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Martin Oberascher

Innovative Concepts and Applications for Smart Water Cities

Towards Integrated Management of Network-based Urban Water Infrastructure

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Innovative Concepts and Applications for Smart Water Cities

Towards Integrated Management of Network-based Urban Water Infrastructure

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Kurzfassung

Weltweit sind Smart Cities im Entstehen, die ökonomische, institutionelle, soziale und technische Konzepte in Interaktion mit bestehender Infrastruktur verbinden. Ziel dabei ist es, den urbanen Lebensraum nachhaltiger zu gestalten und die Lebensqualität zu erhöhen. Durch die Digitalisierung im Bereich der urbanen Wasserinfrastruktur (UWI) kann zudem die Leistungsfähigkeit von existierender Infrastruktur als Maßnahme gegen zukünftige Herausforderungen (Klimawandel, Urbanisierung und Instandhaltung bestehender Infrastruktur) erhöht werden. Ein wesentliches Element dabei sind zuverlässige und effiziente Informations- und Kommunikationstechnologien (IKT) für den Datenaustausch (z.B.: Überwachung von Umweltparamatern) und die (technische) Verflechtung unterschiedlicher Beteiligte. Zurzeit kommen jedoch IKT und eine systemweite Betrachtung im Bereich der UWI kaum zur Anwendung und der Einsatz ist vorwiegend auf die Hauptpunkte in den Netzwerken beschränkt (z.B.: Mischwasserüberläufe bzw. Übergabepunkte bei Druckzonen). In diesem Zusammenhang ermöglicht das Internet of Things (IoT) auch an abgelegenen und unterirdischen Anlagen eine großflächige Installation von Messgeräten, wodurch die Datenverfügbarkeit deutlich ansteigt. Dadurch entstehen auch neue Konzepte für die Bewirtschaftung der netzwerk-basierten UWI.

Daher ist das Ziel dieser Dissertation zu der Entwicklung von Smart Water Cities durch die Entwicklung von innovativen Konzepten im Bereich von urbanen Entwässerungs- und Trinkwassernetzwerken (inkl. grüner Infrastruktur) beizutragen.

Um die Umsetzung von IKT zu unterstützen, wurde in einer Literaturstudie die Eigenschaften (z.B.: Übertragungsrate, Reichweite) und Limitierungen (z.B.: Energiebedarf) von einer Vielzahl an Kommunikationstechnologien erhoben. Zudem wurden existierende und neue Anwendungen im Bereich der netzwerk-basierten UWI auf die erforderliche zeitliche (z.B.: Sekunden zu Monate) und räumliche (z.B.: Haushalt bis Stadt) Auflösung von Mess- und Kontrolldaten analysiert. Wie die Ergebnisse zeigen, ist dabei eine Abstimmung zwischen Anwendungszweck und Kommunikationstechnologie für die Umsetzung eines effizienten Mess- und Steuerungsnetzwerkes erforderlich. Jedoch werden diese Anforderungen in bestehenden Empfehlungen nur ungenügend berücksichtigt. Daher wird ein umfangreiches Rahmenwerk vorgestellt, das Forschende, Netzwerkbetreibende und Entscheidungstragende bei der Auswahl geeigneter Kommunikationstechnologien für gewählte Anwendungen oder realisierbare Anwendungen bei einem bestehenden Kommunikationsnetzwerk unterstützt.

Zudem wurde die smarte Regentonne (SRT) als ein IoT-basierter Mikrospeicher für das Regenwassermanagement entwickelt und die Auswirkungen auf Haushalts- und Gemeindeebene untersucht. Die SRT besteht aus einer herkömmlichen Regentonne, die mit einem in Echtzeit kontrollierbaren Ventil ausgestattet ist. Dadurch kann die SRT durch die Verwendung von hochaufgelösten Wettervorhersagen vor einem Niederschlagser-

eignis entleert werden, wodurch die Rückhaltekapazität erhöht werden kann. Um die Auswirkungen auf Gemeindeebene untersuchen zu können, wurde die open-source Simulationssoftware „Smartin“ entwickelt. „Smartin“ ermöglicht die Simulation von IoT-basierten Mikrospeichern in einem gekoppelten Modell aus Entwässerungs- und Trinkwassernetzwerk und unterstützt zudem eine höhe räumliche und zeitliche Auflösung. Als Fallstudie wurde dabei die bestehende Infrastruktur einer alpinen Gemeinde virtuell mit SRT ausgestattet. Wie die Ergebnisse zeigen, bietet eine großflächige Installation von SRT bei einem integrativen Verbesserungsansatz eine gute Alternative zu anderen erforderlichen Systemerweiterungen. Um Verschlechterung zu vermeiden ist jedoch eine koordinierte Kontrollstrategie und eine ausreichende Berücksichtigung von digitalen Unsicherheiten (z.B.: Genauigkeit von Wettervorhersagen, Zuverlässigkeit in der Datenübertragung) erforderlich.

Am Ende dieser Arbeit werden noch reale Erfahrungen mit smarten Anwendungen vorgestellt. Der Campus Technik der Universität Innsbruck (auch „Smart Campus“ bezeichnet) wurde mit innovativer Messsensorik ausgestattet, wodurch alle Wasserflüsse zu und vom Campusgelände in Echtzeit überwachen werden können. Dadurch stellt der „Smart Campus“ ein ideales Testgelände für innovative Anwendungen im Bereich der netzwerk-basierten UWI dar. Als beispielhafte Anwendungen werden dabei der Prototyp der SRT und ein Frühwarnsystem für Wasserverluste vorgestellt. Die Umsetzung eines hochaufgelösten Messnetzwerkes ist aufwändig und erfordert entsprechendes Wissen und stellt dadurch eine Herausforderung in der Umsetzung speziell für kleine Gemeinden dar. In diesem Zusammenhang zeigten die Analysen des Wasserverlustmanagements bei kleinen Gemeinden in Tirol (Österreich), dass auch einfache Ansätze eine Verbesserung im Betrieb erzielen können. Zum Beispiel sind einfache Kennzahlen, die auf der Massenbilanz basieren, für die Bewertung des Netzzustandes geeignet. Zudem bewirken staatliche Förderungen und Echtzeitmessungen des Gesamtzuflusses eine Reduktion der Wasserverluste im Netzwerk.

Neben den Vorteilen im Betrieb bedeutet eine hohe Anzahl an digitalen Elementen auch zusätzliche Risiken (z.B.: höhere Vulnerabilität gegenüber cyber-physischen Angriffen, ökologische Fragestellung durch die Verwendung von Batterien, Erfordernis einer auf das Gesamtsystem abgestimmten Kontrollstrategie). Daher wird eine adäquate Behandlung und Adressierung dieser Punkte ein wichtiger Faktor für den zukünftigen Erfolg von Smart Water Cities sein.

Abstract

Smart cities are emerging worldwide, including economic, institutional, social, and technical concepts in interaction with existing infrastructure to achieve sustainability and increase quality of life. Additionally, digitalisation projects in the field of urban water infrastructure (UWI) aim to increase capacity of existing infrastructure to deal with future challenges caused by climate change, growing of urban population, and maintenance. Therefore, efficient and reliable information- and communication technologies (ICT) represent a key factor for the exchange of measurement data (e.g., monitoring environmental parameters) and interconnections between different participants. However, ICT and system-wide management are not yet widely deployed and mainly concentrated on main points in network-based UWI (e.g., combined sewer overflows, inlet point of district meter areas). In this context, especially the Internet of Things (IoT) concepts enables a large-scale implementation of measurement devices even at underground and remote structures, increasing data availability significantly. Following, new possibilities in the management of network-based UWI are emerging.

The research aim of this doctoral dissertation is to contribute to the ongoing development of smart water cities by developing innovative concepts in the field of urban drainage and water distribution network including nature-based solutions.

To assist the implementation of ICT, a literature review was performed to determine features (e.g., data rate, transmission range) and limitations (e.g., energy consumption) of different communication technologies. Additionally, existing and new applications in the field of network-based UWI were summarised to provide a comprehensive overview over required required temporal (e.g., seconds to months) and spatial resolution (e.g., household to city scale) of measurement and control data. As can be concluded, an efficient monitoring and control network requires a coordination between usable communication technology and intended application, which is not sufficient considered by existing recommendations. Therefore, a detailed framework is presented, which can be used by researchers, network operators and stakeholders to identify suitable communication technologies for different applications or to define applications for an existing communication network.

Furthermore, the smart rain barrel (SRB) concept is introduced as an IoT-based micro storage for rainwater harvesting and effects on household and municipality scale were investigated. The SRB consists of a conventional rain barrel, which is extended by a remotely controllable discharge valve. Therefore, the SRB can be emptied before rain events by applying high-resolution weather forecast to increase detention volume. To evaluate the effects on municipality scale, the open-source simulation tool "Smartin" was developed, which is capable to simulate IoT-based micro storages in a coupled model of urban drainage and water distribution network with high temporal and spatial detail.

As case study, the existing infrastructure of an Alpine municipality was hypothetically retrofitted with SRBs. The simulation results show, that a large-scale implementation of SRBs provides a good alternative to required system extensions in case of integrated performance improvement. However, to avoid system deterioration, a coordinated control strategy and sufficient consideration of digital uncertainties (e.g., accuracy of weather forecast, reliability of data transmission) is necessary.

Finally, smart applications in real-world experiences are presented. First, a campus of the University of Innsbruck, called "Smart Campus", was equipped with innovate measurement devices to measure water flows to and from the area to gain real experiences with ICT. Subsequently, the "Smart Campus" represents an ideal testing bed for innovative concepts in the field of network-based UWI. As exemplary applications a prototype of the SRB, which is under operation during the summer months, and a warning system for water losses are presented. However, the implementation of a high-resolution measurement network is time-consuming and requires appropriate expertise, thus making a major challenge for small municipalities. In this context, analysis of water loss management in small municipalities in Tyrol (Austria) showed that also simple approaches can improve system operation. For example, performance indicators based on mass balance can be used for evaluation of network performance, while state funding and online measurements of inflows can reduce water losses in the network.

Additionally to the benefits for operation, a large-number of digital components also involves further risks (e.g., increasing vulnerability to cyber-physical attacks, raising ecological questions due to battery-powered devices, or requiring a coordinated integration to avoid system degradations). Therefore, an adequate addressing of these issue will be important for the future success of smart water cities.

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1 Introduction

1.1 Motivation

Climate change (e.g., longer dry periods, higher temperatures, short periods of heavy rainfall), urbanisation (e.g., increase urban population and sealed surface) and maintenance (e.g., ageing infrastructure) require an adoption of existing infrastructure in Alpine areas and represent therefore present and future challenges of urban water management. As a possible measure, controlled systems implemented in urban water infrastructure (UWI) aim to increase hydraulic and/or quality-related capacity of existing infrastructure (García et al., 2015; Yuan et al., 2019). These technologies are widely applied in centralised facilities (e.g., treatment plants) (Newhart et al., 2019; Yuan et al., 2019), whereas a usage in the water networks is mainly limited to the main points. Thereby, combined sewer overflows (Mollerup et al., 2016; van Daal et al., 2017) and inlet points of district meter areas (Creaco et al., 2019) represent exemplary measuring and control points in urban drainage and water distribution network, respectively. Furthermore, system complexity and management efforts are further increased by frequently integrating decentralised solutions (e.g., nature-based solutions) (Fletcher et al., 2015).

In this context, the Internet of Things (IoT) as part of smart cities development includes low-cost sensors in combination with innovative wireless communication technologies. This enables a large-scale implementation of communicating 'items', which significantly increases data availability (Li et al., 2014). As measuring equipment can even be integrated at underground and remote installation places, new possibilities for monitoring and controlling of network-based UWI are emerging (Kerkez et al., 2016). This development is particularly noticeable in the case of smart nature-based solutions, including monitoring sensors and discharge valves controllable in real-time. However, up to now, these systems are mainly investigated at household scale (Xu et al., 2020), and impacts and benefits of a widespread implementation are relatively unknown.

Furthermore, system-wide management and control will gain in importance in future as stated by Yuan et al. (2019). This requires an integrated approach on the requirements of urban drainage and water distribution network including nature-based solutions (1) for implementing efficient monitoring and controlling systems, (2) for adequate modelling and simulation tools, and (3) for comprehensive analyses of the effects of different applications. Additionally to this integrative view, there is also a transformation from purely technological solutions to smart city approaches noticeable. In general, smart cities are an innovative concept for managing urban cities and are emerging worldwide. Smart cities are characterised by including social, technical, economic and institutional concepts to improve quality of life and to achieve sustainability (Ahvenniemi et al., 2017; Silva et al., 2018), leading subsequently to the development of smart water city frameworks.

1.2 Aim and Objectives

The research aim of this doctoral dissertation is to develop innovative concepts and applications in the field of network-based UWI and to contribute to the ongoing development of smart water cities.

Thereby, the research aim is further subdivided into the four objectives summarised in Table 1.1. Additionally, each objective is broken down in sub-objectives.

Table 1.1: Overview of investigated research objectives.

No.	Research Objective
1	**Literature review: data requirements and communication technologies for network-based UWI**
1.1	Identifying the necessary temporal and spatial resolutions of measurement data for a wide range of applications applied to UWI networks
1.2	Outlining the features and usage of a variety of wireless and wired communication for UWI networks
1.3	Providing a guideline for usable communication technologies for monitoring and controlling UWI networks with different spatial and temporal resolutions of measurement data
2	**Proposing the smart rain barrel (SRB) concept**
2.1	Conceptualisation of the SRB as an IoT-based solution for smart rainwater harvesting
2.2	Developing a high-resolution simulation tool for integrated control of SRBs in the context of UWI
2.3	Assessing the impacts on household and municipality scale
3	**Performance optimisation of a large-scale implementation of SRBs as IoT-based micro storages**
3.1	Improving different control strategies for a large-scale implementation of IoT-based micro storages on the performance of UWI
3.2	Analysing the impacts of digital uncertainties associated with smart rainwater harvesting
3.3	Investigating the impact of a large-scale implementation of IoT-based micro storages on system resilience
4	**Smart applications in real-world implementation**
4.1	Implementing a high-resolution measurement and control network at the Smart Campus
4.2	Developing and operating a prototype of the SRB
4.3	Identifying usable performance indicators and influences of state funding for water loss management in small municipalities

1.3 Structure of this Thesis

This thesis is structured as followed: Chapter 1 includes the introduction into the topic, a description of the research objectives and structure of this dissertation. Chapter 2 addresses data requirements of applications and features and limitations of communication technologies to provide a guideline for monitoring and controlling networks of network-based UWI. In Chapter 3, the SRB concept is presented including an investigation of impacts on household and municipality scale. Following, Chapter 4 aims to improve the performance of a large-scale implementation of SRBs by investigating different control strategies and digital uncertainties associated with smart rainwater harvesting. Additionally, smart applications in real-word implementation are presented in Chapter 5. Finally, Chapter 6 summaries the key findings of this dissertation including a critical discussion and lessons learned, which are completed by possible future research topics.

Table 1.2 gives an overview of the chapters with the research questions covered. As this thesis is a cumulative dissertation, reference is made to the papers addressing them.

Table 1.2: Overview of chapters with research objectives covered and papers addressing them.

Section	Research Objective	Paper
Chapter 1	-	-
Chapter 2	1.1, 1.2, 1.3	Paper I
Chapter 3	2.1, 2.2, 2.3	Paper II, III
Chapter 4	3.1, 3.2	Paper IV, V
Chapter 5	4.1, 4.2, 4.3	Paper VI, VII
Chapter 6	-	-

To highlight the integrative aspect of this cumulative dissertation, Figure 1.1 shows the key areas of the UWI each paper covers. In this context it is worth highlighting, that the majority of the papers address issues from at least two key areas.

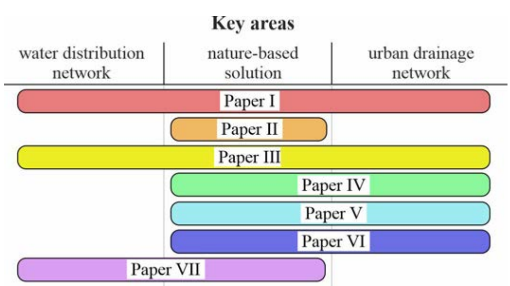

Figure 1.1: Highlighting the integrative aspect of the papers used for this dissertation.

1.4 List of Papers

The dissertation is based on six journal articles (five already published and one submitted) and one conference proceeding:

Paper I:
Oberascher, Martin; Rauch Wolfgang; Sitzenfrei Robert (submitted). Towards a smart water city: A comprehensive analysis of applications, data requirements, and communication technologies. Manuscript under revision, submitted to Sustainable Cities and Society. Impact factor 7.587 (2020)

Paper II:
Oberascher, Martin; Zischg, Jonatan; Kastlunger, Ulrich; Schöpf, Martin; Kinzel, Carolina; Zingerle, Christoph; Rauch, Wolfgang; Sitzenfrei, Robert (2019). Advanced Rainwater Harvesting through Smart Rain Barrels. Proceedings of the World Environmental and Water Resources Congress 2019. May 19–23, 2019. Pittsburgh, Pennsylvania, United States. Publication listed on the Web of Science.

Paper III:
Oberascher, Martin; Kinzel, Carolina; Kastlunger, Ulrich; Kleidorfer, Manfred; Zingerle, Christoph; Rauch, Wolfgang; Sitzenfrei, Robert (2021). Integrated urban water management with micro storages developed as an IoT-based solution – The smart rain barrel. Environmental Modelling & Software. Impact factor 5.228 (2020). Publication listed on the Web of Science.

Paper IV:
Oberascher, Martin; Rauch, Wolfgang; Sitzenfrei, Robert (2021). Efficient integration of IoT-based micro storages to improve urban drainage performance through advanced control strategies. Water Science and Technology. Impact factor 1.915 (2020). Publication listed on the Web of Science.

Paper V:
Oberascher, Martin; Dastgir, Aun; Li, Jiada; Hesarkazzazi, Sina; Hajibabaei1, Mohsen; Rauch, Wolfgang; Sitzenfrei, Robert (2021). Revealing the Challenges of Smart Rainwater Harvesting for Integrated and Digital Resilience of Urban Water Infrastructure. Water. Impact factor 3.103 (2020). Publication listed on the Web of Science.

Paper VI:
Oberascher, Martin; Kinzel, Carolina; Rauch, Wolfgang; Sitzenfrei, Robert (2020). Einblicke in eine „Smart Water City“ - ein Projekt der Universität Innsbruck (insights into a "Smart Water City" - a research project of the University of Innsbruck - only available in German). Wasserwirtschaft Wassertechnik: Das Praxismagazin fuer das Trink- und Abwassermanagement.

Paper VII:
Oberascher, Martin; Möderl, Michael; Sitzenfrei, Robert (2020): Water Loss Management in Small Municipalities: The Situation in Tyrol. Water. Impact factor 3.103 (2020). Publication listed on the Web of Science.

The faculty requirement for a cumulative dissertation is at least 3 articles accepted for publication in recognised journals (e.g., Web of Science listed). This dissertation contains a total of four already published articles (one Environmental Modelling & Software, two Water, one Water Science and Technology) and one submitted manuscript

(Sustainable Cities and Society), in which the submitter is the first author. Thereby, this dissertation fulfils the requirements of the faculty. As all publications are collaborative works (several authors), Table 1.3 describes the contribution to the individual articles using following terms and abbreviations:

MR: main responsibility - development and implementation of the task was carried out independently under the advice of the supervisors

SR: joint responsibility - development and implementation of the task was carried out by the project team, whereby a significant contribution was made to successful completion

C: contributed - a contribution was made to achieve task objectives

NA: not applicable

Table 1.3: Contribution to papers on which this dissertation is based on.

		Manuscript			Submission	
Paper	Conception	Data collection and software	Analysis and interpretation	Draft preparation	Submitting author	Response reviewer
I	MR	MR	MR	MR	MR	NA
II	SR	SR	MR	MR	MR	NA
III	SR	SR	SR	MR	MR	MR
IV	MR	MR	MR	MR	MR	MR
V	SR	MR	SR	SR	MR	MR
VI	SR	C	C	MR	MR	MR
VII	SR	SR	SR	MR	MR	NA

2 Applications and Communication Technologies

2.1 Paper I

Oberascher, M., Rauch, W., Sitzenfrei, R., 2021. Towards a smart water city: A comprehensive analysis of applications, data requirements and communication technologies for integrated managment. Manuscript under revision, submitted to Sustainable Cities and Society.

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Towards a smart water city: A comprehensive review of applications, data requirements, and communication technologies for integrated management

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A R T I C L E I N F O

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A B S T R A C T

Smart cities are an innovate concept for managing urban cities to enhance sustainability and increase quality of life for citizens. Although urban water infrastructure (UWI) performs important functions in a city (e.g., supply of drinking water), information and communication technologies (ICT) and system-wide management of network-based UWI are not yet widely deployed. Therefore, this review summarises first both existing and potential applications related to network-based UWI, characterised by different spatial and temporal resolution of measurement and control data. Second, a comprehensive analysis of ICT is provided, which is extended with exemplary applications in the field. The analysis reveals that a coordination between intended application and usable communication technology is required to realise an efficient monitoring and control network in the field of UWI networks. To overcome this limitation, a detailed framework is developed, which can be used by researcher, network operators, and stakeholder to identify suitable communication technologies for different UWI applications or to determine possible applications for an existing ICT system. Following, the applicability of the framework is demonstrated by selected examples. As the framework also indicates, an integrated approach towards smart water cities requires the combination of different communication technologies to satisfy all specifications.

Abbreviations

ADSL	asymmetric digital subscriber line
AI	artificial intelligence
API	application programming interface
BB-PLC	broadband powerline communication
BLE	bluetooth low energy
CSO	combined sewer overflow
DSL	digital subscriber line
DWTP	drinking water treatment plant
eDRX	extended discontinuous reception mode
GPRS	general packet radio service
GSM	global system for mobile communications
HDSL	high data rate digital subscriber line
IDF	intensity-duration-frequency
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IWA	International Water Association
LAN	local area network
LoRa	long rang
LoRaWAN	long range wide area network
LPWAN	low power wide area networks
LTE	long term evolution
LTE eMTC	long term evolution enhanced machine-type communication
LTE-M	long term evolution for machines
M-Bus	Meter-bus
M2M	machine-to-machine
MMS	multimedia message service
NAN	neighbourhood area network
NB-IOT	narrow band Internet of Things
NB-PLC	narrowband powerline communication
NBS	nature-based solution
NFC	near-field communication
PAN	personal area network
PCL	powerline communication
PON	passive optical networks
PSWM	power saving mode

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PWDMS	personal water demand management strategies
RFID	radio frequency identification
RTC	real-time control
RWH	rainwater harvesting
SCADA	supervisory control and data acquisition
SMS	short message service
UDS	urban drainage network
UMTS	universal mobile telecommunications system
UWI	urban water infrastructure
VDSL	very high-speed digital subscriber line
WAN	wide area network
WDM	wavelength division multiplexing
WDN	water distribution network
Wi-Fi	wireless fidelity
WM-Bus	wireless Meter-bus
WWS	water supply systems
WWTP	wastewater treatment plant

1. Introduction

Smart cities represent an innovative concept for managing of urban environments and are emerging worldwide. Thereby, smart cities aim to achieve sustainability and to improve quality of life by including technical, institutional, economic, and social concepts in interaction with existing infrastructure (Keshavarzi et al., 2021; Silva et al., 2018). As stated by Ahad et al. (2020), a key factor for the development of smart cities are efficient and reliable information and communication technologies (ICT) to monitor environmental parameters and to ensure interconnections between different areas and participants. Especially the Internet of Things (IoT) concept enables an easy large-scale implementation of measurement equipment due to the evolution of low-cost sensors in combination with innovative and wireless data transfer technologies (Mohanty et al., 2016).

With regard to urban water infrastructure (UWI), ICT were previously widely found in centralised facilities, such as drinking water and wastewater treatment plants (Newhart et al., 2019; Yuan et al., 2019), whereas control opportunities for system parts distributed over the area are now concentrated on main points. For example, ICT is implemented at combined sewer overflows (CSOs) in the urban drainage network (Mollerup et al., 2016; van Daal et al., 2017) or inlet points of the district meter areas of the water distribution network (Creaco et al., 2019). These data are collected and analysed centrally by a supervisory control and data acquisition (SCADA) system, which is also applied for regulating control equipment in the field of UWI (Franco et al., 2019; Yuan et al., 2019). In this context, the IoT concept enables novel approaches for monitoring and controlling of network-based UWI (Kerkez et al., 2016), even in remote or underground structures. Additionally, as outlined by Yuan et al. (2019), integrated control and system-wide management of UWI is still only occasionally applied.

