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The role of deep learning in urban water management: A critical review

Guangtao Fu [a,*], Yiwen Jin [a], Siao Sun [b,*], Zhiguo Yuan [c], David Butler [a]

[a] Centre for Water Systems, University of Exeter, Exeter EX4 4QF, United Kingdom
[b] Key Laboratory of Regional Sustainable Development Modelling, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
[c] Advanced Water Management Centre, The University of Queensland, QLD, 4072, Australia

A R T I C L E I N F O

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A B S T R A C T

Deep learning techniques and algorithms are emerging as a disruptive technology with the potential to transform global economies, environments and societies. They have been applied to planning and management problems of urban water systems in general, however, there is lack of a systematic review of the current state of deep learning applications and an examination of potential directions where deep learning can contribute to solving urban water challenges. Here we provide such a review, covering water demand forecasting, leakage and contamination detection, sewer defect assessment, wastewater system state prediction, asset monitoring and urban flooding. We find that the application of deep learning techniques is still at an early stage as most studies used benchmark networks, synthetic data, laboratory or pilot systems to test the performance of deep learning methods with no practical adoption reported. Leakage detection is perhaps at the forefront of receiving practical implementation into day-to-day operation and management of urban water systems, compared with other problems reviewed. Five research challenges, i.e., data privacy, algorithmic development, explainability and trustworthiness, multi-agent systems and digital twins, are identified as key areas to advance the application and implementation of deep learning in urban water management. Future research and application of deep learning systems are expected to drive urban water systems towards high intelligence and autonomy. We hope this review will inspire research and development that can harness the power of deep learning to help achieve sustainable water management and digitalise the water sector across the world.

1. Introduction

Computer simulations have been playing an increasingly significant role in water management since they were pioneered for the planning and design of water resources systems in the Harvard Water Programme in 1955 (Reuss, 2003). Physically-based models have been developed over many years to represent the Urban Water System (UWS) at varying levels of complexity and widely used to support its planning, operation and management (e.g., IWA, 2019). However, the advance of physically-based models has now essentially stalled due to the challenges in 1) the complexity of UWSs and their interactions with other systems such as ecosystems and climate systems, particularly in capturing human perceptions, behaviours and cascaded impacts, 2) the difficulty in determining modelling assumptions, various processes and model structures and calibrating a large number of model parameters, which can lead to the equifinality problem, 3) data scarcity and uncertainty for high resolution modelling, 4) intensive computing power required by real-time simulation and optimisation and 5) human resources and skills required by model development and maintenance, which makes it difficult to transfer from one UWS to another. On the other hand, machine learning, which is a subset of Artificial Intelligence (AI) allows systems to learn directly from data, examples and experience without pre-defined rules, and is being recognised as a potentially disruptive technology to transform global economies, environments and societies (The Royal Society, 2017). This is happening against the backdrop of transformations required to address pressing challenges, including climate change, biodiversity loss, and the COVID-19 pandemic (Butler et al., 2016). Machine learning will undoubtedly play a key role in the transformation of the scientific discipline and practice in the water sector (IWA, 2019) and help tackle water challenges such as resource efficiency, water supply, water pollution, flooding and drought, contributing to achieving the water-related United Nations' sustainable development goals (Mehmood et al., 2020; Vinuesa et al., 2020).

Deep learning, a subset of machine learning, is regarded as one of

* Corresponding authors.
E-mail addresses: g.fu@exeter.ac.uk (G. Fu), suns@igsnrr.ac.cn (S. Sun).

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driving forces for recent breakthroughs in AI. Deep learning typically uses large, multi-layer artificial neural networks (ANNs) to process large raw data sets, thus also termed as deep networks. Conventional machine learning technologies such as multi-layer perceptron (MLP) neural networks are limited in their ability to process raw data and need domain expertise for data processing before learning. Deep learning helps to solve this problem and enables automatic feature extraction using multiple levels of representations from raw data to more abstract levels (Lecun et al., 2015). Popular deep learning algorithms include Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Autoencoders, Graph Neural Networks (GNNs) and Deep Reinforcement Learning (DRL). These deep learning algorithms have had great success in many areas such as image recognition and have already been applied across a range of industry sectors such as healthcare and finance. In the water sector, the power of deep learning is increasingly recognised with research publications, case studies and applications growing at a rapid speed (Shen, 2018; Makropoulos and Savic, 2019). This is therefore a good point in time to examine the current application of deep learning techniques in urban water management and provide a perspective of deep learning research in advancing water engineering and boosting practical application of Dl techniques to real-world water problems.

This paper aims to provide a critical review of the role of deep learning in the planning and management of UWSs. We will examine the progress of deep learning research and application in key urban water challenges and discuss potential directions where advances in deep learning research are needed to boost the development of intelligent UWSs and the digitalisation process in the water sector. The remaining paper is organised as below: Section 2 introduces the advances in deep learning in comparison to conventional machine learning; Section 3 reviews deep learning application to urban water management, including demand prediction, leakage detection, contamination detection, sewer defect and blockage assessment, wastewater system prediction, urban flooding, asset monitoring and system control; Section 4 presents future research challenges; and conclusions are drawn in Section 5.

2. Advances in deep learning

Historically AI has been through several ‘highs’ and ‘lows’, but recently deep learning is driving the development and application of AI across various industries. Compared to conventional machine learning, deep learning has advanced in many aspects as discussed below.

First, it enables the automatic extraction of features from raw data through multiple levels of representation learning starting from raw data to higher, more abstract levels (Lecun et al., 2015). This eliminates the requirement of feature engineering and domain knowledge to extract features from raw data before they are fed into machine learning algorithms. Further, this improves the learning capacity through amplification of important patterns and suppression of irrelevant variations in the input data, together with the exponential advantage in representing complex non-linear functions from stacking a large number of hidden layers in deep networks (Lecun et al., 2015; Shen, 2018).

Second, the wide adoption of the rectified linear unit activation function, which is simply a half-wave rectifier $f(x) = \max(x, 0)$, and its variations brings the following advantages (Goodfellow et al., 2016): 1) fast training of deep networks due to computation savings from its derivatives (which is 1 for a positive input, otherwise 0) and error terms; 2) solving the vanishing gradient problem due to its higher gradients and linearity; 3) allowing the activation of hidden layers to output true zero values for negative inputs, which leads to sparse representation, a desirable property in representation learning, while the sigmoid activation function can only learn to approximate a zero output, e.g. a value very close to zero but not a true zero value.

Third, the development of the stochastic gradient descent method has made the training of deep networks very efficient, especially for large datasets as it randomly selects a small subset (called a mini-batch) from the training dataset each time, and this process is repeated until the training is converged. The stochastic gradient descent method has been improved with many extensions, such as Adam (Kingma and Ba, 2015) which has gained popularity for deep learning applications. Further, the network training has been made more computationally efficient and effective with a range of techniques including improved architectures, unsupervised pre-training, weights sharing, model compression and distillation, and regularization methods (e.g., dropout) (Lecun et al., 2015; Shen, 2018).

Finally, the success of deep learning is also built on the advances in hardware accelerators such as graphics processing units (GPU) and the availability of large datasets. Data parallelization is a commonly used GPU strategy for accelerating deep learning training, well aligned with mini-batch training. In the strategy, a copy of the network is stored and trained on its own mini-batch of data in each GPU, and its computed gradients and losses are then transferred to the shared processor (e.g., CPU) for aggregation before being rebroadcast to GPUs for parameter updates. This strategy substantially accelerates the training of deep networks for large datasets and improves the learning capacity of deep networks.

Architectures of several popular deep learning algorithms including autoencoders, LSTMs, CNNs, DRL and GNNs and their key features are shown in Fig. 1, together with the conventional multi-layer perceptron ANN. More information about these architectures is provided in Supplementary Material, together with a brief introduction of machine learning and MLP neural networks. Other networks such as Generative Adversarial Networks (GAN) and transformers (Vaswani et al., 2017) are discussed in the literature (Xu and Liang, 2021; Goodfellow et al., 2016).

3. Deep learning applications

Deep learning has been used in a wide range of application areas in urban water management, predominantly covering anomaly detection, system prediction, asset assessment, system operation and planning and maintenance (Fig. 2). Anomaly detection is a type of diagnostic analytics, which aims to identify various failure events (e.g. leakages, contamination events, blockages and cyber-attacks). System prediction and asset assessment provide an understanding of the current and future states of the UWS being hydraulic or asset conditions. System operation, planning and maintenance are optimisation problems aiming to identify the best solutions given specific constraints. Deep learning can play a role in all the key issues in the life cycle of the UWS, with a diverse range of architectures for different problems. At present, however, there are few well-tested deep learning algorithms or products readily available for solving UWS problems. A number of challenges related to data and algorithmic development hinder the development and implementation of deep learning approaches in the water sector (Fig. 2).

The latest applications are reviewed and categorised in detail in the following sections: water supply and distribution systems (Section 3.1), urban wastewater systems (Section 3.2), urban flooding (Section 3.3) and cyber security and asset monitoring (Section 3.4). Reinforcement learning, as an emerging approach for prescriptive analytics, has just started to receive applications in system control and operation, hence it is reviewed in Section 3.5. Gaps in industrial application are discussed in Section 3.6. Table 1 provides a summary of the latest developments of the key problems reviewed, covering the aspects of popular algorithms, data requirements, case studies and advantages. Most problems are related to classification, anomaly detection and regression tasks using images or time series data; CNNs, LSTMs and their hybrids are amongst the most popular models for solving these problems.

3.1. Water supply and distribution systems

3.1.1. Demand forecasting

Demand forecasting is a typical time series forecasting problem,

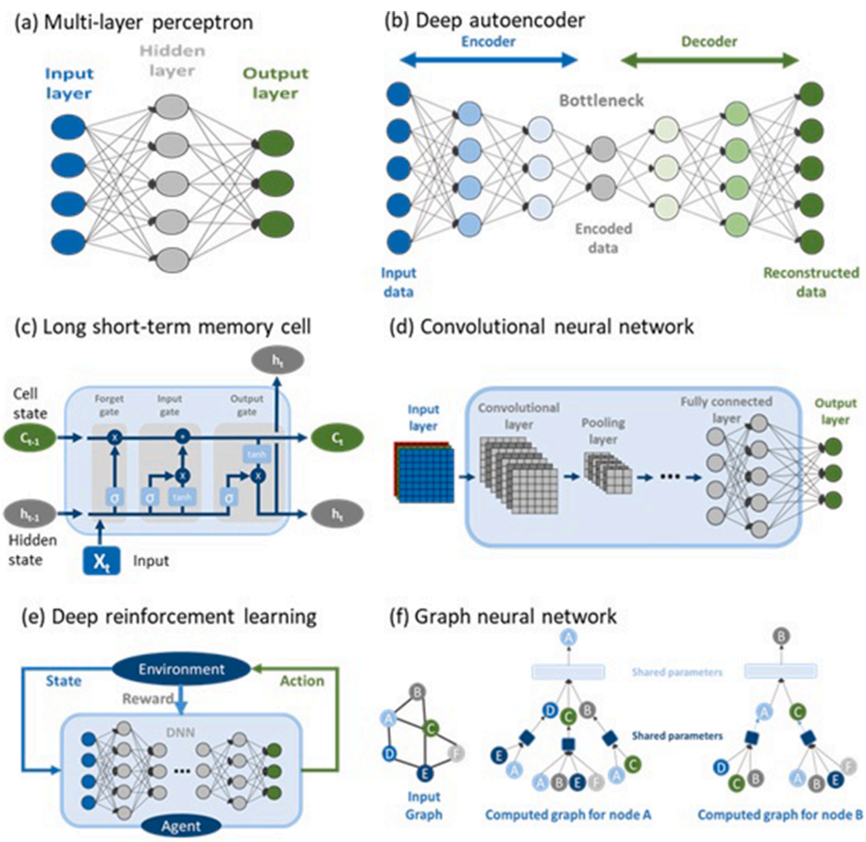

Fig. 1. Multi-layer perceptron neural network and popular deep learning algorithms. (a) a fully-connected three-layer neural network with non-linear activations such as sigmoid, (b) autoencoders typically composed of two symmetrical parts: encoder and decoder, which are trained to reconstruct the inputs by passing through a bottleneck layer and thus a unsupervised learning method, (c) LSTM cells typically consisting of a forget gate, input gate and output gate are the key building block for LSTM networks, which can learn long-term dependencies in time series, (d) CNNs use convolution and pooling to extract higher-order features from input images, (e) DRL combines reinforcement learning and deep learning to train an agent for maximum returns through interaction with the environment, (f) GNNs are designed for graph-structured data to represent diverse relationships via message passing between graph nodes.

