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The Key Technologies of Intelligent Urban Drainage Management

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Keywords: Urban waterlogging; Intelligent Drainage Management Platform; Eyes-Brain-Hands theory; Flood-control; Smart urban water management

As all we know, China is still enjoying the fast development of urban areas, and has established ten clusters of cities, especially in the Southeast of China. However, many mega-cities are continuously suffering from the threats of extreme rainstorm events due to rapid urbanization and global climate change. In order to achieve the effective regulation of the urban drainage cycle, an Intelligent Drainage Management Platform (IDMP) has been developed based on Eyes-Brain-Hands theory. The Eyes part is composed of intelligent monitoring and novel monitors on the water-IoT(Internet of Things) platform as well as big data tech, which provides accurate data and achieve the comprehensive perception of weather and water variables. The Brain part of the system is the multi-coupled urban drainage operation model, through which the tendency of future water regime can be predicted and the intelligent emergency decision can be made in real-time. The Hands part is the unified command platform, on which various hydraulic structures including reservoirs, pumps and sluices can be remotely operated, and rescue forces and materials are efficiently coordinated and dispatched to give full play to flood control forces. The three sub-systems are linked together to form a complete closed-loop system, enhancing defences constantly to minimize the impact of disasters. Relevant technologies have been successfully applied in Fuzhou, providing great help to reduce urban waterlogging.
Assessing the Resilience of Water Distribution Networks Under Different Sensor Network Architectures and Data Sampling Frequencies

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Keywords: smart urban water management, resilience assessment, water distribution networks, sensor networks

EXTENDED ABSTRACT

Introduction

Leakages and other infrastructure failures represent major challenges confronting the reliability, efficiency, and resilience of water distribution networks (WDNs). Timely identification and accurate localization of these anomalies is paramount to mitigate water and revenue losses, and avoid unwanted cascading effects. Previous resilience studies have demonstrated that the topology of WDNs affects their resilience, for instance to pipe failures. Moreover, several methodologies have been proposed in the last decades to identify optimal sensor locations in a WDN and monitor physical variables (e.g., pressure, flow, concentration of contaminants) in relation to specific objectives, including water contamination monitoring and leakage detection. Yet, most of the studies on optimal sensor placement in WDNs assume constant data logging frequency or number of available sensors, and do not comparatively analyze the influence of different sensor network architectures in relation to different WDN topologies. Here, we develop a simulation-based approach for WDN resilience assessment to quantify the influence and trade-offs of different sensor network architectures, data sampling frequencies, and WDN topologies on automatic leakage identification and localization capabilities.

Methods and Materials

The simulation-based approach for WDN resilience assessment under different sensor network architectures and data sampling frequencies we propose here is composed of the following four steps.

First, we selected two different WDNs with heterogeneous sizes and topologies. We rely on the state-of-the-art benchmark WDNs Net3 and Modena (see Figure 1): Net3 is smaller and comprises 97 nodes connected by 117 pipes and has tree-structure dead ends; Modena represents an average-size WDN with 272 nodes and 317 pipes. Modena is characterized by a loop/grid configuration, in contrast to Net3.

Second, we simulated the two selected WDNs using WNTR [1] with a time horizon of four months and a simulation step of 5 mins under randomized leak scenarios. In each scenario, the leak starting time, the leak size, and the location of the leaking pipe are randomly sampled. We sampled a total of 40 leak scenarios for each network.

Third, we post-processed the simulated time series of node pressure to emulate different sensor network architectures, with varying numbers of sensors and different data sampling frequencies. We generated in total five different random sensor placement scenarios with various sensor-to-node ratios (10%, 25%, 50%, 75%, and 100%) and aggregated the pressure data to 5 mins, 15 mins, 30 mins, and 1 hour. As a result, we analyzed 4000 combinations of leak scenarios, sensor network architectures (i.e., number of sensors and sensor placements), and data sampling frequencies for each network.

Finally, for each combination of scenarios we performed leak identification and localization using the LILA state-of-the-art algorithm [2]. Leakage identification and localization are assessed in terms of time until detection (i.e., the difference between its actual start time and its detection time) and the distance between the position of the sensor where the leak was identified and its actual location.
Results and Conclusions

Our preliminary results (see Figure 2) provide insights on the trade-offs between leak detection performance and temporal as well as spatial resolutions of pressure sensor data, which shows also dependencies on the WDN topologies. For Net3, time to detection tends to be primarily affected by data sampling frequencies, whilst distances of detection show higher dependency on the number of active sensors. This is nonetheless distinct for Modena, where the distances of detection are in a narrower range, likely due to the different, more articulated topology, sensor placement, and the effect of signal noise on the accuracy of the leak detection algorithm. Two major improvements to be prioritized for future investigation are (i) the implementation of an optimal sensor placement module to upgrade the current randomized sensor placement procedure and (ii) the comparative assessment of different leak identification and localization methods to achieve more generalizable conclusions.

REFERENCES


IoT platform for failure management in water transmission system

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Keywords: Decision support system, wireless sensor, digitalisation, smart urban water management, remote sensing and data assimilation

EXTENDED ABSTRACT

Introduction

The operation of water transmission networks, (WTN), responsible for conveying water from the sources to the regulation tanks in municipalities, is conditioned by the dispersion of these networks throughout the territory. Thus, WTNs are made up of pipes tens of kilometres long, located in non-urban areas, which makes daily monitoring of the key points difficult. Systems based on the Internet of Things (IoT) are enabling decentralised monitoring of large hydraulic networks, providing access to real-time information from any point with an internet connection. To achieve an efficient management of these large hydraulic infrastructures, their digitization is essential. Only in this way is it possible to apply BigData techniques to the recorded data, facilitating the daily management of facilities, making them safer and more resilient to adverse situations [1].

This work shows the development and implementation of an IoT platform aimed at fault detection in WTNs using open-source software (Figure 1). Its core is a decision tree algorithm, which detects and classifies faults using only the pressure data recorded by the linked network of low-cost wireless pressure sensors. Upon detection of a fault, the system sends alerts and estimates the maximum repair time without causing supply outages, facilitating the management of repair works. The applicability of the proposed system has been tested in a real WTN.

Materials and Methods

The proposed platform facilitates a comprehensive management of failures in WTNs, enabling the analysis of each incident and estimate the time available to carry out repairs. Its functional modules are described next.

Failure detection module: This module analyses sensor pressure data to detect failures in real time. The fault detection algorithm can recognise the following incident types: incident 1 (sensor failure), incident 2 (supply cut-off), incident 3 (leak downstream of the sensor) and incident 4 (leak upstream of the sensor). The pressure analysis algorithm for failure detection is based on the application of the decision tree methodology [2]. Fault detection is a binary classification problem whose solution determines whether the fault exists or not. The algorithm generates an alert when the pressure received from each sensor in time t is below a dynamic threshold. This parameter defines the lower pressure that allows detecting the occurrence of failures in WTN when the recorded pressure is below it.

A dynamic threshold is estimated for each sensor, being a function of SF (security factor, %) and n (number of data used in threshold calculation). So, the threshold is adapted to the pressure conditions at each specific measurement point. The value of n that ranges between 3 and 40 depends on the type of monitored network. In networks with frequent sudden
pressure changes it is necessary to set a low value of n, to quickly adapt the threshold to pressure variations. In networks with constant pressures, a higher value of n can be set, to avoid false positives of network failures. The choice of the optimal SF, that varies between 5% and 50%, is a complex process that is mainly based on the performance of the decision tree algorithms.

**Alert module:** This module receives the results of the fault detection module. When a fault is detected, an alert message via SMS/email is sent. Its purpose is to allow users to visualize the results of the failure detection module as soon as the failure occurs and to act accordingly.