In order to assist the implementation of ICT and a system-wide management in the field of UWI, a literature review was performed (1) to obtain information about the required temporal and spatial resolution for a wide range of applications in the field of UWI and (2) to obtain an overview of applicable communication technologies. It can be concluded from literature review, that research articles can be categorised into two fields: (1) optimisation of mostly one application without going into detail about data transmission technology of required measurement and control data (application-related); or (2) description of a real-word implementation of ICT for an intended application, where it is unknown for which applications it can additionally be used (implementation-based). As the review also showed, the usable communication is strongly dependent on spatial and temporal requirements of UWI applications, which is currently not sufficient considered by existing publications

The aim of this review is therefore to provide a comprehensive guideline as a first decision-making tool for researcher, network operators and stakeholders for the implementation of ICT in the field of UWI and to support development of future SCADA systems. The focus of this work is on applications related to urban drainage and water distribution networks, as ICT is relatively mature at centralised (treatment) facilities. The presented guidelines can be used for single applications and also contribute to the ongoing deployment of smart water cities. The detailed objectives of this work are as follows:

- Presenting a technical framework for ICT networks for UWI with interoperability to already existing approaches and smart city research
- Identifying the necessary temporal and spatial resolutions of measurement data for a wide range of applications applied to UWI networks
- Outlining the features of a variety of wireless and wired communication for UWI networks
- Providing a guideline for usable communication technologies for monitoring and controlling UWI networks with different spatial and temporal resolutions of measurement data

2. Material and method

A systematic literature review was conducted to gain an overview of utilised applications in the field of UWI and to obtain information about the required spatial and temporal resolutions of the data. Using the terms "smart water networks" or "operation urban water" as search topics in the Web of Science produces 1623 and 2093 matches, respectively. Following, the search was carried out manually to cover a wide range of different applications. The search strategy can be described as following: (1) using the defined applications in Table 1 as a search string in various databases (e.g., Web of Science, Scopus, IEEE, etc.), (2) reviewing of a sufficient description of applied measurement and control data and/or used communication technology, and (3) detailed analysis of these parameters and inclusion as relevant literature. In total, this review comprises 303 references, whereas 286 studies specifically related to UWI and communication technology were investigated in detail, including review papers, journal articles, conference proceedings, and standards (see Fig. 1).

Fig. 2 gives a short overview of the structure of this work and shows how the guideline for the implementation of any monitoring and control networks in the field of UWI can be applied. Table 1 summarises the reviewed applications for water distribution networks, nature-based solutions, and urban drainage networks and is divided into real-time operations and applications based on historical data. After selecting an intended application in Table 2. Tables 4–6 give information about the required temporal and spatial resolutions of measurement data for the realisation of this application. In the next step, the information can be used to determine an appropriate communication technology by using Table 8 for real-time operations and Fig. 5 for aggregated and historical data.

Table 1
Applications in the field of the UWI classified into the five subsections.

	System	Water distribution network (WDN)	Nature-based solutions (NBS)	Urban drainage network (UDN)
Smart city application	Real-Time with human interactions	PWDM – educational PWDM -legislative PWDM – maintenance PWDM - technical Water pricing -peak Water pricing - scarcity	Maintenance	Flooding Precipitation
RT-Operation	Real-Time	Contamination (data-driven, model-based) Cyber-physical attacks Hydropower control Integrated control (WDN – NBS) Leakage detection (data-driven, model-based) Pump scheduling / Tank filling / Service pressure	Irrigation control Discharge control (quality / quantity)	CSO control (frequency, quality) Flooding control External inflow detection Integrated control (UDN – NBS) Public health Wastewater-based epidemiology
Performance optimisation	Historical (time series)	Design hydropower Model calibration (quantity, quality) Specific peak factor (unique, distributed) Water loss estimation Water pricing billing	Design RWH Monitoring (micro-climate, performance, maintenance)	Design CSO (frequency, quality) Design heat recovery IDF-curves Model calibration (quantity, quality)
Design	Historical (peak)	Pipe Pump Water tank	Bio-retention and detention ponds Vegetated swales (eventually in combination with UDN)	Pipe Pumps Storage
Strategic Master Planning	Historical + future (time series)	Future development of UWI Future water pricing – scarcity Water source planning	Future development of UWI	

The framework of this study can also be interpreted in the opposite direction. In other words, with an existing communication network (e.g., implemented for a smart city of other infrastructure fields); the boundary conditions for the temporal and spatial resolution of measurement data are predefined, further defining the possible applications for UWI.

3. Technical framework for ICT networks

The description of the technical framework for monitoring and controlling networks is based on the experiences and guidelines of smart city projects. Additionally, frameworks for smart city projects support the implementation of heterogeneous devices but can also be utilised for any kind of network. The technical architecture of smart cities can be divided into sub-layers, where each layer is assigned to specific tasks and functions to successfully realise a smart city project (Jnr et al., 2019). Therefore, existing frameworks of smart UWI (Fu and Butler, 2021; Li et al., 2020) and IoT architectures (Jnr et al., 2019; Li et al., 2020; Nauman et al., 2020; Seng and Ang, 2018; Sethi and Sarangi, 2017) have been utilised and adapted to the requirements for this work. The technical architecture applied in this work is illustrated in Fig. 3 and consists of physical, perception, communication, middleware, processing, and application layers.

As stated above, the aim of this work to develop a guideline for the implementation of ICT in the field of UWI. Therefore, perception, communication, and application layers are linked together, which can be identified as the primary step towards the realisation of a monitoring and controlling network in the field of UWI. The middleware layer contains the hardware and software requirements for the network operator for a functioning data management and can/should have the same structure used in other infrastructure areas to ensure interoperability. Due to the wide scope of this subject, the middleware layer is beyond the scope of this work; for more information, refer to Ngu et al. (2017) and Razzaque et al. (2015). In contrast, the software and hardware requirements of the processing layer depend on the chosen applications and, therefore, are not further discussed.

4. Physical layer

The functioning and structure of UWIs are generally known. However, this work is intended to provide a holistic view of UWI and an interface for other infrastructure sectors. Therefore, the structure of the individual subsystems will be described briefly divided into the following three key areas:

- The water supply system (WSS) supplies the urban population with drinking water in sufficient quantity and quality under a wide range of changing operating conditions caused by water demand fluctuations and rare events, such as fire flows. The water supply system can basically be divided into the following areas: (1) sources of drinking water; (2) if necessary, drinking water treatment plants (DWTP); (3) water distribution network (WDN) consisting of pipes and water tanks as static elements and pumps, valves, and hydropower stations as control capabilities; (4) end users consuming the delivered drinking water.
- The urban drainage system (UDS) ensures an environmentally tolerable disposal of treated wastewater into receiving water bodies to ensure public health, and safe stormwater runoff with following areas: (1) urban drainage network (UDN) consisting of pipes, storages, gates, and pumps; the UDS can be intended as a separate sanitary and stormwater system or a combined sewer system, which is characterised by combined sewer overflows (CSOs); and (2) wastewater treatment plants (WWTP)..
- A modern, integrative concept is moving away from these centralised systems towards decentralised and public solutions for on-site measures (Fletcher et al., 2015) and, hence, are also called

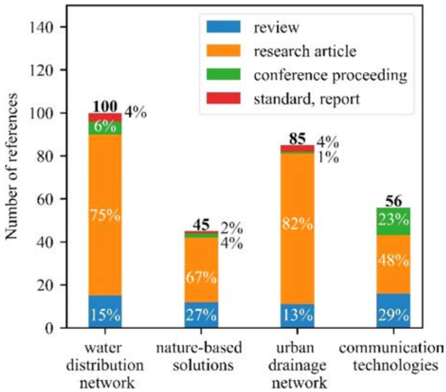

Fig. 1. Overview of the investigated studies related to the management of UWI.

Table 2
Definition of applied system levels with corresponding spatial resolution.

System level	Corresponding spatial resolution
1	Household scale (e.g., flats, buildings)
2	Nature-Based solution
3	Network nodes
4	Grid arrangement of approx. 100 - 500m width
5	Examination area (e.g., district metering area, catchment area of CSO)
6	Total area (e.g., municipality, city)
CP	Critical point (e.g., in WDN area with low water pressure)
HP	Hydropower unit
P	Pump
V	Valve
WWTP	Wastewater treatment plant

nature-based solutions (NBS). In this regard, NBS can include rainwater harvesting systems (RWH) to substitute drinking water, or green roofs for houses, permeable pavements, bio-retention and detention ponds, vegetated swales, and trees for public spaces to reduce rainwater runoff including an improvement of water quality or mitigate urban heat islands (Ruangpan et al., 2020).

5. Perception and application layer

ICT is currently widely applied in centralised system components, such as treatment plants for drinking water and wastewater (Yuan et al., 2019). Therefore, the focus of this work is on system components distributed over the area (WDN, UDN, and NBS). For further details about centralised system parts, refer to relevant literature, for example, for DWTP (Bakker et al., 2013; Boccelli et al., 2007; Gupta and Shrivastava, 2010; Yuan et al., 2019) and for WWTP (Fernandez-Arevalo et al., 2017; Khiewwijit et al., 2015; Newhart et al., 2019; Yuan et al., 2019).

The applications identified in the literature review reveal major differences between the required temporal and spatial resolution of the perception layer. Therefore, the investigated applications are classified into the following five subsections with similar characteristics regarding data requirements: (1) strategic master planning using historical and future data, (2) design based on peak loads, (3) performance optimisation aiming to improve the ongoing process through historical time patterns, (4) real-time operations utilised with real-time data, and (5) smart city applications, including real-time data with human interactions. Table 1 provides a short summary of the reviewed principal applications divided into three key areas: WDN, UDN, and NBS.

As described above, the perception layer consists of sensor nodes monitoring the environmental parameter. To decouple the rapid development of (low-cost) sensors and the long-term applications, following analysis are simplified by using the measurement parameter (e.g., water flow, temperature, etc.) for evaluation. For more information about (real-time) monitoring methods including hardware sensors, refer to relevant literature for WDN (Creaco et al., 2019), UDN (Bertrand-Krajewski et al., 2021) and NBS (Garcia et al., 2020; Kumar et al., 2021).

Table 4 – 6 summaries data requirements for all presented applications in Table 1 subdivided into WDN, UDN, and NBS, respectively. The

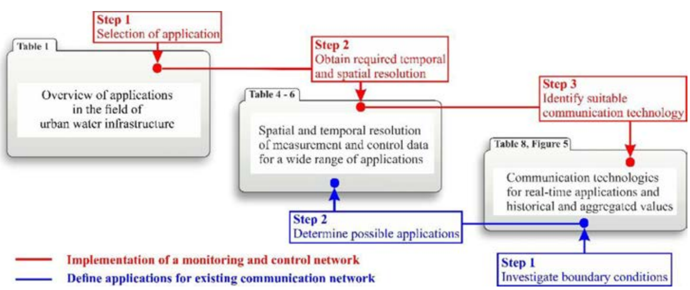

Fig. 2. Overview of the structure of this work.

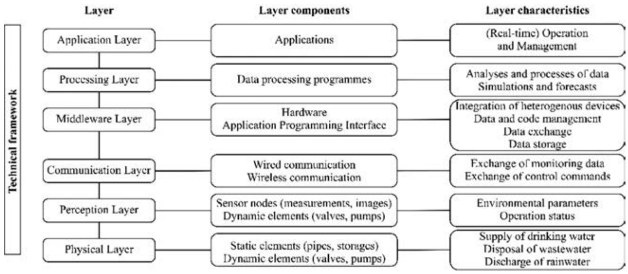

Fig. 3. Overview of the presented technical framework for the UWI divided into six layers.

Table 3
Definition of applied temporal resolution.

Colour	Corresponding temporal resolution
■	1 s – 5 min
■	5 min – 10 min
■	10 min – 1
■	1 h – 1 d
■	1 d – 1 m
■	1 m – 1

tables are structured as followed: (1) each application is listed in a separate row in the first column; (2) next column contains information about the network abstraction for model-based approaches; (3) column 3 – 6 provides information about temporal and spatial resolution for various measurement and control data; and (4) references are specified in the last column. In the tables, spatial resolution is indicated by an abbreviation in the table header, while the temporal resolution is highlighted in colour. Thereby, used abbreviations and colour is described in Table 2 and 3. Following, higher resolutions (e.g., system level 1) can be easily aggregated for applications with lower resolution (e.g., system level 3).

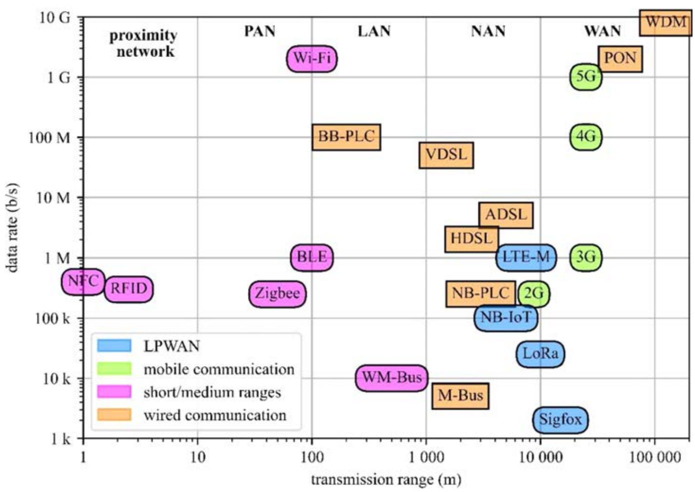

Fig. 4. Overview of the different data transfer technologies regarding distance and data rate and categorised into wired communication (rectangles) and wireless communication (rounded) based on the results of Abdelwahab et al. (2019), Ahmad et al. (2016). Ding et al. (2020), Mekki et al. (2019), and Sikimić et al. (2020).

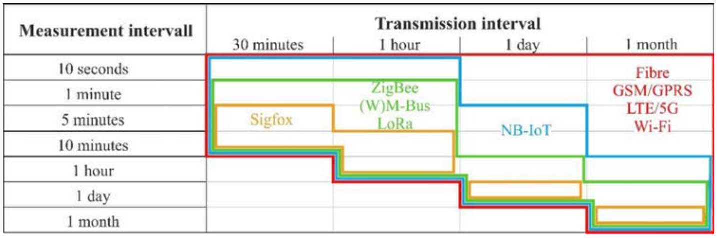

Fig. 5. Recommended communication technologies for historical and aggregated measurement values.

5.1. Strategic master planning

Through strategic master planning, the future development of UWI is investigated at a large scale. This process deals with essential issues, such as how to adapt existing infrastructure to future challenges, rather than with the assessment of single elements. As these processes include the involvement of planners and decision makers for long-term planning, the principal challenge is to appropriately predict and evaluate these transformations under associated uncertainties (e.g., different models for climate change) (Serrao-Neumann et al., 2017). Therefore, decision support tools are developed capable of analysing and evaluating different scenarios regarding economic and ecological impacts in a manageable way, as they should show the possible consequences of the choices made by decision-makers (Rygaard et al., 2014).

5.2. Design

The objective of the design process is to determine the required size of pipes and the location and operational status of additional system components (e.g., water tanks, storage tanks, pumps, or valves) in new systems, or as an extension or renovation of existing systems due to changing requirements (Mala-Jetmarova et al., 2018).

Table 4
Applications related to the WDN with required spatial and temporal resolution of measurement and control data. For information about spatial and temporal resolution, refer to Table 2 and 3.

Application	Network abstraction	Quantity 1	3	4	5	6	Pressure 1	3	4	5	6	Service P	V	HP	Additional data	References
Calibration (quantity)	3															Kapelan et al. (2007), Rathi et al. (2020)
Calibration (quality)	3														Quality (level 4)	Dini and Tabesh (2016), Nejjari et al. (2014)
Contamination (data-driven)	--														Quality (level 4)	Muharemi et al. (2019), Osmani and Mahmud (2020)
Contamination (model)	3														Quality (level 4)	He et al. (2018), Krause et al. (2008)
Cyber-physical attacks	3														Quantity (tanks); images (seconds)	Abdelhafidh et al. (2017), Housh and Ohar (2018), Taormina et al. (2018)
Design (pipe, pump)	3														Peak factor	EN 805 (2000); Creaco et al. (2016), Gurung et al. (2016), Jung et al. (2013), Marques et al. (2015), Zheng and Zecchin (2014)
Design (water tanks)	4														Quantity (source)	EN 1508 (1999)
Design (hydropower)	3 (- 6)					( )									Quantity (source)	Fecarotta et al. (2014), Möderl et al. (2012), Pugliese et al. (2018)
Development of UWI	4														Precipitation (level 6)	Behzadian and Kapelan (2015), Makropoulos et al. (2008), Willuweit and O'Sullivan (2013), Zeisl et al. (2018)
Hydropower control	3		*												Quantity (tanks)	Monteiro et al. (2018), Samora et al. (2016), Sitzenfrei and von Leon (2014)
Integrated control (WSN and NBS)■	3														Soil moisture (level 2)	--
Leakage (data-driven)	--				1				1							Farah and Shahrour (2017), Jung et al. (2015b), Romano et al. (2014), Sun et al. (2019), Wu et al. (2016)
Leakage (model-based)	3		*,4		1				1	1						Mirats-Tur et al. (2014), Perez et al. (2014), Sanz et al. (2016), Sophocleous et al. (2019), Huang et al. (2020)
Pump scheduling	5														Quantity (tanks)	Alvisi and Franchini (2017), Jung et al. (2015a), Quintiliani and Creaco (2019), Sun et al. (2020b)
PWDM – educational	--	3														Beal et al. (2016), Fielding et al. (2013), Liu et al. (2016), Otaki et al. (2017)
PWDM - legislative	--															Enqvist and Ziervogel (2019), Willis et al. (2009)
PWDM - maintenance	--	2														Britton et al. (2013), Luciani et al. (2018), McCary and Heaney (2018), (Patabendige et al., 2018), (Schultz et al., 2018)
PWDM - technical	--															Abdallah and Rosenberg (2012), Bennett et al. (2013), Horsburgh et al. (2017), Suero et al. (2012)
Service pressure	3														Pressure (CP)	Campisano et al. (2020), Creaco and Walski (2018), Creaco (2017), Giustolisi et al. (2017), Page and Creaco (2019), Page et al. (2018), Page et al. (2016)
Specific peak factor (unique)	--					1										Balacco et al. (2017), Gato-Trinidad and Gan (2012)
Specific peak factor (spatial)	--	( )			1											Del Giudice et al. (2020), Gargano et al. (2017)
Water loss estimation	--															Ociepa et al. (2019), Oviedo-Ocaña et al. (2020), Lambert and Hirner (2000)
Water pricing billing	--															--
Water pricing - peak	--															Cole et al. (2012), Rougé et al. (2018)
Water pricing - scarcity	--														Quantity (source)	Lopez-Nicolas et al. (2018), Macian-Sorribes et al. (2015), Molinos-Senante (2014)
Water source planning	C														Precipitation (level 6)), quantity (source)	Fraga et al. (2017), Pluchinotta et al. (2021), Ray et al. (2012), Risbey et al. (2007),

( ) = possibility, *downscaled to same temporal resolution as other data; [1]also used with 5 min – 10 min in literature, [2]also used with 10 min – 1 h in literature, [3]also used with 1 d – 1 m in literature, [4]also used with 1 m – 1 y in literature,

Table 5
Applications related to the UDN with required spatial and temporal resolution of measurement and control data. For information about spatial and temporal resolution, refer to Table 2 and 3.

Application	Network abstraction	Precipitation 2	3	4	5	6	Quantity 2	3	4	5	6	Service P	V	WWTP	Additional data	References
Calibration (hydraulic)	3													T	(social media)	Shahed Behrouz et al. (2020), Broekhuizen et al. (2020), Brouwer et al. (2017), Tscheikner-Gratl et al. (2016), Kleidorfer et al. (2018)
Calibration (quality)	3														Quality (level 5)	Kaeseberg et al. (2018), Ledergerber et al. (2019)
Chemical dosing	5														Quality (level 5)	Chen et al. (2014), Li et al. (2019b)
CSO control (frequency)	5														Quantity (WWTP) Quantity (storage)	Kerkez et al. (2016), Montestruque and Lemmon (2015), Ruggaber et al. (2007), Schütze et al. (2018), Sun et al. (2020a), van Daal et al. (2017)
CSO control (quality)	5				1							1	1	1	Quantity (storage) [1] Quantity (river) [2] Quality (river) [2] Quantity (WWTP) [2] Quantity (WWTP) [2]	Ly et al. (2019), Meng et al. (2017), Rauch and Harremoës (1999), Vanrolleghem et al. (2005)
Design (pipe, pump, storage, NBS)	3															Cunha et al. (2016), Hesarkazzazi et al. (2020), Rosbjerg and Madsen (2019), Zhou et al. (2019), Zischg et al. (2019)
Design (CSO - frequency)	3															Jean et al. (2018)
Design (CSO – quality)	5														Quantity (river) Quality (river)	Riechel et al. (2016)
Design (heat recovery)	--														Temperature (level 5))	Cipolla and Maglionico (2014), Kretschmer et al. (2016)
Development of UWI	4														Water demand (level 4)	Behzadian and Kapelan (2015), Makropoulos et al. (2008), Willuweit and O'Sullivan (2013), Zeisl et al. (2018)
External inflow detection	5														Quality (level 5)	Zhang et al. (2018a)
IDF curves	--															Madsen et al. (2017), Madsen et al. (2009), Mikkelsen et al. (2005)
Integrated control UDN and large-scale NBS (basin) quality)	3														Quantity (storage) Weather forecasts	Abou Rjeily et al. (2018), Gaborit et al. (2013), Muschalla et al. (2014), Sharior et al. (2019), Zhang et al. (2018b)
small-scale NBS	N														Cameras Weather forecasts	Oberascher et al. (2021c)
Public health	--														Biomarkers (level 6)	Gracia-Lor et al. (2020), Krizman-Matasic et al. (2019), Xiao et al. (2019)
Wastewater-based epidemiology	--														Biomarkers* (level 5)	Hata and Honda (2020), Sims and Kasprzyk-Hordern (2020)

[1]also used with 5 min – 10 min in literature, [2]also used with 10 min – 1 h in literature

Optimisation methods for WDN aim to reduce construction costs for new or future extensions while ensuring minimum pressure on the network (De Corte and Sörensen, 2013). Essentially, network elements (e.g., pipes and pumps) are designed on peak demands for node extractions (for example, peak hour or fire flow as critical loading conditions), whereas water tanks can be designed based on daily maximum demand to adjust fluctuations in the water demand of the supply area. General peak factors for design approaches can be extracted from standards (e.g. EN 805 2000) or can be determined by long-term series of inflow measurements (refer to next chapter). However, as stated by Diao et al. (2019), a finer spatial resolution of the peak factor (e.g., distributed at the district level) can lead to lower life cycle costs by better mapping of spatially distributed water consumption (Diao et al., 2019).

Similar to WDN, UDN is optimised towards minimum construction costs, but with the aim of avoiding flooding under current or future climate and population scenarios (Yazdanfar and Sharma, 2015). Therefore, design storm events with defined durations and return periods are widely used. The return period depends on the selected risk approach, ranging from low to very strong impact and assigned to return periods for rain events of 1 to 50 years (EN 752, 2017). Design storm events are basically generated using intensity-duration-frequency (IDF) curves (Balbastre et al., 2019), which are either provided by national standards or can be determined by long-term rainfall series (refer to next chapter).

5.3. Operation Optimisation

Applications assigned to operation optimisation rely on historical data; however, compared with the design process, they require time series with actual values instead of extreme events. This category also includes the calibration of numerical models to represent the real behaviour appropriately (Bach et al., 2014; Tscheikner-Gratl et al., 2016), which are widely used in all five subdivisions.

An exemplary application for the WDN is the abstraction of case-specific peak factors for the maximum hourly and daily water demand used for design approaches. Additionally, reading of water meters installed in households are used to create individual water bills related to the amount of drinking water used (Fuente, 2019; Hoque and Wichelns, 2013) and can be used to analyse water loss in the supply network (Al-Washali et al., 2016; Gupta and Kulat, 2018). In the case of a pressure surplus, feasibility studies focus on the identification of suitable sites with high energy production rates for pumps as turbines or micro hydropower stations to generate electricity.

In the context of NBS, time series are used to design rainwater harvesting (RWH) systems to substitute non-drinking water applications during dry weather periods (Campisano et al., 2017). As NBS are relatively new system elements, research has also focused on understanding and identifying fundamental principles by monitoring long-term behaviour (e.g., hydraulic, biological, maintenance, and micro-climate) (Kumar et al., 2021), including the development of numerical models.

As mentioned above, the engineering approach to the hydraulic design of UDN is based on designing storm events using IDF curves to create synthetic rain events. IDF curves are created using real rain events and are commonly based on long-term precipitation measurements (Svensson and Jones, 2010; Wright et al., 2020). In contrast, scientific research also determines the integrated performances of NBS (and correspondingly the design) by applying long-term rainfall series (Li et al., 2019a; Liu et al., 2021; Saniei et al., 2021). Additionally, long-term time series have been applied to the design of CSO structures (Botturi et al., 2020). As short-term impacts, in particular, can critically change river quality (Riechel et al., 2016), the river perspective should be included in the design process (e.g., EU (2000)).