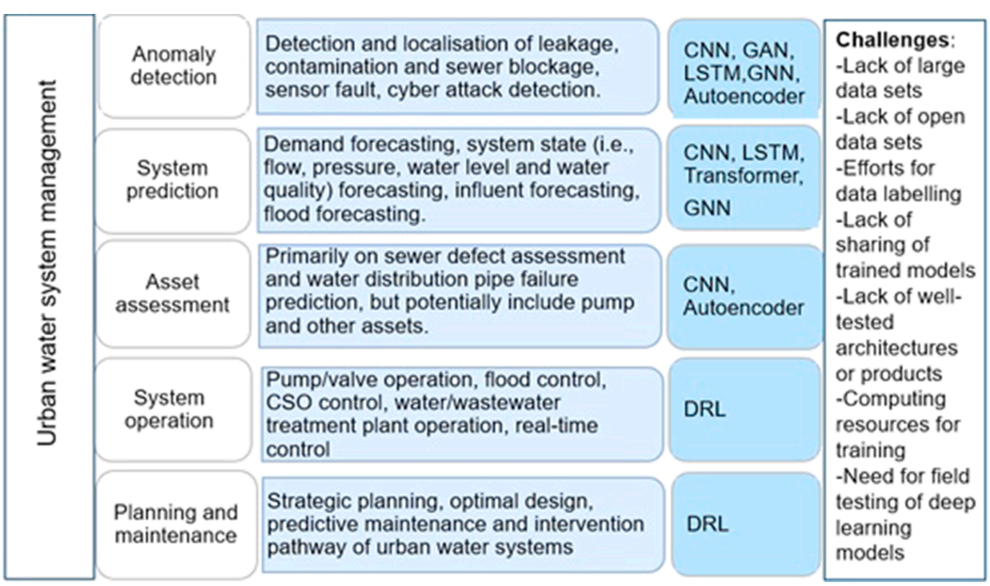

Fig. 2. Key application areas in urban water management and relevant architectures of deep learning.

which is normally regarded as a supervised learning problem, thus LSTM models have been predominantly used to learn the time dependence in historical data.

LSTM models are able to predict hourly or sub-hourly demands by capturing the features from the previous time-step demands without considering other weather and demographic factors. A Gated Recurrent Unit (GRU) based RNN was able to achieve more accurate and reliable water demand predictions with 15 min and 24 h forecast horizons than traditional machine learning models (Guo et al., 2018). The performance of LSTM models in high temporal resolution (i.e., 15 mins and 1 h) demand predictions was further confirmed by Mu et al. (2020) through comparisons with AutoRegressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM) and random forest models, in particularly for handling demand spikes. LSTMs are able to predict the daily water demand profile at a 1 h time step in an online learning setting with a few days learning from scratch, so they can be used to generate demand predictions for optimising the next day pump operation, which is particularly useful for small water suppliers with limited

Table 1
Application of deep learning in urban water systems.

System	Problem	Popular algorithm	Data requirement	Case study	Open access dataset	Advantage
Water supply and distribution systems	Short-term demand forecasting	LSTM, hybrid CNN-LSTM	Historical demand data, weather and demographic data	Pilot study in Cairo (Nasser et al., 2020)	–	High temporal resolution (15 mins), handling peak demands
	Leakage detection and localisation	1-D and 2-D CNNs	pressure, flow, acoustic and vibration signals	Real-world network case studies, synthetic data from hydraulic models (e.g., Javadiha et al., 2019; Zhou et al., 2019b)., laboratory test beds (Shukla and Piratla, 2020; Cody et al., 2020)	The BattLeDIM 2020 dataset (Liu et al., 2019)	High accuracy, automatic detection and alarm generation
	Contamination detection	LSTM, hybrid CNN-LSTM, GAN, GNN	Water quality (e.g., chlorine, pH, conductivity, turbidity) and flow rate	Real-world sensor datasets (Li et al., 2019a)s	The GECCO challenge dataset (Muharemi et al., 2019) and The CANARY data set (U.S. EPA, 2012; Z. L. Li et al., 2022)	Considering correlations of multivariate time series
	Water pipeline inspection	Autoencoders	CCTV videos	Pipeline field survey (Jiao et al., 2021)	–	High efficiency in processing videos
	Cyber attack detection, soft sensing	LSTM, autoencoders and GNN	System state variables	Test-bed systems (e.g., Deng and Hooi, 2021), synthetic data, benchmark networks (e.g., Taormina and Galelli, 2018)	The BATADAL dataset (Taormina et al., 2018)	Accurate prediction
	Real-time control such as pump scheduling	DRL	Demand data, hydraulic models	Benchmark networks - Anytown and D-town (Hajgató et al., 2020)	–	Automation and robust control in an uncertain environment
Urban wastewater systems	Sewer defect detection and assessment	CNNs (e.g., R-CNNs and YOLO)	CCTV videos	Sewer surveillance data (e.g., Hassan et al., 2019; Kumar et al., 2020b; Wang et al., 2021b)	The Sewer-ML dataset with 1.3 million images (Haurum and Moeslund, 2021)	Automatic assessment and decision support
	Prediction of water quality, flow and depth including CSOs	LSTM	Rainfall data, observed flow and water depth data	Pilot WWTP (Dairi et al., 2019), real-world sewer systems such as Drammen, Copenhagen (Zhang et al., 2018a)	–	Improved predictive accuracy and generalisation
	Flood forecasting	CNNs, U-NET	Urban catchment data, rainfall data, flow	Synthetic data generated using flood models (Guo et al., 2021b; Li et al., 2021)	Flood risk maps such as those from the UK Environment Agency. The data and code in the study (Guo et al., 2021b) are publicly available.	Fast and accurate prediction, up-scaling
	Data processing of urban catchments, weather and flood data	CNNs, autoencoders	Aerial photography, LiDAR data, satellite data and radar weather data	Real-world urban catchments and cities (Yang and Cervone, 2019; Iqbal et al., 2021)	Global and local data sets at varying resolutions	More accurate, higher-resolution data, automatic data processing
	Soft sensing, surrogate modelling	LSTM, hybrid CNN-LSTM and GNN	System state variables	Test-bed systems, synthetic data, benchmark networks (e.g., Cheng et al., 2020)	–	Fast and accurate system monitoring and prediction
	Flood control, CSO control, wastewater plant operation	DRL	Rainfall, hydraulic models	Real world networks, Benchmark Simulation Model, laboratory plant (e.g., Bowes et al., 2021; Hernández-del-Olmo et al., 2016 & 2018)	The case study data and code from the study (Bowes et al., 2021) are publicly available.	Automation and robust control in an uncertain environment

historical data (Kühnert et al., 2021).

With the increasing adoption of smart water meters, LSTMs can be used to provide reliable water demand predictions based on water consumption data and thus offer opportunities for water utilities to optimise resources and operations. Nasser et al. (2020) showed that the LSTM outperformed SVMs and random forest models using aggregated 10-minute smart metre data of 2–20 households from a pilot study in Cairo, however, it fails to predict the peak demands.

Recent studies showed that hybrid deep learning models achieve high performance in daily water demand predictions when weather and demographic factors are considered. Du et al. (2021) developed a hybrid LSTM model for daily water demand forecasting, which combines two LSTMs with discrete wavelet transformation and principal component analysis to pre-process the raw data: one LSTM uses de-noised demand sequence to predict the baseline trend, and the other LSTM uses the demand residuals to predict the artificial noise, while the principal components of weather and holiday factors are also used as input to both networks. Hu et al. (2019) applied the CNN to extract the features of the previous five-day water consumption data and the daily maximum temperature, before they are passed to the bi-directional LSTM model for daily water demand prediction, and the hybrid CNN-LSTM model achieved higher predictive accuracy than LSTM, Bi-LSTM and CNN. Data preprocessing techniques such as time series signal decomposition can facilitate feature extraction and thus improve the predictive accuracy of GRU-based models (Hu et al., 2021).

In summary, previous research shows the LSTM and its hybrid algorithms are the most popular deep learning approach for water demand forecasting and they outperform traditional machine learning methods due to the capacity in capturing temporal dependence. However, applications are limited to short-term demand forecasting with the forecast time step of less than one day.

3.1.2. Leakage detection and localisation

Deep learning approaches for leakage detection and localisation can be roughly grouped into two categories: classification and prediction-based approaches. The classification approach trains deep learning models on labelled data (i.e., pressure, flow, acoustic and vibration signals) to identify normal and abnormal events. A major disadvantage of this approach is the effort in collecting and labelling a large amount of data, though hydraulic models can be used to generate synthetic data for training (e.g., Javadiha et al., 2019; Zhou et al., 2019b). The prediction-based approach generally uses deep learning models to predict the system states (pressure or flow) and then classify the residuals between predicted and measured state values using a threshold. In the literature, CNNs are the predominant deep learning approach to leakage detection and localisation and in most studies they are trained using labelled data to classify normal and abnormal events. There are a few prediction-based deep learning approaches in the literature, and one example used a LSTM to predict water demand, which achieved a high detection accuracy, high true positive rate and low false positive rate (Wang et al., 2020). The following review will focus on the CNNs-based classification approach, organised by data sources, i.e., pressure/flow data, acoustic/vibration and their input format.

CNNs have been trained on pressure data for multi-point leakage detection. Six CNN models were trained by Fang et al. (2019) using pressure data, which were collected from a Water Distribution System (WDS) in a laboratory platform and manually labelled for leakage events. The best CNN model achieved an accuracy of 97.33% and 92.11% when 21 and 8 pressure sensors were used, respectively. It was observed that accuracy decreases for multi-leak events, from 96.43% for single-point leakage to 91.56% for three-point leakage. The high accuracies achieved are partially due to the high number of sensors used (between 8 and 21 sensors for a network of 400 m), which is impractical for real-world networks.

The idea of using hydraulic models to generate pressure data with a large number of leak events for training was proposed by Zhou et al. (2019b). Hydraulic models have been used for synthetic data generation before, however, data were generated under normal conditions with no or limited number of leakage scenarios. Zhou et al. (2019b) developed a fully-linear DenseNet to effectively extract leakage features in the WDS so that leaks could be localised to the pipe level. Once trained off-line using a large number of leakage signals (e.g., 200 leak events per pipe), the model was used online to locate leaks using real-time pressure data from in situ or mobile loggers. Results from two WDSs show that the model is able to accurately identify the pipe where leaks occur. Similarly, synthetic leakage data were used for CNN training (Javadiha et al., 2019) and autoencoder training (Fan et al., 2021). However, they produced pressure residual maps from the differences between pressure measurements provided by sensors and pressure estimates obtained from a hydraulic network model, and then converted the maps to 2D images to train CNNs for leakage localisation. The pressure residual maps characterise the impact of all possible leak localizations but might be affected by uncertainties in hydraulic modelling. Indeed, the impacts of hydraulic model uncertainties, such as random demands and leak sizes, were considered when synthetic data are used for leakage localisation (Javadiha et al., 2019; Zhou et al., 2019b) and leakage detection (Fan et al., 2021).

Acoustic and vibration signals, which are generated by leaks from pressure changes by cracks when elastic waves are propagated through the pipe, can be learnt by CNNs (Kang et al., 2018; Nam et al., 2021) or autoencoders (Cody et al., 2020) to classify normal or abnormal events. Kang et al. (2018) trained and tested a one-dimensional CNN on a dataset consisting of 1580 normal and 660 abnormal 10-second signals pairs, collected from six accelerometer sensors in a looped WDS in Seoul. The dataset was segmented into 1-second signals and labelled for learning. The detection accuracy was improved by data preprocessing through a general denoising method and a bandpass filter for extraction of leak frequency bands or by integrating a SVM into the CNN to provide a diverse feature classification. In the study of Shukla and Piratla (2020), a CNN model adapted from a pre-trained AlexNet network was used to detect leaks on polyvinyl chloride (PVC) pipelines using scalogram images, which are the wavelet transformation of raw acceleration signals without any preprocessing such as noise reduction or application of filters, from an experimental pipeline test bed, and it can predict leakage sizes and locations, in addition to leakage detection. An autoencoder was applied by Cody et al. (2020) based on spectrograms of acoustic data, which uses a 2D CNN for preprocessing of the spectrograms, followed by a variational autoencoder layer to reach the latent layer. The autoencoder was tested using data collected from a laboratory test bed that was connected to a municipal water system via a service line, thus ensuring realistic baseline variation, and it achieved an accuracy of 97.2% for detecting a 0.25 L/s leak. In addition to leakage detection, the autoencoder model has been used to detect the anomalies of the internal surface of water pipelines using CCTV video (Jiao et al., 2021).

The input data format for CNNs has been studied in the literature as it is closely related to feature extraction and thus affects the detection accuracy. As CNNs are well-suited for processing 2D images, previous research attempted to convert one-dimension pressure signals to 2D images for leakage detection and localisation (Javadiha et al., 2019; M. Zhou et al., 2019a), or convert acoustic signals to 2D images (Cody et al., 2020). However, this process may lead to the loss of some useful information and increase in computational costs (Zhou et al., 2021). Thus, one-dimensional CNNs (1D CNNs) are now often employed to directly process original 1D time series signals for leakage detection and localisation. For example, 1D CNNs were used extract features directly from vibration signals (Kang et al., 2018) and pressure data (Fang et al., 2019; Zhou et al., 2021). However, the raw signals (i.e., acoustic data) could be transformed through different techniques such as Fast Fourier Transform (FFT), wavelet transforms, and time-domain features, before being input to a 1D CNN for training. Rahimi et al. (2020) showed that converting the acoustic signal to a 1D image through FFT can effectively help detect leakage in plastic and composite water tanks and thus significantly improve the performance of CNNs. In this direction, a new advance is the development of a novel time-frequency CNN by Guo et al. (2021a), which can capture the leakage spectrograms through three different resolutions, i.e., high-frequency, high-time, and transitional time-frequency resolutions.

Attempts to apply CNNs to other aspects of leakage detection have been made such as transfer learning to fine tune CNNs building on the knowledge from a pre-trained CNN model such as AlexNet (Shukla and Piratla, 2020; Zhou et al., 2021), and leakage zone identification using spatial clustering and CNNs (Hu et al., 2021b). Further efforts have been made to use satellite images for leakage detection by training a CNN model. However, such approaches do not support real-time continuous monitoring and are more suitable for large leaks, and tend to result in high rates of false alarms owing to the resolution of the satellite images (Shukla and Piratla, 2020).