**Failure repair management module:** The purpose of this module is to determine the maximum repair time of a failure, MRT, or the duration of a maintenance task. The MRT is equivalent to the duration of the time interval between the detection of the failure and the time when users (inhabitants of a municipality) will be unable to satisfy their demands because of the supply failure. This concept is the basis for the optimal management of human and material resources needed to fix failures. The MRT can be estimated by the WTN manager analysing the behaviour of the network under different fault scenarios. These scenarios are defined by the water levels in the affected tanks and the hourly demand curve in the corresponding municipalities, data required by the hydraulic simulator EPANET [3].

### Results and Discussion

Using a 4-pressure sensor network, data were collected from a real WTN over a period of 12 months. As an example, a fraction of the pressure 15-minute records of one of the sensors is shown in figure 2. In the full data series, a total of 40 incidents (20 incidents of type 1, 5 incidents of type 2, 9 incidents of type 3 and 6 incidents of type 4) were detected. Each of the failures is defined by its pressure, date, time and duration, location, and type of incident.

![Figure 1. Pressure evolution in July in a representative sensor.](image)

The values of the performance parameters of the failure detection algorithm indicate that the number of false negatives is very low (recall: 0.95), as well as the number of false positive prediction (precision:0.974). Additionally, accuracy (0.999), means that the algorithm’s predictions are almost 100% correct. Also, the F1score (0.962) close to 1, showing that the algorithm is working properly, was studied as the classes were not balanced (only 40 incident events in 12 months of 15-minute data).

### Conclusions

Fault detection based on fixed thresholds require a relatively large data set to fix their value, and do not detect small leaks linked to small drops in pressure records. The proposed threshold is a dynamic threshold that updates its value with each new data sending cycle, thus adapting to the evolution over time of the WTN loading conditions. With the dynamic threshold, the fault detection algorithm proposed in this work can detect the small leaks that would not be detected considering a fixed threshold.

The web platform presented in this work is comprehensive support tool to manage failures occurring in WTN. Its most relevant function is the detection and classification of incidents in the network. The main elements of the proposed tool are based on open-source software, so that the water company can control of all the stages of the failure detection process (data collection, storage, analysis, visualisation, and warning) without the support of an external service. The platform has been successfully applied to a real WTN during the one-year trial period.

### REFERENCES


Open-source IoT platform for smart irrigation systems

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Keywords: remote sensing and data assimilation, modelling and visualisation tools, Internet of Things, smart irrigation

EXTENDED ABSTRACT

Introduction

Nowadays, smart irrigation is becoming an essential part of agriculture, where water and energy are an increasingly limiting factors. The Internet of Things (IoT) emerges as the natural choice for smart water management applications [1]. Its importance will grow in the coming years, in an agricultural sector where the optimal use of resources and environmental sustainability are more important every day. However, implementing smart irrigation is not an easy task for most farmers, since it is based on the knowledge of the different aspects that influence crop water requirements. These measurements are taken using different types of sensors, which have been greatly developed in recent years and their cost has become cheaper. However, most of them offer the information in commercial IoT platforms which are closed, do not allow the integration with other platforms, and usually support a limited number of sensors. These problems limit their potential use in decision making.

In this work a low-cost IoT open-source system for smart irrigation is developed, that can be easy integrated with other platforms and support a large number of sensors.

Methods and Materials

The architecture of the IoT system (Figure 1) is divided in three layers.

![IoT System Architecture](image)

The fist layer is made up of smart, energy-efficient devices that have been developed with the aim of being compatible with different connections and protocols. The datalogger uses the Arduino MKR family of microcontrollers that support Low Power Wide Area Networks (LPWAN), Global System for Mobile (GSM), Wi-Fi and Bluetooth connectivity. It supports analog, SDI-12 and RS-485 protocols, so many sensors can be used. In addition, a printed circuit board (PCB) has been developed to control the power of the sensor and adjust the voltage of this sensor to the circuit operating voltage of 3.3V. The PCB has a rechargeable lithium-ion 18650 battery with 2600 mAh and 3.7V that is charged via a 250mA solar panel.

The second layer is the Backend. The FIWARE framework has been used, which is an open-source platform that provides a set of APIs (Application Programming Interfaces) and is based on a microservice architecture. The advantages of using FIWARE is that software architects can exploit a consolidated set of open-source solution aimed at handling specific IoT problems [2]. The main component of FIWARE is the Orion-LD Context Broker, which uses the Next Generation Service Interfaces – Linked Data (NGSI-LD) APIs [3]. All other microservices connect to the context broker via its API and each of them performs a specific task. The IoT Agent microservice manages IoT devices and sends sensor values to the context broker. QuantumLeap is another microservice that stores the sensor data in a persistence database and the Authentication Server takes care of user control. Two databases have been used, the first one is MongoDB which is a No-SQL database that stores the context data and user information, the second one is crateDB which is another No-SQL database where the sensor data is stored.
The last layer is the Frontend. This layer contains the graphical interface of the platform that interacts with Layer 2 using the NGSI-LD API via the Hypertext Transfer Protocol (HTTP). This layer has been created using the ReactJS library.

The platform can be deployed on cloud servers and supports the ARM computer processor architecture, used by many minicomputers today.

Results and Discussion

The proposed IoT system has been tested in a super-intensive olive plantation located in Cordoba, Spain. The farm covers an area of 40 ha and has three main irrigation sectors with an irrigation rate of 2500 m$^3$/ha. The soil type is sandy-clay-loam.

The platform has been deployed on a Raspberry PI 4 with Internet connectivity for external access. Three dataloggers have been installed, one for each irrigation sector. These dataloggers control four soil sensors, three of them measuring soil moisture, electrical conductivity and temperature at different depths, and the last one measuring soil water potential. The connection of these sensors to the PCB is done through a jack connector. Due to the remote location of the farm, the Arduino MKR FOX 1200 microcontroller with SigFox connectivity has been chosen.

The sensor data are displayed in a dashboard, developed in this work. Figure 2 shows the moisture graphs at different depths during the month of June 2021. In these graphs the irrigation strategy followed by the farmer can be seen. A soil potential sensor has been installed to be able to obtain, over time, the soil moisture release curve.

Conclusions

The design of a complete open-source IoT system for smart irrigation system is presented. The system is a multilayer platform, consisting of a series of energy-efficient intelligent devices connected to an IoT platform that is based on a microservices architecture. The platform uses the FIWARE framework alongside customised components and can be deployed using edge computing and/or cloud systems. This allows it to be adapted to the farmer’s needs, reducing costs and increasing safety. In addition, an energy efficient open source datalogger has been designed. The datalogger support a wide range of communications and protocols. The open-source availability of data collected from the different sensors will facilitate the integration of the data into soil-water-plant-atmosphere models and their use as decision support systems for optimal irrigation management.

REFERENCES


Investigating Water Quality Sampling Frequency in Urban Surface Freshwater

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Keywords: water quality; sampling frequency; smart urban water management; smart cities; wireless sensors network.

EXTENDED ABSTRACT

Introduction

Resilient and accurate water quality monitoring systems are key to the protection of our drinking, recreational and ecosystem-supporting bodies of water. The largest strains on water quality in the UK typically occur within urban areas, with degradation occurring through point and diffuse sources of pollutants, alteration of natural flow through built-up areas and changes to water temperature (Miller and Hutchins, 2017). The development of new equipment for in-situ high-frequency monitoring in recent decades is beginning to make complete understanding of water quality and processes possible, hence we enter a new era of water quality monitoring network design (Kirchner et al., 2004; Halliday et al., 2015; Chen and Han, 2018). Data obtained from high-frequency sensors deployed in Bristol’s Floating Harbour have been used to determine the optimum sampling frequency to optimize information transfer.

Methods and Materials

Many signals within water quality parameters exhibit cyclic variability. These are commonly found to have annual, weekly, or diurnal variation. Adequately representing the periodicity of signals of water quality parameters is fundamental to avoid misrepresenting water quality changes.