5.4. Real-Time Operation

Real-time operations use actual system states measured to improve the ongoing operation. Basically, they can be classified into real-time control (RTC) and fault detection. As outlined under the subdivision design, the networks are designed for one specific use case, whereas the systems are operated under dynamic loading conditions (García et al., 2015). To overcome this limitation, the existing infrastructure can be equipped with RTC technology to increase the performance efficiency in view of changing loading conditions caused by climate change and urbanisation (García et al., 2015; Yuan et al., 2019).

As stated by Creaco et al. (2019), RTC applied in WDN aims to regulate the service pressure by increasing the pressure to supply the requested drinking water (e.g., variable speed pumps) or by decreasing pressure to avoid an increase in leakages and pipe bursts (e.g., pressure reducing valves). Additionally, applications related to water tanks, which are utilised as temporal storage volumes, include schedule pumping to fill water tanks or control pumps as turbines or micro hydropower systems using surplus drinking water and pressure to generate electrical power. As described, NBS are relatively new system elements; therefore, the number of exemplary applications is limited. One example is an automatic irrigation system to deliver the plants, bushes, and trees with the required amount of water (Garcia et al., 2020). Recently, decentralised storage volume has been equipped with RTC technology to decrease peak runoffs in UDN and improve water quality (Brasil et al., 2021; Xu et al., 2020a). The RTC implemented in stormwater systems aims to improve CSO performance, to increase utilisation factor of available storage volume, or to avoid flooding by controlling valves at central storage facilities (e.g., ponds and tanks) (García et al., 2015; Lund et al., 2018). Therefore, the control strategy can also include wastewater treatment capacities and quality parameters of sewers and receiving rivers. In this context, precipitation measurements, in particular, should be provided in sufficient number and with sufficient temporal resolution, because rain events have a decisive influence on UDN performance (Cristiano et al., 2017).

As shown in the literature, RTC can be subdivided into three categories differing in time of action: feedback, feedforward, and proactive control. The first, feedback control, measures the actual system states and sets action to reach the desired aim, whereas feedforward control detects disturbances upstream and corrects the performance of downstream elements (Yuan et al., 2019). The last control strategies, proactive control, include forecasts of future development to set actions before the event happens. This can include weather forecasts (Löwe et al., 2016; Lund et al., 2018) or water demand estimations (Brentan et al., 2017; Pacchin et al., 2019; Pesantez et al., 2020; Walker et al., 2015; Wong et al., 2010) to predict the expected system output for the next time steps.

In contrast, fault detection aims to identify and detect faults and unusual processes and, if possible, to react automatically to minimise damage. Exemplary applications for WDN are leakage detection (Zaman et al., 2019), contamination warning systems (Zulkifli et al., 2018), and recognising cyber-physical attacks (Hassanzadeh et al., 2020). Therefore, data-driven techniques identify outliners in measurement data, whereas model-based techniques rely on numerical models capable of simulating the real performance to identify and locate incidents. In this context, model-based techniques enable better fault management but require real-time consumption data. For the urban drainage network, exemplary applications are to detect rainwater inflows and infiltrations into sanitary sewers (Zhang et al., 2018a) or analyses of wastewater quality for the early detection of infectious disease spreads (Mandal et al., 2020; Sims and Kasprzyk-Hordern, 2020). However, thus far, wastewater-based epidemiology requires detailed laboratory analysis that limits the utilisation.

To conclude this chapter, the parameters of the perception layer can be detected via real or software-based (soft) sensors, which are computer models applied for parameters, whose determination is either time-consuming (e.g., requiring laboratory analysis) or difficult to measure (e.g., water quality) (Newhart et al., 2019; Yuan et al., 2019). Soft sensors values are estimated using parameters that are easier to detect, such as hydraulic parameters (e.g., water flow, water level, and water pressure) and some physical and chemical parameters (e.g., conductivity, turbidity, and pH).

5.5. Smart City Applications

Smart city applications integrate the urban population into the management of UWI; one of the best explored areas is the field of personal water demand management strategies (PWDMS), which uses measurements of water consumption to reduce the residential water demand at the household level by using data from individual water meters (Cominola et al., 2015). In this context, Cominola et al. (2018) used a simulation approach to show that hourly or daily resolutions are sufficient for a breakdown into major end uses, because the approximate amount of water used for main applications can be very well estimated by using average values. However, if a time series is needed (exact amount and time of use), a maximum temporal resolution of 1 min is required to perform accurate end-use disaggregation.

Additionally, the term citizen science describes the involvement of the public in research, ranging from contributory (collecting data only) to collaborative (collecting and analysing) and co-created (an active engagement in the entire scientific progress) projects (Bonney et al., 2009). Njue et al. (2019) stated that the contributory model is currently the most common form in hydrology and engages the population to monitor water levels in rivers, groundwater, and precipitation. Moreover, the deployment of private weather stations is an option for gathering precipitation and temperature data at high spatial resolution. Furthermore, public participation (e.g., through questionnaire) and historical data (e.g., images and social media) can also be used to improve urban water management, e.g., by mapping and improving urban flood risk (Bhattacharya-Mis and Lamond, 2016; Huang et al., 2018; Sarmento Buarque et al., 2020). In the future, this approach could be transferred to the management and maintenance of the increasing number of NBS for example, through images taken from urban population from the actual state.

Moreover, as indicated by the water-energy-nexus (Chang et al., 2020; Djehdian et al., 2019), a smart city framework requires the integration of multiple infrastructure areas for integrated performance improvements. As demonstrated by Babel et al. (2021), a joint management of water and energy networks results in both water and energy savings. At small scale, water related applications can be integrated into the smart home environment, e.g., optimising the performance of warm water heaters (Passenberg et al., 2016; Zhou et al., 2014). Recent research focuses also on the use of public property for real-time monitoring, e.g., applying already installed surveillance cameras to detect flooding (Leitão et al., 2018; Moy de Vitry et al., 2019a) or to estimate rainfall intensity (Jiang et al., 2019).

6. Communication Layer

Communication technologies can generally be divided into wired communication using a cable for data transmission, whereas wireless communication applies electromagnetic waves for the exchange of information. Therefore, Fig. 4 provides an overview of current communication technologies with (theoretical) data rate and transmission ranges. For more information, Table 7 summaries key properties with focus on UWI including exemplary applications.

6.1. Wired Communication Technologies

For detailed overview including characteristics of wired communication technology, refer to relevant literature (Abdelwahab et al., 2019; Frenzel, 2018; Kabalci, 2016), whereby two communication technologies are primarily of importance for UWI. First, fibre optic communications represent the backbone of the worldwide internet and second, Meter-Bus (M-Bus) as an European standard is used for the remote

Table 6
Applications related to NBS with required spatial and temporal resolution of measurement and control data. For information about spatial and temporal resolution, refer to Table 2 and 3.

Application	Precipitation 2	Weather parameter[1] 2	Quantity 2	Soil moisture 2	Soil temperature 2	Air temperature 2	Run-off 2	Service V	Additional data	References
Design (Bio-retention, detention ponds, vegetative swales)	(beige)								(eventual in combination with UDN)	Ghodsi et al. (2020), Zischg et al. (2018)
Design (RWH)	(beige)								Water demand (level 1)	Campisano and Lupia (2017), Cipolla et al. (2018), EN 16941-1 (2018), Semaan et al. (2020)
Discharge control (quantity)			(blue)					(blue)	Precipitation (level 5) Weather forecasts	Liang et al. (2019), Oberascher et al. (2021b), Xu et al. (2020b)
Discharge control (quality)			(blue)	(blue)				(blue)	Precipitation (level 5) Water quality Weather forecasts	Persaud et al. (2019), Shen et al. (2020)
Irrigation control				(green)		(green)		(green)	Air humidity	Garcia et al. (2020), Sales et al. (2015), Serena et al. (2020)
Micro-climate (evapotranspiration)	(beige)	(beige)		* (beige)					Eddy covariance* Stomatal conductance* Irrigation demand	Ma et al. (2018), Vulova et al. (2019)
Micro-climate (temperature)		(green)		* (green)	* (green)	* (green)			Wind speed/direction*	Georgakis and Santamouris (2017), Hall et al. (2015), Roth and Lim (2017), Schaffitel et al. (2020), Lehnert et al. (2021)
Monitoring (hydraulic)	(dark blue)	(dark blue)					(dark blue)			Brunetti et al. (2016), Palermo et al. (2019), Peng and Stovin (2017)
Monitoring (biologic)		[1] (blue)		*,[1] (blue)					Stomatal conductance*,[1]	Caplan et al. (2019), Marchionni et al. (2019), Tu et al. (2020)
Monitoring (maintenance)	* (dark blue)	* (dark blue)	* (dark blue)	* (dark blue)					Images	Razzaghmanesh and Borst (2018), Tu and Traver (2018)

[1]air temperature, air humidity, atmospheric pressure, solar radiation, wind speed, wind direction wind; * = multiply measurement points; [1]also used with 10 min – 1 h in literature

reading of gas, electricity, oil, and water meters (Ahmad et al., 2016; De Craemer and Deconinck, 2010; Šastný et al., 2013). In UWI, M-Bus is therefore used as a wired method for read-out of water meters (Cherukutota and Jadhav, 2016; Oberascher et al., 2020).

Summarised, installation of wired communication networks requires considerable efforts, and is less flexible than wireless communication, therefore primarily used in fixed installations. Compared to wireless communication, wired communication technologies provide following key factors: (1) providing a high quality of service as packet losses due to operation or disturbances are low, (2) requiring little maintenance work because of the fixed installation, (3) supporting a bidirectional communication for a timely transmission of measurement values and control commands, and (4) realising almost any transmission interval through the independence of batteries. Following, wired communication technologies represent a highly reliable solution for few measuring points, applications based on high-resolution measurements (e.g., seconds) and for real-time control (e.g., regulating service pressure in WDN or CSO outflow).

6.2. Wireless Communication Technologies

6.2.1. Short and Medium Ranges

The classification of short and medium ranges includes a wide range of wireless communication technologies with a transmission range of 1 to 500 m. For more information, refer to relevant literature (Ding et al., 2020; Lalle et al., 2021; Oliveira et al., 2019; Sikimić et al., 2020). Due to the limited range, these communication technologies are primarily utilised in surrounding area of buildings.

For interest in UWI are ZigBee, Wireless fidelity (Wi-Fi) and Wireless M-Bus (WM-Bus). ZigBee is applied for smart home applications and industrial monitoring (Ford et al., 2017), e.g.; IoT-based irrigation system in UWI (Saraf and Gawali, 2017). Wi-Fi is commonly used in public hot spots to provide a broadband connection to the Internet for mobile devices (laptops and smart phones), however due to high data rates, energy consumption is very high (Ding et al., 2020; Kabalci, 2016; Oliveira et al., 2019; Sikimić et al., 2020). For UWI, Wi-Fi is applied for monitoring water usage in buildings (Gautam et al., 2020; Horsburgh et al., 2017; Melville-Shreeve et al., 2021). To overcome the limitations of the wired M-bus, Wireless Meter-Bus (WM-Bus) is proposed as an alternative for communication with utility meters (Ahmad et al., 2016; Šastný et al., 2013; Spinsante et al., 2014), and is therefore commonly applied for read-out of water meters (Antzoulatos et al., 2020; Luciani et al., 2018; Spinsante et al., 2014).

6.2.2. Cellular communication networks

Cellular communication networks cover large areas using radio waves for data transmission. The areas are divided into so-called cells with defined sizes, each of which has a base station for connecting mobile devices inside the cell or within different cells to the internet. Depending on the stage of development, cellular communication can be divided into five generations, namely 1G, 2G (e.g., GSM, GPRS), 3G (e.g., UMTS), 4G (e.g., LTE), and 5G. For more information, refer to relevant literature (Abdelwahab et al., 2019; Arshad et al., 2019; Lalle et al., 2021; Sikimić et al., 2020). Especially, 5G is designed to fulfil Internet-of-Things requirements of future smart city developments by providing high data rate and number of connected devices including lower latency for real-time application (e.g., self-driving vehicles) (Arshad et al., 2019; Kumar and Gupta, 2017; Rao and Prasad, 2018).

Regarding UWI, cellular communication networks cover a large area supporting easy installation in remote areas. Additionally, cellular technologies allow two-way communication. Therefore, 2G technologies (GSM, GPRS) are widely applied for monitoring and controlling of UDN (Abbas et al., 2017; Kerkez et al., 2016; Loftis et al., 2018; Maier et al., 2020; Montestruque and Lemmon, 2015; Wong and Kerkez, 2018) and WDN (Li et al., 2017; Pastor-Jabaloyes et al., 2018; Perez et al., 2014; Quevedo et al., 2010). However, owing to the high data rates and continuous monitoring of mobile devices for new data packets, the energy consumption is high (Pointl and Fuchs-Hanusch, 2021) and not suitable for a long maintenance-free operation of battery-powered devices. Therefore, three kind of approaches can be found in literature: (1)

Table 7
Properties of communication technologies and intended purpose with focus on UWI.

Intended purpose		• Monitor household power consumption	• Data exchange in telephone networks	• **Backbone of worldwide internet** • **Monitoring and control of UWI** (Fiorelli et al., 2013)	• **Water meter** (Cherukutota and Jadhav, 2016; Oberascher et al., 2020)
Further information		• Abdelwahab et al. (2019) • Frenzel (2018) • Kabalci (2016)			• Ahmad et al. (2016) • De Craemer and Deconinck (2010) • Šastný et al. (2013)
Properties (with focus on UWI)				• **Require additional energy supply** • **High material and installation costs** • **High reliability**	• **Remote reading of meters (EN13757)**
Technology	Wired Communication	Power-line communication (PLC)	Cooper wire (DSL)	**Fibre optic (PON, WDM)**	**Meter-Bus (M-Bus)**

Intended purpose		• **Monitoring and control of UDN** (Blumensaat et al., 2017; Ebi et al., 2019; Oberascher et al., 2020) • **Monitoring and control of WDN** (Antzoulatos et al., 2020; Oberascher et al., 2020; Saravanan et al., 2017)	• Monitoring of WDN (Di Gennaro et al., 2019; Perez-Padillo et al., 2020)
Further information		• Chaudhari et al. (2020) • Ding et al. (2020) • Lalle et al. (2021) • Mekki et al. (2019) • Oliveira et al. (2019) • Raza et al. (2017)	
Properties (with focus on UWI)		• **Sleeping mode** • **Unlicensed frequency bands** • **Fair-use policy (duty cycle)** • **Downlink after successful uplink** • **High-scalability**	• Sleeping mode • Unlicensed frequency bands • 140 uplink packets, 4 downlink packets • Unopen business model (proprietary base station) • High-scalability
Technology	*Low power wide area networks (LPWAN)*	**Long range wide area network (LoRaWAN)**	Sigfox

higher capacity of batteries to increase life-time (Abbas et al., 2017); (2) decreasing transmission interval (e.g.; transmission of multiply measured values aggregated into a joint data packet) (Montestruque and Lemmon, 2015; Pastor-Jabaloyes et al., 2018; Perez et al., 2014; Quevedo et al., 2010; Riaz et al., 2016) or (3) inclusion of alternative energy sources (e.g., connection to the electrical grid, or self-charging solar batteries) (Li et al., 2017). Cellular technologies use licensed and regulated frequency bands (Abdelwahab et al., 2019; Chaudhari et al., 2020) thereby providing high reliability for data transmission.

6.2.3. *Low Power Wide Area Networks*

Low power wide area networks (LPWAN) are a communication group enabling the large-scale implementation of multiple devices by supporting long-range and ultra-low-power operations. LPWAN operates as cells with a base station for each cell (e.g., one base station can connect up to ten-thousand devices) and uses low bandwidths, which limit data rates but increase the energy budget for each transmitted bit. Additionally, the transceivers are turned most of the time ('sleeping mode'), as data transmission is the process that demands the most energy and are, therefore, unreachable. Leading LPWAN technologies are long range wide area network (LoRaWAN) and Sigfox operating in unlicensed frequency bands, and narrow band IoT (NB-IoT) technology, which can coexist with GMS and LTE cellular networks under licensed frequency bands (Mekki et al., 2019). For a technical description including characteristics of the various technologies refer to literature (Chaudhari et al., 2020; Ding et al., 2020; Mekki et al., 2019; Oliveira et al., 2019; Raza et al., 2017).

However, LPWAN are relatively new technologies, therefore experience in UWI is still limited. Especially LoRaWAN is commonly used for monitoring of UDN (Blumensaat et al., 2017; Ebi et al., 2019; Oberascher et al., 2020) and WDN (Antzoulatos et al., 2020; Oberascher et al., 2020; Saravanan et al., 2017), whereas application of Sigfox and NB-IoT is mostly applied to prototypes (Anand and Regi, 2018; Di Gennaro et al., 2019) or coverage analysis (Abbas et al., 2020; Nashiruddin and Yusri, 2020; Pennacchioni et al., 2017; Purnama and Nashiruddin, 2020).

Following factors influence functionality of implemented LPWAN: First, they are usable for delay-tolerant applications and not designed for critical applications with high reliability or fast response times (Chaudhari et al., 2020; Raza et al., 2017). Second, unlicensed bands are subject to a fair-use policy, therefore maximum number of uplink and downlink data packets is limited. Additionally, interferences have to be

	• Contactless payment	• Contactless identification of objects	• Exchange of multimedia data (headsets)	• Smart home applications (Saraf and Gawali, 2017)	• **Water consumption** (Gautam et al., 2020; Horsburgh et al., 2017; Melville-Shreeve et al., 2021)	• **Water meter** (Antzoulatos et al., 2020; Luciani et al., 2019; Spinsante et al., 2014)		• **Monitoring and control of UDN** (Abbas et al., 2017; Kerkez et al., 2016; Loftis et al., 2018; Maier et al., 2020; Montestruque and Lemmon, 2015; Wong and Kerkez, 2018) • **Monitoring and control of WDN** (Li et al., 2017; Pastor-Jabaloyes et al., 2018; Perez et al., 2014; Quevedo et al., 2010)	• Backbone of worldwide internet
	• Ding et al. (2020) • Lalle et al. (2021) • Oliveira et al. (2019) • Sikimić et al. (2020)					• Ahmad et al. (2016) • Šastný et al. (2013) • Spinsante et al. (2014)		• Arshad et al. (2019) • Abdelwahab et al. (2019) • Lalle et al. (2021) • Sikimić et al. (2020)	
					• **High energy consumption**	• **Remote reading of meters (EN13757)**		• **Licensed frequency bands** • **High energy consumption**	• Licensed frequency bands • High energy consumption
Short and Medium Ranges	Near-field communication (NFC)	Radio frequency identification (RFID)	Bluetooth (BLE)	ZigBee	**Wireless fidelity (Wi-Fi)**	**Wireless Meter-Bus (WM-Bus)**	*Cellular communication*	**2G (GSM, GPRS)**	3G (UMTS), G (LTE), 5G
• Monitoring of WDN (Di Gennaro et al., 2019; Perez-Padillo et al., 2020) • Chaudhari et al. (2020) • Ding et al. (2020) • Lalle et al. (2021) • Mekki et al. (2019) • Oliveira et al. (2019) • Raza et al. (2017)		• Monitoring of WDN (Anand and Regi, 2018)							
• Sleeping mode • Unlicensed frequency bands • 140 uplink packets, 4 downlink packets • Unopen business model (proprietary base station) • High-scalability		• Sleeping mode with sporadic time slots • Licensed frequency bands (cellular) • High-scalability							
Sigfox		Narrow band Internet of things (NB-IoT)							

expected in unlicensed bands (e.g., packet losses), which increase with number of connected devices and connection quality (Blenn and Kuipers, 2017; Varsier and Schwoerer, 2017), and cannot offer the same quality of service as the NB-IoT using licensed bands. Third, most devices are currently battery-powered, requiring (1) a trade-off between battery capacity and transmission intervals for maintenance-free operation (Pointl and Fuchs-Hanusch, 2021); or (2) alternative energy sources (e.g., energy harvesting based on water flow or outdoor light) to reduce dependence on batteries (Pimenta and Chaves, 2021). As a reference for LoRaWAN, Ebi et al. (2019) recommend an approximately distance of 500 m between gateway and installation places below ground, whereas Pointl and Fuchs-Hanusch (2021) concluded, that LPWAN enables measurement and transmission intervals between 5 min and 30 min without increasing maintenance efforts (e.g., change of batteries). However, as stated by Singh et al. (2020) and Pimenta and Chaves (2021), energy demand is strongly dependent on local installation conditions (e.g., receiving quality) and can therefore deviate considerable for real-word implementation.

7. Framework for implementation of smart water networks

In literature, several frameworks can be found discussing suitable communication technologies for smart water grids for various applications (Buurman et al., 2020; Lalle et al., 2021; Malik et al., 2018; Panousopoulou et al., 2018; Sammaneh and Al-Jabi, 2019), without considering data requirements of UWI. However, owing to the different properties of communication technologies, the usable communication is strongly dependent on spatial and temporal requirements. To overcome this limitation, this chapter provides a comprehensive analysis including recommendations for real-time operations and applications based on historical data.

Simplified, following scenarios can be distinguished: (1) low number of measurement points and/or critical applications (e.g., timely real-time control) with high requirements on quality of received measurement data including both hardware sensor and communication technology, and (2) large-scale implementation of measuring devices with the aim to monitor environmental parameters can have lower requirements, therefore justifying the usage of low-cost sensors and communication technologies operating in public frequency ranges (e.g., LoRaWAN). The further chapter 7 will mainly deal with the requirements for communication technologies, which can also be transferred for the quality of the hardware sensors used.

7.1. Comprehensive analyses for real-time operations

For the appropriate selection of usable communication technology for real-time applications, intended purpose, desired properties, and a trade-off between installation and maintenance efforts and reliability are decisive. Table 8 provides an overview of the recommended communication technologies for different real-time operations and is based on the findings of the review process; however, different approaches might be possible and local feasibility analyses should be conducted before implementation. For more information, the detailed usage of this table is explained in the next paragraphs.

First, monitoring and control operations have distinctly different requirements. Monitoring comprises the exchange of environmental parameters, requiring a unidirectional connection between sensors, base stations, and the central system. In contrast, real-time control implies the modification of regulation devices and controllers, whereby an exchange of status notification and control commands is included. Therefore, a bidirectional connection is required, which is provided by nearly all reviewed communication technologies. However, the number of downlinks may be limited, as is the case with LPWANs.

The next decision criterion is the desired properties. Simple text packets, consisting of a measurement value, a time step, and an identification number, have packet sizes in bytes. Compared to the up-to-date communication technologies with data rates in Mb/s or even Gb/s, technologies with low data throughput in kb/s can also be applied. In contrast, images with storage sizes in MB require communication technologies with high data throughput. Additionally, for deploying images with high temporal and spatial resolutions, such as surveillance cameras, the transmission fees for cellular communication may have an impact on the decision process. Some real-time applications are time sensitive, meaning that the control process should take place immediately, whereas the control process ranges from seconds to minutes. However, LPWAN technologies – which spend most of the time in sleeping mode and are, therefore, unreachable – can be used only for delay-tolerant applications. LoRa and Sigfox, which operate in the public frequency range with expected packet losses, can be utilised in delay-tolerant applications, where delays and packet losses have a limited influence on system performance. For example, LoRa and Sigfox could be an alternative for controlling decentralised solutions in combination with proactive control strategies, including future development. In contrast, the NB-IoT represents an exception, as the NB-IoT also has a sleeping mode and operates in the licensed frequency range. Therefore, a high-quality service is provided, allowing the use of peak hour pricing.

Finally, a trade-off must be made between installation and maintenance efforts and the reliability of data transmission. Wired and cellular communication enable a high-quality service providing nearly every transmission interval. However, energy demand is high, requiring an additional energy source for a long maintenance-free operation. Additionally, laying the cables needed for wired communication or power supply means additional construction work. This point makes cellular and wired communication suitable for only a few installation sites but impractical for large-scale roll-out. LPWAN enables long transmission ranges, requiring only a few base stations to cover large areas. However, using LoRa and Sigfox also implies data packet losses. Therefore, the NB-IoT can be applied for a low number of installation sites, for example, deployment on district and city scales, as reliability is high. In contrast, LoRa and Sigfox can be provided for large-scale deployment, as investment costs for deployment are lower. Owing to the increased energy demand with higher transmission intervals, LPWAN is not recommended for high temporal resolutions in a large-scale roll-out. A solution can be (1) downscaling of coarser measuring intervals through gap-filling methods (Kirstein et al., 2021), or (2) short- and medium-range technologies, which can be used, for example, to monitor precipitation distributed over the system or filling depths in NBS; M-Bus, a wired communication, can be applied for monitoring water consumption in households. Owing to limited ranges and high installation and maintenance efforts, these technologies require the inclusion of the public for operation and network measurement. However, this means, that the measurement network is no longer the responsibility of the infrastructure operator, requiring a combined approach with the public.

7.2. Comprehensive analysis of applications based on historical data

Applications based on historical data do not need to transmit data in real time. Instead, measurement data can be aggregated into a joint data packet and transmitted periodically. The most important decision criteria for choosing the communication technology are the relationship between the measurement interval and transmission interval, the desired quality of service, and spendable investment fonds. Fig. 5 provides an overview of the recommended communication technologies, whereas the detailed usage is described in the following paragraph.