In summary, CNNs are the only widely used deep learning method for leakage detection using either flow/pressure data or acoustic/vibration data, and the focus has been on how to best capture anomalous signals by improving training data size or data format transformation. However other deep learning algorithms such as LSTM, GAN and GNN should be explored to capture spatial and temporal relationships from multi-source and multi-site data.

3.1.3. Contamination and water quality

One challenge in anomaly detection in high-volume data is the unbalanced data problem due to the typical low frequency of anomalous events and highly variable and dynamic sensor data. This was tackled in the water quality anomaly detection competition series organised at the Genetic and Evolutionary Computation Conference (GECCO), where the real-world drinking water quality dataset used is extremely imbalanced with the ratio of abnormal events being 1.452% only. When tested on this dataset, a balanced LSTM model, which includes a fixed rate of 10% positive samples in each batch of training data, was shown to achieve a higher F1 score (a combined measure of the model's precision and recall) of 0.7819 than the standard LSTM and other machine learning methods (Qian et al., 2020). Using the same data set, Muharemi et al.

(2019) also showed that the LSTM and a 'deep' network (with three hidden layers of six neurons each) have a high performance with an F score of 0.9 outperforming traditional machine learning methods except SVM, when all methods were trained using time series cross validation. However, all the methods generalized badly to a new data set. Chen et al. (2018a) used a 1D CNN, consisting of two convolutional, two max-pooling layers and two fully connected layers (each with 128 neurons) to extract the features in raw water quality data before they are fed into a bi-directional LSTM, and they claimed the CNN-LSTM approach was suitable for water quality detection problems but no performance results were provided. In general, deep learning methods outperform traditional machine learning methods in terms of feature learning accuracy and fewer false positive rates, though a fair comparison between different studies is difficult due to different datasets, models and parameters employed (Dogo et al., 2019).

The broad range of possible anomaly types poses another challenge in water quality anomaly detection. Water quality data from in-situ sensors are likely to encounter the following common anomalies with decreasing priority: large sudden spike, low variability (persistent values), constant off-set, sudden shift, data oscillation, drift and small sudden spike (Leigh et al., 2019). Rodriguez-Perez et al. (2020) applied LSTMs to classify different types of river water quality anomalies considering two parameters (i.e., turbidity and conductivity) separately, and they found that sudden spikes and small sudden spikes are more likely to be detected when the LSTM model is trained using 'normal' water quality data, whereas long-term data drift is more likely to be detected when anomalous data are included in the training dataset. They concluded that the LSTM model considerably minimized false detection rates in comparison with the regression-based ARIMA approach, though its performance varied for different water quality parameters and monitoring sites.

Water quality anomaly detection has made use of multivariate time series data from water quality sensors. This is distinct from leakage detection which normally relies on flow and pressure data or acoustic signals. The GECCO challenge dataset includes chlorine oxide, pH value, redox potential, electric conductivity, turbidity, temperature and flow rate, so all these parameter data are input into an machine learning model to identify anomaly events directly (Muharemi et al., 2019). However, this approach needs labelled data for training. In another direction of research, machine learning models can be used to predict a water quality parameter value using other parameter data so the residuals between estimated and observed data can be used for outlier classification for each parameter, which can then be fused for anomaly event detection (Arad et al., 2013; Li et al., 2022b). To fully exploit complex multivariate correlations, GAN-based approaches have been developed as they can consider the entire variable set concurrently in order to capture the latent spatio-temporal interactions amongst the variables. It has been shown that GAN models are well-suited for complex anomaly detection problems and have superior performance over existing unsupervised methods when the generator and discriminator are both represented by a LSTM network (Li et al., 2019a). GNN-based approaches can effectively learn the relationships between multiple sensors and allow users to deduce the root cause of a detected anomaly. Experiments on two real-world sensor datasets show that a novel attention-based GNN approach detects anomalies with higher accuracies (including precision, recall and F1) than baseline approaches including deep autoencoders, LSTM, and GAN models (Deng and Hooi, 2021). More importantly, GNN (in particular attention-based networks) can provide a certain level of interpretability for the detected anomalies as attention weights indicate the importance of the neighbouring nodes (sensors) in modelling the node's behaviour.

In summary, the availability of open quality data boosted the application of various deep learning methods (LSTM, GAN, and GNN) to contamination detection, however, their performance needs to be further tested on measured data which represent the multivariate complexity in the real world.

3.2. Urban wastewater systems

3.2.1. Sewer defect and blockage

The internal surface condition of sewers is traditionally assessed manually using Closed-circuit television (CCTV) videos by professional inspectors. This process is labour-intensive and time-consuming. In recent years, CNNs have been widely used for automated sewer defect detection, more specifically for the following tasks: 1) image classification: classifying CCTV images according to contained defects; 2) object detection: identifying the types of defects and their locations; 3) semantic segmentation: labelling the pixels belonged to a defect.

Image Classification. Kumar et al. (2018) trained a series of binary-classification CNNs, each for a single type of defect only. To reduce the time required for training, a single CNN was set up to classify the frames into multiple defect classes by Meijer et al. (2019). Apart from sewer defects, Gutierrez-Mondragon et al. (2020) trained a CNN to identify the obstruction level of sewer pipes. Some popular CNNs in the computer vision domain have been tested on sewer defect detection. For instance, Hassan et al. (2019) fine-tuned AlexNet to extract feature maps from sewer frames. To tackle the imbalance between the datasets of defective and normal pipes, a hierarchical classification structure was used: a high-level classification that classifies normal and defective pipes, followed by a low-level classification that classifies defective pipes into specific types of defects (Xie et al., 2019). Similarly, ResNet18 was adopted by Li et al. (2019b) in the hierarchical structure, which contains residual learning operations to enhance learning process (He et al., 2016). Chen et al. (2018b) used a lightweight network called SqueezeNet for high-level classification, and InceptionV3 for low-level classification due to its relatively high recognition ability.

Various techniques have been considered in CNNs to improve efficiency and accuracy. For example, Chen et al. (2019) improved a binary classification CNN for sewer defects by introducing a cost-sensitive activation layer and Cost-Mean Loss. Kumar et al. (2020a) leveraged a CNN interpretation technique called class activation mapping to visualize the learnt weights and then guide the adjustments of CNNs. Moreover, the text shown in the sewer inspection frames normally includes the pipe property and the driving distance from the starting point, which reveals the location of the frames. Therefore, CNNs were used to extract the distance and thus determine the location of defective frames (Moradi et al., 2020).

Object Detection. Prior research aimed to detect not only the types of defects, but also the locations of defects in the frames. Further, multiple types of defects may be contained in the same image, which is a difficult issue for classification models. Object detection models can be applied to solve these issues. Current CNN-based approaches can be mainly divided into two groups: 1) region-based or two-stage detection, which means that regions of interests need to be first extracted by a separate network, 2) one-stage detection, in which no region is required. A two-stage detection method called faster R-CNN were used by Cheng & Wang (2018) and Zhang et al. (2018d). Specifically, Cheng & Wang (2018) used the Zeiler-Fergus network as the CNN part for feature extraction, while Zhang et al. (2018d) used VGG-16 to extract features. In contrast, Yin et al. (2020) used a one-stage network called YOLOv3 for real-time automated sewer defect detection. Kumar et al. (2020b) carried out a comparison of three methods, i.e., YOLOv3, faster R-CNN and single-shot detector, and concluded that YOLOv3 is suitable for onsite detection due to its faster speed, while faster R-CNN is more suitable for offsite review due to its superior detection accuracy. Moreover, in Wang et al. (2021a), defect tracking was proposed based on the detection results of a faster R-CNN to facilitate the counting of the number of defects across consecutive video frames.

Semantic Segmentation. Semantic segmentation models can annotate each pixel of detected objects in the images. Kunzel et al. (2018) applied a two-data-stream CNN named Full-Resolution Residual Network (FRRN) to unrolled and stitched CCTV frames for automatic detection and classification of defects and structural elements in sewer pipes. Pan et al. (2020) segmented sewer defects by adding feature reuse and attention mechanism blocks in CNN-based U-Net. Wang & Cheng (2020) integrated a deep CNN with dilated convolution called DilaSeg with a recurrent neural network (RNN) formulated from dense conditional random field (CRF), where DilaSeg works for feature map extraction and CRF-formulated RNN is responsible for resolving the local ambiguities. Furthermore, sewer condition assessment was proposed by Wang et al. (2021b) to evaluate the severity of operation and maintenance defects, based on semantic segmentation results.

In summary, the superpower of CNN-based algorithms in image processing has been leveraged for sewer defect detection, with YOLO and faster R-CNN showing a clear advantage over other deep learning and traditional machine learning methods, however, only a few types of defects were considered in most studies so future work should investigate more defect types aiming to provide a condition assessment for sewers.

3.2.2. System state prediction

Recent research showed that GRU and LSTM models have a better performance than traditional ANNs in predicting CSO water depth. Using monitored water depth and rainfall data in a real-world case study, the deep learning models improve the generalisation for multi-site CSO prediction by leveraging spatio correlations across multiple sites in addition to making use of temporal trends at individual sites (Zhang et al., 2018a).

Sewer flow and water depth are commonly predicted based on rainfall data and observed flow and water depth data at previous time steps. In the case of predicting CSO water levels, Palmitessa et al. (2021) investigated the predictive accuracy of LSTM networks in scenarios of limited or missing antecedent observations, and they found that LSTM networks were capable of compensating for the missing observed data with the other input data (e.g., time of the day and rainfall intensity). Because infiltration process is not negligible, use of groundwater level data as an additional input can improve the performance of LSTMs in predicting the flow at various sites of a sewer system (Sufi Karimi et al., 2019).

Application of predicted system behaviours to operation practices have been demonstrated in the literature. The high predictive capability of LSTMs in sewer flow modelling was used for improving in-sewer storage control in order to reduce overflow at the WWTP (Zhang et al., 2018b), and for the operation of the WWTP (Zhang et al., 2018c). Dairi et al. (2019) developed a hybrid RNN-RBM method to predict multivariate water quality influent time series, which was then used for anomaly detection. This approach can help monitor and detect abnormal influent conditions that can affect the operation of WWTPs, thus improving operational resilience. Amongst six GRU and LSTM variants, the LSTM model shows an overall high accuracy in predicting the influent flow, influent temperature, influent biochemical oxygen demand (BOD), effluent chloride, effluent BOD, and power consumption in a WWTP (Cheng et al., 2020). The COD mass flow in the WWTP was predicted based on 1-minute measured data for temperature, pH, NH3-N, sewage inflow and influent COD, with a hybrid CNN-LSTM model, which can support the development of feedforward control systems for aeration and chemical dosing (Wang et al., 2019).

Similar to demand prediction, RNN and LSTM models have been predominantly used for prediction of the key state variables of urban wastewater systems including water quality, flow and water level at various components and CSOs in both the sewer system and the WWTP. However, more work is needed to identify the complex relationships between variables in both wastewater system and demand prediction.

3.3. Urban flooding

3.3.1. Data processing for hydrodynamic flood modelling

The predictive accuracy of hydrodynamic flood models significantly relies on high resolution data (e.g., catchment and weather data), however, the availability of such data is a main challenge in many cities. Deep learning can play a key role in processing big data of aerial photography, LiDAR data, satellite data and radar weather data to generate high resolution, multispectral data for improving urban flood modelling (Pollard et al., 2018).

Deep learning has gained wide application in remote sensing, due to its power in information extraction from raw images. The most commonly used models are CNNs, RNNs, autoencoders and their hybrids. Applications include image segmentation, land use classification, terrain attribute extraction, object identification (e.g. building, bridges), and multi-source image fusion, however, a detailed review of these areas is out of the scope of this review and more information can be found in Shen (2018) and other reviews in the field of remote sensing and hydrology. Processing raw images with deep learning provides high-resolution urban catchment data, particularly useful for areas with low-resolution images. The availability of semantic information from CNN-based classification enables large-scale 3D city reconstruction (Zhu et al., 2017), which could be potentially used for flood damage assessment, flood emergency planning, and real-time flood decision analytics. Notably, remote sensing imagery has been used for disaster assessment during a flood event using deep learning (Yang and Cervone, 2019; Iqbal et al., 2021).

Deep learning can be applied to provide high resolution weather and flood data where no such data are available. CNNs have been used to improve the accuracy of rainfall nowcasting at high spatial resolution (Barrington et al., 2019), estimate flood extent using images from unmanned aerial vehicles (Hashemi-Beni and Gebrehiwot, 2021) and monitor water depth using CCTV videos (De Vitry et al., 2019) and crowdsourced photos (Alizadeh and Behzadan, 2021). Accurate representation of rainfall and flood depth at high resolution provides high quality data to calibrate urban flood models.

3.3.2. Urban flood forecasting

In the last several years, deep learning has been extensively studied for river flow and flood forecasting and fluvial flood inundation in hydrology (Kabir et al., 2020; Xu and Liang, 2021; Xu et al., 2020), however, it has not received much attention in urban pluvial flood predictions mainly due to the challenge in learning large datasets of high resolution urban catchment features (Li et al., 2021) and lack of measured flood and water infrastructure data. Flood data in urban areas are generally unavailable compared to the availability of long river flow records such as the large data set of 30 years from several hundred basins (Nearing et al., 2021).

A few studies have showed that CNNs are capable for urban flood prediction. One example is a hybrid model developed by (Guo et al., 2021b) to predict the maximum flood depth for rainfall events. This hybrid model uses a convolutional autoencoder to process the urban catchment data and a feedforward fully connected neural network, which is attached to the latent layer of the autoencoder, to process the hyetograph data. Five terrain surface feature maps including elevation, slope, aspect, curvature and masque, are divided into patches to train the CNNs. The model provided accurate predictions for areas of different characteristics (e.g., flat, steep, around buildings, upstream and downstream) when tested on three case studies. The autoencoder model was later improved by adding skip connections from encoding blocks to decoding blocks, applying average pooling in the encoding part and converting rainfall time series into 9 event characteristics (Löwe et al., 2021). CNNs were also tested for the assessment of urban surface water flood risks using catchment data and outperformed traditional machine learning methods such as Naïve Bayes (Li et al., 2021).