Zhou (1996) defines the minimum sampling frequency to achieve this in terms of harmonic analysis. For a time-series sampled at a given constant interval Δt, harmonics can be observed at frequencies from 1/(nΔt) to 1/(2Δt). Any harmonics at higher frequencies than 1/(2Δt), the Nyquist frequency, fold into the signal to appear at lower frequencies. This is known as aliasing and can be avoided by selecting a sufficient minimum sampling rate to capture the highest frequency significant periodic fluctuations in the signal. For a signal with a frequency of the highest significant harmonic f_H, the minimum sampling frequency to avoid aliasing f_S,min = 2f_H (Rorabaugh, 1986; Zhou, 1996).

In this paper, the frequencies f_H and f_S,min are obtained for each signal. The signals are prepared using the detrend function and the frequency amplitude spectra obtained using a Fast Fourier Transform. From the amplitude spectra, the highest frequency harmonics are identified to find the minimum required sampling rate.

Data used in this study was collected using three EXO2 water quality sondes from YSI Inc. These are multiparameter sondes equipped with up to seven sensors capable of measuring a wide range of variables (YSI, 2019), found to be largely successful in the field by (Snazelle, 2015; Snyder et al., 2018). For the purposes of this study, turbidity, fDOM (fluorescent dissolved organic matter, a surrogate for dissolved organic content), conductivity, temperature, and dissolved oxygen (DO) were considered sufficient to capture changes in the harbour due to weather, pollutant, and tidal stimuli. Data has been collected with a 5 minutes frequency (0.0033 Hz) in 3 different locations along the Harbour.

Results and Discussion

The frequency analysis applied to the time series of temperature, dissolved oxygen (ODO), and fDOM has shown that the sampling interval between two measurements should be at least 6 hours (see Figure 1).

The water temperature sampling intervals resulted as 12 hours and 6 hours intervals were expected since water temperature vary in response to diurnal and seasonal changes in solar radiation.

Similar results are obtained for the dissolved oxygen since it is highly dependent on temperature and salinity. In the Floating Harbour dissolved oxygen is mainly affected by temperature changes since levels of salinity are quite low compared to sea water so the effect of changes in salinity on dissolved oxygen is neglectable.

The dissolved organic matter is measuring the fDOM (fluorescent dissolved organic matter), a fraction of CDOM that fluoresces when it absorbs light of a certain spectrum. The CDOM (coloured dissolved organic matter) is a naturally occurring dissolved matter that absorbs UV light in water. It’s usually made-up material that is released from the breakdown of plant material. The observed values for fDOM in the Floating Harbour vary significantly in the three different sites due to different landscape characteristics, also showing a diurnal change due to the important influence of solar radiation on the measurements.
For the turbidity measurements there is no constant periodicity in the recorded time series, resulting in noisy frequency spectrum. This shows that turbidity in the Floating Harbour is not controlled by a cyclic phenomenon but by external forces. It was unexpected that the scouring operations happening in the harbour did not have an immediate effect on the turbidity measurements. This might because the sites chosen for the sensors were not reached by the main flow during scouring operations, further analysis including hydrodynamic modelling will be needed to have a better understanding.

The conductivity measurements show a high correlation to the tide affecting the Bristol Channel and River Avon. Concluding that the tides are primarily responsible for the cyclic variation of conductivity in the Floating Harbour, a monitoring frequency must be high enough to capture the extreme levels of conductivity caused by the tidal water entering the harbour. As very high tides are not strictly periodic in time, the method used thus far for the frequency analysis is not completely applicable.

Figure 1. Fast Fourier transform signal for the monitored parameters at 3 different locations.

Conclusions

Using the time series of water quality data available in Bristol Floating Harbour to analyse the frequency components of each water quality parameter at each different site to quantify the Nyquist frequency and supposed minimum sampling rate for determination of periodic fluctuations, as proposed by Zhou (1996) and Khalil & Ouarda (2009) it has been possible for most of the monitored water quality parameters to identify reasonable frequencies to monitor water quality determinants without loss of information.

REFERENCES

Making river health data from citizen science projects more engaging for the public

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Keywords: modelling and visualisation tools; river health; citizen science; nutrient pollution; WaterBlitz

Citizen science projects are popular with local river trusts in the UK as a way of raising public awareness of issues like river health. The data gathered by volunteers as part of these projects can also provide useful data for the trusts to inform their conservation strategies and other work. Most river trusts rely on multi-purpose GIS tools for visualising the data they collect. However, it can be difficult to make the data accessible and engaging using these tools alone.

To demonstrate the advantages that a dedicated visualisation tool can bring, Riskaware (a scientific software consultant based in Bristol, UK) has worked with their local rivers trust, the Bristol Avon Rivers Trust (BART), to help them develop such a tool for their WaterBlitz citizen science project. As part of the project, BART supplies their volunteers with freshwater sampling kits to collect data on the waterways in their catchment.

Results from the WaterBlitz project collected over the last 5 years can be viewed in the visualisation tool which is available for everyone to access at https://bristolavonriverstrust.org/waterblitz/ and can be used on any device with an internet browser. The tool has many novel features including the projection of data from the sampling sites onto a map of the watercourses to allow users to understand how sites are connected in terms of the overall water system.

BART has received lots of great feedback about the tool. They believe it has excellent potential for it to be used more widely and enhanced to support other applications.
Real-time Ensemble Forecast and Data Assimilation of High-resolution Urban Flood Inundation Based on Distributed GPU Parallelization

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Keywords: modelling and visualisation tools; flood simulation; high performance computing; probabilistic forecast; particle filter

EXTENDED ABSTRACT

Introduction

Modern large cities feature wide areas and strong spatial heterogeneity. The intensity and evolution of urban flood events are affected by multiple sources of uncertainty such as precipitation and underlying surface conditions. In order to comprehensively describe the uncertainty of input and output factors, a numerical model of ensemble forecast is constructed, and the probability distribution of forecast results is described with Monte Carlo samples. The complexity of a two-dimensional flood model grows exponentially with its spatial resolution, and ensemble forecast further exacerbates the demand for computational resources. Hence, advanced parallel computing technology must be adopted to ensure simulation efficiency.

Methods and Materials

Figure 1. Parallel programming optimization design of deterministic (a) and ensemble (b) forecast models

To realize high-resolution, real-time ensemble forecast, CUDA-based heterogeneous computing technologies and a distributed storage multi-GPU system are used. Based on the ensemble forecast model, a particle filter based on sequential importance resampling is established to enable the assimilation of hydrological observations and improve...
forecast accuracy. The shallow water equation is decoupled on the x-y direction, and the inertial form of the Saint-Venant equation is chosen to realize explicit iteration. The GPU thread structure is designed based on the spatial coordinates of the orthogonal grid, and the SIMT feature of the GPU is fully utilized by aligning data structure and thread indices. Multiple independent model instances are placed on each GPU so that host-device communication is only needed at output and assimilation steps. Methods including asynchronous data copy are incorporated to improve scalability.

Results and Discussion

![Figure 2. Probabilistic forecast results with data assimilation](image)

Taking the urban area around Baimahe River, Fuzhou City as an example, a 2-dimensional flood model with 3 m spatial resolution and 3.93 million units is constructed, and 8 Tesla P100 GPUs are used for parallel calculation of 96 model instances. Under these settings, the ensemble simulation of a 1-hour hydraulic process takes 5.5 minutes, which achieves a 1000+ speedup compared with non-parallelization modeling. The calculation results show that the particle filter method effectively constrains simulation uncertainty while providing the confidence intervals of key hydrological elements such as river flow, submerged area, and submerged water depth.