The transmitted data volume depends on the measurement and transmission interval. For example, an increase in the measurement interval and a decrease in the transmission interval lead to a higher number of measurement points. Subsequently, the packet size is increasing, which is important when using LPWAN. As stated in Chapter 6, the maximum packet sizes for Sigfox, LoRa, and NB-IoT are 12, 243, and 1600 bytes, respectively, influencing the usability of these technologies. For calculation, a storage size of 2 bytes per measurement value was assumed. Another decision criterion is the desired quality of service. LoRa and Sigfox operate in the public frequency range, and data packet losses are probable. If a continuous time series is needed, cellular or wired communication is recommended, whereas short- and medium-range technologies may be considered as an alternative for high spatial resolutions (e.g., household and NBS). As mentioned above, these technologies require either an additional power supply for a long-maintenance-free operation or a joint approach between public and network operators. The transmission interval in Fig. 5 is limited to one month; a monitoring network with higher transmission intervals can be realised, but will raise economical questions. In this regard, manually readings could also be an option. Examples are the drive-by method for water meter readings installed at quarterly or yearly intervals or manual readings of flow meter devices installed at the city scale at monthly time steps.

7.3. Exemplary usage of the proposed framework

The functionality of the proposed framework is illustrated by two examples: (1) choosing a suitable communication technology for the intended use and (2) determining possible applications for an existing communication network:

(1) Water losses in WDN represent a common challenge for operation, being on average 23% in Europe (EurEau, 2017). Therefore, a water supply operator might decide to implement an early warning system for detection and localisation of water leakages in real time. The intended process aims for a model-based approach, requiring following parameters in a temporal resolution of 5 – 10 min as shown by Table 4: (1) water consumption at household level; (2) water pressure in a grid arrangement of max. 500 m, and (3) water inflow and pressure at the inlet points of the district metering area. Based on the recommendations in Table 8, the use of following communication technologies is suggested: (1) (W)M-Bus for water meters installed at the households, (2) LoRaWAN for water pressure sensors distributed over the area as packet losses are acceptable due to the high number of installed devices, and (3) GPRS at inlet points for a reliable transmission. Additionally, as Table 4 also indicates, the water consumption data can be used for the application 'PWDM – educational'. As an appropriate identification of different types of water usage (e.g., time of use with exact water volume for washing machines, toilet flushing, and garden irrigation) requires a temporal resolution of 1 s – 5 min, it is also possible to encourage customers for an efficient use of drinking water by providing feedbacks on daily analysis.

(2) A municipal infrastructure operator considers using an already existing LoRa network for data communication and is searching

Table 8
Recommended communication technologies for real-time applications depending on intended purpose, desired properties, and a trade-off between installation, maintenance efforts, and reliability. For information about spatial resolution, refer to Table 2.

<table>
<tr><th rowspan="3">Purpose</th><th>Properties</th><th colspan="18">Installation / maintenance effort and reliability</th></tr>
<tr><td>Transmission interval</td><td colspan="6">1 s – 5 min</td><td colspan="6">5 -10 min</td><td colspan="6">10 min – 1 d</td></tr>
<tr><td>Scale of implementation</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>1,</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td></tr>
<tr><td rowspan="2">Real-time monitoring</td><td>Text</td><td colspan="4">ZigBee[1]
Wi-Fi[1]
(W)M-Bus[1,2]
LoRa[3]</td><td colspan="2">Fibre
GSM/GPRS[4]
NB-IoT[3]</td><td colspan="4">ZigBee[1]
Wi-Fi[1]
(W)M-Bus[1,2]
LoRa</td><td colspan="2">Fibre
GSM/GPRS[4]
NB-IoT</td><td colspan="4">ZigBee[1]
Wi-Fi[1]
(W)M-Bus[1,2]
LoRa[5]
Sigfox[5]
NB-IoT[6]</td><td colspan="2">Fibre
GSM/GPRS[4]
NB-IoT</td></tr>
<tr><td>Images</td><td></td><td colspan="3">Fibre
Wi-Fi[1]</td><td colspan="2">Fibre
LTE/5G[4]</td><td></td><td colspan="3">Fibre
Wi-Fi[1]</td><td colspan="2">Fibre
LTE/5G[4]</td><td></td><td colspan="3">Fibre
Wi-Fi[1]</td><td colspan="2">Fibre
LTE/5G[4]</td></tr>
<tr><td rowspan="2">Real-time operation</td><td>Delay-sensitive</td><td colspan="4" rowspan="2">ZigBee[1]
Wi-Fi[1]</td><td colspan="2" rowspan="2">Fibre
GSM/GPRS[4]</td><td colspan="4" rowspan="2">ZigBee[1]
Wi-Fi[1]</td><td colspan="2" rowspan="2">Fibre
GSM/GPRS[4]
NB-IoT[3]</td><td colspan="4">NB-IoT</td><td colspan="2">Fibre
GSM/GPRS[4]
NB-IoT</td></tr>
<tr><td>Delay-tolerant</td><td colspan="4">LoRa
Sigfox[3]</td><td colspan="2">NB-IoT</td></tr>
</table>

[1]requires involvement of public; [2]alternative for water meters; [3]possible to a limited extent - requires feasibility study on site (not recommended); [4]requires additional energy sources; [5]peak -hour pricing – not recommended; [6]peak -hour pricing – alternative;

for real-time applications in the field of UWI. Furthermore, a capacity analysis of the existing LoRa network showed that additional sensors with a transmission interval between 1 h – 1 d can be integrated without additional packet loss. The operator is interested in the application for WDN is peak-hour pricing (Table 4), however, due to possibility of packet losses LoRa is not recommended (as referenced in Table 8). Similar, no application can be defined for UDN (Table 5). However, as Table 6 shows, 'irrigation control' for NBS would be a possible application. For implementation, measurements of soil moisture, air temperature, air humidity, and a controlled valve for automatic irrigation processes are required.

8. Critical discussion, future challenges, and security

As this work deals with the digitalisation of UWI, a discussion on future challenges, security, and privacy issues cannot be avoided. However, this is a topic concerning all digitalisation projects or smart city research, and only a short description with special emphasis on UWI is provided. For more detailed discussions, the reader is referred to further literature (e.g., Ahad et al. (2020), Balogun et al. (2020), Bibri and Krogstie (2017), and Silva et al. (2018)).

First, digitalisation and smart city projects have to create an added value to improve ecological and economic sustainability, which can be simplified expressed by subtracting benefits from efforts. Following, the efforts can be described as investment (e.g., installation of measuring devices and communication network) and operational (e.g., operation and ongoing maintenance) costs for the implementation of a monitoring and control network. Additionally, owing to the lack of connections to the power grid in remote and underground structures (and to obtain a flexible design), battery-powered devices will be significant for monitoring UWI and will raise ecological issues. In contrast, RTC implemented aims to improve system performance and to decrease environmental impacts, such as greenhouse gas emissions or releases of harmful substances into receiving waters. However, evaluation of these benefits (e.g., savings in drinking water, reduction of combined sewer overflow) is very strongly depending on respective weighting factors and local preferences. Therefore, a trade-off between the deployment of resources and the desired effect is essential for achieving sustainability and should be carried out individually for each project. Consequently, this topic opens up future research topics including a detailed analysis of ecological and economic impacts.

Furthermore, decision process and real-time controlling requires a reliable database, whereas quality of measurement data received at the central control system are subject to various sources of error. For example, time series of measurements include data uncertainty and noise, whereby the deviation depends on quality of implemented sensor and boundary conditions. Consequently, appropriate methods for data validation and quality assessments are required, for more information and usable methods refer to Bertrand-Krajewski et al. (2021). Additionally, using LPWAN implies packet losses, which subsequently results in data gaps. In this context, technologies based on artificial intelligence (AI) brings up new possibilities for evaluation and analysis of big data, including machine learning. Up to now, these technologies are widely applied to accelerate simulations, to improve forecasts, to detect failures, and to assist by optimisation problems in the field of UWI (Doorn, 2021). However, it is expected, that AI will be also deployed in automation and control in future as it is already the case in other infrastructure areas (Savić, 2021). Subsequently, implementing any kind of AI for controlling requires the sufficient consideration of ethical related issues, e.g., how to distribute the resource drinking water in the case of water scarcity (Doorn, 2021; Savić, 2021). Additionally, a large-scale implementation of controllable IoT devices requires a sufficient consideration of uncertainties associated with digital parameters (e.g., accuracy of measured data or reliability of data communication technologies) to avoid degradation of system performance (Oberascher et al., 2021a). Following, these issues should be addressed by future research.

More information about system performance can increase the detection of physical attacks (e.g., contamination) and cyber-physical attacks (e.g., hacker attacks on critical system points) but also increases the vulnerability of the entire system (Housh and Ohar, 2018; Rasekh et al., 2016; Taormina et al., 2017). This may be further intensified, as the development of smart water cities is currently beginning, and the number of participants can be expected to increase strongly in the future. Additionally, water consumption measured at the household scale reveals user-specific behaviour (Boyle et al., 2013; Cominola et al., 2015). Time series on a minute scale provide especially detailed insights about personal lifestyles and used household appliances. The usage of such personal data can also be subject to additional applicable laws, for example, the European General Data Protection Regulation (GDPR) (2016/679/EU, 2016). However, daily measurements provide sufficient conclusions, for example, for estimating the number of inhabitants. Therefore, dealing with security and privacy issues in an appropriate way will be an important factor for the success of future smart (water) city research (Braun et al., 2018; Habibzadeh et al., 2019; Moy de Vitry et al., 2019b).

Additionally, the realisation of a monitoring and control network at an NBS or block scale in a practical and realistic way requires the involvement of the public for installation and maintenance operations. However, as Derkzen et al. (2017) showed, the positive effects of NBS on the environment are mostly unknown to the public. Therefore, increasing the awareness of the population about functionalities and future challenges is required to promote the digitalisation of the UWI down to the end areas. Additionally, as concluded by Blumensaat et al. (2019), UWI is not yet ready for transition into digital systems, whereas the willingness of infrastructure operators to implement new technologies for the management of UWI is limited (Yuan et al., 2019). To further increase smart water city development, future research needs to focus on how to overcome these barriers caused by economic, technical, regulatory, and human reasons. In this context, serious gaming represents a promising approach to increase interest of urban population in UWI challenges and following increase willingness of participation (Ewing and Demir, 2021; Novak et al., 2016; Predescu et al., 2021; Savic et al., 2016).

9. Summary and conclusions

The importance of system-wide management of urban water infrastructure (UWI) in interaction with urban population and other infrastructure areas will increase in the future. As control opportunities are relatively mature in centralised facilities (e.g., drinking water and wastewater treatment plants), our focus is on networks, including system elements distributed over the area in question. In this context, this review summarises a wide range of applications in the field of UWI networks for a comprehensive analysis of the spatial and temporal resolutions of measurement data, which are needed for a wide range of applications and not limited to a single application. For example, inflow measurements of drinking water at the district scale are utilised for real-time operations, such as service pressure or leakage detection; however, this information is also required for case-specific network designs. In contrast, each communication technology has different characteristics and limitations, constraining its use to specific applications. Moreover, an integrated approach towards smart water cities requires the combination of different communication technologies to satisfy all specifications.

Therefore, this work presented a detailed guideline as a decision-making tool for researcher, network operators and stakeholders for the technical realisation of such systems and to further support SCADA and smart city development. However, the requirements of the measurement and control network are strongly related to the desired applications. The three key steps are summarised as follows:

- Identifying the desired applications applied to the UWI networks
- Extracting the required temporal and spatial resolutions needed for these applications
- Choosing a communication technology, which meets the requirements

Conversely, if a communication network already exists (e.g., from a smart city project) and is intended to be used for applications related to UWI networks, the two key steps are as follows:

- Investigating the boundary conditions for the temporal and spatial resolution of measurement data
- Determining of possible applications applied to the UWI networks

Generally, the establishment of a monitoring and control network initially requires investment costs. Moreover, measurement devices utilised for UWI are primarily installed in remote or underground structures and require batteries for power supply. Therefore, balancing measurement devices, intended applications, and prognostic effectiveness is necessary to achieve economic and ecological sustainability as one of the primary pillars of smart cities.

Additionally, the number of participants is expected to increase strongly in the future as the development of smart cities is in its initial stages. The ongoing digitalisation of the UWI also includes water meters used for monitoring personal water consumption and will eventually raise security and privacy issues. These developments open up new possibilities for the operation of UWI but also expose the vulnerability of the UWI to new risks (e.g., cyber-physical attacks), requiring future research.

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2.2 Additional Information Communication Technologies

In Paper I, applicability of data transmission technologies is mainly supported by real applications, while features of communication technologies are only briefly discussed. Therefore, a certain prior knowledge is required to understand the potential and limitations of different communication technologies for optimal choice. To overcome this limitation, this section provides an additional comprehensive description of the presented communication technologies, whereas the specifications of each communication technology are taken from the literature. As a result, the performance of communication technologies in terms of range may differ for real applications but provides good insights into the theoretical background. In general, communication technologies can be divided into wired communication using a cable for data transmission, whereas wireless communication applies electromagnetic waves for the exchange of information.

2.2.1 Wired Communication Technologies

Wired communication networks use wired-based technology for data transmission. In the following sections, four different wired communication technologies are identified and briefly described.

The first, power-line communication (PLC), uses the powerlines of the electrical grid as the transmission medium for communication. PLC can be categorised into narrowband PLC (NB-PLC) and broadband PLC (BB-PLC). The data rate and distance are 10-500 kb/s and 3 km for NB-PLC and 14-200 Mb/s and 200 m for BB-PLC. PLC uses existing powerlines, is widely available, and supports two-way communication. However, signal quality is affected by electromagnetic interference and, therefore, depends on the number of connected devices. The principal application of PLC is communicating with smart meters to monitor household power consumption (Abdelwahab et al.; Kabalci, 2016).

An alternative for utility meters is Meter-Bus (M-Bus), a European standard used for the remote reading of meters specified in EN13757 that is adapted according to requirements and designed to collect consumption data from gas, electricity, oil, and water meters. M-Bus has a low (2-10 kB/s) data rate and maximum distance of a few kilometres and provides two-way communication, including power supply for meters (Ahmad et al., 2016; De Craemer and Deconinck; Šastný et al.).

Another technology based on wire is the digital subscriber line (DSL), which uses a copper wire utilised in telephone networks for data exchange and can be subdivided into asymmetric DSL (ADSL) (data rate: 1-8 Mb/s, distance: 5 km), high date rate DSL (HDSL) (data rate: 2 Mb/s, distance: 3.5 km), and very high speed DSL (VDSL) (data rate: 15-100 Mb/s, distance: 1.5 km). As telephone networks are already existing infrastructure, DLS is especially widely available in urban areas. DSL enables two-way communication but requires an additional source, for example, power grid, for power supply (Abdelwahab et al.; Frenzel, 2018; Kabalci, 2016).

In fibre optic communications, cables with thin plastic or glass cores are used to transmit data via light waves. The major advantages of fibre optic communication are the ability to maintain high data rates over long distances and resilience against radio and electromagnetic interferences. Fibre optic communication can be categorised as passive optical networks (PON) (data rate 1.2-2.4 Gb/s, range 10-60 km) for local WANs, whereas wavelength division multiplexing (WDM) with data rates of up to 1000 Gb/s and ranges of 1000 km represent the backbone of the worldwide internet. However, material and installation costs for fibre optic networks are high, and an additional power supply is required (Abdelwahab et al.; Frenzel, 2018; Kabalci, 2016).

With regard to water infrastructure systems, wired communication networks offer high reliability and quality of services, because packet losses due to operation or disturbances are low. Additionally, wired communications support bidirectional communication, allowing a timely transmission of measurement values and control commands. However, installation requires considerable effort, and is less flexible than wireless communication, resulting in use primarily in fixed installations. Furthermore, devices using DSL and fibre optic communications for data transmission require an additional power supply. However, through the independence of batteries, almost any transmission interval can be realised. Fibre optic communications are intended for connections with a high amount of transmitted data, whereas PLC, M-Bus, or DSL can be used to connect single devices installed in the urban water infrastructure.

2.2.2 Wireless Communication Technologies

2.2.2.1 Short and Medium Ranges

Near-field communication (NFC) can transmit data through magnetic coupling and enables two-way communication when two devices are placed side-by-side. NFC operates in the 13.56 MHz frequency band, with data rates of up to 848 kb/s. However, the range is very low and limited to a maximum distance of 0.1 m. One important application of NFC is contactless payment (Oliveira et al., 2019; Sikimić et al.).

Another technology for proximity networks is radio frequency identification (RFID), in which the reader emits radio waves and the identified device answers by sending back the identification number. The typical RFID range is 0.1-5 m, with a data rate of 500 kb/s. RFID is primarily used for contactless identification of devices (Oliveira et al., 2019). Bluetooth is capable of forming small networks for the exchange of data between movable devices. Bluetooth operates in the 2.4 GHz frequency band and is based on the Institute of Electrical and Electronics Engineers (IEEE) standard 802.15.1. Because of high energy consumption, Bluetooth Low Energy (BLE) was developed to transmit data at a rate of up to 1 Mb/s over a range of 100 m. An application for BLE is the exchange of multimedia data, such as wireless headsets (Ding et al., 2020; Oliveira et al., 2019; Frenzel, 2018).

ZigBee is built based on the IEEE standard 802.15.4 and a wireless communication for PAN and uses the unlicensed frequency bands for data transmission (global: 2.4 GHz; in Europe 868 MHz and North America 915 MHz), with a data rate of 20-250 kb/s and a transmission range of 10-100 m. ZigBee allows two-way communication and requires low power for data transmission and, therefore, is applied for smart home applications and industrial monitoring (Ahmad et al., 2016; Ding et al., 2020; Frenzel, 2018; Oliveira et al., 2019). To overcome the limitations of the wired M-bus, Wireless Meter-Bus (WM-Bus) is proposed as an alternative for communication with utility meters (gas, electricity, oil, and water). WM-Bus can transmit data at a rate of 32 kb/s over a distance of 500-1000 m in the unlicensed frequency bands (169 and 868 MHz). Additionally, WM-Bus requires low energy consumption and enables two-way communication. Compared to M-Bus, WM-Bus provides easy implementation and supports the retrofitting of households with remote readable utility meters (Ahmad et al., 2016; Šastný et al.; Spinsante et al., 2014).

Wireless fidelity (Wi-Fi) is standardised through the IEEE 801.11 family and is commonly used in wireless local area networks (WLANs). Wi-Fi is used in public hot spots to provide a broadband connection to the Internet for mobile devices (laptops and smart phones). Wi-Fi uses 2.4-5 GHz frequency bands for data transmission and provides high data rates (up to 7 Gb/s), with a range of 100 m. Because of the high data rates, energy consumption is very high (Ding et al., 2020; Kabalci, 2016; Oliveira et al., 2019; Sikimić et al.).

2.2.2.2 Cellular Communication Networks

Cellular communication networks cover large areas using radio waves for data transmission. The areas are divided into so-called cells with defined sizes, each of which has a base station for connecting mobile devices inside the cell or within different cells. Depending on the stage of development, cellular communication can be divided into five generations, which are standardised by the International Telecommunication Union and 3GPP (Arshad et al.; Sikimić et al.).

In the early 1980s, the 1st generation (1G) was introduced as an analogue system, allowing only voice operations (Arshad et al.). The 2nd generation (2G) launched in the 1990s switched to digital systems and enabled the transmission of data packets. The 2G global system for mobile communications (GSM) and general packet radio service (GPRS) operate at 900-1800 MHz frequency bands with data rates of 14-170 kb/s and ranges of 1-10 km. In 2000, the 3rd generation (3G) was introduced to further improve quality of service and security. Short message service (SMS), multimedia message service (MMS), and video conferences were established. The maximum data rate and range could be increased through 3G to 2-14 Mb/s and 10-50 km, respectively. An exemplary technology standard under 3G is the universal mobile telecommunications system (UMTS). In 2010, the 4th generation (4G) was launched including long-term evolution (LTE) technology; 4G uses the 2-8 GHz frequency bands and enables a broadband connection with data rates of up to 100 Mb/s. Although 2G, 3G, and 4G are primarily designed for voice, text, or video communication, the 5th generation (5G) also targets machine-to-machine (M2M) communication. The primary improvements compared to 4G are a higher data rate (1 Gb/s), reduced energy demand, and a higher number of connected devices. In addition to the classical applications of cellular networks between human users, 5G supports M2M for IoT applications, including high-quality services for critical communications. The anticipated start for 5G is 2020 (Abdelwahab et al.; Arshad et al.; Chaudhari and Borkar, 2020).

Regarding urban water infrastructure, cellular communication networks cover a large area supporting easy installation in remote areas. Additionally, cellular technologies allow two-way communication. However, owing to the high data rates and continuous monitoring of mobile devices for new data packets, the energy consumption is high and not suitable for a long maintenance-free operation of battery-powered devices. Therefore, a connection to the electrical grid is necessary to overcome this limitation. Cellular technologies use licensed frequency bands, which require a license for usage, increasing the operational costs of mobile devices (Abdelwahab et al.; Chaudhari et al., 2020). As the usage of these bands is strictly regulated, cellular technologies provide high reliability for data transmission.

2.2.2.3 Low Power Wide Area Networks

The transmission range of the presented short-medium communications is short, making the large-scale implementation of devices unreasonable. In comparison, cellular technologies are designed to cover large areas, but owing to high energy demand, battery lifetime is limited, resulting in increasing maintenance efforts. Additionally, the construction and operating costs of cellular devices are high due to complexity and license fees. Low power wide area networks (LPWAN) are a new communication group enabling the large-scale implementation of multiple devices. The key characteristics of LPWAN are long-range and ultra-low-power operations. LPWAN operates as cells with a base station for each cell and uses low bandwidths, which limit data rates but increase the energy budget for each transmitted bit. In addition, the transceivers are turned most of the time, as data transmission is the process that demands the most energy (Chaudhari et al., 2020; Raza et al., 2017).

The long range (LoRa) works in the unlicensed frequency bands (Europe 868 MHz, North America 915 MHz, and Asia 433 MHz) and uses proprietary spread spectrum technology from Semtech Corporation. This technology allows the modulation of signals by spreading narrow-band signals over wider channel bandwidths. Six spreading factors (SF7 to SF12) are used by LoRa; a higher spreading factor enables longer distances but reduces data rates, are 0.3-50 kb/s for LoRa, with a maximum packet length limited to 243 bytes. LoRa has range of 5 and 20 km in urban and rural areas, respectively. To exchange downlink commands, LoRa devices listen for a short time for a reply after each uplink transmission to the base station. LoRaWAN, built on LoRa technology and standardised by the LoRa Alliance, supports the development of LoRa networks and their integration into the Internet (Ding et al., 2020; Chaudhari et al., 2020; Oliveira et al., 2019; Mekki et al., 2019; Raza et al., 2017). As LoRa transmit in the unlicensed (public) frequency bands, the duty cycle regulates the maximum number of allowed data packets. For example, the duty cycle is 1 % in the 868 MHz bands, allowing a total transmission time of 36 s per hour (Adelantado et al., 2017; Bankov et al.).

Similar to LoRa, Sigfox operates in the unlicensed frequency bands but uses an ultra-narrow bandwidth (100 Hz) for very low data transmission. As a result, the ranges of Sigfox are 10 km and 40 km for urban and rural areas, respectively (twice as high as LoRa but with a lower data rate of 100 b/s). The number of uplink packets per day is limited to 140 with a maximum payload length of 12 bytes, including 4 downlink packets. If the 140 packets are distributed equally over the day, the minimum transmission interval is 10 min. As with LoRa, a downlink can only be received during a short time after an uplink transmission to the base station. LoRa allows the development of private LoRaWAN networks, but the Sigfox network requires a proprietary base station (Ding et al., 2020; Oliveira et al., 2019; Mekki et al., 2019; Raza et al., 2017). Due to this unopen business model and strict regulations regarding uplink messages, the interests of industry and academia have shifted to LoRa (Ding et al., 2020).

Long term evolution for machines (LTE-M), also called LTE enhanced machine-type communication (LTE eMTC), is a standard developed from 3GPP, which operates in LTE frequencies. LTE-M is a simplified version of LTE for IoT requirements and, therefore,

Table 2.1: Comparison of NB-IoT, LoRa, and Sigfox regarding network costs (adapted from Mekki et al. (2019)).