In summary, deep learning has found more applications in data processing than in flood prediction, with most algorithms based on CNNs. However, it is worth investigating other architectures such as hybrid CNN-LSTM algorithms to improve flood predictive accuracy in the future.

3.4. Cyber security and asset monitoring

Water and wastewater infrastructure is considered as one of the main targets for cyberattacks amongst 16 critical infrastructure systems by the US Department of Homeland Security, and it is not uncommon to see cybersecurity incidents reported. For example, 25 cyber security incidents were reported in 2015 alone in the US, making the water and wastewater sector the third most targeted sector after manufacturing and energy sectors (Hassanzadeh et al., 2020). Thus the security of urban water infrastructure has drawn increasing attention in the practical and research communities.

Deep learning methods, including LSTM, autoencoders and GNN models, have enabled significant improvements in cyber-attack detection in high-dimensional datasets. A LSTM model was developed to detect cyber-attacks in a water treatment system, and was trained using data under normal conditions and evaluated using 36 different attack scenarios (Inoue et al., 2017). Autoencoders were also tested with 14 attack scenarios considering various components such as pumps, tanks and controllers in a benchmark water distribution system (i.e., C-Town), and results showed autoencoders substantially outperform traditional machine learning methods, i.e., XGBoost and LightGBM (Taormina and Galelli, 2018). Erba et al. (2020) evaluated different evasion attacks which modify anomalous data to evade deep autoencoder-based detectors. Using two datasets from water treatment test-bed systems with various attack scenarios, a novel attention-based GNN approach was shown to outperform a set of baseline models including LSTM, autoencoders and hybrid models (Deng and Hooi, 2021). Tsiami and Makropoulos (2021) showed that a convolutional GNN was able to leverage the inherent interdependencies of the SCADA data for cyber-attack detection in water distribution systems and interpret model predictions based on feature interdependencies. A deep generative model with variational inference was developed for cyber-attacks based on autonomously learnt normal system behaviours from raw observations such as pump pressure and tank water level (Chandy et al., 2019).

Research and innovation in UWS development should be prioritised to mitigate the substantial risks and vulnerabilities that are created from water digitalisation and the uptake of AI technologies in the water sector. It is particularly urgent to develop cybersecurity best-practice guidelines for UWSs, as part of critical national infrastructure. As explained above, deep learning-based methods, including LSTM, autoencoders and GNN models, could be used to increase cybersecurity and enable significant improvements in cyber-attack detection in high-dimensional datasets. For example, adversarial machine learning has been used to fool detection algorithms (Erba et al., 2020], and insight gained could help develop new deep learning detection methods. These methods, however, need to be tested with more cyber-attack scenarios from the real-world UWSs and consider network traffic data (Taormina et al., 2018).

In addition to anomaly detection, deep learning can be developed as a soft sensor or a surrogate model for water asset monitoring. It is common that measurements in water systems are not available due to either no sensors or faults in the cyber system. Soft sensing has been considered as a solution to replace missing measurements (primary measurements) with predicted values based on the other measurements (secondary measurements) available. 2D CNN and LSTM models were trained using one-minute operation data collected from 100 sensors for one year in a water treatment works and their results were combined using multiple linear regression to achieve a significantly higher predictive accuracy (measured by root mean square errors) than individual CNN and LSTM models (Cao et al., 2018). This ensemble model can be used as a soft sensor to predict flow and water level, in case of any missing data from the 100 sensors. Similarly LSTM models can also provide accurate predictions for key variables in wastewater treatment plants (WWTP) (Cheng et al., 2020). The use of deep learning models as a surrogate of hydraulic models was also demonstrated using a deep belief network, which is a variant of multi-layer perceptron networks with stacked restricted Boltzmann machines (Wu and Rahman, 2017). A GNN based on K-localized spectral filtering was used to re-construct the pressures at all nodes from a limited number of nodal pressure measurements, and this approach was shown achieving a relative error below 5% on average with an observation ratio of 5% when tested with three benchmark networks (Hajgató et al., 2021). This shows the promise of using GNNs as a soft sensor or a surrogate model for pressure monitoring across the entire network. In addition to system states, GNNs were used to fill missing pipe attribute data (i.e., diameters and materials) in wastewater networks (Belghaddar et al., 2021). A CNN model was used to monitor the changes of the Fat-Oil-Grease layer and various hydraulic processes in the pump sump in a wastewater system (Moreno-Rodenas et al., 2021), and could potentially be used to predict pump sump failure.

In summary, cyber security and asset monitoring have received significantly increasing research efforts with a diverse range of algorithms including LSTM, autoencoders and GNN models tested. However, the research questions in these areas are similar to those in leakage, contamination, and blockage detection and localisation and thus data and experience could be shared.

3.5. System control and operation

DRL has emerged as a new technology for real-time control and operation and has received applications in many fields including water resources and hydropower reservoir operation (Xu et al., 2021). However, DRL has not received much attention in UWSs. Applications are mainly reported in urban drainage systems and WWTPs which are introduced below. Only one application was found in water distribution systems, and it tested the DQN-based DRL for pump control using two benchmark water distribution systems, i.e., Anytown and D-town (Hajgató et al., 2020). The pump speed was determined considering the system states - nodal pressures and pump speed ratios, and maximizing a reward which was formulated considering the three objectives including the number of nodes exceeding the required pressure ranges, pump efficiency and feed ratio of the pumps. They showed that the DQN can achieve comparable results to some commonly used optimisation algorithms.

3.5.1. Flood control of urban drainage systems

DRL has been used for flood risk management through developing control strategies of retention (or detention) ponds. Mullapudi et al. (2020) developed a DQN based DRL algorithm for real-time, non--predictive control of a distributed stormwater system with multiple detention ponds, which has an objective of achieving desired water levels and flows in the system using the water level and outflows at each control site as the state variables. The algorithm was effective for control of individual detention ponds but it was proven challenging for system-level control with multiple ponds due to temporal dynamics, system interactions and high dimensionality.

Research has shown that flood control of urban drainage systems can be improved through policy-based deep learning with incorporation of rainfall forecasts into decision making. Bowes et al. (2021) applied a DDPG actor-critic algorithm to flood control of urban drainage systems which operates the valves at the bottom of retention ponds. Different from DQN-based approaches, this algorithm can control valves over a continuous action space. It was tested on a hypothetical urban catchment which has two sub-catchments, two retention ponds controlled by valves and a tidally influenced water body. The outputs from SWMM simulations were used to train the algorithm. The system state is represented by the current flood depth and volume at the ponds and downstream nodes, the current valve positions, the sum of the 24 h rainfall forecast for each subcatchment, and the mean value of the 24 h tide forecast. The actions that the agent can take at any step are to close or open any valve to any degree. The reward is formulated based on how well the agent prevents flooding and maintains certain target pond water depths. RL is shown to outperform model predictive control (MPC) and rule-based control strategies, by effectively learning to proactively manage pond levels using current and forecast conditions. Further, the DDPG algorithm is shown to be robust when considering uncertainties in input data (i.e., rainfall forecasts) and system states (i.e. water level) (Saliba et al., 2020).

Previous research has shown the promise of using DRL for automated control of urban drainage systems to reduce flooding. However, a number of challenges arose from learning real-time control rules for complex systems, for example, the formulation of reward functions to guide system behaviours, control of multiple distributed storage tanks, handling of multiple objectives, use of future forecasts and choice of different DRL approaches (Blumensaat et al., 2019; Bowes et al., 2021; Mullapudi et al., 2020).

3.5.2. Wastewater treatment plants

RL has been applied to reduce operational costs in WWTPs. Using a WWTP Benchmark Simulation Model 1 (Gernaey et al., 2014), Hernández-del-Olmo et al. (2016) showed that RL can better control the DO set points of a proportional-integral (PI) controller considering the system state variables (i.e., ammonium and DO concentrations) and save operational costs when compared to manual operation and ammonium-based PI controllers. Q-learning based RL was also tested for the control of the advanced oxidation process of phenols using Fenton's reagent in a laboratory plant (Syafiie et al., 2011) and for optimising the hydraulic retention time of anaerobic and aerobic reactors (Pang et al., 2019).

In a model-free RL approach, it is important to introduce a shadowing period for RL to learn from human operations before the RL agent is deployed to control the WWTP. Hernández-del-Olmo et al. (2018) showed that an initial shadowing period of 30 days improves dramatically the agent's learning speed and reduces significantly the operational cost, though a longer shadowing period can make the learning more effective

In addition to the traditional RL, a few applications of DRL have been made in WWTPs. A policy-based DRL was developed for energy consumption reduction through controlling pumps between primary and secondary treatment, and it used probabilistic inflow forecasts to minimize energy consumption and reduce the number of alarms for tank level exceeding the limits (Filipe et al., 2019). Further, a multi-agent DDPG approach was applied to control dissolved oxygen and chemical dosage in a WWTP under continuous action and state spaces (Chen et al., 2021). In this approach, various reward functions were tested in order to develop sustainable control strategies.

In summary, various policy- and value-based DRL approaches have been applied to system control of UWSs, though the number of applications is limited and most in urban wastewater systems. Compared to the other deep learning algorithms, however, there was lack of comparisons of DRL applications with non-deep learning methods such as evolutionary optimisation.

3.6. Real-world application

The application of deep learning methods to UWSs is still at an early stage as most reported studies have used benchmark networks, synthetic data, and laboratory-based or pilot systems. Real-world systems and monitoring data have been used in the literature, however, they were mainly for model development and demonstration of deep learning potential in comparison to traditional machine learning models. The studies reviewed generally aimed to demonstrate improved performances of deep learning in comparison to traditional machine learning models or to develop an improved deep learning architecture through comparing different architecture designs. To the best of our knowledge, there is no reporting of deployed applications into day-to-day operation and management of real-world UWSs with measurable benefits or lessons learned from an innovative use of deep learning technology. learning. That is, no deep learning methods have reached the slope of enlightenment stage on the Gartner hype cycle curve (Fig. 3).

The water applications reviewed have received varying levels of attention and have advanced to different stages of maturity (Fig. 3). Leakage detection is the most popular problem for deep learning research in urban water management, which is mainly due to data availability and the drive to reduce leakage and resources (i.e., water and energy) consumption world-wide. Recall that various sensors have been deployed in the water industry to collect water demand, pressure, acoustic and vibration data, all of which have been applied to leakage detection. Leakage detection is perhaps in the stage of trough of disillusionment on the Gartner hype cycle curve where deep learning fails to deliver the high expectation but interest in developing new methods and tools continues as demonstrated by the Battle of the Leakage Detection and Isolation Methods (Liu et al., 2019). It is likely to move to the next stage – slope of enlightenment – where it will receive wider practical implementation. A strategy towards wider industrial implementation may involve demonstrating the reliability of deep learning technologies through pilot studies, benchmarking with domain knowledge and other existing methods, collecting more field data for performance improvement and developing the next generation of deep learning models. This process may be iterative and the slope of enlightenment can be long, thus it is key to establish close collaborations between deep learning researchers and water companies before mainstream adoption starts to take off, reaching the Plateau of Productivity.

Sewer defect detection is largely at the same stage on the Gartner curve as leakage detection. This problem was expected to capitalize on the power of deep learning in image processing (Lecun et al., 2015), however, challenges have arisen due to lack of large data sets and the effort required for labelling, the complexity of various defects and the difficulty in providing direct support for pipe maintenance investments. Building on more open access images recently made available (Haurum and Moeslund, 2021) (Table 1), research should focus on how deep learning methods are developed to streamline sewer condition assessments for directly supporting investment decisions. On the contrary, research on contamination detection, though having received much attention, is based on simplified case studies and data sets, and it needs to make a breakthrough in tackling the complexity of real pollution events before reaching the peak of inflated expectations.

Application of deep learning to asset monitoring has received high expectations as part of the recent development of predictive maintenance. Predictive maintenance seeks to maximize the value of assets throughout their lifecycle building on predicted system states, which are normally learnt from large amounts of data. Compared with other systems such as manufacturing systems where the benefit of predictive maintenance has been demonstrated, UWSs are more complex with a

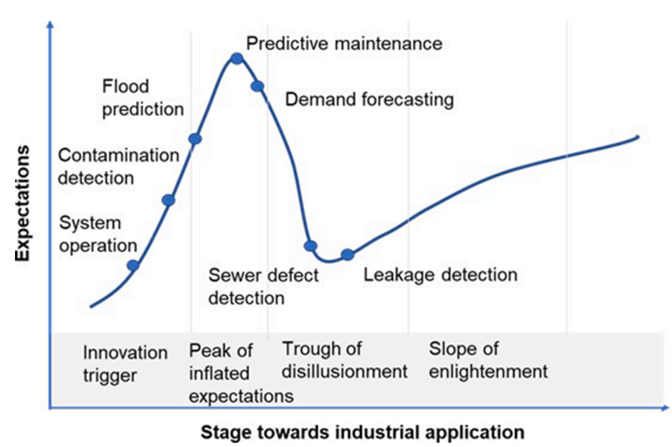

Fig. 3. Deep learning application to urban water management problems on the Gartner curve.

large number of components and state variables affected by highly uncertain environments, but generally with less data for deep learning training. The deep learning algorithms developed in the literature are piecemeal, unscalable and lack generalisation for real-world UWSs. Amongst system state prediction problems, short-term demand forecasting has received the most attention and achieved high predictive accuracy, but medium- and long-term forecasting suffers from similar data availability and uncertainty- challenges in real-world problems.