Conclusions

This paper uses particle-filter-based ensemble data assimilation method to improve the accuracy of flood forecast model, and uses CUDA-based high-performance computing technology to improve model calculation efficiency. In this way, real-time high-resolution two-dimensional flood ensemble forecast is realized.
FORECASTING OF IRRIGATION WATER DEMAND AT FARM LEVEL FOR ENERGY TARIFF PERIODS USING COACTIVE NEURO-GENETIC FUZZY SYSTEMS

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Keywords: demand modelling and management; decision-making under uncertainty; farmer’s behaviour modelling; artificial intelligence; irrigation scheduling

EXTENDED ABSTRACT

Introduction

Irrigated agriculture uses nearly 70 % of the total water consumption in the world. This value accounts for up to 90 % of the total water resources in arid developing countries [1]. In Europe, irrigated agriculture uses around 33 % of total water used although this figure may reach over 80 % in Southern Europe countries [2] and in the whole Mediterranean region. Thus, efficient water use is essential in a sustainable agricultural system because of reduced water availability mainly in arid and semi-arid regions like Spain. Consequently, water scarcity and the increase in energy demand and their associated costs in pressurized irrigation systems are causing serious challenges for irrigated agriculture and water user associations (WUA). In addition, most of these pressurized irrigation systems has been designed to be operated on-demand where irrigation water is continuously available to farmers complexing the daily decision-making process of the water user association’ managers. Know in advance how much water will be applied by each farmer and its distribution during the day would facilitate the management of the system and would help to optimize the water use and energy costs.

Artificial intelligence (AI) techniques have been applied to solve different problems of water resources management and planning. Research also works focused on the prediction of water demand at irrigation district level, using neuro-genetic algorithms. However, an optimal daily decision making in WUAs requires not only the knowledge of the of irrigation events occurrence and the applied irrigation depths but their hourly distribution. Since electricity tariffs are organized in hourly periods, the knowledge of the hourly distribution of water consumption would be useful for the optimal contracting of these tariffs. In this work, a hybrid model combining Multiple-input Multiple output (MIMO) of an Adaptive Neuro Fuzzy Inference System (ANFIS) known as Co-active Neuro-Fuzzy Inference System (CANFIS) has been developed to forecast one-day ahead the distribution in energy tariff periods of the irrigation depths applied at farm level. CANFIS has been optimized by the multiobjective GA NSGA-II [3]. The model which was developed in Matlab™ and integrated as toolbox was validated and tested in a real WUA.

Methods and Materials

Canal del Zújar Irrigation District (CZID) was selected as real WUA to validate and test the forecast model developed in this study. The model was trained and tested with data from the 2015, 2016, 2017 and 2018 irrigation seasons. This WUA, located in Southwest Spain. Sector II was selected for this work because of the high amount of available data.

A previous step to generate the hybrid model is needed to reduce the dimension of the input space and identify the significant inputs from the full set of possible inputs. In this work, an adaptation of the methodology developed by Lin et al. (1996) has been used in this work to identify the significant inputs. Lin et al. (1996) determined automatically the most significant inputs for a single output variable using fuzzy curves and fuzzy surfaces. Because of the MIMO (Multiple input -Multiple output) nature of the hybrid model developed in this work, an extension N dimensional of the fuzzy curves and fuzzy surfaces have been developed. Thus, the fuzzy curves have been extended to a beam of N-fuzzy and fuzzy surfaces have been transformed to N-dimensional fuzzy curves. The number of output variables of the predictive model defined the N-dimensionality of the fuzzy curves and surfaces.

The hybrid model developed to forecast one-day ahead the distribution in energy tariff periods of the irrigation depths applied at farm level implemented a CANFIS to model the human (farmers) thinking, artificial neural network to find
the relationship between the rules which makes up the CANFIS model and genetic algorithm to optimize the hyperparameters of the ANN and CANFIS.

Results and Discussion

The most important inputs for the model developed in this work were obtained from a set of 21 potential inputs following the methodology previously described. Only information about the two expensive (P1 and P2) and the cheapest (P6) tariff periods (hour of the day of each period) as well as the total amount of the irrigation water, weekend and the day of year and week (MI4 and MI6) is required for the forecasted model.

Three forecasting models were developed for rice, maize and tomato (Fig. 1) (Ir, Im and It, respectively). For Ir, the R² values ranged from 0.57 for P4 to 0.91 for P6. However, the SEP values ranged from 36.58% in P6 to 11.95% in P3. Similarly, the R² values for Im and It models ranged from 0.64 in P4 to 0.90 in P6 and from 0.82 in P2 to 0.94 in P6, respectively. The SEP values for these two models ranged from 38.86% in P6 to 12.62% in P5 and from 30.94% in P6 to 12.13% in P5, respectively. For the three models, the highest R² value was obtained in P6 but with the highest SEP value. Contrary, the lowest SEP value was found in P5 for Im and It models and in P3 for Ir model.

![Figure 1. Scatterplots between observed and estimated irrigation volume (test set) applied in each tariff period for Ir.](image)

Conclusions

The forecasting models developed in this work provide the amount of water that each farmer of the WUA is going to apply in each energy tariff period one day ahead. The aggregation of this information for the total number of farmers in the WUA provides the total amount of water one day in advance but discriminated by energy tariff period. In addition, the farms are geopositioned so managers will know in advance which pipes can be overloaded. Thus, with these models, the manager has an overview about the circulating flows in the network the day after but also the distribution of water demand and therefore the power requirements in each tariff period could be estimated. This information can be very valuable for the optimum contracting of the electricity tariff with the supplying company.

REFERENCES

Combined Clustering and Prediction of Daily Water and Energy Usage in Multi-family Residential and Commercial Buildings

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Keywords: demand modelling and management; smart urban water management; water-energy nexus; clustering;

EXTENDED ABSTRACT

Introduction

As the threat of climate change intensifies and water and energy resources are becoming increasingly scarce, the need for novel demand reduction strategies to conserve water and energy resources has increased. Simultaneously, there has been a rapid increase in the use of meters continuously monitoring for water and energy consumption, collecting data with high temporal resolution that can provide insight into customer water and energy usage patterns. Analysis of the usage data can reveal customer consumption trends and the underlying causes of customer usage, which can be used to plan for future demands, as well as devising demand management strategies to reduce customer demands. Previous works in this topic have focused on extracting water end energy usage patterns [1, 2], determining the explanatory variables which influence end user demands [3, 4], and modelling future water and energy demands based on historical usage data [5, 6]. While many works have focused on demand patterns of single-family residential customers, water and energy patterns of the commercial and multi-family residential sectors remain unexplored, and insights drawn from residential sectors may not apply to other building uses. In addition, while few studies have explored joint water and energy consumption patterns, there has not yet been an analysis of the underlying drivers of observed water and energy consumption patterns. This study seeks to illuminate the differences between water and energy consumption in multi-family residential and non-residential buildings, determine if general building characteristics can adequately segment buildings based on their usage profiles, and investigate the accuracy of a parametric and non-parametric model to predict future consumption.

Methods and Materials

Daily water and energy consumption data from 70 buildings on the campus of the University of Texas at Austin (UT Austin) were analyzed in this study. The duration of available data differs between buildings, spanning from 2009 to 2017, with data available for all buildings between April 2014 and June 2017. Buildings range in total floor area (20,372 m² to 69,275 m²), number of floors (2 to 38), and are designated as one of five usage categories: classroom and academic, housing, office and administration, public assembly and multipurpose, and research laboratory. For each building, water and energy consumption data was analyzed on the basis of usage intensity (consumption per building area) in order to compare consumption levels between buildings, and normalized consumption (between 0 and 1 compared to annual minimum and maximum) in order to analyze variability in consumption of a particular building throughout a year.