Technology	License fee	Deployment costs	Device costs
NB-IoT	∼ 500 MM € / MHz	∼ 15000 € / base station	>20 €
LoRa	Free	∼ 1000 € / base station	3-5 €
NB-IoT	Free	∼ 4000 € / base station	2 €

fully compatible with LTE cellular networks and used for M2M communication. The maximum data rate is 1 Mb/s less than that of LTE, and LTE-M is adapted with power saving mechanisms, which allows a sleeping node of the devices to increase the battery lifetime (Ding et al., 2020; Chaudhari et al., 2020; Oliveira et al., 2019; Mekki et al., 2019; Raza et al., 2017). Like LTE-M, narrow band IoT (NB-IoT) technology is also specified from 3GPP, and can coexist with GMS and LTE cellular networks under licensed frequency bands. Additionally, NB-IoT technology is based on LTE, but LTE functionalities are reduced to a minimum to increase battery lifetime and to decrease costs. The NB-IoT offers a data rate of up to 200 kb/s and a range of 1 and 10 km in urban and rural areas, respectively. Although there is no rule for the maximum number of data packets per day, a single packet size is limited to 1600 bytes (Ding et al., 2020; Oliveira et al., 2019; Mekki et al., 2019; Raza et al., 2017). To save energy, the NB-IoT can enter a sleeping node by turning the radio (power saving mode-PSM). However, extended discontinuous reception mode (eDRX) provides sporadic time slots during the PSM for additional downlink traffic (Martinez et al., 2019; **?**).

The following section focuses on LoRa, Sigfox, and NB-IoT, which are the leading LPWAN technologies (Mekki et al., 2019). LoRa and Sigfox operate in the unlicensed bands, whereby interferences are expected and cannot offer the same quality of service as the NB-IoT using licensed bands. To provide high-quality services, the NB-IoT needs additional power for synchronisation with the base station. However, as all technologies are in a sleeping mode with the radio turned off most of the time, battery lifetime for all technologies is expected to be in years (Gaddam and Rai; Mekki et al., 2019). However, the lifetime of the battery is strongly dependent on the number of transmissions, as shown in Figure 2.1 for LoRa for different spreading factors (SF7, SF10, and SF12) and battery types (AAA and Baby C). The lifetime is simplified by only considering the transmission energy demand for a packet size of 12 bytes. The expected transmission time is taken from Adelantado et al. (2017) and Noreen et al., and transmission energy is extracted from Morin et al. (2017) and adjusted to the authors' experiences with LoRa devices.

All three technologies provide high data ranges, and only a few base stations can cover entire cities with outdoor and indoor connections. Although LoRa supports the development of private networks, the NB-IoT depends on the existing LTE networks for coverage. Additionally, one base station can connect up to 50000 devices with LoRa and Sigfox and 100000 devices with NB-IoT. Table 2.1 shows NB-IoT has the highest costs (Gaddam and Rai; Mekki et al., 2019). Another important point is that LPWANs are usable for delay-tolerant applications and not designed for critical applications with high reliability or fast response times (Chaudhari et al., 2020; Raza et al., 2017).

Wireless communication networks can be classified into five groups according to coverage: (1) proximity networks operating in the contact range (up to 10 m), (2) per-

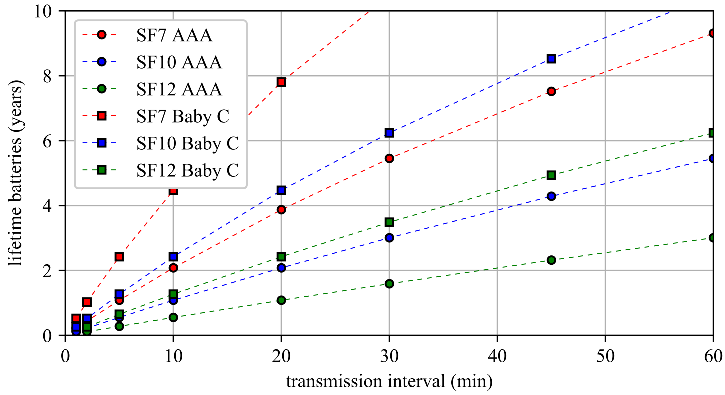

Figure 2.1: Estimation of the lifetime for battery LoRa device batteries using different transmission intervals and spreading factors for AAA and Baby C batteries.

sonal area network (PAN) operating in short ranges (10-100 m), (3) local area network (LAN) operating in short/medium ranges (100–1 000 m), (4) neighbourhood area network (NAN) operating in medium ranges (1-10 km), and (5) wide area network (WAN) with long ranges (> 10 km) (Mekki et al., 2019; Mahmoud and Mohamad, 2016). In this work, these definitions are also applied to wired communication. Figure 2.2 summarises all of the mentioned communication technologies regarding transmission range and data throughput.

2.2.3 Concluding remarks

In this subchapter, the theoretical background to communication technologies was explained as additional information to Paper I. Each communication technology has different characteristics and limitations, thereby influencing the spatial and temporal resolution of transmitted measurement data. For example, LoRa as an represantive for LPWAN operates in public frequency bands, whereby package losses has to be expected and is therefore not suitable for critical and time-dependent applications (e.g.: control of CSO valves, peak-hour pricing). On the other hand, LoRa is very well suited for large-scale monitoring of NBS (e.g., temperature, soil moisture for irrigation). Subsequently, one of the main conclusion is, that an efficient monitoring and controlling network in the field of UWI requires a coordination between intended applications and transmission technology. However, it also important to mention, that practical experiences can only be transferred to other case studies to a limited extent, since quality of wireless communication technologies also depends on characteristics at the installation site (e.g., how many sources of interference are there from buildings and ground). Therefore, it is recommended to perform a specific and on-site analysis of the ranges and transmission quality before implementation.

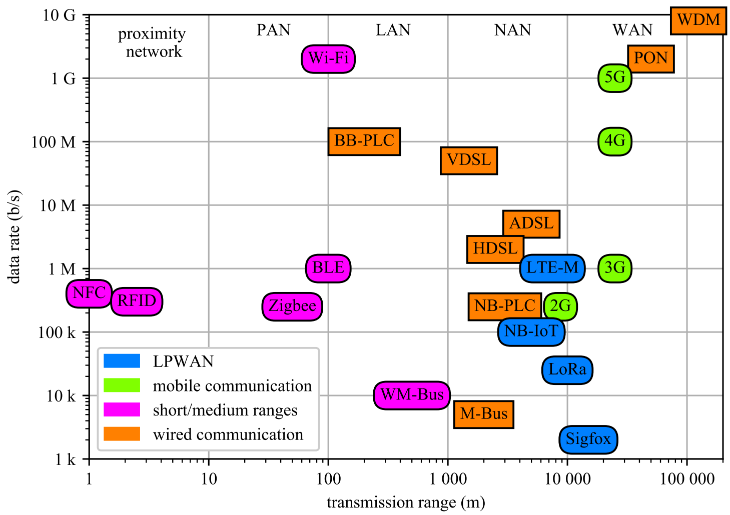

Figure 2.2: Overview of the different data transfer technologies regarding distance and data rate and categorised into wired communication (rectangles) and wireless communication (rounded).

3 Smart Rain Barrel Concept

3.1 Paper II

Oberascher, M., Zischg, J., Kastlunger, U., Schöpf, M., Kinzel, C., Zingerle, C., Rauch, W., Sitzenfrei, R., 2019. Advanced Rainwater Harvesting through Smart Rain Barrels. In: World Environmental and Water Resources Congress 2019 : Watershed Management, Irrigation and Drainage, and Water Resources Planning and Management https://doi.org/10.1061/9780784482339.008.

Advanced Rainwater Harvesting through Smart Rain Barrels

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ABSTRACT

Recent technological advances in information and communication technology (ICT) have opened new opportunities for monitoring and controlling of micro-scale low impact development (LID) practices almost in real-time. In this work, the smart rain barrel (SRB) concept combines LID and ICT in one system allowing new possibilities for the operation and management of small storage volumes used as temporary storage for stormwater control as well as for rainwater harvesting. To support the development of the SRBs, the effectiveness of the SRB concept on household scale is evaluated by using a 1-year rainfall series combined with real weather forecasts for that period. Results show, that stormwater retention is clearly increased by adding weather forecast to control strategies, while the amount of substituted potable water decreases with increasing accumulation time of the weather forecast. However, as the main purpose of rainwater harvesting is the substitution of potable water used for irrigation, the main challenge for small storage volumes used for both rainwater harvesting and stormwater control, is the accurate prediction of the stormwater runoff.

Keywords: Internet of Things, irrigation demand, real time control, smart stormwater management, weather forecast

INTRODUCTION

In recent decades, the urban water infrastructure became more diverse and complex requiring a decentralized approach towards local problems (Fletcher et al. 2015). For a sufficient assessment and management, this also demands an expanded, integrated view on the urban water cycle to efficiently and sustainably manage the available resources (Sitzenfrei 2015). Such decentralized measures are for example rain barrels, which can have manifold impacts on different aspects of the urban water cycle (e.g. substituting water demand, reducing peak runoff, reducing emissions to the receiving water body, cooling by increasing evapotranspiration, reduction of energy requirements, etc.).

Rain barrels are micro-scale Low Impact Development (LID) practices and can be used as temporary storage for stormwater control as well as for rainwater harvesting. However, there is still a knowledge gap on how these systems actually have an impact on the different aspects of the urban water cycle and what the integrated, overall optimal performance is. Palla et al. (2011) investigated the optimal performance of rainwater harvesting systems with a suitable behavioral model and evaluated the efficiency with a 30 years long-term simulation. Sitzenfrei et al. (2017) investigated the impact of rainwater harvesting on water demand and the existing central water supply network. With an hourly time step and water quality analysis performed with Epanet2, the highest impact of rainwater harvesting was identified at locations with low density urban forms (single family house). In such areas, there is often a minimal diameter in the potable water supply network in place and demand reductions worsen the usually already critical water quality in these areas significantly. An et al. (2015) investigated the potential of rainwater harvesting on a rooftop garden and showed the temperature reduction for that measure which counteracts the urban heat island effect. Notaro et al. (2017) determined the optimal size (volume) of rainwater harvesting systems in order to reliably operate the system for garden irrigation and toilet flushing in a Mediterranean climate. In their daily water balance simulations, they showed, that the system is greatly affected by climatic conditions. Ward et al. (2012) showed with an empirical assessment of performance, that the actual performance for a non-domestic rainwater harvesting system differs from the ideal design assumption but that the capital payback is still between 6 and 11 years. They especially outlined the importance of monitoring data. When moving towards a multipurpose utilization, the requirements for monitoring data are different. Campisano and Modica (2015) investigated in this regard the necessary time resolution for rain water harvesting systems by varying their analysis with 5 minutes and up to 24hours time steps. The investigation focused on water saving efficiency and stormwater retention performance. It was determined that daily simulations are sufficient for water saving efficiency and at least an hourly time step is required for performance assessment of tank retention. Especially for small tanks, even a 5 min time step is required to reduce intense rainfall runoff peaks. For sufficient multi-purpose evaluations, still more empirical data is needed (Campisano et al. 2017). Recent technological advances in information and communication technology (ICT) have opened up new opportunities for monitoring and controlling of such systems almost in real-time. Kerkez et al. (2016) showed the potential of low-cost sensors and controllers in the urban water cycle and how the negative environmental impacts can be reduced. Di Matteo et al. (2019) demonstrated the potential of smart rain water harvesting (opening and closing of valves) to reduce peak flows within a simulation-based optimization process. Oberascher et al. (2019) presented the potential of real time control of smart rain barrels (SRB) with weather forecasts and showed that already with a simple control strategy significant benefits could be achieved for the overall system performance.

The SRB in this work is integrated in an urban testbed as part of the smart cities' initiative: the smart university campus Innsbruck. That urban testbed has the aim to explore smart (ICT) LID controls and real time control. Our SRB concept combines LID and ICT in one system allowing new possibilities for the operation and management of small storage volumes. To show the effectiveness of the SRB concept, a SRB device is evaluated at household scale by using a 1-year rainfall series combined with historical weather forecasts of the Austrian Weather Service

ZAMG (Zentralanstalt für Meteorologie und Geodynamik). The rainfall data is available in 10-minute time steps and the forecast data at 15-minute time steps making it possible to use very small storage volumes such as e.g. rain barrels. Such accuracy is also needed for a targeted and timely control of the SRB. One of the applications of our SRB includes various control options to further decrease potable water consumption for garden irrigation. In combination with the weather forecast, different control strategies can be applied, distinguishing between dry and wet weather periods. For rainy days, the main purpose is to ensure a fully filled SRB at the end of the rain event, while the stored water is used for irrigation during dry periods. In addition, the storage volume of the SRB is varied within a range of 0.1 and 1.0 m³ to determine the optimum size for the SRB under the consideration of water efficiency (e.g. water savings) and stormwater control (e.g. peak stormwater discharge reductions and emission control). The results show that both significant irrigation water saving and runoff reduction can be achieved with the SRB. However, a simplified estimation of the predicted roof runoff without consideration of the forecast error, as used in this study, is not suitable to ensure a fully filled SRB at the end of every rainfall event. Furthermore, to allow conclusions on the effectiveness in reducing peak runoff rate in the sewer system, a joint approach of sewer system and SRBs in urban areas is needed in future. This study provides an evaluation of the SRB concept as a tool to enhance stormwater and water demand management strategies to reduce potable water consumption in urban areas through intelligently controlled, small storage volumes. In this work, the SRBs are numerically simulated, but self-developed and constructed SRBs are situated on the campus area of the University of Innsbruck in the near future.

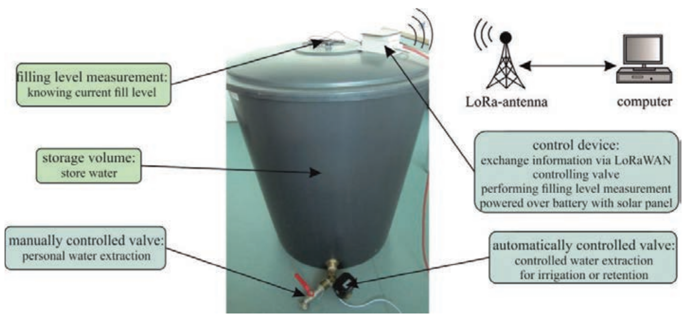

Figure 1: Development of the SRBs and their main components

METHODS

To test the applicability of the SRB concept, several computational simulations with PySWMM (https://github.com/jennwuu/pyswmm) were performed for assessing the potential effect of a single SRB on stormwater runoff and potable water savings used for irrigation. This information is afterwards used for the development and construction of real SRBs as shown in Figure 1. The SRB consists of a storage volume, a manually controlled valve for personal water extraction, a valve for automatically controlling the outflow, a filling level measurement device inside the SRB and a communication module (control device and antenna) allowing the implementation of the SRB into smart water cities projects. Information on filling levels and commands for valve opening and closing are transmitted wirelessly over LoRaWAN being part of the Internet of Things (IoT) development. LoRaWAN is a low-power and long-range data transfer technology (Augustin et al. 2016) and therefore particularly suitable for battery-powered devices at remote locations. As a result, our SRB concept equipped with LoRaWAN supports the subsequent installation at household level allowing the communication with other smart LID applications without a central database. It is important to note that this work supports the development of the SRBs, which are situated on the campus area of the University of Innsbruck in the near future.

Real-time control (RTC) strategies including weather forecast: The RTC strategies for the SRBs can be seen in Figure 2 showing the control steps based on the weather forecast for a single day. At the beginning of the day, the day is categorized as either a day with rainfall or a day without rainfall according to the daily rainfall forecast. In the case of rainfall, the predicted amount of rainfall for a specific prediction period is determined and the roof runoff is estimated in a simplified way by using a discharge coefficient. Depending on the roof runoff, two control strategies can be distinguished afterwards: (i) the expected roof runoff is lower than the available storage volume, and (ii) the expected roof runoff exceeds the available storage volume of the SRB. While in the first case no RTC is needed, the outlet of the SRB is opened in the second case. This condition is evaluated in every simulation step, and if possible, the outlet is closed to ensure a fully filled SRB at the end of the rainfall event providing a maximum volume for irrigation purposes. For days without rainfall, the daily water demand for irrigation is calculated and the needed water is extracted from the SRB through targeted RTC. The irrigation volume exceeding the volume provided by the SRB is taken from the potable water supply.

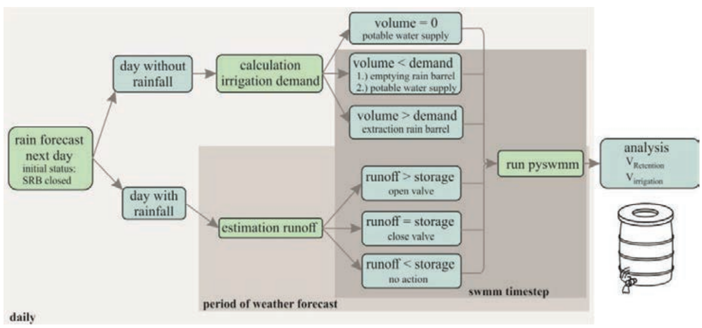

Figure 2: RTC strategy of the SRB for a single day based on weather forecasts.

To simplify the calculations, it is assumed that on days with rainfall, no irrigation is needed, regardless of the predicted amount of rainfall. At the end of the simulation, the used amount of water for irrigation and the quantity of runoff retention is determined and compared to the reference state, defined as a rain barrel without the ability of emptying before the rainfall (no forecast), i.e. water is only extracted for irrigation.

Case Study: For the case study, a hypothetical urban subcatchment located in Innsbruck (Austria) was used. It was assumed that the catchment consists of a single-family house with 100 m² roof area utilized for runoff collection and a 500 m² green area for irrigation. For the simulation, a one-year rainfall series from a weather station of the Austrian Weather Service (ZAMG) was used. The rain data were available in 10-minute steps and the year had a total rainfall amount of 891 mm being approximately in the average rainfall amount of the last 30 years. Additionally, historical weather forecasts over a period of 24 h were available in 15 min steps. The weather forecasts were extracted from the Integrated Nowcasting through Comprehensive Analysis (INCA) system. The INCA system combines numerical models, surface observations and radar rainfalls for providing weather forecasts in high spatial and temporal resolutions. Furthermore, information on cell movement and development is used to determine direction and speed of the cells for short-term predictions (Haiden et al. 2011). For the simulations, different time intervals for the weather forecasts, called accumulation times, were used ranging from 30 min to 24 h. Furthermore, the SRB volumes were varied in a range from 0.1 to 1.0 m³ allowing an easy installation at existing households. As Innsbruck lies in the moderate climate zone of the northern hemisphere, the irrigation period was set between April and September. Based on statistical analysis of water consumption of Austrian single-family houses (Neunteufel et al. 2012), an average water demand of 0.4 l / (m² · d) is regarded for irrigation purpose resulting in an irrigation demand of 200 l per dry day for the presented case study.

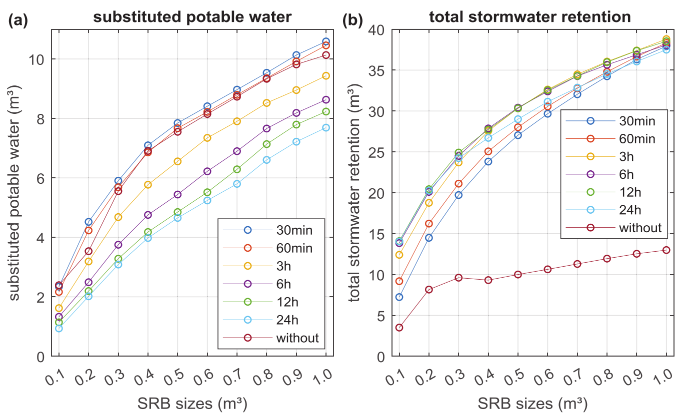

Figure 3: Simulation results for different SRB sizes and periods of weather forecast for two performance measures: (a) provided water for irrigation purposes, and (b) total stormwater retention of the roof runoff.

Numerical implementation: For the hydrodynamic simulations, a python wrapper for SWMM5 called PySWMM (https://github.com/jennwuu/pyswmm) was used. PySWMM supports a step-by-step simulation of SWMM input files allowing the implementation of control rules based on weather predictions. At first, an ordinary SWMM input file was created consisting of a single subcatchment representing the roof area, a rain barrel as LID object of the roof area and an outlet. After starting the simulation, three analyses with different time steps were performed as presented in Figure 2: (i) daily evaluations of the rainfall amount of this day, (ii) expected roof runoff for the chosen forecast period (ranging from 30 min to 24 hours) and (iii) analysis of the control rules at SWMM routing timesteps including performance analysis of the above mentioned RTC rules. In the model, the outlet of the SRB was closed or opened by changing the drainage coefficient of the rain barrel, a feature that is supported by PySWMM.

RESULTS AND DISCUSSIONS

Figure 3 shows the simulation results for the SRB located at a single-family house. In the simulations, the SRB's sizes and the period of the weather forecast were modified and compared to the reference state without rainfall forecast. Figure 3(a) presents the provided water for irrigation purposes and in Figure 3(b) the total amount of stormwater retention is plotted.

Substituted potable water: As expected, the substituted potable water is increasing with higher volumes of the SRB. A total of 56 irrigation days during the irrigation period requires a total water volume of 11.2 m³ needed for irrigation purposes. Instead of potable drinking water, the water for irrigation can be substituted through our SRB concept between 1.0 (16 %) and 10.5 m³ (95 %) depending on the SRB size (from 0.1 to 1.0 m³) and accumulation time of the weather forecast (from 30 minutes to 24 hours) as shown in Figure 3(a). Interestingly, the amount of substituted potable water decreases with increasing accumulation time of the weather forecast. If rainfall is forecasted, the quantity of roof runoff is estimated in a simplified way by using the predicted amount of rainfall of the accumulation time and a discharge coefficient. Based on this estimation, the SRB is emptied until the desired storage volume is available. By overestimating the roof runoff, the SRB is emptied too much, resulting in a not fully filled SRB at the end of the rainfall event and thus reduces the substituted potable water. However, the quality of the weather forecast is higher for low accumulation times, which explains the nearly identical results of the weather forecast for accumulation times ranging from 30 – 60 min compared to the reference state without information over future rainfall.

Stormwater retention: For the considered year, the total roof runoff for the single-family house with a roof area of 100 m² is 89.1 m³. The results show that stormwater retention varies between 7.2 m³ (8 % of total runoff) and 38.8 m³ (43 %) depending on SRB size. As can be clearly seen in Figure 3(b), the total amount of stormwater retention by adding weather predictions to the RTC strategies is significantly higher as compared to the reference state (without knowing future rain events) even for small storage sizes (e.g. 0.1 m³). Since emptying the SRB needs time, using longer periods of weather forecasting generally results in higher volumes of stormwater retention. This effect is more important for small storage volumes, which are frequently emptied and filled during the period, than for larger storage volumes with lower frequencies.

SUMMARY AND CONCLUSIONS

Rain barrels are micro-scale Low Impact Development (LID) practices and can be used as temporary storage for stormwater control as well as for rainwater harvesting. Recent technological advances in information and communication technology (ICT) have opened new opportunities for monitoring and controlling of such applications almost in real-time. Our smart rain barrel (SRB) concept combines LID and ICT in one system allowing new possibilities for the operation and management of small storage volumes. In this study, a hypothetical urban subcatchment consisting of a roof area of 100 m² for rainwater collection and a green area of 500 m² for irrigation was considered and equipped with different SRBs sizes ranging from 0.1 – 1.0 m³. For the simulations, rain data in 10 min steps and weather predictions available in 15 min steps were used. The substituted potable water for irrigation purposes and the amount of stormwater retention during the investigation period were determined as performance measures. Results show, that potable water used for irrigation can be reduced between 16 to 95 % and a total stormwater retention of 8 to 43 % can be achieved depending on the SRB size and the period of weather forecast.

By adding control rules based on future weather forecasts to storages used for rainwater harvesting, the main challenge is the accurate prediction of the stormwater runoff. While an overestimation of the predicted stormwater runoff increases the total amount of stormwater retention, the reduction of potable water as the main purpose of rainwater harvesting is significantly lower compared to uncontrolled storages. As the forecast error increases with increasing accumulation time, a simplified estimation of the predicted roof runoff without consideration of the forecast error, as used in this study, is not suitable to ensure a fully filled SRB at the end of every rainfall event. Furthermore, the consideration of forecast errors gets more important for low storage sizes as they are frequently emptied and filled during the period.

This study shows the advantages of a single SRB located at a single-family house for stormwater retention. While the total amount of stormwater retention was determined, the impact on the peak runoff rate was not taken into consideration. Therefore, the implementation of SRBs in an urban area requires the consideration of the sewer system to allow conclusions on the effectiveness in reducing peak runoff rate in the sewer system. However, especially for small storage volumes that are frequently emptied and filled, a joint approach of sewer system and SRBs is needed to effectively reduce peak runoff rates. For example, in the worst case, the SRBs are already fully filled before peak runoff occurs. Furthermore, when implementing a group of SRBs in an urban area, a controlled communication of opening and closing commands between the SRBs is needed. For example, fast emptying of a group of SRBs to provide additional volume for stormwater retention at the same time can lead to an overload of the drainage system even before rainfall.