Flood prediction using AI technology at the river basin and catchment scales was rising rapidly in recent years, though its role in hydrology is still debated (Nearing et al., 2021). This was partially driven by efforts from big technology companies such as Google (Nevo et al., 2019). However, the application of deep learning to urban flooding, where only a few studies were reported (e.g., Guo et al., 2021b; Li et al., 2021), needs more research to tackle flood flashiness and high resolution urban features.

Examples of system operation have showed the benefits of DRL technology as discussed in Section 3.6, which, however, have not been fully appreciated by the water research communities. DRL, as the only deep learning algorithm that can provide solutions to operation optimisation problems, has been mainly tested in the areas of flood control in the sewer system and wastewater treatment operation. Further, it has received many more applications in urban wastewater systems than water distributions systems as reviewed earlier. This is not surprising as optimal operation problems traditionally draw more attention in urban wastewater systems than water distribution systems. In addition to optimal operation problems, DRL can also solve optimal long-term planning, maintenance and management problems (Fig. 2), such as intervention pathway development (Sadr et al., 2020), where solutions at a time step depend on the solutions chosen at previous time steps. However, it has received no applications in this area. The potential impacts and challenges of DRL are discussed in the two future research areas – multi-agent systems and digital twins – in Sections 4.4 and 4.5.

Overall, it has been demonstrated that deep learning is able to achieve higher efficiency and accuracy than traditional machine learning models when applied to classification, anomaly detection and regression tasks in UWSs (Table 1). However, significant research gaps remain in the development of deep learning methods to gain more understanding of the processes, systematically improve reliability, resilience and sustainability of UWSs, and ultimately building autonomous UWSs (Butler et al., 2016). Research advances in the areas identified in Section 4 will help bridge the gaps and propel the application of deep learning to industrial implementation.

4. Future research challenges

We believe that, in time, deep learning will fundamentally transform how UWSs will be planned, managed and operated in response to environmental and social challenges as has already been achieved in some sectors such as the finance and retail sectors (The Royal Society, 2017). At the same time, deep learning has started to substantially transform some scientific disciplines, such as high-energy physics, astronomy and computational biology (Shen, 2018), and is already transforming water research as reviewed in Section 3. Here we discuss five potential research challenges that need to be addressed to advance water engineering and science and boost deep learning-powered application to solve real-world water problems in the face of environmental change. Fig.4 illustrates the key research areas. In addition to research challenges, the industrial application of AI in the water sector is affected by many other challenges such as data silo, public policy, water regulation, culture, work force, institutional management and wider AI ecosystem (Garrido-Baserba et al., 2020; IWA, 2019), which are not discussed in this review.

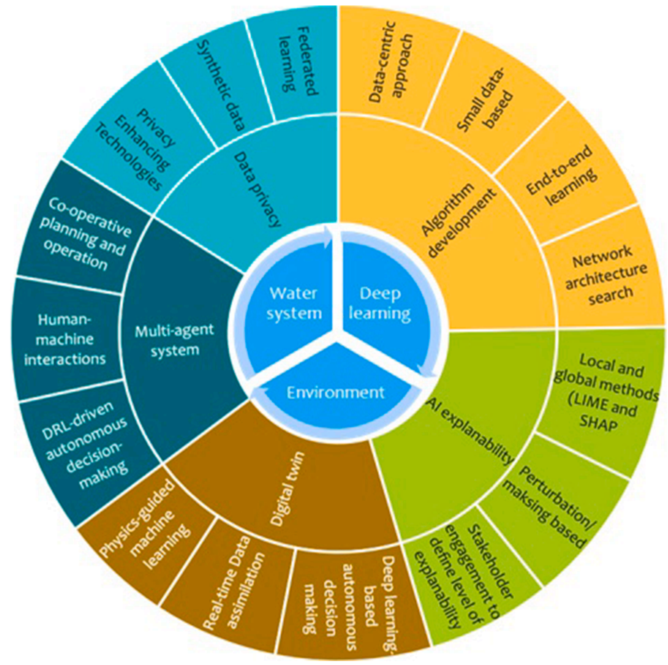

Fig. 4. Five key research challenges in use of deep learning (more generally AI) for urban water system management to tackle social-environmental change.

4.1. Data privacy

The availability of big data was one of the driving factors that lead to the breakthroughs in deep learning, at the same time, this technology is bringing challenges and risks that are related to data such as availability, quality, accessibility, security, privacy and cyber-attack. For example, the high-resolution water consumption data from smart meters can reveal personal privacy and behaviours, so how can water companies be willing to open their data for deep learning development while they should recognise privacy invasion and associated risks arising from data sharing in the legal framework for data protection, such as the new EU General Data Protection Regulation?

Privacy Enhancing Technologies (PETs) should be developed and deployed to support effective data sharing and collaborative learning over distributed data. PETs provide a solution to share data and train AI algorithms without the need of pooling data or sharing raw data. This might be particularly suitable for deep learning-based approaches, which could be potentially trained using data across distributed data centres or mobile devices (sensors) in different water utilities. PETs have been extensively studied in the computer science and machine learning research communities, in particular with a huge surge in fundamental research. However, their application to the water sector at scale requires further research. Amongst many PETs, federated learning has received growing interests as it helps to protect data generated on a device (or a water utility) by training a deep learning model locally and sharing model updates such as gradient data instead of raw data. Federated learning has been deployed by many big technology companies, so they can play a critical role in supporting privacy-sensitive applications in the water sector where the training data are distributed at the edge (Li et al., 2020), .

Use of synthetic data is an emerging approach to significantly accelerate the development of deep learning models. This approach can make use of the high-fidelity models that have been invested in the water sector in the last decades to generate large data sets for deep learning training. amongst other advantages, it can effectively reduce data privacy risks and increase the size of training data sets. As reviewed in Section 3, many studies relied on synthetic data generated by physically-based UWS models for deep learning training. GAN can produce new (both structured and unstructured) data sets that resemble the training data set with similar data structures and spatiotemporal dependencies, thus represents an important research area for wide adoption of deep learning technologies in data-limited situations.

4.2. Algorithmic development and learning system design

Designing an appropriate algorithm to a given problem is a key challenge in the development of deep learning models and this will encourage their application to real-world water problems. Some choices (e.g. supervised or unsupervised, regression or classification) are trivial and straightforward when the real-world water problem is clearly formulated and the training data (e.g., time series or image data) are identified. However, in many cases it is a difficult task to choose a proper method given a myriad of deep learning algorithms available. For example, CNNs, LSTMs, GANs and hybrid algorithms have all been used for contamination detection (Section 3.1.3). Even when the algorithm is chosen, the next challenge results from determining its architecture to achieve the best performance. For example, amongst many other factors, the input data format (1D or 2D), the number of convolution layers, and the size of the filters need to be determined for a CNN before it can be trained with the data. The network architecture is normally designed and tested manually, which is a time-consuming and error-prone process. However, this problem, referred to as a network architecture search (NAS) problem, can be solved using optimisation algorithms. NAS is a subfield of automated machine learning, which aims to automate the task of applying machine learning to real-world problems, covering the entire process from the raw data to model deployment. Previous research has shown that NAS approaches outperform manually designed network architectures on many tasks such as computer vision, however, applications in water management are limited with a few studies such as design of CNNs for algal classification in river catchments (Park et al., 2019). Further, the capacity of NAS in designing a hybrid network (e.g., CNN+LSTM) needs to be investigated for complex water problems.

End-to-end learning is enabled by deep learning to train a single learning model for complex problems, which normally consist of a sequence of tasks that are solved by learning models separately. End-to-end learning allows a single model to produce the required outputs directly from inputs, without deep knowledge of the specific, intermediate tasks. One example is sewer condition assessment, which normally involves the following tasks: 1) image pre-processing to remove noise and improve the image quality, 2) image segmentation to detect pipe components and pipe defects, 3) feature extraction using feature descriptors such as histograms of orientated gradients, Scale Invariant Feature Transform or GIST, 4) defect classification according to different types of defect, and 5) condition assessment to determine defect severity and grading. Each of the tasks can be conducted using a range of machine learning models. With end-to-end learning, however, a single possibly complex model can be trained for sewer condition assessment using raw images. This learning approach thrives on a very large training data set to achieve a certain accuracy, which is a key factor limiting its application to solving real-world problems.

Development of small data-based deep learning approaches is essential to advance the application of deep learning in the water sector. Though data are being collected at an unprecedented speed in the sector, big data are in many cases still not available for urban water infrastructure systems (Makropoulos and Savic, 2019), especially compared with other sectors such as finance and retail. The superior performance of deep learning approaches normally relies on large amounts of training data, however, new approaches should be developed for deep learning models with small data. First, more efforts are needed to investigate how to iteratively improve the quality of existing data in order to improve the performance of a fixed AI model. This is a data-centric AI approach promoted by Ng (2022), which plays a key role in the development of AI products in industry. Second, transfer learning is an approach to exploit deep learning models that are trained using external data from another task, beyond the available data on the current task, but it has received less attention in urban water applications and should be further studied to leverage the benefits of the recent AI advances. Third, incorporating domain knowledge into deep learning models is another approach to reduce the need for large datasets in order to boost accuracy. Domain knowledge based deep learning has been applied to fault diagnosis of pipelines (Feng et al., 2021) and medical image analysis (Xie et al., 2021). In UWS design problems, domain knowledge (e.g., physical laws) has been demonstrated to significantly improve the optimisation efficiency (Liu et al., 2020), however, research is required for real-world deep learning applications, though the potential of incorporating domain knowledge into deep learning for image analysis tasks has been demonstrated using different approaches, such as fusing hand-crafted features into deep learning at the input-, feature- and decision-levels and attention mechanism designed to represent radiologists' knowledge (Xie et al., 2021).

4.3. Explainability

AI explainability has drawn increasing attention as AI technologies are increasingly used in our society. Many machine learning (in particular deep learning) models are used as 'black boxes' which can provide accurate predictions once trained, but it is difficult to explain how these predictions are generated or what features are important in making such a prediction. Explainability is a key principle or embedded in other principles such as transparency, fairness and accountability in many AI development frameworks adopted by companies and governments for building trustworthy AI systems (The Royal Society, 2019), thus it is discussed below.

It is widely recognised that there is a trade-off between performance and explainability in AI models. For example, linear regression has high explainability but suffers from low performance, and deep learning suffers from low explainability but has high performance. The trade-off should be explicitly explored by AI system developers and made clear to users, aiming at achieving a good balance between performance and explainability. Compared to conventional machine learning algorithms, developing explainable deep learning has unique difficulties arising from (Samek et al., 2021): 1) multi-scale and distributed nature of network representations, 2) instability from the high depth of networks, 3) searching a reference data point on which to base the explanation, 4) evaluation of explainability which allows for comparisons of AI methods and solutions.

A diversity of approaches have been developed to interpret deep learning at the global and local levels in the literature but need to be tested on UWS applications. Local explainability aims to understand what input features contribute positively or negatively to each decision (or sample), while global explainability focuses on making the entire process of model reasoning transparent and understandable, contributing to model validation and knowledge discovery. Often, developers and users need different levels of explainability, for example, users need local approaches to understand how a specific decision is made from the data while developers might need global approaches to understand how an AI system works (The Royal Society, 2019). The most influential inputs or features in determining an output can be identified through perturbation, masking or removing different parts of inputs to analyse how the output changes. These approaches provide a local level of explainability effects. Interpretable models (e.g., linear regression) can be developed to approximate a deep learning model locally and globally for explanations. A popular method is called local interpretable model-agnostic explanations (LIME), for text and image classification problems. Another method SHAP (SHapley Additive exPlanations) was applied to identify the most important environmental factors and their interactions for beach closure (L. L. Li et al., 2022).

The need for explainable AI varies in different domains. Many UWS applications (Table 1) in the water sector are rather different from those in some sectors such as healthcare and justice, where the decision of AI systems has a big impact on people. For example, the outcome of deep learning-based leakage detection systems has no direct consequences on customers from false positive predictions, and they can still be deployed without giving rise to concerns about explainability, in particular when their accuracy has been well validated. In many UWS planning and management applications, deep learning systems are not used for automated decision-making, instead their predictions are fed into a complex human decision-making process. In the example of leakage detection, the detection results can be verified by experienced operators or collecting real-time data using mobile loggers and then used to inform network maintenance investment decision-making. From a wider perspective, however, increasing the explainability of machine learning systems is desirable for developing better AI models and applications in the water sector due to 1) explainability can help us extrapolate an machine learning system's behaviour to situations in which it has not been explicitly tested (The Royal Society, 2017), and identify situations in which it may fail and 2) explainability should be developed in a wider context of AI principles. However, stakeholder engagement should be used to define what form of explainability is useful for UWS applications.

4.4. Multi-agent systems

A multi-agent system consists of multiple intelligent agents which interact in a shared environment to achieve common or conflicting goals. An agent can be a software component, robot, or person. Each agent typically has its own observations of the environment, actions and goals, but critically it interacts with other agents through its actions or changes to the shared environment. The agents can be cooperative, competitive, or mixed. Multi-agent systems can be used to tackle dynamic interactions between different components of the UWS system and the environment, which become important with increasing system complexity and uncertainty. Agent-based models have been widely applied to river basin and hydrological systems, with a goal to understand the collective behaviours of multiple agents and develop land and water management options (Yang et al., 2009). However, there are few applications of multi-agent systems in the UWS, focusing on designing agents and solving a technological problem. Potential applications are discussed below.