In the first stage of analysis, characteristic weekly patterns for water intensity (WI), normalized water consumption (WN), energy intensity (EI), and normalized energy consumption (EN) were determined. For each metric and building, all weekly patterns during the year of 2015 were categorized on the basis of consumption level (LOW, MEDIUM, and HIGH) and by level of variation between weekdays and weekends. A one-sided Wilcoxon rank-sum statistical test was used to test if the difference between weekday and weekend consumption was statistically significant (CURVED) or not statistically significant (FLAT) at a p-value of 0.05. After consumption patterns for each week were extracted, characteristic weekly patterns were determined for each building and each metric by taking the median daily values of all the patterns in the most frequent categorization. As a result, each building was characterized by a weekly pattern for each of the four metrics.

Next, clustering was employed to determine similarities of consumption patterns within each metric, and then buildings, which behaved similarly across multiple metrics, were grouped into meta-clusters. Because there is no ground-truth for clustering buildings, multiple clustering methods were utilized, i.e., k-means, k-medoids, and agglomerative hierarchical clustering with ward, average, and complete linkage, and then a consensus function was utilized to create clusters with the most similarity between the outputs of the different clustering methods. Once clusters for each metric were determined, the cluster labels for each metric and building were further clustered to find groups of buildings which behave similarly across all four metrics. Agglomerative hierarchical clustering was utilized to find a partitioning that maximizes the consensus among the results of the different clustering methods, rendering buildings in cluster partitions which behave similarly in at least three of the four consumption metrics.
In the last phase of the analysis, linear regression (parametric) and bootstrap-aggregated decision tree (non-parametric) models were utilized to model daily water and energy consumption in each building. Linear regression models were formulated using the least absolute shrinkage and selection operator (LASSO) method to optimize model formulation for accuracy and sparsity. Input features to each model included building information (use designation, building name, year built, number of floors, and building area), temporal information (whether each day was a week day or weekend, season and whether academic classes were in session), and relevant timeseries information (previous day consumption, previous week consumption, monthly median consumption, and average daily temperature). For each meta-cluster, a specific LASSO model was formed only using data from buildings in each meta-cluster, as well as an overall LASSO model for all buildings. One decision tree model was created using all buildings to train the model, since the data is parsed during the model training process. For each building, 75% of the available data was used for model training, and 25% for model testing.

**Results and Discussion**

As a result of clustering, between two and three clusters were formed for each metric, and 10 distinct meta-clusters were formed, in which buildings behaved similarly across the majority of the four metrics. When segmented by building use designation, except for one of the metaclusters which contained only buildings designated as housing, all metaclusters contained buildings from at least two different building use designations, suggesting that general building use designation alone is not an appropriate indicator of water and energy consumption patterns. Interestingly, results revealed that buildings belonging to the same meta-clusters do not necessarily share similar water and energy consumption patterns, i.e., demonstrating dissimilarities between water and energy usage.

Overall, the bootstrap-aggregated decision tree model outperformed the LASSO models when predicting the daily water and energy consumption for each building, indicating that for this application, the non-parametric model outperformed the parametric model. Among the LASSO models, the models trained using the data from each meta-cluster outperformed the model trained on data from all available buildings, indicating that the partitioning of buildings into meta-clusters provided a useful segmentation based on water and energy consumption. Based on the out-of-bag predictor index obtained from the bootstrap-aggregated decision tree model, which indicates the sensitivity of each input variable on the model outputs, the building descriptors, i.e., building name, use designation, year built, number of floors, and building area, were the least sensitive model parameters, further corroborating the earlier observation that general building information is not adequate to delineate buildings based on their general characteristics.

**Conclusions**

In the context of resource conservation and climate change adaption in urban environments, this work investigated potential dissimilarities in water and energy consumption among commercial and multi-family residential buildings. Further, a novel approach was developed to segment buildings based on their water and energy consumption patterns. The results from this study highlight the value derived from continuously monitoring for water and energy consumption. Although this study analyzed data from university buildings, these buildings are comparable to the typical water and energy consumption published by the United States Energy Information Agency, hence the results of this study apply beyond academic buildings. Future work could explore the effect of seasonality on the makeup of building meta-clusters, or explore additional input features to the predictive models (such as building occupancy) to determine what other building features could help predict water and energy consumption. Overall, the results from this study advance the understanding of drivers, similarities, and prediction methods related to water and energy consumption, and further serve to advance demand side management policies to further resource conservation goals.

**REFERENCES**


Real-Time Control of Stormwater Reservoirs for Flood Risk Mitigation

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Keywords: Real-time operation, Smart urban water management, Control theory, 2-D Routing, 1-D Routing

EXTENDED ABSTRACT

Introduction

Flood control in stormwater systems is typically performed by static operations in hydraulic devices such as gates, pumps and tunnels. Along with the development of non-expensive sensors, wireless communication, microprocessors and microcontrollers, newer opportunities to enhance flood management using control theories become evident. Control theory, although has been applied to combined sewer systems, and drinking water systems ¹, ², is a relatively new technique in urban drainage infrastructure systems ³, ⁴.

Urban drainage facilities as reservoirs, channels, and storage nodes are generally expensive and require useful land. Decision-makers can adapt the existing facilities to meet future climate change and urbanization conditions by properly controlling the flow in the drainage systems through real-time control approaches. The objective of this project is two-fold: (1) develop a linearized extended Kalman-Filter state-space representation of the rainfall-runoff process into (i) cells, (ii) reservoirs and (iii) channels, and (2) compare the efficiency of control strategies obtained by an optimization-based approach and rule-based approaches in a hypothetical study case. We compared the results of a non-convex near-optimal model predictive controller solved as a non-linear optimization problem using the pattern search method with rule-based controls of Passive Control (i.e., all valves opened), Detention Control (i.e., valves fully opened after 6-h of the end of the inflow) and On/Off Control (i.e., valves are fully opened if a water level of 3.0 m is reached). A 25-yr, 12-hr followed by a 10-yr, 12-hr design storm for San Antonio - Texas was tested in a hypothetical case study.

Methods and Materials

The model consists in solving the dynamic wave shallow water equations using an explicit finite difference scheme assuming the kinematic wave simplification for the cells of the watershed (2-D) and diffusive wave for the (1-D) channel sub-reaches. For these systems, the Manning’s equation is assumed as the stage-discharge relationship and for the outlet of the channel, the gradient boundary condition is considered. Flood routing in reservoirs is solved using a forward Euler explicit discretization applied in the reservoir water balance equation. Consecutive linearizations are performed every time-step assuming prior states as operation points. A linear state-space representation of the dynamics coupled with the non-linearities can be written in Equation 1 and the model parameters are presented in Table 1.

\[
x(k + 1) = A(k)x(k) + B(k)u(k) + \Phi(k,x(k),u(k)) \\
y(k) = Cx(k)
\]

where \(A(k) \in \mathbb{R}^{n \times n}\) is the state or system matrix, \(x(k) \in \mathbb{R}^{n}\) is the state vector, \(B(k) \in \mathbb{R}^{n \times m}\) is the input matrix, \(u(k) \in \mathbb{R}^{m}\) is the input vector, \(\Phi(k,x(k),u(k))\) is a disturbance matrix that can account for data noise, cyber-attacks, non-linearities in the models, system-bias and reference setpoints, \(C(k) \in \mathbb{R}^{p \times m}\) is the output matrix where states are measured and \(y(k)\) is the output function and \(k\) is a time-step indicator.