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3.2 Paper III

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Integrated urban water management with micro storages developed as an IoT-based solution – The smart rain barrel

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A R T I C L E I N F O

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Real-time control
Smart rainwater harvesting
Urban water infrastructure
Weather forecasts

A B S T R A C T

Low cost sensors are emerging alongside innovative data transfer technologies, allowing the integration of smart solutions for the decentralisation of water infrastructure. In this work, the smart rain barrel (SRB) concept is introduced as an IoT-based solution for advanced rainwater harvesting. The SRB consists of a rain barrel extended by a discharge valve, which is centrally controlled. This concept offers (1) individual control of each implemented SRB with its incorporation into the integrated water system management and (2) a simple large-scale implementation of additional storage units as an alternative to future expansion of existing infrastructure. The open-source software "Smartin" is developed by hypothetically retrofitting an Alpine municipality with SRBs to evaluate the effects of the latter on the urban water infrastructure. Compared to uncontrolled rain barrels, a simple coordinated control strategy already clearly improves the performance of the integrated system by reducing combined sewer overflow and addressing drinking water demand.

1. Introduction

Climate change, urbanisation and maintenance are present and future challenges for urban water infrastructure. Urbanisation and loss of infiltration capacity of natural areas increase peak runoff while reducing groundwater recharge (Fletcher et al., 2013; McGrane, 2016; Miller et al., 2014). Moreover, climate change has modified the intensity, duration and frequency of rain events (Berggren et al., 2012; Willems et al., 2012), and has resulted in higher temperatures (Bastin et al., 2019), thereby increasing the demand for irrigation water (Parkinson et al., 2016). Through the interaction between climate change and urbanisation, the probability of overloading the existing urban drainage systems (Yazdanfar and Sharma, 2015) and the impacts on natural water resources (Cominola et al., 2015) have increased. To counteract this trend locally, the existing infrastructure, which mainly consists of central solutions, has been extended in the last decades by decentralised system applications such as green infrastructure (GI) (Fletcher et al., 2015; Yazdanfar and Sharma, 2015) with the aim to store rainwater and to increase infiltration and evapotranspiration. Examples of GI are green roofs, infiltration trenches, rain gardens, rainwater harvesting (RWH) systems, whereat the focus of this article is on RWH systems.

The main objective of RWH is to retain rainwater runoff with minor impurities, for example from roof surfaces, in decentralised rainwater storage tanks to substitute drinking water used in non-potable water applications such as irrigation and toilet flushing (Campisano and Modica, 2015; Khastagir and Jayasuriya, 2010; Okoye et al., 2015). Apart from a drinking water reduction, RWH systems present a local source control option to reduce runoff into the drainage system due to the detention of precipitation (Campisano and Modica, 2016; Imteaz et al., 2011). Therefore, a large-scale implementation of RWH systems offers advantages for operation of urban drainage systems, too. For example, the flood volume as well as the caused damage can be reduced as shown by Huang et al. (2015) and Jamali et al. (2020) through a simulation approach with SWMM5. However, as can be seen from the results of single RWH systems, the efficiency of water saving and stormwater detention is determined by factors such as storage volume, roof area, precipitation and water consumption (Fewkes and Butler, 2000), but also subject to seasonal fluctuations due to different withdrawal quantities and precipitation amounts during summer and winter

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months (Barry and Coombes, 2015). Furthermore, the conventional RWH system is strongly dependent on the withdrawal quantities and the corresponding user behaviour in terms of storm water management (Palla et al., 2011; Sample and Liu, 2014). Higher withdrawal volumes also deplete the stored volumes more rapidly, meaning that more storage volume is available for stormwater detention (Quinn et al., 2020). As a result, these systems are only conditionally suitable for the reduction of extreme rain events, as they are likely to be already filled by the time that the rainfall peak occurs (Schubert et al., 2017; Vaes and Berlamont, 2001).

Developments in the field of "Smart Cities" have contributed to the evolution of the Internet of Things (IoT) in the water sector. Low cost sensors are emerging along with innovative data transfer technologies, which allow for the integration and networking of individual system components with the overall system (Li et al., 2014; Ray, 2018). However, these are rarely implemented in real-time workflows of urban water systems (Li et al., 2020; Wong and Kerkez, 2016) but novel innovative solutions are increasingly emerging (Creaco et al., 2019; Kerkez et al., 2016; Moy de Vitry et al., 2019). For example, the outflow of a storage unit can be changed by real-time controlled valves allowing an effective use of the available storage volume by emptying the storage units prior to precipitation events. Xu et al. (2018) demonstrated through a simulation approach, that applying weather forecasts in combination with real-time control (RTC) technology to RWH systems reduces the frequency of complete filling and thus prevents overflow. As Di Matteo et al. (2019) and Liang et al. (2019) showed in a simulation-optimised process, a coordinated control of individual smart rainwater tanks can also reduce the peak runoff in sewer systems even for rare rain events that occur over long durations with prior knowledge of future weather conditions. Roman et al. (2017) integrated the irrigation requirements into a smart RWH system, increasing the efficiency of both the drinking water conservation and the detention effect. However, the discharge of rainwater leads to a conflict between the two contradicting objectives namely, (1) discharge the rainwater as fast as possible to provide the maximum storage capacity for the next event; and (2) to store rainwater as long as possible for substituting as much drinking water as possible. This was demonstrated by e.g., Behzadian et al. (2018) and Zeisl et al. (2018) using a conceptual model run on a daily basis.

Previously described studies investigated smart rainwater storage tanks larger than 1 m^3. The approach presented in this work uses "smart rain barrels" as a system-wide implemented IoT-based solution with real-time controlled micro storages (between 200 l and 500 l). Just like conventional rain barrels, the SRB can also be used to retain rainwater for irrigation purposes. While the benefits are evident at the local level, large scale advantages (potable water peak flow, reduction of flooding volume or combined sewer overflow) are usually limited. To mitigate the disadvantages of the small storage size relative to the overall system, new ways of operation are developed and implemented. For example, if an insufficient rainwater amount is forecasted to meet the estimated irrigation demands, drinking water can be taken from the potable supply system during off-peak hours to fill up the deficits. On the other hand, sufficient capacity can be provided for rain events by emptying the SRB before heavy rain events. Therefore, the SRB is conceptualised as an IoT-based solution allowing for each SRB to be controlled individually in real-time. To achieve these benefits, weather forecasts with high temporal resolutions from a meteorological service are implemented into the control strategy as they can clearly increase the detention effects of single micro storages as shown by Oberascher et al. (2019). Besides, using weather forecasts for the operation of real-time controlled systems has a positive effect on the performance of the entire system, such as by reducing the combined sewer overflows (Courdent et al., 2015; Gaborit et al., 2013; Löwe et al., 2016).

Due to the small storage size, the SRBs can be placed on the surface. As a result, the installation of SRBs into the existing systems can be relatively easy, thereby allowing for large-scale retrofitting of the urban water infrastructure. Therefore, the SRB represents a successful IoT-based link between water supply and the urban drainage system. The effectiveness of a single SRB has already been proven through the operation of a prototype at the University of Innsbruck and numerical simulations at the household level (Oberascher et al., 2019). The aim of this paper is a model-based upscaling to an entire case study to investigate the effects of the SRB on the urban water infrastructure by a large-scale implementation and the development of control strategies for multiple SRBs.

In addition to the positive effects of RWH systems (reduction of drinking water demand and stormwater runoff), a reduction in consumption in the existing water infrastructure can also increase the risk of water stagnation and associated water quality problems in water supply networks, and deposits in combined sewers (Grandet et al., 2010; Sitzenfrei et al., 2013, 2017). Therefore, an integrated modelling of urban drainage and water distribution network as well as water tanks on high temporal and spatial resolution is required to be able to fully investigate the effects of RWH systems. Recent research studies (Behzadian et al., 2018; Sitzenfrei et al., 2017), that have followed this integrative approach, are mainly based on conceptional models, e.g.: UrbanBEATS or WaterMet[2], run on daily respectively hourly time steps. In addition, Sitzenfrei and Rauch (2014) investigated the effects of decentralised solutions on dry weather flows in combined sewer systems by coupling EPANET2 and SWMM5, applying an hourly time step too. In contrast, hydrological process of urban drainage systems, e.g. combined sewer overflows, take place in timesteps of seconds or minutes, requiring a higher temporal resolution for an adequate modelling.

To evaluate the effects of the SRBs on the urban water infrastructure, the open-source software "Smartin" is developed and presented in this work. The key features of "Smartin" are (1) allowing individual control of each implemented SRB based on weather forecasts and current system states, (2) choosing between perfect and historical (= real) weather forecasts (3) using a high spatial and temporal resolution for the necessary simulation of micro storages, (4) coupling of urban drainage and water supply systems for high temporal resolutions and (5) developing and testing of integrated real time control mechanisms. The software is written in Python using several open source Python packages for the simulation of the hydrodynamic model SWMM5 (Gironás et al., 2010) for the urban drainage system and the quasi-stationary model EPANET2 (Rossman, 2000) for the water supply system. To test the developed software, we focus on an experimental retrofitting of an existing urban water infrastructure in an Alpine municipality with SRBs. Besides, historical weather forecasts from the Austrian national weather service are included into the control strategy. Additionally, different control strategies are applied to analyse the impacts of a large-scale implementation on the water supply (e.g. substituted drinking water, changes in water pressure and age) and on the urban drainage system (e.g. changes in combined sewer overflows and flooding).

The objectives of this work are:

- Proposing the smart rain barrel (SRB) concept as an IoT-based solution for a networked water infrastructure.
- Development of a high-resolution simulation tool which allows a large-scale implementation of the SRBs and the real-time control of each individual rain barrel as well as a coordinated control in the context of the urban water infrastructure.
- Providing a proof of concept of the hypothetical retrofitting of existing infrastructure in a case study.
- Analysing the impacts of different control strategies including various weather forecast conditions on both the urban water supply and drainage system in an integrated model.

2. The "Smart rain barrel" concept as an IoT-based solution

The concept presented in this work aims to compensate the disadvantages of micro storages used for rainwater harvesting (e.g. small volume compared to the entire system, depending on user behaviour) by smart approaches. The concept should be suitable for large-scale implementation in new building areas as well as for retrofitting in existing urban areas. This concept results in the following practical requirements for micro storages: (1) ensuring simple implementation in already existing infrastructure, (2) independent RTC of each micro storage due to different connection areas and user behaviours (e.g. opening and closing of discharge valves depending on the current filling level) and (3) energy efficiency in operation because batteries are needed for power supply (e.g. limiting the numbers of control actions per day).

In order to meet these conditions, the SRB concept was developed as RTC micro storages. The main part is a conventional rain barrel available in hardware stores and extended to an IoT-based solution as shown in Fig. 1. A rainwater collector is used to connect the rainwater downpipe of roof areas with the SRB, wherein the SRB and rainwater collector act as connected vessels and therefore preventing SRB overflow. This is also the reason why no further emergency or backup strategy is needed for loss of power or data connection. The SRB has a manually controllable valve for personal water withdrawal and an automatically controllable valve at the bottom for irrigation and detention management. The SRB is equipped with a solar panel and a rechargeable buffer battery for power supply, whereat the solar panel is able to recharge the battery with the sunshine duration on a clear summer day. The SRB is controlled centrally. The measured values and control commands are sent via low power wide area technology LoRaWAN (LoRa Alliance, 2017). LoRaWAN is an innovative data transfer technology for IoT applications (Bardyn et al., 2016; Song et al., 2017); it is characterised by low energy consumption and high transmission ranges and therefore particularly suitable for battery-powered sensors. In addition, high-resolution weather forecasts are used in the control strategy to increase the efficiency of the existing storage volume. The prototype shown in Fig. 1 has been in operation at the University Campus of Innsbruck during the summer months since October 2019. In addition, Fig. 2 illustrates a schematic cross-section of the SRB for more information.

The effects of a single SRB for a single household have been investigated by Oberascher et al. (2019). As the results show, the storm water detention volume of the SRB can be increased by up to 300% compared to the uncontrolled rain barrel, whereas 16–90% of the irrigation requirements can be satisfied by the SRB depending on the storage volume. The impact of the RTC is most significant if the rain barrel is partly or completely filled due to previous rain events, i.e. when the dry weather period between two rainfall events is too short. Through the RTC, the SRB can be emptied before the next rain event to provide more volume for storm water retention than in the conventional rain barrel. However, emptying the SRB depends on the predicted amount of precipitation. If the predicted rain volume is less than the actual rain, the

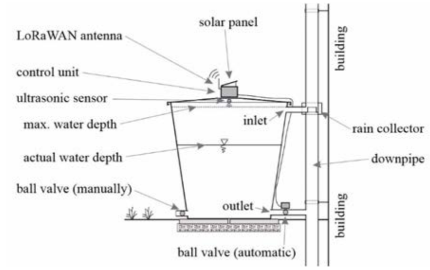

Fig. 2. Schematic cross-section through the SRB including description of characteristics elements.

SRB would only be partially filled by the end of that rain event. Therefore, water savings decrease with higher weather forecast periods due to uncertainties in precipitation forecasts.

Fig. 3 shows the idealised functionality of the SRB concept for a real rainfall event in comparison with a conventional (uncontrolled) rain barrel, both of which have a storage volume of 0.5 m^3. Both storage units have a connected impervious area (roof area) of 145 m^2. For this exemplary case, a perfect weather forecast with a forecast period of 2 h is chosen for the SRB, meaning that the forecasted amount of rain matches perfectly with the real rainfall event. Additionally, it is assumed that future weather developments are updated every hour. Because of past rainfall events and subsequent irrigation activities, both operating semantics are partially filled before the predicted rainfall event, as can be seen from Fig. 3. In the example, the rain events mostly take place between 13:15 and 13:30 with a total rainfall amount of 3.7 mm and a maximum intensity of 0.3 mm/min resulting in a peak outflow of 0.74 l/s from the sub-catchment into the drainage system. In the idealised example, the first time of update is at 12:00 and future weather developments are recorded for the next 2 h. The total inflow to the SRBs is estimated by the simplified approach described by: roof area × discharge coefficient × rainfall volume, and was calculated to be 0.51 m^3. Because the estimated inflow to the SRB was higher than the total storage volume, the SRB receives a control command to completely empty itself before the rain event. As a result, the discharge valve of the SRB opens automatically and closes again at 12:17 when the SRB is emptied. This allows the entire storage volume of the SRB to be used as a detention volume. Therefore, almost the entire roof discharge can be captured by the SRB and the peak outflow during the rain event is reduced by 80%. In contrast to the SRB, the conventional rain barrel is already fully filled by the time the peak intensity is achieved, meaning

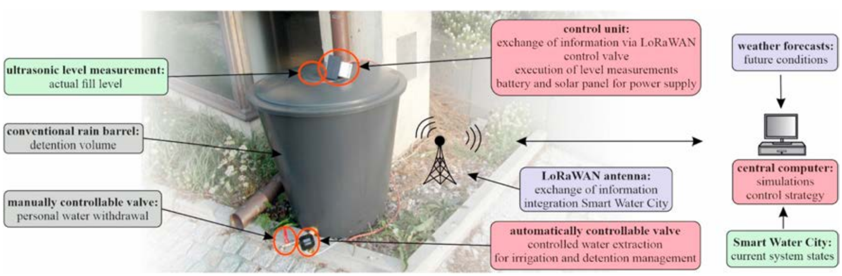

Fig. 1. Installed prototype of the SRB and description of the system components.

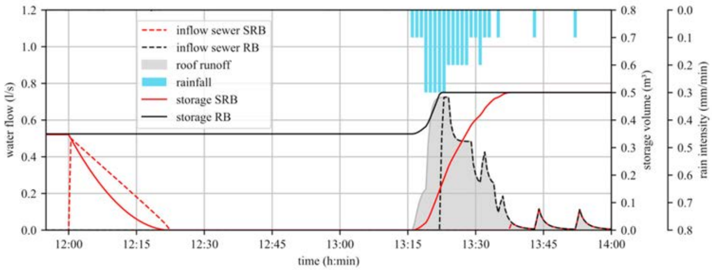

Fig. 3. Illustration of the exemplary functionality of the SRB compared to a conventional (uncontrolled) rain barrel.

that the peak outflow into the drainage system cannot be reduced. After the rainfall event, both operating approaches are fully filled to provide as much rainwater for irrigation purposes as possible.

In contrast to Oberascher et al. (2019), who focused on one single SRB applied at household-scale, this paper investigates a model-based upscaling of SRBs to an entire case study.

3. Methods

In order to analyse the impacts of the presented SRB concept on the urban water infrastructure, the software "Smartin" was developed. "Smartin" implements micro storages in a selected number of buildings, each with one connection to the urban drainage as well as to the water supply system. The micro storages are RTC, allowing the discharge of rainwater before a precipitation event to provide additional storage volume. If the micro storage cannot cover the irrigation demand with rainwater alone, the micro storages are automatically filled with drinking water during hours with lower water consumption to satisfy the irrigation needs. As a result, "Smartin" can be used for modelling of the RTC of micro storages developed as an IoT-based solution in a coupled model of urban drainage and water supply systems. It was specifically designed for the use of any kind of micro storages to make the software generally applicable. The SRBs represent a special case of the micro storages and were used in the case study to test the software. Stormwater Management Model (SWMM5) (Gironás et al., 2010) and EPANET2 (Rossman, 2000) are used to simulate urban drainage and water supply, respectively. Coupling of the separated systems namely, urban drainage, water supply and micro storage volumes, was achieved via Python programming language and usage of several open-source Python packages.

3.1. Integrated modelling of micro storages as IoT-based solutions in the context of urban water infrastructure: "Smartin"

The setup of "Smartin" is illustrated in Fig. 4. It consists of two main components, the urban drainage and the water supply model. Weather forecast, rainfall data and current simulation results are individually used for the RTC of the micro storages during rain events. During dry periods, the stored rainwater is used for irrigation purposes and the irrigation demand is determined as a function of temperature and daily rainfall. In case the stored rainwater cannot satisfy the irrigation demand, drinking water from the water supply system is automatically extracted during off-peak hours. Finally, the amount of harvested rainwater and the demand for the drinking water are used as input parameters for the water supply simulation. For the water supply assessment, water demand is represented by a dynamic model consisting of seasonal; temperature dependent and hourly factors (see also 3.1.2). In the case of nodes with micro storages, the water demand is reduced due to the harvested rainwater and the shift of water demand from the peak hours to (night) hours, when there is lower demand for drinking water.

3.1.1. Urban drainage systems: PySWMM

SWMM5 is a hydrodynamic model for urban drainage to numerically calculate water flows in sewers (Gironás et al., 2010). The low impact development (LID) type rain barrel was chosen for the model representation of the micro storages. The LID type rain barrel consists of a storage layer and a drain layer. The storage layer provides the detention volume of the micro storage, while the drain layer represents the outflow. Based on the chosen land designation and the degree of penetration, properties are randomly selected as locations for micro storage volumes. Next, a LID type rain barrel is created for each property to

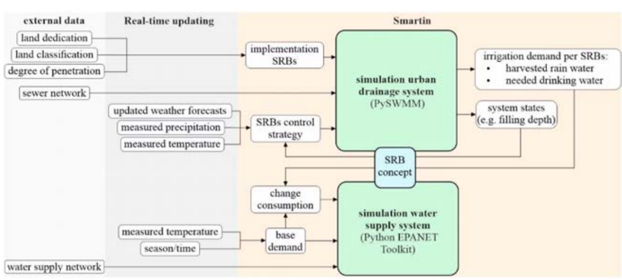

Fig. 4. Main components in "Smartin".

individually control each micro storage. The selection of the rain barrel size depends on the roof area, where a rain barrel size corresponding to a precipitation quantity of 6 mm was adopted as the reference value. Furthermore, the LID type rain barrels are assigned to the respective properties.

In "Smartin", PySWMM as a Python wrapper for SWMM5 (McDonnell et al., 2020), is used for the simulations. In contrast to native SWMM5, PySWMM provides three key features, which are essential for micro storages developed as IoT-based solutions: (1) simulation of micro storages as well as changing parameters during the simulation, (2) accessibility of results during simulation and (3) the ability to add control strategies at each routing step of SWMM5.

First, SWMM5 allows the implementation and simulation of micro storages at household level by using the LID type rain barrel. However, it is not possible to implement variable discharge heights or advanced control rules that allow joint control with the entire network. Moreover, the network has only one drainage pathway, which means that it is impossible to empty the micro storages for drainage and irrigation separately. PySWMM is intended as the interface to SWMM5 and thereby allows for the separate manipulation of each SWMM5 element including LID parameters. In addition, some flow parameters (e.g. inflows to nodes, LID drain parameters, etc.) can be modified during simulation. As previously described, the LID type rain barrel consists of a storage layer and a drain layer. Storage dimensions can only be set before simulation, while drain values can be changed during simulation. In the case of the micro storages, the drain coefficient can be set either to zero (no discharge) or to a specific discharge value, allowing the controlled opening or closing of the drain. Furthermore, the outlet node of LIDs can be changed during simulations through PySWMM. This has the advantage that two outlets can be used: one for rainy weather as a connection to the sewer network and one outlet for irrigation purposes.

Second, PySWMM creates a coding interface to the binary output file. In native SWMM5, simulation results for LID elements are written into a separate text-based file after simulation. In contrast, simulation results including LIDs can be accessed directly via PySWMM. This functionality is used in "Smartin" to query the current water depth in the various micro storages and filling levels in the drainage system in order to determine the current state of the system. For example, the drain is opened or closed based on the system states by setting drain coefficients.

Finally, PySWMM supports a step-by-step simulation of SWMM5 input files. This gives the possibility of implementing advanced control options after each simulation step. For example, weather forecasts can be included in control options. Due to the functions described above the drain of the micro storages can be controlled in real-time. By estimating the predicted inflow to the micro storage, the valve can be opened to create detention space if necessary. If the predicted volume of inflow is equal to the detention volume, the valve is closed to achieve full filling of the micro storage during the rainfall and therefore the maximum possible volume for irrigation is provided.

3.1.2. Water supply system

EPANET2 is a simulation tool for the analysis of pressure and quality in systems under pressure, such as the water supply system, where the time dynamics are obtained by the sequence of quasi-stationary states (Rossman, 2000). The EPANET programmer's toolkit is an extension to native EPANET2 and allows the manipulation of the network as well as the operation parameters (Rossman, 1999). This enables a long-term simulation with different hourly extraction volumes of drinking water on a global scale and also allows the demand for each node to be changed individually as needed for the simulation of the micro storages.

Fluctuations in drinking water consumption are considered based on seasonal, climatic and hourly components (Gato et al., 2007; Zhou et al., 2002) and determined by the following function:

$$W_{h,i} = W_{b,i} * f_{m,i} * f_{c,i} * f_{h,i} \quad (1)$$

where $W_{h,i}$ is the hourly water demand or source abstraction (l/s), $W_{b,i}$ is the base demand or base abstraction (l/s), $f_{m,i}$ is the monthly adaptation factor (−), $f_{c,i}$ is the climate-based adaption factor (−) and $f_{h,i}$ is the hourly adaption factor (−). It was assumed, that no hourly changes were to be expected in the drinking water sources, thus $f_{h,i}$ was set to 1 for the source pattern. Temperature has the greatest impact on regression models for water consumption (Neunteufel et al., 2014; Opalinski et al., 2019). Therefore, the climate-based adaption factor $f_{c,i}$ is calculated using the regression formula

$$f_{c,i} = \alpha_{0,i} + \alpha_{1,i} * T_{m,d} + \alpha_{2,i} * T_{m,d}^2 + \alpha_{3,i} * T_{m,d}^3 \quad (2)$$

where $\alpha_{0,i} \dots \alpha_{3,i}$ are calibration factors and $T_{m,d}$ is the daily mean temperature. The EPANET programmer's toolkit is utilised via Python programming language using the Python EPANET Toolkit provided by Open Water Analytics (https://github.com/OpenWaterAnalytics/epanet-python/tree/dev/epanet_python/epanet_python).

3.1.3. Control strategies for urban drainage systems

The control strategies for the micro storages implemented in this case study can be divided into dry and wet weather schemes. During the rainy season, the SRBs are operated dynamically by means of RTC to reduce peak run-off rates in the main sewer system and still ensure a fully filled storage unit at the end of rainfall. For the dry period on the other hand, the strategy is to use the stored water for irrigation purposes. The workflow of the urban drainage simulation can be seen in Fig. 5, where the control strategies are divided according to the different durations of update. For example, control strategies for the rainy weather are run on an hourly basis, depending on the chosen update time step of weather forecasts, while the irrigation command is executed only once a day. The description of control strategies assumes a partially filled micro storage and is defined as

$$V_{TOTAL,i} = V_{STO,i} + V_{DET,i} \quad (3)$$

where $V_{TOTAL,i}$ is the total available volume of the micro storage, $V_{STO,i}$ is the rainwater storage volume currently in use and $V_{DET,i}$ the detention volume as the remaining volume, which can be used for rainwater detention. As an initial assumption, the drain is closed at the beginning of the simulations.