Co-operative multi-agent systems are needed for autonomous decision-making of optimal planning and operation problems. In particular, multi-agent systems can be combined with the latest DRL technology to develop an autonomous decision-making framework that can generate optimal actions in response to a dynamic environment. One example is the development of a multi-agent DRL approach to simultaneously optimise DO and chemical dosage in a WWTP (Chen et al., 2021). Similarly this framework could be applied to control of storage tanks and SuDS measures (e.g., retention/detention ponds) in the sewer system, control of water tanks and pumps in the water distribution system, or co-operation of multiple drones in flood emergency operations. These system components, represented by multi-agents, can autonomously act to achieve the objectives defined. In the example of pump operations, an agent can be designed to control pumps in one part of the water network to meet peak demands by keeping high pressure and another agent can be designed to control pumps in an adjacent part of the water network to maintain low pressure for leakage management. The two agents need to co-operate with each other to meet conflicting operation objectives in the water network through effective handling of dynamic environments. In doing so, the application of multi-agent systems could build a more decentralized, highly efficient UWS system. In addition, agents representing various stakeholders such as landowners, urban planners and water users can negotiate their interest in the UWS planning and management.

Human-machine interactions can be a key research area in the field of multi-agent systems and they could be useful in real-time operation and disaster recovery of a complex UWS. For example, in the case of emergency operation in the aftermath of flooding, the behaviour of human agents should be incorporated in assessing the effectiveness of rescue and recovery operations by other agents such as unmanned aerial vehicles. Strategic planning and optimal design problems are extremely challenging with a large scale of problem domain, a large number of stakeholders, a wide range of deep uncertainties and interactions with the environment, thus human-machine interactions can be key to tackle these problems as in multi-objective optimisation problems (Tang et al., 2020).

4.5. Digital twins and autonomous systems

The concept of digital twins has generated great interest and momentum in the water sector. Though sharing many similar characteristics, a digital twin is different from a traditional model which often operates in isolation from the physical world. Amongst many definitions of digital twin (e.g., Makropoulos and Savic, 2019; Therrien et al., 2020), IBM defines it as a virtual representation of a physical system across its lifecycle, using real-time data to enable understanding, learning and reasoning. Though there is no consensus on the form of a digital twin, it should have the following key features: 1) data-driven coupling of mathematical models (i.e., physically-based, machine learning or hybrid) with the physical UWS that they represent, 2) integrated with real-time data streams from sensor networks so as to represent the true state of the current physical system, 3) able to analyse 'what if' scenarios and provide predictions of the future state, 4) closing the loop from the digital twin to the physical system through design, maintenance and operation strategies derived from the digital twin, and 5) continuously updated with data from the physical world and used in (near) real time simulations for improved system performance and services. The development of digital twins will be transformational in how we interact with, manage and control the physical system.

To date, the machine learning component is largely missing in the development of digital twins in the water sector. To the best of our knowledge, all the reported examples of digital twins were based on physically-based models (Bartos and Kerkez, 2021; Garrido-Baserba et al., 2020; Pesantez et al., 2022; Valverde-Pérez et al., 2021), though a few used machine learning to enhance the performance of hydraulic models such as estimation of the operating speed of pumps (Bonilla et al., 2022) or the influent to the WWTP (Valverde-Pérez et al., 2021). The deep learning applications reviewed in Section 3 can potentially be a key part of digital twins, enabling the UWS become an autonomous system through automated operation. Machine learning is a powerful technology to not only help improve our understanding of physical systems, but also provide solutions to improve system performance. The development of explainable AI can further provide an insight into system processes. Physics-guided machine learning is a new research direction that leverages the knowledge on the system (e.g., physical constraints or process-based theories) to develop more accurate, generalizable machine learning models, and it has found many applications in hydrology (Nearing et al., 2021) and water quality (Varadharajan et al., 2022) and is potentially useful to develop digital twins of UWSs.

In the development of digital twins, we envision much of the future advance regarding deep learning application will come from the development of systems that combine CNNs and LSTM networks to understand and predict system behaviours and then use DRL to decide where to search for optimal interventions. Once realised, this will significantly empower the digital twin towards achieving high intelligence and autonomy. However, this advance is going to be hard won, requiring a great deal of concerted and sustained fundamental research and development in all five challenges to fully materialize the promise of digital twins.

5. Conclusions

Deep learning has been widely recognised as a potentially disruptive technology in the age of Industry 4.0 and has already transformed many sectors. A critical review on the role of deep learning in urban water management has found the following key points:

1) Deep learning has showed great potential in urban water management relating to five key application areas, including anomaly detection, system prediction, asset assessment, system operation and planning and maintenance. However, no attempts have been made to solve strategic planning, optimal maintenance and intervention development problems.
2) The application of deep learning methods in the water sector is still at an early stage as most studies used benchmark networks, synthetic data, laboratory-based or pilot systems to test the performance of deep learning methods. It lacks reporting of deployed applications with measurable benefits or lessons learned from an innovative use of deep learning technology.
3) Deep learning application to different problems has advanced to different stages of maturity on the Gartner hype cycle curve but none has reached the stage of industrial application. Sewer defect detection and leakage detection are believed to be more advanced than other applications. Significant research efforts are required in the development of deep learning methods to fill knowledge gaps in understanding water processes and improve system performance before they can gain wider adoption in the water sector.
4) Further research on the five challenges, i.e., data privacy and cybersecurity, algorithmic development, explainability and trustworthiness, multi-agent systems and digital twin, is recommended for shaping urban water management fuelled by deep learning technology. The great promise of deep learning lies in its empowerment of digital twins towards high intelligence and autonomy of UWSs, which we expect will be materialised through the development of deep learning systems that combine CNNs and LSTM networks to understand and predict system behaviours and then use deep reinforcement learning to decide where to search for optimal interventions

We hope this review will spark thoughts and actions on future research and applications that harness the power of deep learning to help the digitalisation of urban water systems and inspire more researchers to join in the water intelligence community to revolutionize water research and practice.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Supplementary materials

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References

Alizadeh Kharazi, B., Behzadan, A.H., 2021. Flood depth mapping in street photos with image processing and deep neural networks. Comput. Environ. Urban Syst. https://doi.org/10.1016/j.compenvurbsys.2021.101628.

Arad, J., Housh, M., Perelman, L., Ostfeld, A., 2013. A dynamic thresholds scheme for contaminant event detection in water distribution systems. Water Res. 47, 1899–1908. https://doi.org/10.1016/j.watres.2013.01.017.

Barrington, L., Bromberg, C., Hickey, J., Burge, J., 2019. Machine learning for precipitation nowcasting from radar images. In: 33rd Conf. Neural Inf. Process. Syst. (NeurIPS 2019). Vancouver, Canada.

Bartos, M., Kerkez, B., 2021. Pipedream: an interactive digital twin model for natural and urban drainage systems. Environ. Model. Softw. 144, 105120 https://doi.org/10.1016/j.envsoft.2021.105120.

Belghaddar, Y., Chahinian, N., Seriai, A., Begdouri, A., Abdou, R., Delenne, C., 2021. Graph convolutional networks: application to database completion of wastewater networks. Water (Basel) 13, 1681.

Blumensaat, F., Leitão, J.P., Ort, C., Rieckermann, J., Scheidegger, A., Vanrolleghem, P. A., Villez, K., 2019. How urban Storm- And wastewater management prepares for emerging opportunities and threats: digital transformation, ubiquitous sensing, new data sources, and beyond - a horizon scan. Environ. Sci. Technol. 53, 8488–8498. https://doi.org/10.1021/acs.est.8b06481.

Bonilla, C.A., Zanfei, A., Brentan, B., Montalvo, I., Izquierdo, J., 2022. A digital twin of a water distribution system by using graph convolutional networks for pump speed-based state estimation. Water (Switzerland) 14. https://doi.org/10.3390/w14040514.

Bowes, B.D., Tavakoli, A., Wang, C., Heydarian, A., Behl, M., Beling, P.A., Goodall, J.L., 2021. Flood mitigation in coastal urban catchments using real-time stormwater infrastructure control and reinforcement learning. J. Hydroinformatics 23, 529–547. https://doi.org/10.2166/HYDRO.2020.080.

Butler, D., Ward, S., Sweetapple, C., Astaraie-Imani, M., Diao, K., Farmani, R., Fu, G., 2016. Reliable, resilient and sustainable water management: the Safe & SuRe approach. Global Challenges 1 (1), 63–77. https://doi.org/10.1002/gch2.1010.

Cao, K., Kim, H., Hwang, C., Jung, H., 2018. CNN-LSTM coupled model for prediction of waterworks operation data. J. Inf. Process. Syst. 14, 1508–1520. https://doi.org/10.3745/JIPS.02.0104.

Chandy, S.E., Rasekh, A., Barker, Z.A., Shafiee, M.E., 2019. Cyberattack detection using deep generative models with variational inference. J. Water Resour. Plann. Manage. 145 (2), 04018093.

Chen, K., Wang, H., Valverde-Pérez, B., Zhai, S., Vezzaro, L., Wang, A., 2021. Optimal control towards sustainable wastewater treatment plants based on multi-agent reinforcement learning. Chemosphere 279, 130498. https://doi.org/10.1016/j.chemosphere.2021.130498.

Chen, Y., Zhong, S., Chen, K., Chen, S., Zheng, S., 2019. Automated detection of sewer pipe defects based on cost-sensitive convolutional neural network. In: Proceedings of the 2019 2nd International Conference on Signal Processing and Machine Learning. https://doi.org/10.1145/3372806.3372816.

Chen, X., Feng, F., Wu, J., Liu, W., 2018a. Anomaly detection for drinking water quality via deep bilSTM ensemble. GECCO 2018 Companion - Proc. In: 2018 Genet. Evol. Comput. Conf. Companion, pp. 3–4. https://doi.org/10.1145/3205651.3208203.

Chen, K., Hu, H., Chen, C., Chen, L., He, C., 2018b. An intelligent sewer defect detection method based on convolutional neural network. In: 2018 IEEE International Conference on Information and Automation. China.

Cheng, T., Harrou, F., Kadri, F., Sun, Y., Leiknes, T., 2020. Forecasting of wastewater treatment plant key features using deep learning-based models: a case study. IEEE Access 8, 184475–184485. https://doi.org/10.1109/access.2020.3030820.

Cheng, J.C.P., Wang, M, 2018. Automated detection of sewer pipe defects in closed-circuit television images using deep learning techniques. Autom. Constr. 95, 155–171.

Cody, R.A., Tolson, B.A., Orchard, J., 2020. Detecting leaks in water distribution pipes using a deep Autoencoder and Hydroacoustic spectrograms. J. Comput. Civ. Eng. 34, 04020001 https://doi.org/10.1061/(asce)cp.1943-5487.0000881.

Dairi, A., Cheng, T., Harrou, F., Sun, Y., Leiknes, T., 2019. Deep learning approach for sustainable WWTP operation : a case study on data-driven in fl uent conditions monitoring. Sustain. Cities Soc. 50, 101670 https://doi.org/10.1016/j.scs.2019.101670.

De Vitry, M.M., Kramer, S., Wegner, J.D., Leitão, J.P., 2019. Scalable flood level trend monitoring with surveillance cameras using a deep convolutional neural network. Hydrol. Earth Syst. Sci 23, 4621–4634.

Deng, A., Hooi, B., 2021. Graph Neural Network-Based Anomaly Detection in Multivariate Time Series. In: Proceedings of the AAAI Conference on Artificial Intelligence, 35, pp. 4027–4035.

Dogo, E.M., Nwulu, N.I., Twala, B., Aigbavboa, C., Dogo, E.M., Nwulu, N.I., Twala, B., Aigbavboa, C., Dogo, E.M., 2019. A survey of machine learning methods applied to anomaly detection on drinking-water quality data drinking-water quality data. Urban Water J 16, 235–248. https://doi.org/10.1080/1573062X.2019.1637002.