Table 1. Model parameters, states and outputs of each individual system

<table>
<thead>
<tr>
<th>System</th>
<th>Parameters</th>
<th>States</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cells</td>
<td>Green and Ampt Infiltration Parameters, Manning’s coefficient, Cell Resolution</td>
<td>Water Surface Depths in each cell (mm)</td>
<td>Outlet Flow (m³/s)</td>
</tr>
<tr>
<td>Reservoirs</td>
<td>Stage-Area-Discharge Equations</td>
<td>Water Surface Depths (m)</td>
<td>Maximum Water Level (m)</td>
</tr>
<tr>
<td>Channels</td>
<td>Manning’s coefficient, Cross Section Area and Hydraulic Radius Equation, Gridded Bathymetry</td>
<td>Water Surface Depths in each sub-reach of the channel (m)</td>
<td>Maximum Water Level (m) and Outlet Hydrograph (m³/s)</td>
</tr>
</tbody>
</table>
Using a moving prediction horizon of 8 hours, control horizons of 2 hours and control intervals of 1 hour, the performance of the optimization-based control algorithm was compared to the static-rules approach considering four goals: (a) minimization of control efforts and deviations in the reservoir water level, (b) and penalization of solutions where the maximum water level in the reservoir and in the channel were larger than a reference water level as showed in Equation 2.

\[
\min_{\mathbf{u}_t} \sum_{k=0}^{N_p-1} J(x_{t+k}, \mathbf{u}_{t+k}) = \rho_u \| \Delta \mathbf{u}_t \|_2^2 + \rho_r \| \Delta h^r \|_2^2 + \rho_{rm} \left( \max(h^r - h^{ref}_r, 0) \right) + \rho_c \left( \max(h^c - h^{ref}_c, 0) \right)
\]

subject to: watershed, reservoir and channel dynamical system of equations with \( \mathbf{U} \) and \( \mathbf{X} \) the feasible sets of the control signal (i.e., \( \mathbf{u}(k) \in [0;1] \) and \( x(k) > 0 \)). \( J \) is the cost function (e.g., a quadratic function where weights are given for deviations in the control input \( (\rho_u = 10^{-2}) \) and in the water level in the reservoir \( (\rho_r = 0.01) \). Moreover, penalizing functions applied in maximum thresholds for reservoir water level \( (h^r \geq 5.5 \, m) \) and channel water level \( (h^c \geq 1.80 \, m) \) were \( (\rho_{rm} = 0.01) \) and \( (\rho_c = 10^{6}) \), respectively. \( N_p \) is the number of time-steps within a prediction horizon. Figure 1 shows the performance results, parameters assumed and watershed and reservoir dimensions.

**Results and Discussion**

Results indicate that the control approach satisfies the water level in the channel boundary condition while not extensively varying the controls in the reservoir. The model predicts the second event and releases water before to avoid flooding in the channel. All other static-based control rules failed in avoid flooding in the channel.
Conclusions

Real time control strategies can provide peak flow reduction, increase residence time and if properly applied to stormwater facilities, can adapt the existent infrastructure to future demands of climate change and urbanization. For future works, we will apply the mathematical model in a real urban drainage system and assess the potential benefits of this controlling approach for long-term simulations rather than single design storms.

REFERENCES


Numerical Modelling of Flow over Sharp-Crested Rectangular Contracted Weir

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Keywords: modelling and visualisation tools, diversion systems and water transfers, CFD, multiphase flow modelling, weirs

EXTENDED ABSTRACT

Introduction

Weirs are flow control structures that can be used for flow diversion purposes. They are classified according to section geometry or their length in the flow direction. For sharp-crested rectangular weirs, Rehbock [1] derived stage-discharge equations. In contracted geometries, streamlines curve at the approach flow leading to variations in flow structures. For this case, [2] proposed an equation for discharge as a function of the opening rate at the section (ratio of opening width to total width, \( b/B \)). We developed CFD models to test their accuracy in modelling weir flow. For the contracted weir cases, flow structures were visualised upstream of the weir.

Methods and Materials

The interFoam solver of OpenFOAM was selected for modelling because of its ability to handle multiphase flow. It includes forces due to surface tension in the momentum equation to be used at the interfacing cells. The density in each computational cell is calculated considering the ratio of each phase (\( \alpha \)) in it. An additional transport equation for \( \alpha \) is used to define the interphase. We tested a RANS approach with the eddy viscosity concept for two turbulence models which are \( k-\varepsilon \) as defined by [3] and [4] and \( k-\omega \) SST as defined by [5]. Initially, a uniform weir case was modelled by using a two-dimensional approach. Two meshing strategies were applied with varying refinements. For each model, we refined the mesh around the weir structure by defining mesh planes as given in Figure 1(a). As a result, two different meshes included 4,848 and 19,392 computational cells. The weir height was kept constant (10 cm) and the simulations were conducted for 13 unit discharge values \( (q) \) from 0.01 to 0.25 \( \text{m}^3/\text{s} \). The aims in these simulations were to test the abilities of the turbulence models, to see the effect of different meshing strategies and to test the models at varying discharges.

For contracted weir flow, three-dimensional models were developed. The geometries included various opening rates from 0.05 to 0.9 (Figure 1(b)). Three meshing strategies were applied. Starting with a coarse mesh, refinements were applied in rectangular blocks, first at the interface level, then upstream of the weir. The finest mesh in these simulations contained 672,660 computational cells. Apart from testing the ability of the numerical models by validating them with the relation defined by [2], flow structures were visualised upstream of the weir which are related with the weir coefficient definition. Two unit discharge values were selected as 0.025 \( \text{m}^3/\text{s} \) and 0.050 \( \text{m}^3/\text{s} \). For the large discharge, 9 opening rates (0.1 to 0.9) were tested. For the small discharge, an additional opening rate of 0.05 was tested.

Figure 1. Two of the computational meshes used in the study (a) Fine mesh for 2D simulations (b) Finest mesh for 3D simulations at b/B=0.1

Results and Discussion

We compared the results of the two turbulence models in the 2D approach. The \( k-\omega \) SST model managed to solve for the nappe shape more successfully than the \( k-\varepsilon \) model did. Quantifying the results gave close correlations for the dimensions.
defining the nappe shape as given by [6]. Besides, the comparison of stage-discharge relations obtained from the k-ω SST model and the formula of [1] gave better correlations than the k-ε model did. The model, independent of the meshing strategy, predicted the stage-discharge relation within a 1% error limit at all tested discharge values. Details of this part are not presented here to save space. With the knowledge from the uniform weir simulations, only the k-ω SST turbulence model was used in the contracted weir simulations. We compared the resulting stage-discharge relations with the formula of [2] for varying b/B and for two discharge values (Figure 2). Even with the coarsest mesh, the model predicted the relation well. The largest deviations are observed at b/B=0.05 which is out of the range for the empirical formula of [2].

Figure 2. Comparison of the upstream flow depths with [2] for varying b/B (a) for q = 0.025 m$^3$/s (b) for q = 0.050 m$^3$/s

At the finest meshes for both discharge values, visualisation of corner vortices upstream of the weir was achieved by using the Q-criterion [7] (Figure 3 (a)). These vortices behaved in a symmetrical manner. Sourced from the sides, they carried mass and momentum to the centre. They were observed close to the bed. The streamlines curve more at the sides compared to the mid portion of the flume as a result of decreasing streamwise velocity at the sides. Figure 3 (b) shows the simulated free surface for b/B = 0.1 and q = 0.050 m$^3$/s.

Figure 3. (a) Corner vortices upstream of the weir coloured with vorticity contours plotted over computational mesh for b/B = 0.05 and q = 0.025 m$^3$/s. (b) Simulated free surface for b/B = 0.1 and q = 0.050 m$^3$/s

Conclusions

CFD modelling by using the interFoam solver of OpenFOAM coupled with a k-ω SST turbulence model successfully simulated the uniform and contracted flow over a sharp-crested rectangular weir. Nappe shapes over the crest were reproduced accurately. By using the Q-criterion, we could visualize the corner vortices upstream of the weir that occur due to the flow contraction.