After the simulation starts, the current simulation time ($t_{SIM,D}$) is queried at each simulation step of SWMM5. As recommended by EN 16941-1 (2018), the efficiency of rainwater harvesting systems should be investigated at the end of the selected time step. It was assumed that irrigation takes place once a day, and therefore 23:00 was chosen as the automatic irrigation time ($t_{IRRIGATION}$). If t_{SIM} is greater than or equal to $t_{IRRIGATION}$, crop evaporation was calculated as a reference value for the irrigation quantity by following the recommendations of the Food and Agriculture Organization of the United Nations (Allan et al., 1998). It is assumed, that the irrigation area is well-watered and thereby provides the ideal agronomic conditions. Based on this assumption, crop evapotranspiration (ET_c) (mm/day) is used to compute the water demand. Evapotranspiration is estimated by using the Hargreaves equation requiring only temperature data as the input variable (Hargreaves and Samani, 1985) and an alternative when wind speed, humidity and solar radiation data are absent (Allan et al., 1998). Additionally, it is assumed that the growing season is characterised by a constant water demand. Considering these simplifications, the daily ET_c is calculated as

$$ET_C = C_{adj} * \left(T_{m,d} + 17.78\right) * \sqrt{\left(T_{max,d} - T_{\min,d}\right)} * R_a * K_C \quad (4)$$

where C_{adj} (−) is a calibration parameter for the Hargreaves equation, $T_{m,d}$, $T_{max,d}$ and $T_{min,d}$ are the average, maximum and minimum daily temperatures (°C), respectively, R_a is the water equivalent of extraterrestrial radiation (mm/d) and K_C (−) is the single crop coefficient. In the software, temperature measurements are used for the temperature parameters, C_{adj} (Haslinger and Bartsch, 2016) and K_C (Allan et al.,

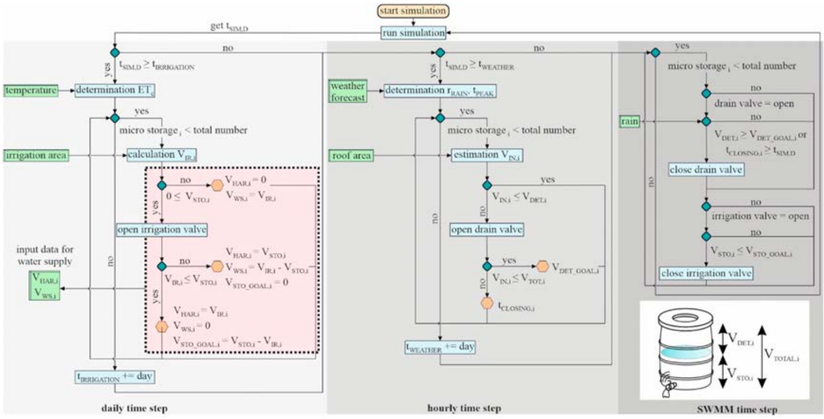

Fig. 5. Workflow urban drainage simulation divided into different temporal resolution (daily, update time step weather forecast and time step simulation) with rule-based control.

1998; Simonne et al., 2007) are extracted from literature, while R_a is calculated according to the formulas given by Allan et al. (1998). In the next step, irrigation demand ($V_{IR,i}$) is determined individually for each micro storage by using crop evaporation, the daily amount of rainfall and irrigation area and comparing with the available storage volume. If the micro storage is empty ($V_{STO,i} = 0$), no rainwater can be extracted for irrigation purposes and the entire irrigation volume is taken from the drinking water supply. If the micro storage is filled ($V_{STO,i} > 0$), the irrigation valve is opened, and the amount of rainwater useable for irrigation purposes is calculated ($V_{HAR,i}$). In case the stored rainwater cannot satisfy irrigation requirements, drinking water is used for the remaining irrigation requirements. The required amount of drinking water ($V_{WS,i}$) is calculated as $V_{WS,i} = V_{IR,i} - V_{HAR,i}$. Finally, a closing target value ($V_{STO\_GOAL,i}$) is set corresponding to the amount of rainwater provided by the micro unit, and determined through $V_{STO\_GOAL,i} = \min(V_{STO,i} - V_{IR,i}, 0)$. Furthermore, $V_{HAR,i}$ as well $V_{WS,i}$ per day is saved and used as the input parameter for the water supply simulation. In the last step, the $t_{IRRIGATION}$ for the next day is calculated by adding a day to the current $t_{IRRIGATION}$.

If t_{SIM} is equal or greater than update time of the weather forecast ($t_{WEATHER}$), control strategies for rainy weather are executed. The key element here is the implementation of weather forecasts. As a result, the future rainfall expectations, the amount of rainfall (r_{RAIN}) and time of peak intensity (t_{PEAK}) are known for the chosen period of forecast (referred as accumulation time in the subsequent sections). Next, the inflow to each micro storage ($V_{IN,i}$) is estimated based on the forecasted precipitation and the roof area of the property, and compared with the available volume for rain detention ($V_{DET,i}$). Subsequently, three different control strategies can be distinguished for the case of rainy weather. In the first control strategy, the inflow $V_{IN,i}$ is lower than the available storage $V_{DET,i}$. Since the full filling of the micro storage is not achieved, no further control action is needed. If $V_{IN,i}$ greater than $V_{DET,i}$, the drain valve is opened, and the micro storage starts emptying. In the 2nd control strategy $V_{IN,i}$ is lower than $V_{TOTAL,i}$. Therefore, an emptying target ($V_{DET\_GOAL,i}$) is specified to retain the entire precipitation in the micro storage and to guarantee a fully filled micro storage at the end of the precipitation event for irrigation purposes. However, if $V_{IN,i}$ is greater than $V_{TOTAL,i}$, the 3rd control strategy is applied. The exact time of maximum intensity (t_{PEAK}) is determined and used as the closing time ($t_{CLOSING,i}$) for the drain valve to reduce peak run off in the sewer system. Finally, next $t_{WEATHER}$ is calculated by adding the update time step of the weather forecast to the current $t_{WEATHER}$.

The prototype of the SRB was developed as an IoT-based solution using LoRaWAN to exchange measurement values and control commands. However, LoRaWAN transmits on the public frequency range, which limits the number of data exchanges (LoRa Alliance, 2017), e.g. the duty cycle influences the number of data packets and the packet size. This approach has also been applied to the simulation assuming that only one control command (e.g. open drain valve until a specific filling depth or time is attained) is allowed per weather forecast update time.

3.1.4. Control strategies for the water supply system

The workflow process of the water supply simulation is that first, the hydraulic solver is started, as shown in Fig. 6. In "Smartin", the hourly patterns for the next day are set at the end of the day during the simulation. Therefore, the simulation time ($t_{sim,w}$) is queried for each of the simulation time steps. If $t_{sim,w}$ is greater than the end of day (t_{end_day}), the source and global demand patterns are calculated using Eqs. (1) and (2). First, the demand pattern is set globally for all nodes, then the patterns for all micro storages along with the respective connection nodes to the water supply are changed individually using the simulation results on the used irrigation rainwater ($V_{HAR,i}$) and needed drinking water ($V_{WS,i}$) from the urban drainage model. If drinking water is required for irrigation ($V_{WS,i} > 0$), the micro storages are filled automatically with drinking water. This allows control of the filling time and a shift in water demand from peak hours to hours with lower consumption, e.g. at night. The filling is set to start at 22:00, so that the micro storage can provide the irrigation requirements at 23:00 and the pattern value can be increased by the amount of needed drinking water. However, $V_{HAR,i}$ and $V_{WS,i}$ mean saving of drinking water and therefore a reduction during peak hours. It is assumed that peak hours occur at 17:00 to 18:00 and that 40% of the water requirement during the peak hour is allocated to irrigation. Therefore, a maximum of 40% of the water demand requirements during peak hours can be substituted by the micro storages by providing rainwater for irrigation purposes.

3.1.5. Input parameters and requirements for "Smartin"

To execute the software "Smartin", detailed input files for SWMM5

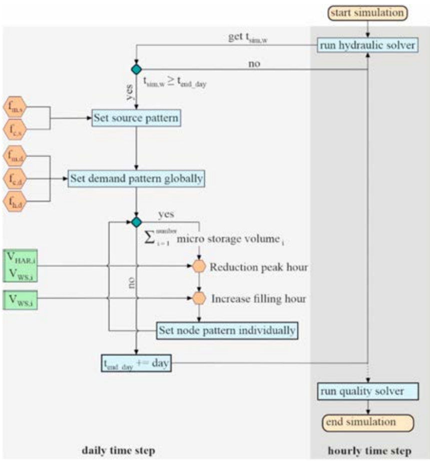

Fig. 6. Workflow water supply simulation.

and EPANET2 are required at property level. Therefore, each property has to be divided into the following subareas: house, access road and green space. Each subarea should be assigned an independent subcatchment in the SWMM5 input file. Additionally, information is needed for each property, regarding the connection point to the water supply system. The subcatchments for the implementation of the micro storages are selected by their name in the SWMM5 input file, where the names of the subcatchments should contain the land classification as well as the land usage in the form "_land classification_land usage_". For example, the name for a house subcatchment (H) in the land classification residential area (R) should include the following form "_H_R_".

The implementation of "Smartin" was accomplished by three main Python functions, whereat the user refers the "run_sim" function as the main application. This function takes the 12 user inputs listed in Table 1. The input parameters allow the user to set installation locations of the micro storage (e.g. degree of penetration, land classification), control options (e.g. uncontrolled or smart), as well as to specify weather forecast parameters (e.g. perfect or real, accumulation period, update time step). The "run_sim" function starts the "sim_drainage" function first and when this function is completed, the "sim_supply" function is executed afterwards.

Table 1
User inputs for "Smartin".

Input parameter	Data type	Description	Default
Year	Number	Chosen year for simulation	N/A
Weather forecast	String	Type of weather forecast (perfect or real)	N/A
accumulation	Number	Weather forecast period in seconds	N/A
Update	Number	Update time step weather forecast in seconds	N/A
Penetration	Number	Penetration rate for micro storage in decimal	N/A
Control	String	Type of control (uncontrolled or smart)	N/A
Number	Number	Number needed for variations	1
swmm_file	String	Name of original SWMM5 input file	'ds.inp'
epanet_file	String	Name of original EPANET2 input file	'ws.inp'
irrigation_start	Date	Start point observation period	21.03
irrigation_end	Date	End point observation period	23.09
classification	String	Type of land classification for implementation	'_R_'

3.2. Case study for testing the software

The functionality of "Smartin" and the effects of SRBs on the urban water infrastructure were tested using a case study of an Alpine municipality in Austria. For the case study, existing infrastructure data of water supply and urban drainage system as well as personalized water consumption data were applied, therefore the case study will be referred to 'Anonyms' in the following. The municipality has about 2900 inhabitants and approximately 630 properties and an area of 15.2 ha is connected to the urban drainage system. Fig. 7(a) shows the land classification for each property in the municipality. The land classifications: residential area, mixed-use area, and agricultural use, were selected as the installation locations for the SRBs because buildings in these areas have both green areas for irrigation and space for installation. In total, 384 properties with a roof area of 8.16 ha can be used for the implementation of the SRBs which corresponds to a degree of penetration of 100%. In addition, the case study area was divided into house, traffic and green areas (Fig. 7(b)) for the area determination for the SWMM model.

The software is intended to be used for RTC applications. To further investigate the quality and uncertainties of weather forecasts, a complete data set consisting of historical forecasts with different forecasting periods as well as the real measure data for the year 2015, is used. Uncontrolled (hence referred to as conventional) rain barrels are only emptied when the stored rainwater is exhausted for irrigation purposes. However, in Austria, irrigation mainly occurs during the summer half-year (21.3–23.9) (Neunteufel et al., 2014). As a consequence, outside this period no rainwater is taken and thereby no detention storage can be provided by the conventional rain barrels. However, the SRBs can also be used in other seasons besides summer half-year because their process of emptying for detention is automated. To make the results comparable, only the summer half-year was considered for the SRBs. Rainfall data available at 1-min intervals from a nearby weather station were used for the investigations. According to the classification of Peel et al. (2007), the case study is located within the Dfb (D = cold climate, f = without dry season and b = warm summer) climate zone. The EN 16941-1 (2018) recommends a rain series of a minimum of 5 years for effectiveness analyses of RWH systems. However, due to the long simulation times, we decided to test the software only for the summer half-year 2015. The precipitation sum for the summer half-year 2015 was 651 mm and thus on average over the years 2015–2019 (+30 mm), with the maximum precipitation in May (152 mm).

3.2.1. Urban drainage system

The municipality has a combined sewer system, with flow direction from southwest to northeast as shown in Fig. 7(e). The case study has an oversized combined sewer overflow structure at the catchment outlet in the north-east (volume of 350 m^3, throttle discharge 50 l/s). To better outline the impact of the state-of-the-art capacities, it was re-dimensioned according to the actual Austrian technical standard RB 19 (2007) (volume of 154 m^3, throttle discharge 22.2 l/s). Together with real information about the capacities of the sewer system and the results of Fig. 7(a) and (b), a detailed SWMM5 input file on property level was created in a semi-automatic process. Rain data, two level measurements and one flow measurement at different points of the sewer systems from a measurement campaign between June and September 2017, were used for model calibration and validation with PCSWMM (CHI). In the simulated summer half-year 2015, the flood volume of stormwater discharging from the sewer manholes was 285 m^3 and the combined sewer overflow volume was 54,950 m^3.

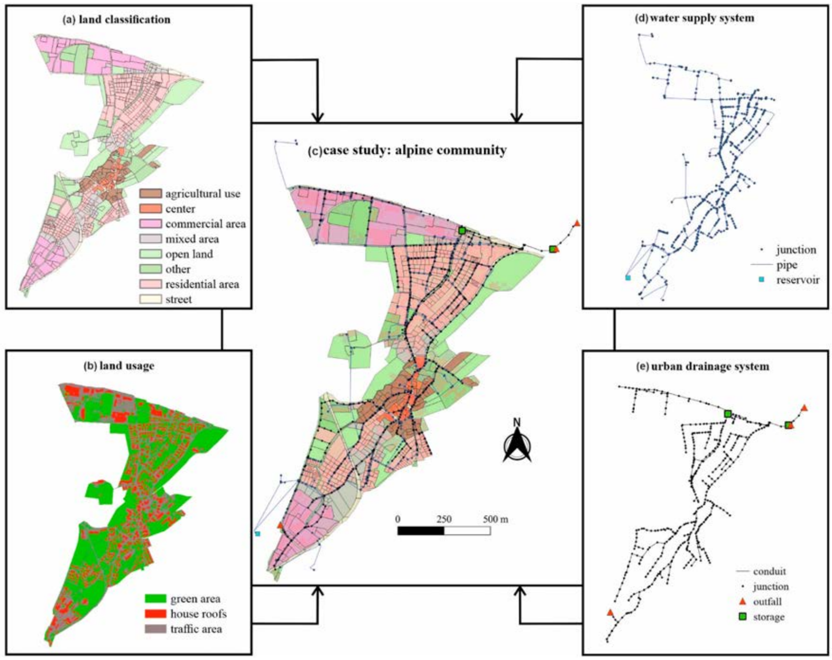

Fig. 7. Overview of the case study with subdivision into land usage and land classification.

3.2.2. *Water supply system*

For the water supply system, the calibrated model of Sitzenfrei and Rauch (2015) was employed. The system is fully gravity driven with an elevated water reservoir (tank volume of 1440 m^3) in the southwest of the case study area. The model was extended by connection of additional households to develop a detailed model at household level as shown in Fig. 7(d). In addition, historical node water consumption was updated by an address-based billing for the years 2017 and 2018. In total, an average of 9.4 l/s (810 m^3/d) water was extracted from the system in these two years, including water losses and public fountains. For the calculation of dynamic water consumption, the monthly and hourly adaption factors were adapted from Sitzenfrei and Rauch (2015), while the climate-based adaption factor was determined using the measurements of the drinking water quantity supplied to the system for the years 2008–2012. As shown for the Austrian daily water demand (Neunteufel et al., 2012), water consumption is increasing with increased length of the dry periods. Eq. (2) was therefore converted to a combined model of temperature and dry period and divided into four different classes (days with precipitation; 1–3, 3–7 and greater than 7 days without precipitation).

3.2.3. *Weather forecasts*

Weather forecasts are one of the key elements in the control strategy of the SRBs. Perfect (i.e. observed weather) as well as real (historical) weather forecasts from the integrated nowcasting through comprehensive analysis (INCA) system (Haiden et al., 2011) were integrated into the control strategy for the consideration of the future weather development. The INCA system is designed to analyse weather developments and for nowcasting different weather parameters in the mountain terrain. It uses grid cells with a resolution of 1 km, thereby allowing the rapidly changing topography of the Alps to be represented in numerical weather forecast models. First, a combined analysis of rain gauge observations and weather radar is performed every 15 min and transferred to the numerical grid. Using a series of these analyses, the precipitation movements are kinematically extrapolated to forecast the field of future precipitation. As the prediction quality decreases with increasing duration due to the kinematic extrapolation, the application of research to operations at mesoscale (AROME) high resolution model (grid resolution 2.5 km) (Wittmann and Meier, 2016) and the integrated forecasting system (IFS) model (grid resolution 9 km) (Malardel et al., 2016) are scaled to a resolution of 1 km and stepwise merged with the INCA system to get a smooth transition up to 48 h.

3.2.4. *SRB parameters*

For the theoretical retrofitting of the case study with SRBs, rain barrels available in normal hardware stores with storage volumes of 200 l, 300 l and 500 l were selected. Likewise, available ball valves were chosen as discharge valves with real diameters, which guarantees approximately 30 min emptying time for the rain barrels. In terms of model implementation, the micro storages consist of a storage layer and a drain layer. The characteristics of the rain barrels with chosen ball valves can be seen in Table 2 showing the SWMM input parameters for both layers with light grey background. The height and area of the storage layer is given by the dimensions of the rain barrels. As

Table 2
Characteristics of implementable micro storages, consisting of storage unit and discharge valve, and SWMM input parameters with grey background.

Rain barrel characteristics	200 l rain barrel	300 l rain barrel	500 l rain barrel
Volume (m^3)	0.200	0.300	0.500
Height (m)	0.730	0.970	0.820
Area (m^2)	0.274	0.309	0.610
Valve diameter (m)	0.025	0.032	0.040
Drain exponent (−)	0.500	0.500	0.500
Drain coefficient (−)	107.5	156.0	123.7
Drainage Time (min)	26:30	21:30	24:30

recommended by Rossman (2015), the drain exponent is set to 0.5 while the drain coefficient is calculated as 60 000*A_{valve}/$A_{storage}$, where A_{valve} is the area of the ball valve and $A_{storage}$ the area of the rain barrel.

If the real green area is used as the irrigation area, the SRBs are normally emptied after one irrigation process. To determine the impact on the performance of the SRBs, a reduced irrigation area of 25 m^2 was assumed. The garden area is automatically irrigated, and the irrigation amount complements the evapotranspiration. The evapotranspiration is calculated according to Eq. (4), whereat the monthly calibration parameter C_{adj} for the Alpine terrain (−) was taken from Haslinger and Bartsch (2016). Therefore, an ideal irrigation model was applied, and the irrigation demand is independent of the real irrigation needs of the properties.

3.2.5. Trials

Table 3 shows the configuration parameters for the simulations. The degree of penetration (fraction of SRB installed to total number possible) was modified for both smart and uncontrolled operation types, while the weather forecast parameters were only applied to the SRB concept. As degrees of penetration 25%, 50%, 75% and 100% were applied. In addition, perfect and real weather forecasts were used to compare the ideal system performance (perfect weather forecasts) with the real effects. Therefore, three different accumulation periods of between 1 h and 12 h were examined in more detail. Both the SRBs and the conventional rain barrels are implemented randomly in “Smartin”. In order to make the results as independent from the implementation location as possible, each configuration was simulated multiple times. However, as the simulation results per configuration showed only minor differences, 10 repetitions were chosen, except in the case of 100% degree of penetration as there is only one possibility. In total, 217 “Smartin” runs were carried out to investigate the effects on the urban water infrastructure. In order to be able to model the discharge process in the sewer network as accurately as possible and to obtain a damping of the peak runoff rate due to increasing flow time (e.g. as a relevant wave for the combined sewer overflows), hydrodynamic modelling of the storm water system is required, which results in the simulation steps in seconds. In addition, each SRB is controlled in real-time, meaning that control actions are executed at every simulation step (e.g. each simulation step the individual filling depth is queried). The combination of SRBs and hydrodynamic modelling greatly increases the simulation time ranging from 30 h (25% penetration rate) to 100 h (100% penetration rate). In contrast to the urban drainage model, the water supply system is calculated quasi-stationary with simulation times in minutes.

Table 3
Configuration parameters for the two operation types for the SRBs and uncontrolled rain barrels.

Parameter	SRB	Uncontrolled
Kind of weather forecast (−)	Perfect, real	–
Accumulation period weather forecast (h)	1; 4; 12	–
Degree of penetration (%)	25; 50; 75; 100	25; 50; 75; 100

4. Results and discussion

Figs. 8–10 illustrate the performance analysis of a large-scale implementation of the SRBs compared to the reference state without SRBs and to uncontrolled rain barrels.

4.1. Performance of smart rain barrels

In average, a storage volume of 468 l was added to each property resulting in an additional storage volume of between 45 m^3 (25% penetration rate) and 182 m^3 (100% penetration rate). As can be seen in Fig. 8(a), the dispersions between the random implementations of the additional storage volume are small. In addition, the results of each configuration scatter only slightly. Therefore, the mean value of each configuration set is selected to illustrate the effects of a large-scale implementation of the SRBs in the following graphs.

Due to the usage of harvested rainwater for irrigation purposes, the conserved drinking water ranges from 5.6 m^3 to 9.4 m^3 per SRB for the summer half year 2015. Upscaling to the case study means the conservation of between 533 m^3 and 3490 m^3 of drinking water depending on the degree of penetration as shown in Fig. 8(c), and corresponds to approximately 65% respectively 430% of daily water consumption of all properties in the case study. Interestingly, the uncontrolled rain barrel represents the optimum value for rainwater harvesting. The inflow to the SRB is estimated using the weather forecasts and based on this estimation, the SRB is emptied to provide additional detention volume. If more precipitation is predicted than what actually falls, the SRB is not completely filled at the end of the rain event and thereby the amount of substituted drinking water is reduced. Therefore, a perfect weather forecast delivers almost the same results as the uncontrolled rain barrel. The small differences with increasing accumulation period (meteorological term for prediction horizon) result from the control strategy for rain events, which does not take the irrigation requirements into account. However, water savings are clearly decreased with increasing accumulation period for the real weather forecast compared to the uncontrolled rain barrel due to increased uncertainty.

The total detention volume for the uncontrolled rain barrel is illustrated in Fig. 8(d) and is between 976 m^3 and 3926 m^3 depending on the degree of penetration (respectively 10.2 m^3 per uncontrolled rain barrel). In comparison, the detention volume of the SRBs is significantly increased by adding weather forecasts to the control strategy. A penetration rate of 25% of the SRBs controlled with a real weather forecast with an accumulation time of 12 h could retain 4089 m^3 rainwater which is more than a 100% penetration of uncontrolled rain barrels. Depending on the degree of penetration, a total of 4089 m^3 to 29 252 m^3 of precipitation could be temporarily retained. In addition, a difference between the accumulation times, i.e. the chosen weather forecast period, is noticeable. At shorter accumulation times the control steps or switching operations are at shorter intervals allowing a more frequent emptying of the SRBs, whereas the highest amount of precipitation could be retained with an accumulation time of 1 h. Therefore, the detention volume decreases with increased accumulation time. Besides, the deviations in total detention volume between the real weather forecast and the perfect weather forecast, as the theoretical maximum of the total retention volume, are low, ranging between 14% for an accumulation time of 1 h and 9% for an accumulation time of 12 h.

The prototype of the SRBs is powered by a rechargeable battery and solar panel, meaning that an additional power supply is not needed, which supports its easy retrofitting to urban areas. Therefore, an efficient and energy saving operation, which is defined by the number of switching operations, is needed. Fig. 8(b) illustrates the total number of switching operations ranging between 10,790 and 325,550. However, the number of switching operations of a single SRB is independent of the degree of penetration ranging from 112 (accumulation time of 12 h, real weather forecast) to 850 (accumulation time of 1 h, perfect weather forecast) emptying processes for providing additional storage volume

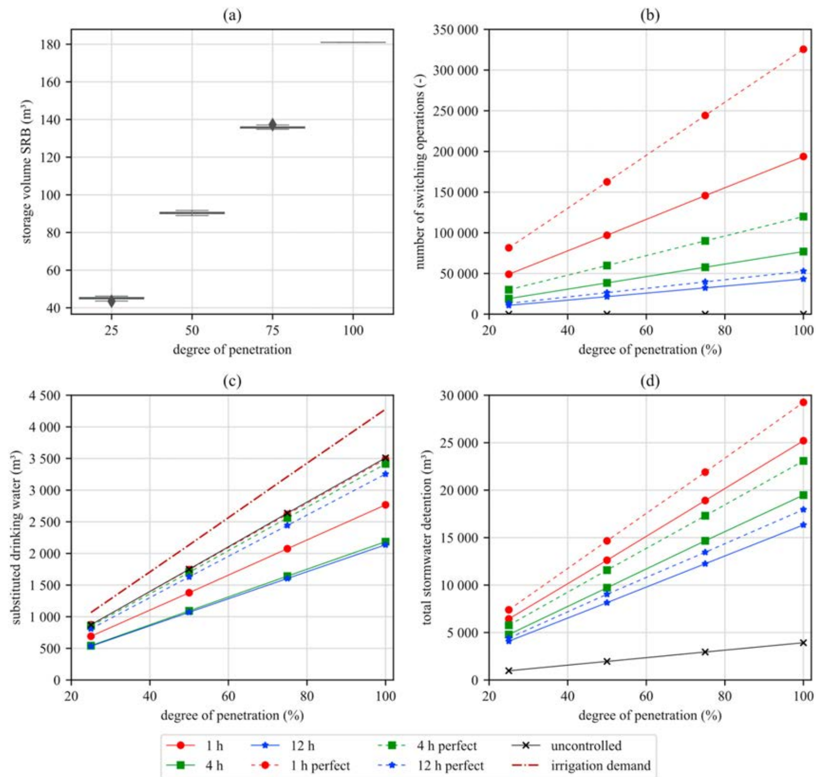

Fig. 8. Performance analysis of the SRB for different degrees of penetration and accumulation times during the summer half-year 2015 over (a) implemented additional storage volume, (b) total number of switching operations, (c) provided rainwater for irrigation purposes and (d) total volume of retained rainwater.

during the summer half-year 2015. The number of switching operations is mainly influenced by the accumulation time; shorter accumulation times evidently increase the number of switching operations. Additionally, applying real weather forecasts reduces the number of switching operations of the SRBs due to an overestimation of the predicted rain amount compared to perfect weather forecasts.

