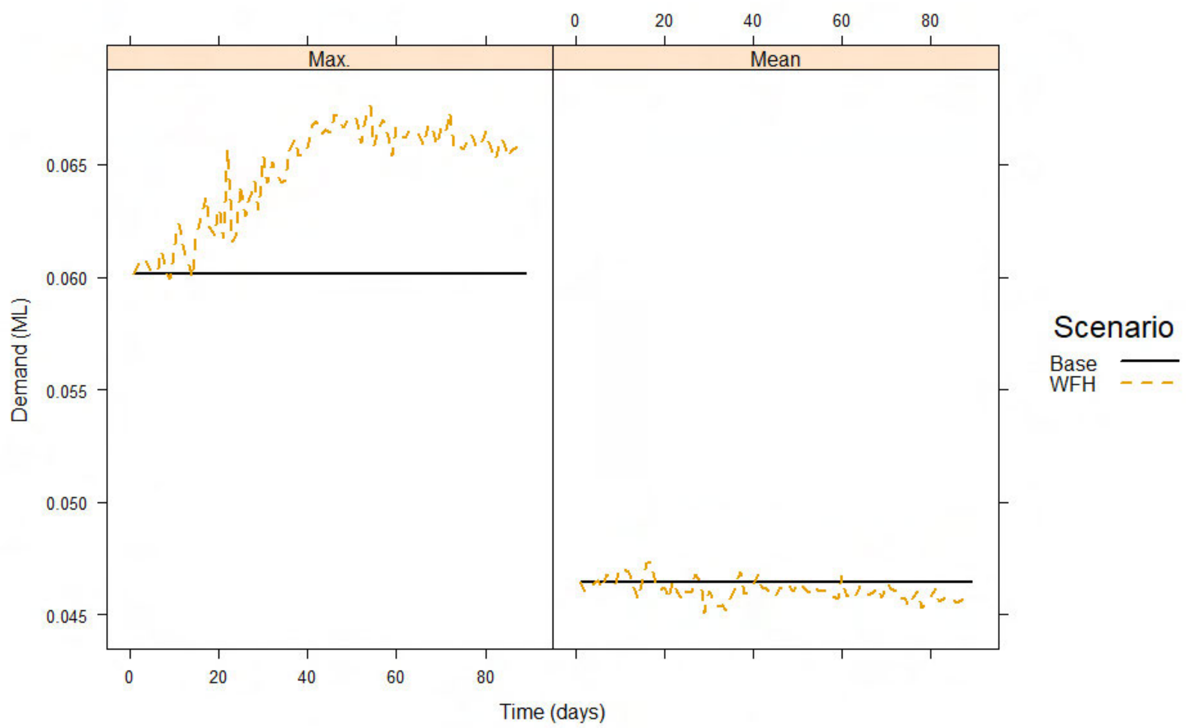

Figure 2. Daily maximum and mean system demand during both scenarios.

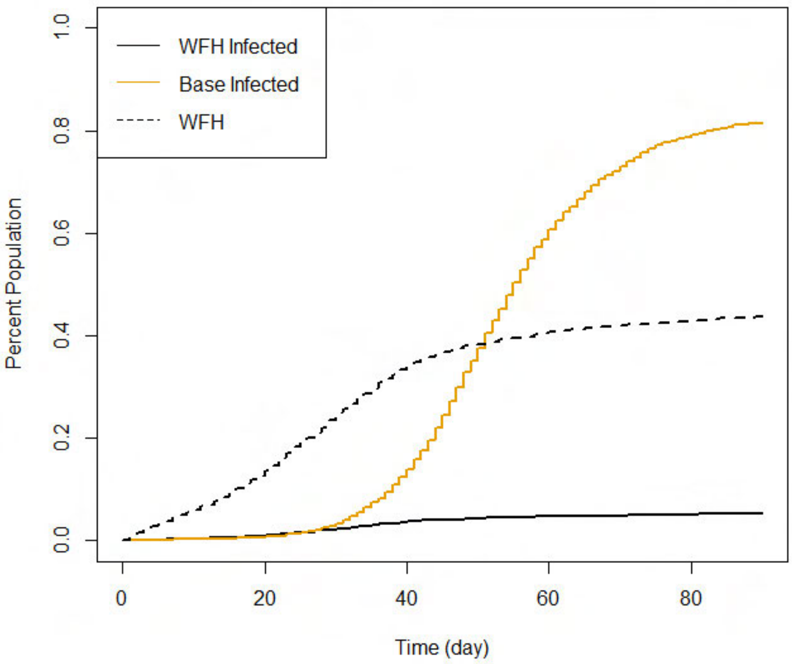

Figure 3. Cumulative percent infected for both scenarios plotted along with the percentage of agents working from home.

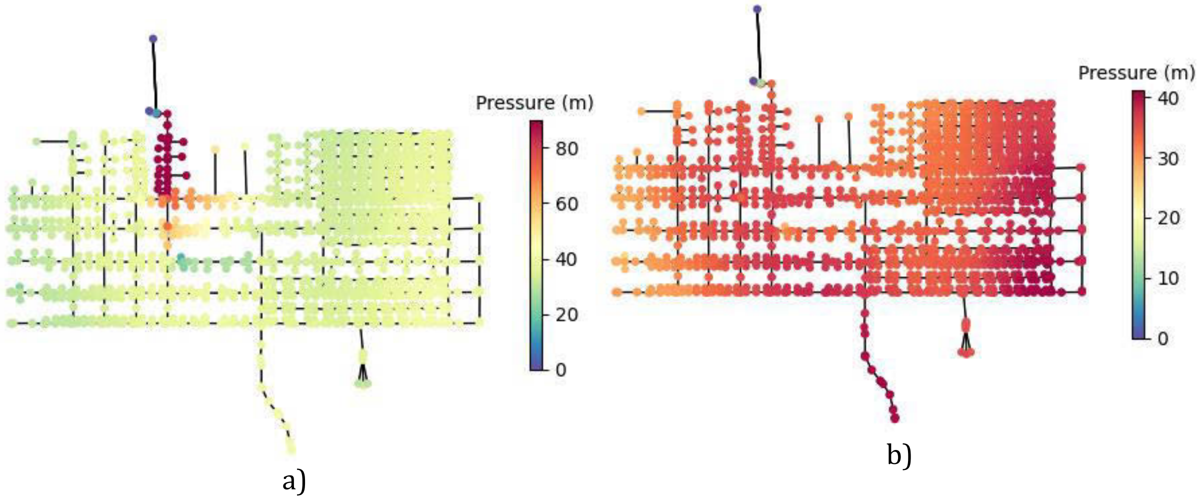

Figure 4. Node pressure comparison between base (a) and WFH (b) scenarios.

5 CONCLUSION

A Bayesian Belief Network was trained using COVID-19 centered survey data from N=6,991 participants to produce a naïve Bayes predictive model for work-from-home prediction. The accuracy and F_1 for the model were 63% and 51%. The BBN was used to simulate agent decisions to work from home within the ABM framework. Trends in overall water demand and system-wide pressure were analyzed and indicated overall changes in system dynamics due to agents working from home. Demand patterns mirrored real-world quantitative and qualitative results, and changes in nodal pressures demonstrate system-wide impacts from agent social distancing.

Future work will continue to explore other BBN models and predictors to tune the decision making model to better match observed patterns, and further analysis will evaluate the range of change in hydraulic performance due to social distancing behaviors during pandemics.

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