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Modelling in Crisis: Mapping the Data Needs and Challenges of Hydraulic Model Development

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Keywords: hydraulic model; water utility; smart urban water management; academia-industry collaborations

EXTENDED ABSTRACT

Introduction

Water infrastructure systems are designed for the provision of services to communities under a set of conditions. When these circumstances change (e.g., due to hazards, crises, or population dynamics), hydraulic models can enable water utilities to quickly evaluate system performance and respond accordingly. These hydraulic models can provide an efficient and cost-effective way to simulate changing conditions, test different response scenarios, and better plan for the future, thereby improving system resiliency. However, hydraulic model development and upkeep are time-consuming processes requiring expensive software, skilled technical staff, and immense amounts of data. Such barriers lead to further disparities between wealthier and/or urban utilities that can afford modelling programs and smaller, rural, and/or resource-constrained utilities that cannot. The amount of data and data processing needed during model development poses significant challenges, especially because the water sector trails other industries in the application of data science and analytics [1]. Further, most modelling literature and technical resources assume the modeller already has all data in the appropriate format and focus only on model building and analysis, excluding data acquisition and processing. While other researchers have put forth steps for improving the use of data analytics in the water sector [2], demonstrated new data management systems and technologies [3, 4], or offered data new classification systems in the hydrology space [5], a classification system for hydraulic modelling data needs does not exist. To address this gap, we developed a hydraulic model of a real-world water distribution system, classified the data needs, documented the data collection and processing stages, and identified key success factors and challenges encountered. While hydraulic models can offer significant benefits to utilities during crisis response, if model development begins at the onset of a crisis, data-related challenges will likely prevent the model from being ready for use before the event is over.

Methods and Materials

The modelled water distribution system is of The University of Texas at Austin campus, a large public university in the southern US that serves ~70,000 people across its 400-acre campus [6]. The university is supplied with water by the City of Austin, Texas but independently maintains and operates its closed water distribution network, therefore serving as a suitable proxy for a small municipal utility or a subsystem of a larger utility. The research team worked closely with campus utilities throughout the model development process to gather data and gain an understanding of system operations.

To map the pathway for efficient data collection, processing, and management in hydraulic model development, we identified the key data sources, types, and processing stages (see Fig. 1). Data types are broadly grouped into three categories: geospatial data, sensor data, and institutional knowledge. Institutional knowledge proved to be particularly critical for delineating system boundaries, deciphering metering systems, and understanding how diverse water users served by the system operate (e.g., residences, labs, onsite power generation facilities, office buildings). Three broad categories of data processing were completed before model-building could begin: performing a mass-balance analysis of system inputs and outputs, preparing in ArcGIS the physical infrastructure data used to build the actual model, and preparing the demand and pressure data that would later be used in calibration and analysis. Model building was completed in the commercial software program Bentley OpenFlows WaterGEMS, while the calibration and analysis were completed using the open-source Python package WNTR[7].

Results and Discussion

Several factors contributed to successful model completion. Working closely in an academic-industry partnership provided key advantages in terms of access to information, personnel, and technology. Our utility partners offered significant assistance with their time, data, and networking connections, and much of the data required already existed. The research team not only had access to commercial software programs (Bentley, ArcGIS), which can be cost-prohibitive for resource-constrained utilities, but also had available personnel, time, funding, and expertise needed to complete the project. Importantly, attracting and retaining talent is one of many critical issues facing the US water sector [8], highlighting the fact that many US utilities do not have the staff or resources to pursue a model development project on their own. Working in such a partnership allowed for the sharing of knowledge and skills needed to develop the model.
Challenges arose surrounding the collection and processing of data. While access to large amounts of data was a critical advantage, siloed data collection efforts across the utility hampered our ability to efficiently collect and process the data due to a wide range of formats and the need to coordinate with several departments. The departmental setup encountered here is typical of many US water utilities, with organizations divided into distinct departments such as operations, customer service, engineering, and finance [9]. Weaknesses of this siloed structure emerge when tasks, such as data collection, cross multiple departments [9], in this case resulting in duplicated efforts, information gaps, and inefficiencies. Further, lack of knowledge transfer within the utility created challenges and delays in finding the appropriate contact to answer questions about issues such as data errors, unclear metering systems, or missing information. Given the importance of institutional knowledge in the modelling process, knowledge transfer among utility managers is critical, especially as concerns grow around retirement among the aging US water workforce [8].

Figure 1. Footprint of data collection and model building processes

Conclusions

Challenges surrounding disjointed data collection efforts, lengthy data processing, and siloed expertise contribute to the most significant obstacle—the time required to develop the model. The project timeline in this case was ~eight months. As such, we recommend utilities incorporate hydraulic model development into emergency response planning efforts, with infrastructure policy and spending to support these endeavours to provide the necessary software, data, and personnel resources. Though hydraulic models can be an important part of a utility’s toolbox, data challenges and time requirements highlight the need to develop and calibrate a model well before a crisis occurs.

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Evaluation and Optimization of Low Impact Development Design for Sustainable Stormwater Management in a Changing Climate
Yasir Abduljaleel and Yonas Demissie

Abstract: The intensity and frequency of extreme storms are increasing due to climate change, posing challenges to stormwater management in highly urbanized areas. Without an adequate and appropriate stormwater system, the increased storms and associated floods continue causing significant damage to infrastructure and loss of life. The Low Impact Development (LID) has become an emerging alternative to the traditional stormwater system to manage the increased stormwater. This study evaluates and optimizes different combinations of LIDs to minimize flows from catchment under past and future storm conditions. The Storm Water Management Model (SWMM), forced by observed and downscaled precipitation from CMIP6, was used to simulate the runoff and apply the LIDs. The results show that permeable pavement alone can reduce the total and peak flows by 52.5% and 31.25%, respectively. Whereas combination Rain barrel, Bio Retention, and Infiltration Trench showed the highest reduction in total flow (65%) and peak flow (51.25). The study demonstrates the identification of the best LID mixes with conventional stormwater management will assist engineers and decision makers to manage the future runoff that was expect to increase by 26.3% over 2040 as compared to the present time.

Keywords: urban watershed; low impact development; stormwater management; Storm Water Management Model (SWMM); climate change.
DYNAMIC RESILIENCE OF WASTEWATER TREATMENT PROCESSES: A PROPOSED APPROACH FOR AGEING ASSETS

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Keywords: Modelling and visualisation, knowledge transfer, dynamic resilience, process stress, decision making under uncertainty

EXTENDED ABSTRACT

Introduction

The UK water companies are coming under extreme pressure from the financial regulator Ofwat due to the Price Review 2019. The review identified that water companies are struggling to secure the long term resilience of their wastewater assets and infrastructure [1]. Evidence of this has also been linked to the privatisation of water companies in 1986, which reduced funding for proactive maintenance [2]. When the lack of maintenance funding is combined with novel, rapidly emerging stressors such as the COVID 19 pandemic and climate change process stresses are generated [3], [4]. These process stresses are the effect of stressors and evident in discrete processes and whole wastewater treatment systems [5]. Therefore, characterising stressors and process stresses independently would offer additional visibility over long term resilience and short-term performance of discrete wastewater processes.

This research proposes dynamic resilience as a methodology for separating and visualising stressors and process stresses. These visualisations are presented as a heat map, combining actual instrument data and existing mechanistic modelling methodologies to present dynamic resilience visually.

Methods and Materials

The methodology proposed in this research is split into three phases. The first phase uses ten years of actual wastewater treatment plant flow data and then cleans it by removing outliers and erroneous values. Data is then clustered using squared Euclidean K-Means clustering, where three clusters are computed, showing a < 20 % classification error at low flow rates. The second phase uses two Activated Sludge Model 1 (ASM1) to perform dynamic simulations, one as a reference or ‘slave’ and the other the ‘master’. The slave condition is based on the standard operating flow characterised by the clustering (cluster 2) in phase 1, and the master varies dynamically about the slave based on the case shown in Table 1. Following simulations, phase three performs computations according to [6] to populate a Self Ordering Window (SOW) for stressors and process stresses.

Table 1. Simulation information for dynamic resilience simulations.