Du, B., Zhou, Q., Guo, J., Guo, S., Wang, L., 2021. Deep learning with long short-term memory neural networks combining wavelet transform and principal component

analysis for daily urban water demand forecasting. Expert Syst. Appl. 171, 114571 https://doi.org/10.1016/j.eswa.2021.114571.
Erba, A., Taormina, R., Galelli, S., Pogliani, M., Carminati, M., Zanero, S., Tippenhauer, N.O., 2020. Constrained concealment attacks against reconstruction-based anomaly detectors in industrial control systems. In: Annual Computer Security Applications Conference, 2020.
Fan, X., Zhang, X., Yu, X.B., 2021. Machine learning model and strategy for fast and accurate detection of leaks in water supply network. J. Infrastruct. Preserv. Resil. 2 https://doi.org/10.1186/s43065-021-00021-6.
Fang, Q.S., Zhang, J.X., Xie, C.L., Yang, Y.L., 2019. Detection of multiple leakage points in water distribution networks based on convolutional neural networks. Water Sci. Technol. Water Supply 19, 2231–2239. https://doi.org/10.2166/ws.2019.105.
Feng, J., Yao, Y., Lu, S., Liu, Y., 2021. Domain knowledge-based deep-broad learning framework for fault diagnosis. IEEE Trans. Ind. Electron. 68, 3454–3464. https://doi.org/10.1109/TIE.2020.2982085.
Filipe, J., Bessa, R.J., Reis, M., Alves, R., Póvoa, P., 2019. Data-driven predictive energy optimization in a wastewater pumping station. Appl. Energy 252, 113423. https://doi.org/10.1016/j.apenergy.2019.113423.
Garrido-Baserba, M., Corominas, L., Cortés, U., Rosso, D., Poch, M., 2020. The fourth-revolution in the water sector encounters the digital revolution. Environ. Sci. Technol. 54, 4698–4705. https://doi.org/10.1021/acs.est.9b04251.
Gernaey, K.V., Jeppsson, U., Vanrolleghem, P.A., Copp, J.B., 2014. Benchmarking of Control Strategies for Wastewater Treatment Plants. IWA Publishing, London, UK. IWA Scientific and Technical Report No. 23ISBN 9781843391463.
Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning. MIT Press.
Gutierrez-Mondragon, M.A., Garcia-Gasulla, D., Alvarez-Napagao, S., Brossa-Ordoñez, J., and Gimenez-Esteban, R., 2020. Obstruction level detection of sewer videos using convolutional neural networks. arXiv preprint. arXiv:2002.01284.
Guo, G., Liu, S., Wu, Y., Li, J., Zhou, R., Zhu, X., 2018. Short-term water demand forecast based on deep learning method. J. Water Resour. Plan. Manag. 144, 1–11. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000992.
Guo, G., Yu, X., Liu, S., Ma, Z., Wu, Y., Xu, X., Wang, X., Smith, K., Wu, X., 2021a. Leakage detection in water distribution systems based on time–frequency convolutional neural network. J. Water Resour. Plan. Manag. 147, 04020101 https://doi.org/10.1061/(asce)wr.1943-5452.0001317.
Guo, Z., Leitão, J.P., Simões, N.E., Moosavi, V., 2021b. Data-driven flood emulation: speeding up urban flood predictions by deep convolutional neural networks. J. Flood Risk Manag. 14, 1–14. https://doi.org/10.1111/jfr3.12684.
Hajgató, G., Gyires-Tóth, B., Paál, G., 2021. Reconstructing nodal pressures in water distribution systems with graph neural networks. arXiv preprint. arXiv:2104.13619.
Hajgató, G., Paál, G., Gyires-Tóth, B., 2020. Deep reinforcement learning for real-time optimization of pumps in water distribution systems. J. Water Resour. Plan. Manag. 146, 04020079 https://doi.org/10.1061/(asce)wr.1943-5452.0001287.
U.S. EPA, 2012. CANARY User's Manual Version 4.3.2. U.S. Environmental Protection Agency, Washington, DC. EPA/600/R-08/040B.
Hashemi-Beni, L., Gebrehiwot, A.A., 2021. Flood extent mapping: an integrated method using deep learning and region growing using UAV optical data. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 14, 2127–2135. https://doi.org/10.1109/JSTARS.2021.3051873.
Hassan, S.I., Dang, L.M., Mehmood, I., Im, S., Choi, C., Kang, J., Park, Y.S., Moon, H., 2019. Underground sewer pipe condition assessment based on convolutional neural networks. Autom. Constr. 106, 102849.
Hassanzadeh, A., Rasekh, A., Galelli, S., Aghashahi, M., Taormina, R., Ostfeld, A., Banks, M.K., 2020. A review of cybersecurity incidents in the water sector. J. Environ. Eng. 146, 03120003 https://doi.org/10.1061/(asce)ee.1943-7870.0001686.
Haurum, J.B., Moeslund, T.B., 2021. Sewer-ML: a multi-label sewer defect classification dataset and benchmark. Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. 13451–13462. https://doi.org/10.1109/CVPR46437.2021.01325.
He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.
Hernández-del-Olmo, F., Gaudioso, E., Dormido, R., Duro, N., 2018. Tackling the start-up of a reinforcement learning agent for the control of wastewater treatment plants. Knowl.-Based Syst 144, 9–15. https://doi.org/10.1016/j.knosys.2017.12.019.
Hernández-del-Olmo, F., Gaudioso, E., Dormido, R., Duro, N., 2016. Energy and environmental efficiency for the N-ammonia removal process in wastewater treatment plants by means of reinforcement learning. Energies 9, 755. https://doi.org/10.3390/en9090755.
Hu, P., Tong, J., Wang, J., Yang, Y., Turci, Oliveira, De, L., 2019. A hybrid model based on CNN and Bi-LSTM for urban water demand prediction. In: 2019 IEEE Congr. Evol. Comput. CEC 2019 - Proc, pp. 1088–1094. https://doi.org/10.1109/CEC.2019.8790060.
Hu, X., Han, Y., Yu, B., Geng, Z., Fan, J., 2021. Novel leakage detection and water loss management of urban water supply network using multiscale neural networks. J. Clean. Prod. 278, 123611 https://doi.org/10.1016/j.jclepro.2020.123611.
Inoue, J., Yamagata, Y., Chen, Y., Poskitt, C.M., Sun, J., 2017. Anomaly Detection for a Water Treatment System Using Unsupervised Machine Learning. IEEE International Conference on Data Mining Workshops, ICDMW. IEEE, New Orleans, LA, USA, pp. 1058–1065. https://doi.org/10.1109/ICDMW.2017.149.
Iqbal, U., Perez, P., Li, W., Barthelemy, J., 2021. How computer vision can facilitate flood management: a systematic review. Int. J. Disaster Risk Reduct. 53, 102030 https://doi.org/10.1016/j.ijdrr.2020.102030.
IWA, 2019. Digital Water: industry leaders chart the transformation journey. https://iwa-network.org/wp-content/uploads/2019/06/IWA_2019_Digital_Water_Report.pdf (accessed 1-4-2021).
Javadiha, M., Blesa, J., Soldevila, A., Puig, V., 2019. Leak localization in water distribution networks using deep learning. In: 2019 6th Int. Conf. Control. Decis. Inf. Technol. CoDIT, pp. 1426–1431. https://doi.org/10.1109/CoDIT.2019.8820627, 2019.
Jiao, Y., Rayhana, R., Bin, J., Liu, Z., Wu, A., Kong, X., 2021. A steerable pyramid autoencoder based framework for anomaly frame detection of water pipeline CCTV inspection. Measurement 174, 109020. https://doi.org/10.1016/j.measurement.2021.109020.
Kabir, S., Patidar, S., Xia, X., Liang, Q., Neal, J., Pender, G., 2020. A deep convolutional neural network model for rapid prediction of fluvial flood inundation. J. Hydrol. 590, 125481 https://doi.org/10.1016/j.jhydrol.2020.125481.
Kang, J., Park, Y., Lee, J., Wang, S., Eom, D., 2018. Novel leakage detection by ensemble CNN-SVM and graph-based localization in water distribution systems. IEEE Trans. Ind. Electron. 65, 4279–4289.
Kingma, D.P., Ba, J.L., 2015. Adam: a method for stochastic optimization. In: 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc, pp. 1–15.
Kühnert, C., Gonuguntla, N.M., Krieg, H., Nowak, D., Thomas, J.A., 2021. Application of LSTM networks for water demand prediction in optimal pump control. Water (Switzerland) 13, 1–19. https://doi.org/10.3390/w13050644.
Kumar, S.S., Abraham, D.M., Jahanshahi, M.R., Iseley, T., Starr, J., 2018. Automated defect classification in sewer closed circuit television inspections using deep convolutional neural networks. Autom. Constr. 91, 273–283.
Kumar, S.S., Abraham, D., Rosenthal, M., 2020a. Construction research Congress 2020: computer applications leveraging visualization techniques to develop improved deep neural network architecture for sewer defect identification. In: Construction Research Congress 2020: Infrastructure Systems and Sustainability. Reston, VA. American Society of Civil Engineers.
Kumar, S.S., Wang, M., Abraham, D.M., Jahanshahi, M.R., Iseley, T., Cheng, J.C.P., 2020b. Deep learning–based automated detection of sewer Defects in CCTV videos. J. Comput. Civil Eng. 34 (1), 04019047.
Kunzel, J., Werner, T., Eisert, P., Waschnewski, J., Möller, R., Hilpert, R., 2018. Automatic analysis of sewer pipes based on unrolled monocular fisheye images. In: 2018 IEEE Winter Conference on Applications of Computer Vision (WACV). https://doi.org/10.1109/WACV.2018.00223.
Lecun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444. https://doi.org/10.1038/nature14539.
Leigh, C., Alsibai, O., Hyndman, R.J., Kandanaarachchi, S., King, O.C., Mcgree, J.M., Neelamraju, C., Strauss, J., Dilini, P., Turner, R.D.R., Mengersen, K., Peterson, E.E., 2019. A framework for automated anomaly detection in high frequency water-quality data from in situ sensors. Sci. Total Environ. 664, 885–898. https://doi.org/10.1016/j.scitotenv.2019.02.085.
Li, L., Qiao, J., Yu, G., Wang, L., Li, H.Y., Liao, C., Zhu, Z., 2022a. Interpretable tree-based ensemble model for predicting beach water quality. Water Res. 211, 118078 https://doi.org/10.1016/j.watres.2022.118078.
Li, D., Chen, D., Jin, B., Shi, L., Goh, J., Ng, S.K., 2019a. MAD-GAN: multivariate anomaly detection for time series data with generative adversarial networks. In: International Conference on Artificial Neural Networks. Springer, pp. 703–716.
Li, D., Cong, A., Guo, S., 2019b. Sewer damage detection from imbalanced CCTV inspection data using deep convolutional neural networks with hierarchical classification. Autom. Constr. 101, 199–208.
Li, T., Sahu, A.K., Talwalkar, A., Smith, V., 2020. Federated Learning: challenges, Methods, and Future Directions. IEEE Signal Process. Mag. 37, 50–60. https://doi.org/10.1109/MSP.2020.2975749.
Li, Z., Liu, H., Luo, C., Fu, G., 2021. Assessing surface water flood risks in urban areas using machine learning. Water (Switzerland) 13, 1–14. https://doi.org/10.3390/w13243520.
Li, Z., Zhang, Chi, Liu, H., Zhang, Chao, Zhao, M., Gong, Q., Fu, G., 2022b. Developing stacking ensemble models for multivariate contamination detection in water distribution systems. Sci. Total Environ. 828, 154284 https://doi.org/10.1016/j.scitotenv.2022.154284.
Liu, H., Shoemaker, C.A., Jiang, Y., Fu, G., Zhang, C., 2020. Preconditioning water distribution network optimization with head loss-based design method. J. Water Resour. Plan. Manag. 146 https://doi.org/10.1061/(ASCE)WR.1943-5452.0001299.
Liu, R., Zhang, Z., Zhang, D., 2019. Leakage detection and isolation in water distribution network based on data mining and genetic optimized hydraulic simulation. pp. 1–5. doi:10.5281/zenodo.3911523.
Löwe, R., Böhm, J., Jensen, D.G., Leandro, J., Rasmussen, S.H., 2021. U-FLOOD – Topographic deep learning for predicting urban pluvial flood water depth. J. Hydrol. 603 https://doi.org/10.1016/j.jhydrol.2021.126898.
Makropoulos, C., Savic, D.A., 2019. Urban Hydroinformatics: past, present and future. Water (Switzerland) 11, 1959.
Mehmood, H., Mukkavilli, S.K., Weber, I., Koshio, A., Meechaiya, C., Piman, T., Mubea, K., Tortajada, C., Mahadeo, K., Liao, D., 2020. Strategic Foresight to Applications of Artificial Intelligence to Achieve Water-Related Sustainable Development Goals. United Nations University Institute for Water, Environment and Health, Hamilton, Canada. UNU-INWEH Report Series.
Meijer, D., Scholten, L., Clemens, F., Knobbe, A., 2019. A defect classification methodology for sewer image sets with convolutional neural networks. Autom. Constr. 104, 281–298.
Moradi, S., Zayed, T., Nasiri, F., Golkhoo, F., 2020. Automated anomaly detection and localization in sewer inspection videos using proportional data modeling and deep learning–based text recognition. J. Infrastruct. Syst. 26 (3), 04020018.
Moreno-Rodenas, A.M., Duinmeijer, A., Clemens, F., 2021. Deep-learning based monitoring of FOG layer dynamics in wastewater pumping stations. Water Res. 202, 117482.

Mu, L., Zheng, F., Tao, R., Zhang, Q., Kapelan, Z., 2020. Hourly and daily urban water demand predictions using a long short-term memory based model. J. Water Resour. Plan. Manag. 146, 05020017 https://doi.org/10.1061/(asce)wr.1943-5452.0001276.

Muharemi, F., Logofătu, D., Leon, F., 2019. Machine learning approaches for anomaly detection of water quality on a real-world data set. J. Inf. Telecommun. https://doi.org/10.1080/24751839.2019.1565653.

Mullapudi, A., Lewis, M.J., Gruden, C.L., Kerkez, B., 2020. Deep reinforcement learning for the real time control of stormwater systems. Adv. Water Resour. 140 https://doi.org/10.1016/j.advwatres.2020.103600.

Nam, Y.W., Arai, Y., Kunizane, T., Koizumi, A., 2021. Water leak detection based on convolutional neural network (CNN) using actual leak sounds and the hold-out method. Water Supply 1–9. https://doi.org/10.2166/ws.2021.109.

Nasser, A.A., Rashad, M.Z., Hussein, S.E., 2020. A two-layer water demand prediction system in urban areas based on micro-services and LSTM neural networks. IEEE Access 8, 147647–147661. https://doi.org/10.1109/ACCESS.2020.3015655.

Nearing, G.S., Kratzert, F., Sampson, A.K., Pelissier, C.S., Klotz, D., Frame, J.M., Prieto, C., Gupta, H.V., 2021. What role does hydrological science play in the age of machine learning? Water Resour. Res. 57 https://doi.org/10.1029/2020WR028091.