<table>
<thead>
<tr>
<th>Actual wastewater plant scale</th>
<th>Simulation</th>
<th>Duration (d)</th>
<th>Flow range (m³.d⁻¹)</th>
<th>Temperature range (°C)</th>
</tr>
</thead>
</table>

Results and Discussion

The outputs of dynamic resilience simulations are shown in Figure 2, with the stressor on the left and process stress on the right. The stressor simulation output in Figure shows the most concentrated stressor at the highest (> 30,000 m³.d⁻¹), and lowest (< 5,000 m³.d⁻¹) flows, where dilution has a more significant influence over the heterotrophic biomass.
concentration. However, stressors that emerge in the lower flow range is not fully characterised due to the lack of data in this area. Therefore, simulations rely on ‘data richness’, so the range and quality of the data used in simulations. This observation can also be seen in the process stresses but at the higher flow range (> 20,000 m$^3$.d$^{-1}$).

![Figure 2. Stressor (left) and process stress (right) on heterotrophic biomass in an activated sludge process.](image)

The most concentrated process stresses occur between 15,000 and 25,000 m$^3$.d$^{-1}$ where concentrations are highest, and homogenous solids and heterotrophic biomass are most likely to overwhelm downstream processes. A typical operational control methodology would be to waste surplus sludge and reduce the heterotrophic biomass concentration manually. However, with instruments such as Mixed Liquor Suspended Solids (MLSS) becoming ever more reliable, it could be possible to output signals to control the dynamics of sludge management in activated sludge processes using the dynamic resilience methodology [7].

Conclusions

This research evaluates a methodology used for the investigation of dynamic resilience in wastewater treatment processes. The methodology presents dynamic resilience as two visual knowledge bases (SOW), that evaluates a 66-day period, where an actual wastewater treatment process experienced dynamic stressors and process stresses. From the case presented, it can be concluded that modelling and data-driven approaches can be combined to characterise and communicate dynamic resilience (SOW). Although, the simulation outputs are primarily based on the quality and richness of data used for simulations and should be considered part of any future studies. If this can be achieved, MLSS instruments could be used to characterise dynamic resilience in real-time, protecting wastewater treatment processes against emergent stressors.

REFERENCES

Optimisation of London’s urban water infrastructure for managing environmental quality and water supply

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Keywords: smart urban water management, downstream impacts of dams, multi-objective optimisation and control, water pollution control, integrated urban water management

EXTENDED ABSTRACT

Introduction

Water quality is an increasingly recommended goal for the management of water systems [1]. A range of studies have addressed how water resources and river quality interact and can be managed in a joint manner [2,3]. However, considerations of water resources and river quality often omit a critical factor – that wastewater systems exist on the same rivers as water supply systems. Actions taken for water supply, for example to abstract a given amount of water, will interact with the wastewater system, for example by changing the flow and dilution in effluent receiving waters [4]. We have identified that over half of the river catchments in England and Wales have both significant abstractions (>2 million litres/day) on and significant wastewater treatment plant (>100,000 people) discharges into the same rivers [4]. Using the CityWat case study of London’s urban water system [4], we investigate how control policies with increasing levels of complexity can improve river quality and supply reliability. We implement an ‘engineering judgement’ policy and a universal approximator policy, both are then optimised with an evolutionary multi-objective optimisation algorithm. The water quality improvements provided by these optimised policies are also compared against the impact on river water quality of adding additional stormwater storage designed to resemble the Tideway Tunnel. We find that, when evaluated in the baseline CityWat model, the more complex policies, although optimal with respect to the water quality and quantity objectives, do not yield significantly better improvements than the optimised engineering judgement policy. We also find that the policies can be augmented with the construction of the Thames Tideway Tunnel to provide further benefits. This implies that infrastructure investments should consider optimisation of operations to further increase river water quality, perhaps incorporating methods such as [7].

Methods and Materials

In Figure 1 we summarise the workflow used in this study that constitutes a ‘direct policy search’ approach [5].

Figure 1. An illustration of the direct policy search process involved in this study. The engineering judgement policy is referred to as abstraction effluent-dilution (AED), while the radial basis function network (RBF) is the universal approximator used.

The working principle of AED, our engineering judgement policy, is to strategically reduce abstractions when combined sewer overflow events might occur to dilute pollution [4]. This occurs when both reservoir levels are above a given threshold (to avoid compromising reliability of supply) and precipitation is greater than a given threshold (thus, an
overflow may occur). As shown in Figure 1, these thresholds are the parameters that are optimised. RBF networks instead translate state variables (as inputs to the network) into decisions (as outputs of the network) via a parameterised series of operations [6]. The network parameters (weights) are optimised.

### Results and Discussion

In Figure 2A we present optimisation results with the baseline simulation (black cross), optimised AED policy (blue points, an optimised RBF network (orange diamonds) and the ‘raw’ implementation of the AED rule presented in [4] (red circle). We first reiterate the findings from [4], that jointly operating supply and wastewater systems can provide significant water quality improvements (red circle dominates black cross). We next find that optimisation provides clear benefits in refining the AED rule (blue points dominate red circle). Finally, we see that, while the optimised RBF network provides some small improvement on the optimised AED rule, these may be considered marginal in comparison to the other differences. This is important when we consider that the performance of the AED rule converges after 1,000 iterations of the optimisation algorithm, while the RBF network takes more than 500,000. The AED rule also has the added benefit of being simple to understand and thus easier to convey to operators.

### Conclusions

This work highlights the importance of considering both supply and wastewater infrastructure in managing urban pollution. We identify that there is great potential from optimising operations within this scope. We show that designed policies appear to perform comparably to universal approximators, although as the system complexity increases (for example, by greatly increasing the amount of stormwater storage available) the more flexible approach appears to be preferable. Finally, we highlight that, while the Thames Tideway Tunnel will dramatically improve water quality, there is still a great deal of opportunity to further improve water quality via application of optimisation and control methods.

### REFERENCES


Robust technology and policy pathways for urban water security

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Keywords: decision-making under uncertainty, smart urban water management, drought management

Increasingly frequent and severe droughts are straining municipal water resources and jeopardizing urban water security. However, the length and severity of droughts are unknown in advance, challenging short-term drought response, mid-term infrastructure planning, and long-term technology innovation investment. Previous literature in urban water modeling developed strategies to expand and diversify urban water supply portfolios to enhance water resilience cost effectively. This literature has also demonstrated that high-resolution, household-level modeling is necessary to represent the real energy footprint of different water technologies and the integration of centralized and decentralized water solutions. This urban-focused modeling scale, however, does not support the characterization of water availability at extra-urban sources resulting from watershed-wide hydrological processes. Conversely, watershed-scale water resources planning characterizes water variability and stress, supports climate change analysis, but overlooks key distributional and technological aspects.

This project develops a watershed-to-end-user decision support tool for cost-effective, adaptive water augmentation pathways to ensure robustness in many climate futures. The novelty of our work lies in a true multiscale framework that captures the complex system dynamics that link climate impacts to household water security (Fig. 1). A robust, multi-objective, evolutionary-based optimization framework is used to derive the technology portfolio, deployment location, and construction timing that defines a city’s Pareto frontier of water resilience and cost. This work informs generalizable guidelines for effective water supply augmentation in an uncertain climate, for instance demonstrating the advantages of small, incremental, investments to building resilience in response to water stress, over large-scale concentrated capacity expansions. Results guide technology innovation investments for municipal water treatment by explicitly valuing technology attributes that enable resilience to water shortages of varying duration, severity, and intensity, bridging the gap between hydrological prediction and technology innovation. We apply this model to the City of Santa Barbara, California, given the time relevance to city planning efforts, the diversified water supply mix, and the relative isolation of the community, enclosed between the ocean and a mountain range.

Figure 1: watershed-to-end use modeling framework to bridge the gap between climate uncertainty, drought characteristics, and technology attributes.