Nevo, S., Anisimov, V., Elidan, G., El-Yaniv, R., Giencke, P., Gigi, Y., Hassidim, A., Moshe, Z., Schlesinger, M., Shalev, G., Tirumali, A., Wiesel, A., Zlydenko, O., Matias, Y., 2019. ML for flood forecasting at Scale 2–5.

Ng A., 2022. MLOps: From Model-centric to Data-centric AI. https://www.deeplearning.ai/wp-content/uploads/2021/06/MLOps-From-Model-centric-to-Data-centric-AI.pdf (accessed 7-3-2022).

Palmitessa, R., Mikkelsen, P.S., Borup, M., Law, A.W.K., 2021. Soft sensing of water depth in combined sewers using LSTM neural networks with missing observations. J. Hydro-Environ. Res. 38, 106–116. https://doi.org/10.1016/j.jher.2021.01.006.

Pan, G., Zheng, Y., Guo, S., Lv, Y., 2020. Automatic sewer pipe defect semantic segmentation based on improved U-Net. Autom. Constr. 119, 103383.

Pang, J., Yang, S., He, L., Chen, Y., Ren, N., 2019. Intelligent control/operational strategies in WWTPs through an integrated Q-learning algorithm with ASM2d-guided reward. Water (Switzerland) 11. https://doi.org/10.3390/w11050927.

Park, J., Lee, H., Park, C.Y., Hasan, S., Heo, T., Lee, W.H., 2019. Algal morphological identification in watersheds for drinking water supply using neural architecture search for convolutional neural network. Water (Switzerland) 11, 1338. https://doi.org/10.3390/w11071338.

Pesantez, J.E., Alghamdi, F., Sabu, S., Mahinthakumar, G., Berglund, E.Z., 2022. Using a digital twin to explore water infrastructure impacts during the COVID-19 pandemic. Sustain. Cities Soc. 77, 103520 https://doi.org/10.1016/j.scs.2021.103520.

Pollard, J.A., Spencer, T., Jude, S., 2018. Big Data Approaches for coastal flood risk assessment and emergency response. Wiley Interdiscip. Rev. Clim. Chang. 9, e543 https://doi.org/10.1002/wcc.543.

Qian, K., Jiang, J., Ding, Y., Yang, S., 2020. Deep learning based anomaly detection in water distribution systems. In: 2020 IEEE Int. Conf. Networking, Sens. Control. ICNSC 2020. https://doi.org/10.1109/ICNSC48988.2020.9238099.

Rahimi, M., Alghassi, A., Ahsan, M., Haider, J., 2020. Deep learning model for industrial leakage detection using acoustic emission signal. Informatics. https://doi.org/10.3390/informatics7040049.

Reuss, M., 2003. Is it time to resurrect the Harvard water program? J. Water Resour. Plan. Manag. 129, 357–360. https://doi.org/10.1061/(asce)0733-9496(2003)129:5(357).

Rodriguez-Perez, J., Leigh, C., Liquet, B., Kermorvant, C., Peterson, E., Sous, D., Mengersen, K., 2020. Detecting technical anomalies in high-frequency water-quality data using artificial neural networks. Environ. Sci. Technol. 54, 13719–13730. https://doi.org/10.1021/acs.est.0c04069.

Sadr, S.M.K., Casal-Campos, A., Fu, G., Farmani, R., Ward, S., Butler, D., 2020. Strategic planning of the integrated urban wastewater system using adaptation pathways. Water Res. 182, 116013 https://doi.org/10.1016/j.watres.2020.116013.

Saliba, S.M., Bowes, B.D., Adams, S., Beling, P.A., Goodall, J.L., 2020. Deep reinforcement learning with uncertain data for real-time stormwater system control and flood mitigation. Water (Switzerland) 12, 1–19. https://doi.org/10.3390/w12113222.

Samek, W., Montavon, G., Lapuschkin, S., Anders, C.J., Müller, K.R., 2021. Explaining deep neural networks and beyond: a review of methods and applications. Proc. IEEE 109, 247–278. https://doi.org/10.1109/JPROC.2021.3060483.

Shen, C., 2018. A transdisciplinary review of deep learning research and its relevance for water resources scientists. Water Resour. Res. 54, 8558–8593. https://doi.org/10.1029/2018WR022643.

Shukla, H., Piratla, K., 2020. Leakage detection in water pipelines using supervised classification of acceleration signals. Autom. Constr. 117, 103256 https://doi.org/10.1016/j.autcon.2020.103256.

Sufi Karimi, H., Natarajan, B., Ramsey, C.L., Henson, J., Tedder, J.L., Kemper, E., 2019. Comparison of learning-based wastewater flow prediction methodologies for smart sewer management. J. Hydrol. 577 https://doi.org/10.1016/j.jhydrol.2019.123977.

Syafiie, S., Tadeo, F., Martinez, E., Alvarez, T., 2011. Model-free control based on reinforcement learning for a wastewater treatment problem. Appl. Soft Comput. J. 11, 73–82. https://doi.org/10.1016/j.asoc.2009.10.018.

Tang, R., Li, K., Ding, W., Wang, Y., Zhou, H., Fu, G., 2020. Reference point based multi-objective optimization of reservoir operation: a comparison of three algorithms. Water Resour. Manag. 34, 1005–1020. https://doi.org/10.1007/s11269-020-02485-9.

Taormina, R., Galelli, S., 2018. Deep-learning approach to the detection and localization of cyber-physical attacks on water distribution systems. J. Water Resour. Plan. Manag. 144, 04018065 https://doi.org/10.1061/(asce)wr.1943-5452.0000983.

Taormina, R., Galelli, S., Tippenhauer, N.O., Salomons, E., Ostfeld, A., Eliades, D.G., Aghashahi, M., Sundararajan, R., Pourahmadi, M., Banks, M.K., Brentan, B.M., Campbell, E., Lima, G., Manzi, D., Ayala-Cabrera, D., Herrera, M., Montalvo, I., Izquierdo, J., Luvizotto, E., Chandy, S.E., Rasekh, A., Barker, Z.A., Campbell, B., Shafiee, M.E., Giacomoni, M., Gatsis, N., Taha, A., Abokifa, A.A., Haddad, K., Lo, C.S., Biswas, P., Pasha, M.F.K., Kc, B., Somasundaram, S.L., Housh, M., Ohar, Z., 2018. Battle of the attack detection algorithms: disclosing cyber attacks on water distribution networks. J. Water Resour. Plan. Manag. 144, 04018048 https://doi.org/10.1061/(asce)wr.1943-5452.0000969.

Tsiami, L., Makropoulos, C., 2021. Cyber—physical attack detection in water distribution systems with temporal graph convolutional neural networks. Water (Basel) 13 (9), 1247.

The Royal Society, 2019. Explainable AI: the basics.

The Royal Society, 2017. Machine Learning: the Power and Promise of Computers That Learn By Example. Report by the Royal Society. https://doi.org/10.1126/scitranslmed.3002564.

Therrien, J.D., Nicolaï, N., Vanrolleghem, P.A., 2020. A critical review of the data pipeline: how wastewater system operation flows from data to intelligence. Water Sci. Technol. 82, 2613–2634. https://doi.org/10.2166/wst.2020.393.

Valverde-Pérez, B., Johnson, B., Wärff, C., Lumley, D., Torfs, E., Nopens, I., Townley, L., 2021. Digital Water: operational digital twins in the urban water sector: case studies. Int. Water Assoc.

Varadharajan, C., Appling, A.P., Arora, B., Christianson, D.S., Hendrix, V.C., Kumar, V., Lima, A.R., Müller, J., Oliver, S., Ombadi, M., Perciano, T., Sadler, J.M., Weierbach, H., Willard, J.D., Xu, Z., Zwart, J., 2022. Can machine learning accelerate process understanding and decision-relevant predictions of river water quality? Hydrol. Process. 36, 1–22. https://doi.org/10.1002/hyp.14565.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I., 2017. Attention is all you need. Adv. Neural Inf. Process. Syst. 2017-Decem 5999–6009.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S.D., Tegmark, M., Fuso Nerini, F., 2020. The role of artificial intelligence in achieving the Sustainable Development Goals. Nat. Commun. 11, 1–10. https://doi.org/10.1038/s41467-019-14108-y.

Wang, X., Guo, G., Liu, S., Wu, Y., Xu, X., Smith, K., 2020. Burst detection in district metering areas using deep learning method. J. Water Resour. Plan. Manag. 146, 04020031 https://doi.org/10.1061/(asce)wr.1943-5452.0001223.

Wang, Z., Man, Y., Hu, Y., Li, J., Hong, M., Cui, P., 2019. A deep learning based dynamic COD prediction model for urban sewage. Environ. Sci. Water Res. Technol. 5, 2210–2218. https://doi.org/10.1039/c9ew00505f.

Wang, M., Kumar, S.S., Cheng, J.C.P., 2021a. Automated sewer pipe defect tracking in CCTV videos based on defect detection and metric learning. Autom. Constr. 121, 103438.

Wang, M., Luo, H., Cheng, J.C.P., 2021b. Towards an automated condition assessment framework of underground sewer pipes based on closed-circuit television (CCTV) images. Tunnell. Underground Space Technol. 110, 103840.

Wang, M., Cheng, J.C.P., 2020. A unified convolutional neural network integrated with conditional random field for pipe defect segmentation. Comput. Aided Civ. Infrastruct. Eng. 35 (2), 162–177.

Wu, Z.Y., Rahman, A., 2017. Optimized deep learning framework for water distribution data- driven modeling. Procedia Eng 186, 261–268. https://doi.org/10.1016/j.proeng.2017.03.240.

Xie, Q., Li, D., Xu, J., Yu, Z., Wang, J., 2019. Automatic detection and classification of sewer defects via hierarchical deep learning. IEEE Trans. Autom. Sci. Eng. 16 (4), 1836–1847.

Xie, X., Niu, J., Liu, X., Chen, Z., Tang, S., Yu, S., 2021. A survey on incorporating domain knowledge into deep learning for medical image analysis. Med. Image Anal. 69, 1–27. https://doi.org/10.1016/j.media.2021.101985.

Xu, T., Liang, F., 2021. Machine learning for hydrologic sciences: an introductory overview. Wiley Interdiscip. Rev. Water 8, 1–29. https://doi.org/10.1002/wat2.1533.

Xu, W., Jiang, Y., Zhang, X., Li, Y., Zhang, R., Fu, G., 2020. Using long short-term memory networks for river flow prediction. Hydrol. Res. 51, 1358–1376. https://doi.org/10.2166/nh.2020.026.

Xu, W., Meng, F., Guo, W., Li, X., Fu, G., 2021. Deep reinforcement learning for optimal hydropower reservoir operation. J. Water Resour. Plann. Manage. 147 (8), 04021045 https://doi.org/10.1061/(ASCE)WR.1943-5452.0001409.

Yang, Y.C.E., Cai, X., Stipanović, D.M., 2009. A decentralized optimization algorithm for multiagent system-based watershed management. Water Resour. Res. 45, 1–18. https://doi.org/10.1029/2008WR007634.

Yang, L., Cervone, G., 2019. Analysis of remote sensing imagery for disaster assessment using deep learning: a case study of flooding event. Soft Comput 23, 13393–13408.

Yin, X., Chen, Y., Bouferguene, A., Zaman, H., Al-Hussein, M., Kurach, L., 2020. A deep learning-based framework for an automated defect detection system for sewer pipes. Autom. Constr. 109, 102967.

Zhang, D., Lindholm, G., Ratnaweera, H., 2018a. DeepCSO: forecasting of combined sewer overflow at a citywide level using multi-task deep learning. arXiv preprint. arXiv:1811.06368.

Zhang, D., Martinez, N., Lindholm, G., Ratnaweera, H., 2018b. Manage sewer in-line storage control using hydraulic model and recurrent neural network. Water Resour. Manag. 32, 2079–2098. https://doi.org/10.1007/s11269-018-1919-3.

Zhang, D., Skullestad, E., Lindholm, G., Ratnaweera, H., 2018c. Hydraulic modeling and deep learning based flow forecasting for optimizing inter catchment wastewater transfer. J. Hydrol. 567, 792–802. https://doi.org/10.1016/j.jhydrol.2017.11.029.

Zhang, Z., Li, B., Lv, X., Liu, K., 2018d. Research on pipeline defect detection based on optimized faster R-CNN algorithm. DEStech Trans. Comput. Sci. Eng. 469–474. https://doi.org/10.12783/dtcse/ammms2018/27322.

Zhou, M., Pan, Z., Liu, Y., Zhang, Q., Cai, Y., Pan, H., 2019a. Leak Detection and Location based on ISLMD and CNN in a pipeline. IEEE Access 7, 30457–30464. https://doi.org/10.1109/ACCESS.2019.2902711.

Zhou, M., Yang, Y., Xu, Y., Hu, Y., Cai, Y., Lin, J., Pan, H., 2021. A pipeline leak detection and localization approach based on ensemble TL1DCNN. IEEE Access 9, 47565–47578. https://doi.org/10.1109/ACCESS.2021.3068292.

Zhou, X., Tang, Z., Xu, W., Meng, F., Chu, X., Xin, K., Fu, G., 2019b. Deep learning identifies accurate burst locations in water distribution networks. Water Res. 166, 115058 https://doi.org/10.1016/j.watres.2019.115058.

Zhu, X.X., Tuia, D., Mou, L., Xia, G.S., Zhang, L., Xu, F., Fraundorfer, F., 2017. Deep learning in remote sensing: a Comprehensive Review and List of Resources. IEEE Geosci. Remote Sens. Mag. 5, 8–36. https://doi.org/10.1109/MGRS.2017.2762307.