4.2. *Impact on urban drainage system*

The SRBs are used for the detention of rainwater, thereby influencing drainage processes in the sewer system (e.g. combined sewer overflow, flooding). Fig. 9(a) shows a flood volume of 285 m^3 from the urban drainage system for the reference state during the summer half-year 2015. As can be seen, adding weather forecasts to the control strategy reduces the flood volume more significantly compared to the reference state as well as to uncontrolled rain barrels. In total, the SRBs can reduce the flood volume by between 7 m^3 (3%) and 115 m^3 (40%) with a clear difference between the accumulation times as well as perfect and real weather forecasts. Because only one control command is allowed per update time step of the weather forecasts, a shorter accumulation time allows therefore more frequent emptying operations. As a result, shorter accumulation times (1 h–4 h) decrease flood volumes better than higher accumulation times (12 h). Interestingly, the difference between real weather forecasts with an accumulation time of 12 h and the uncontrolled rain barrels is small. In addition, the difference between perfect forecasts, as the best possible performance, and real forecasts increases with increasing accumulation time as uncertainties of the real weather forecast are not considered in the control strategy.

Similar to the flood volume, the SRBs can also reduce the combined sewer overflow volume relative to the reference state as demonstrated in Fig. 9(b). The combined sewer overflow volume is 54 950 m^3 for the reference state, and can be reduced by 580 m^3 (1%) to 7670 m^3 (14%) with the SRBs. However, as the results show, a large-scale implementation of SRBs does not necessarily mean an improvement over uncontrolled rain barrels. The SRBs influence the combined sewer overflow volume in two ways. First, they provide additional detention volume and thereby reduce the amount of discharged combined sewer overflow volume. Second, the discharge valves are opened simultaneously at all SRBs creating an additional discharge wave in the sewer system. For example, at a 25% penetration rate of the SRBs the

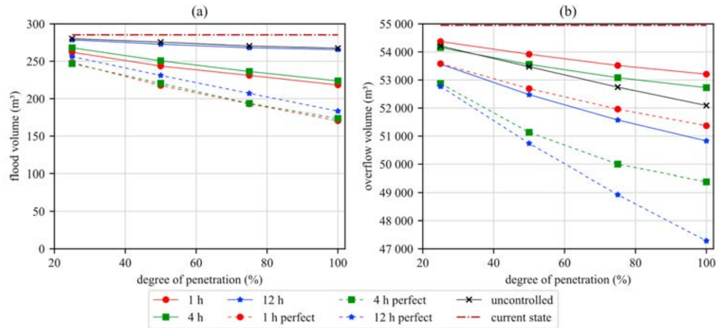

Fig. 9. Impacts of a large-scale implementation of SRBs on the urban drainage system for different accumulation times and degrees of penetration during the summer half-year 2015 for (a) mean flood volume and (b) mean combined sewer overflow volume.

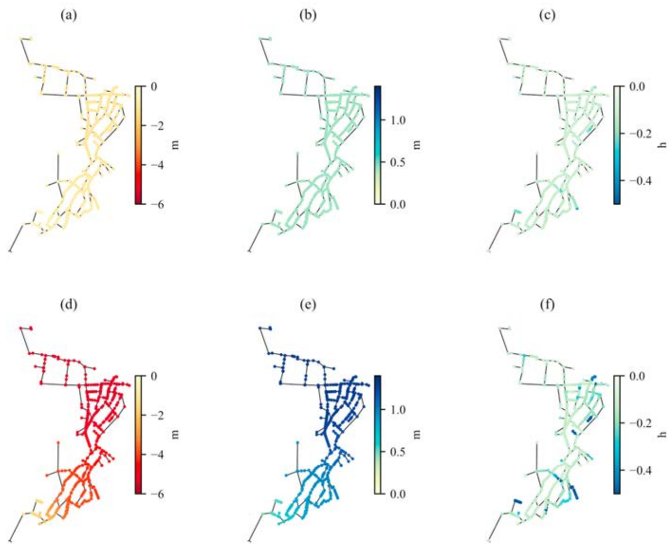

Fig. 10. Simulation results for a 25% penetration rate and perfect weather forecast with accumulation time of 4 h: maximum reduction of water pressure due to filling of the SRBs (a), maximum increase of water pressure during peak hours due to shifting irrigation demands to the night hours (b) and average changes in water age (c); for a 100% penetration rate and real weather forecast with an accumulation time of 4 h: maximum reduction of water pressure due to filling of the SRBs (d), maximum increase of water pressure in peak hours due to the shifting of irrigation demands to the night hours (e) and average changes in water age (f).

additional peak discharge in the sewer system due to the emptying of the SRBs can be up to 25 l/s, which is as high as the throttle discharge to the wastewater treatment plant (22.2 l/s). If the conditions are unfavourable (e.g. partially filled combined sewer overflow tank due to light rain event), an additional overflow event could occur, therefore worsening the system performance. This effect is more common with shorter accumulation times (1 h and 4 h), and frequent emptying phases, while for higher accumulation times (12 h) the detention capacity dominates. Nevertheless, as the results for the perfect weather forecasts show, even short accumulation times and a simultaneous emptying of the SRBs can clearly reduce the combined sewer overflow volume under ideal conditions (perfect control).

4.3. Impact on the water supply system

The SRBs have an impact on the water supply system by reducing the drinking water demand as rainwater is provided for irrigation purposes. The case study shows typical water consumption for smaller municipalities with peak hours in the evening and low water consumption at night. One of the reasons for peak hours is the high external water consumption including in uses such as garden irrigation. In contrast to the uncontrolled rain barrels, the irrigation process of the SRBs is automatic. This means that the SRBs can be filled during hours with low demand for drinking water, supporting a shift in water consumption. Therefore, a large-scale implementation of the SRBs in the case study allows a reduction of these peak hours by substituting rainwater for drinking water and shifting irrigation water consumption from the peak hour to the night hours with lower water consumption.

However, the effects on the water pressure at peak hours are low as can be seen in Fig. 10(b) and (e). Maximum water pressure increases are between 0.4 m for a 25% penetration rate and 1.3 m for a 100% penetration rate. One of the reasons for this is that the SRBs were predominantly implemented in single-family houses while neglecting large water consumers from multi-party buildings, trade or agriculture. Although the single-family houses represent 60% of the buildings, they are only responsible for about 20% of the water consumption. Moreover, it was assumed that irrigation accounts for 40% of the peak demand. If all these factors are considered, only a maximum of 8% of the peak demand can be influenced by the SRBs, which explains the minor increase in water pressure.

Similar to the strategy for rainy weather, the additional water demand for irrigation is satisfied with drinking water from the water supply system by filling the SRBs automatically at the same time between 22:00 and 23:00. Due to the large-scale implementation, a clear reduction in the water pressure at the filling time is noticeable as illustrated in Fig. 10(a) und (d). For a 25% penetration rate, the maximum reduction of water pressure is 1.08 m, while for a 100% penetration rate the water pressure is reduced by 5.4 m. In addition, the pressure reduction is increasing with the increase in the distance to the elevated tank. However, a simplified model with a garden area of 25 m^2 and compensation of the evapotranspiration was used to calculate the irrigation demand. If potable water is needed for irrigation, all SRBs are simultaneously filled with drinking water from the water supply system. Because the drinking water is automatically drawn during the night hours with low consumption, the effects under normal operation are minimal. However, the simultaneous withdrawal can lead to problems in the event of unforeseen events, such as the extraction of fire water. Therefore, the extraction of drinking water for use in irrigation purposes should be in coordination with the water supply performance.

Fig. 10(c) und (f) show the average change of water age for a 25% and a 100% penetration rate of the SRBs, respectively. Due to the large-scale implementation of the SRBs, the water age for all nodes in the water supply system is reduced by a maximum of 0.4 h. It is noticeable that the improvement in water age is achieved mainly at the end nodes or end strands of the water supply system, while nodes in the meshed system show only minor changes. The improvements in water age are achieved by the fact that the automatic irrigation system needs more drinking water for irrigation, suggesting that the SRBs could also be used as a local measure to improve the quality of the drinking water in areas with a high-water age.

4.4. Implementation strategy for the presented SRB concept

Table 4 lists the SRBs components used for the realized prototype of the SRB and adjusted to a rain barrel with a storage size of 500 l. As the statement of costs shows, the electrical ball valve is the most expensive element of the SRB. In total, the material costs are around €475 for one SRB (the low assembling costs are neglected), resulting in material costs of €950 per m^3 storage volume (in series productions the costs are considered to be lower). In contrast, investment costs for a CSO are on average between €600 and €3600 per m^3 (Leimbach et al., 2018).

CSOs have a fixed location and volume, possibly with space problems in urban areas and are used as a long-term measure with a useful live in several decades. In contrast to CSOs, SRBs allow an easy retrofitting of existing infrastructure, where a high number of micro storages can be distributed over the catchment area of urban drainage systems. As a result, SRBs enable a flexible design, both in terms of space and volume, and thus representing an ideal extension of the existing infrastructure against changing environmental challenges. The previous simulations were carried out with one rain barrel per subcatchment, but the flexible design also allows several rain barrels per subcatchments, for example on different downpipes. Fig. 11 shows the results of increased storage volume by adding two SRBs units to the subcatchments. As mentioned above, the uncontrolled rain barrel represents the optimal value for rainwater harvesting, providing already most of the irrigation demand. Therefore, additional units cause only minor improvements. On the other hand, two SRBs per subcatchment can clearly improve system performance regarding CSO overflow and flooding. However, an increased storage volume does not automatically improve systems performance to the same extent, which was also observed by Barry and Coombes (2015). Besides ecological improvements (reduced drinking water demand, flooding and CSO overflows), a flexible design is more adaptable compared to standard approaches and can therefore improve economic lifecycle costs (Deng et al., 2013). However, a detailed life cycle assessment including ecological and economic considerations can be identified as future research item.

Table 4
List of SRBs components including material price.

SRB component	Price (€)
Rain barrel (500 l)	35.00
Electrical ball valve (6/4″)	350.00
Manually adjustable ball valve (3/4″)	10.00
Solar panel	20.00
Electronic equipment (inclusive LoRaWAN)	40.00
Rain collector	20.00
Total costs	**475.00**

The SRBs are intended for a multi-actor partnership between network operators and property owner. For example, the network operator covers the costs for the “smartness” including electrical ball valve and control unit with LoRaWAN antenna, while the property owner carries out the installation and maintenance work. As a result, the network operators have the benefit of additional storage capacity in their system, while the property owners can use their measurement data for an improved understanding of their system (e.g., awareness raising irrigation demand) and can even include their SRB in smart home environment (e.g., automatic irrigation based on soil moisture measurements). As analysed by Castonguay et al. (2018) in a modelling approach, applying only economic policies is not sufficient for an increase of RWH systems. In addition, increasing densification in urban areas and a lack of confidence in future funding from decision-makers and the population are proving to be restrictive conditions for large-scale retrofitting of urban areas with green infrastructure (Haaland and van den Bosch, 2015; Thorne et al., 2018). However, Veronesi et al. (2014) stated that the willingness to pay increases if the population is aware of the climate change or to reduce ecological and health risks caused by CSOs. However, the SRB concept are part of smart water city development. Smart cities are characterised through interactions of existing infrastructure, new technologies and involving the public to increase sustainability (Ahvenniemi et al., 2017). In this context, the SRB concept opens up future research topics for an increased involvement of the public.

4.5. Further discussion and outlook

Since the power supply of the SRB is provided by a solar panel and a rechargeable battery, a Low Power Wide Area Network, namely LoRaWAN, is used for the exchange of measurement data and also for

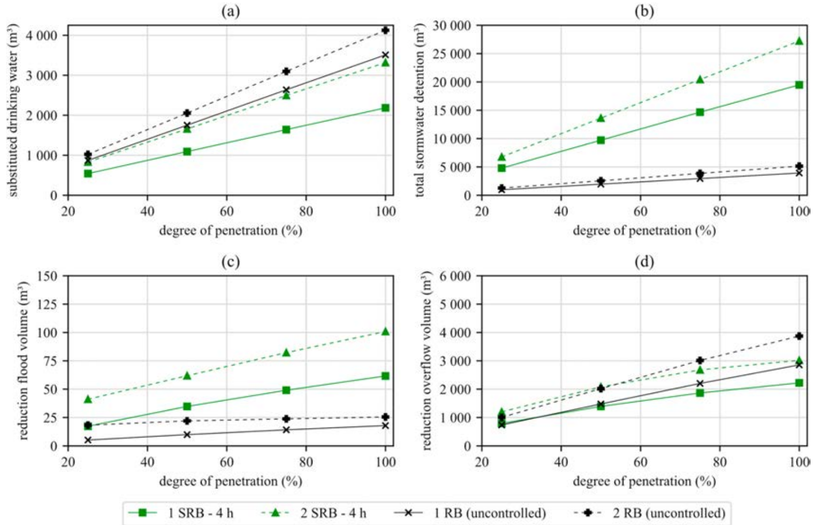

Fig. 11. Performance analysis of one or two SRBs (accumulation time 4 h) compared to uncontrolled rain barrels (RB) per subcatchment for different degrees of penetration during the summer half-year 2015 over (a) provided rainwater for irrigation purposes, (b) total volume of retained rainwater, (c) mean reduction of flood volume and (d) mean reduction of combined sewer overflow volume.

control commands to open the discharge valve. Therefore, the number of switching amounts should be in balance with the achievable improvement of system performance. For example, a higher number of switching operations corresponds to a more frequent emptying of the SRBs and therefore more detention volume can be provided. However, a more frequent opening of the discharge valve leads also to a higher energy consumption which contrasts with the limited energy supply. In addition, a perfect control environment was used in this study, assuming that the control commands are transmitted at any time and without interference to the SRBs. However, in reality a downlink (control command) can only be sent after a successful uplink (measurement value); and packet loss is to be expected, which depends on the connection quality and the number of devices in the LoRaWAN network. In addition, LoRaWAN operates within the public frequency range. Therefore, the number of packages, including the downlinks of the gateway, is regulated.

Currently, a simple rule-based control strategy is applied for the SRBs, whereat the discharge valve is controlled based on future inflows estimated by using weather forecasts. As shown by the results, an effective improvement of the overall system also requires an integration of the current system states to avoid for example additional peak discharge in the sewer system. In this context, future research will focus on finding the optimum for the control system by using machine learning techniques. If 100% of the single-family houses are equipped with SRBs (corresponds to approx. 390 SRBs), the different possibilities of each configuration setup are increasing rapidly. In combination with the chosen high temporal resolution, the calculation time is not practicable anymore. Possible solutions to overcome this limitation is to investigate single rain events with a limited number of SRBs or to combine several SRBs into a joint control group (e.g., via topological cluster analysis). As the first trials show, new approaches are required in order to operate the individual rain barrels as well as the entire system in the best way, potentially also in combination with model predictive control.

In order to take these real boundary conditions into account and to further improve the performance of the SRBs, more advanced control strategies are necessary in future work:

- Including the general conditions of LoRaWAN (limitation of transmission packets, consideration of losses) in the control strategy.
- Coordinated emptying of the SRBs based on the actual system states of the sewer system.
- Coordinated filling of the SRBs with potable water, taking system states of the water supply system into account.
- Integrating model predictive control of the entire system to further improve the overall system performance.

5. Conclusion

In this work, the smart rain barrel (SRB) concept for advanced rainwater harvesting management is presented. The SRB consists of a conventional rain barrel available in normal hardware and improved by a water level measurement device and a remotely controlled discharge valve. Despite their small volume compared to the entire water infrastructure, the SRB concept offers the following advantages compared to conventional rainwater harvesting: (1) using rain barrels with volumes between 200 l and 500 l supports a large-scale retrofitting of existing infrastructure, and (2) the development of the SRB as an IoT-based solution provides the possibility that each SRB can be individually monitored and controlled in real-time and can also be integrated into the overall management of the urban water infrastructure.

In this work, the open-source simulation tool "Smartin" was developed to analyse the impact of a large-scale implementation of SRBs on urban water infrastructure. The software was generally designed for RTC micro storages, with SRBs being a special case. Due to the small storage volumes, a high-resolution spatial and temporal model input at household level was required. The urban drainage system was simulated by applying the hydrodynamic SWMM5. EPANET2 was utilised to model the water supply system. Several open-source Python packages were used to operate the micro storages as IoT-based solutions and for the coupling of the two separate systems, i.e. the urban drainage system and the water supply system. The software was tested in an Alpine municipality using an existing infrastructure and hypothetically equipped with SRBs, to determine the effects of different controls. Adding a large number of SRBs can clearly improve the system performance, although a simplified control strategy was applied (e.g. simultaneous opening of the discharge valve and filling of the SRBs). For the urban drainage system, flood and combined sewer overflow volume could be reduced by 40% and 14%, respectively, compared to the reference state without SRBs. In addition, the security of water supply could be increased through substituting drinking water with rainwater and shifting the drinking water demand from peak hours to the night hours with lower water consumption. However, with increasing numbers of "smart applications" in the system, there is increasing system complexity, and simulation time is also increasing rapidly. In addition, a large-scale implementation of micro storages developed as IoT-based solutions requires a joint consideration of "smart applications" and entire urban water infrastructure to avoid system deterioration (e.g. create an artificial combined sewer overflow due to simultaneous opening of the discharge valves) and to create added value compared to uncontrolled and conventional rainwater harvesting systems. To avoid these problems, a staggered emptying of the SRBs is possible depending on the flow duration and an integration of the filling level of the combined sewer overflow into the control strategy.

In this way, the best possible control strategy is influenced by the duration of the weather forecast period (referring to the number of switching operations) and the desired effect (reduction of drinking water, combined sewer overflows and flooding volumes). In addition, measurement values (actual filling depth) as well as control commands for opening the discharge valve are transmitted via LoRaWAN low-power radio network. As LoRaWAN is operating in public frequency range, the number of the permitted data packages is regulated. As a result, the number of switching operations is limited for a real word implementation. If all these factors are considered in the control strategy, the control strategy becomes much more complicated and offers room for future research work, eventually in combination with machine learning.

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.

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Abbreviations

AROME	application of research to operations at mesoscale
C_{adj}	calibration parameter for Hargreaves equation
ET_c	crop evapotranspiration
GI	green infrastructure
$f_{c,i}$	adaption factor for climate influences
$f_{m,j}$	adaptation factor for month i
$f_{h,i}$	adaption factor for hour i
IFS	integrated forecasting system
INCA	integrated nowcasting through comprehensive analysis
IoT	Internet of Things
K_C	single crop coefficient
LID	Low Impact Development
LoRaWAN	Long Range Wide Area Network
R_a	water equivalent of extra-terrestrial radiation
r_{RAIN}	amount of rainfall for the chosen weather forecast period
RTC	real-time control
RWH	rainwater harvesting
SRB	smart rain barrel
$t_{IRRIGATION}$	irrigation time
$T_{m,d}$	daily mean temperature
$T_{max,d}$	daily maximum temperature
$T_{min,d}$	daily minimum temperature
$t_{CLOSING,i}$	closing time for the drain valve for micro storage i
t_{END_DAY}	end of day
t_{PEAK}	time of peak intensity for chosen weather forecast period
$t_{SIM,D}$	current simulation time drainage
$t_{SIM,W}$	simulation time water supply
$t_{WEATHER}$	update time of the weather forecast
$V_{DET,i}$	available detention volume of micro storage i for $t_{SIM,D}$
$V_{DET\_GOAL,i}$	emptying target volume for micro storage i
$V_{HAR,i}$	useable rainwater for irrigation purposes for micro storage i and day of $t_{SIM,D}$
$V_{IN,i}$	estimated inflow to micro storage i for chosen weather forecast period
$V_{IR,i}$	irrigation demand for micro storage i and day of $t_{SIM,D}$
$V_{STO,i}$	used storage volume of micro storage i for $t_{SIM,D}$
$V_{STO\_GOAL,i}$	closing target value for micro storage i for chosen weather forecast period
$V_{TOTAL,i}$	total available volume of micro storage i
$V_{WS,i}$	drinking water used for irrigation purposes for micro storage i and day of $t_{SIM,D}$
$W_{b,i}$	base demand or base abstraction for node i
$W_{h,i}$	hourly water demand or source abstraction for node i
$\alpha_{j,i} \ldots \alpha_{3,i}$	calibration factors for water demand calculation

Software and data availability

Name of software: **Smar**t Rainwater Harves**tin**g Toolbox (Smartin).

Developer: Unit of Environmental Engineering, Department of Infrastructure Engineering, University of Innsbruck, Austria Contact information: umwelttechnik@uibk.ac.at.

Year first available: 2020.

Hardware required: PC.

Data set software required: To execute the software, detailed input files for SWMM5 and EPANET2 as well as high-resolution weather and forecast data is needed.

Availability and cost: "Smartin" is an open-source software available on GitHub (https://github.com/iut-ibk/Smartin), including a simplified demonstration model. The case study of the Alpine community cannot be made available because of data protection requirements for the high-resolution models and the usage of address-based billing consumption data.

Program language: Python 3.7 (64-bit).

Program size: 7 MB.

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4 Optimisation of IoT-based Micro Storages

4.1 Paper IV

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Efficient integration of IoT-based micro storages to improve urban drainage performance through advanced control strategies

Martin Oberascher, Wolfgang Rauch and Robert Sitzenfrei

ABSTRACT

The smart rain barrel (SRB) consists of a conventional RB with storage volumes between 200 and 500 L, which is extended by a remotely (and centrally) controllable discharge valve. The SRB is capable of releasing stormwater prior to precipitation events by using high-resolution weather forecasts to increase detention capacity. However, as shown in a previous work, a large-scale implementation combined with a simultaneous opening of discharge valves clearly reduced the effectiveness. The aim of this work was to systematically investigate different control strategies for wet weather by evaluating their impact on sewer performance. For the case study, an alpine municipality was hypothetically retrofitted with SRBs (total additional storage volume of 181 m^3). The results showed that combined sewer overflow (CSO) volume and subsequently pollution mass can be reduced by between 7 and 67% depending on rain characteristics (e.g., rain pattern, amount of precipitation) and an applied control strategy. Effectiveness of the SRBs increases with lower CSO volume, whereas more advanced control strategies based on sewer conditions can clearly improve the system's performance compared to simpler control strategies. For higher CSO volume, the SRBs can postpone the start of an CSO event, which is important for a first-flush phenomenon.

Key words | IoT-based solution, real-time control, Smartin toolbox, smart rainwater harvesting, weather forecasts, wet weather

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HIGHLIGHTS

- An alpine municipality is hypothetically retrofitted with 384 smart rain barrels (SRBs) as an IoT-based solution for micro storages utilised for smart rainwater harvesting.
- Control strategies based on sewer conditions show a clear improvement in the system's performance compared with without considering sewer states.
- Efficiency is particularly high if overflow volume is in relation to storage volume of the SRBs implemented.

INTRODUCTION

Rainwater harvesting (RWH) systems aim to substitute drinking water in non-potable water applications (e.g., irrigation, toilet flushing) by retaining rainwater runoff in decentralised storage tanks (Campisano *et al.* 2017). Due to detention of precipitation, RWH systems reduce runoff into drainage systems, and a large-scale implementation can therefore improve system performance (e.g., urban flood management) (Jamali *et al.* 2020). However, the efficiency of stormwater detention is strongly dependent on withdrawal quantities. For example, higher withdrawal volumes during warm periods empty the storage tanks

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faster, and, consequently, more storage volume for rainwater detention is available (Quinn *et al.* 2020).

The development of the Internet of Things (IoT) concept as part of Smart Cities opens up new possibilities in management of urban water infrastructure. For example, innovative communication technologies (e.g., LoRa, NB-IoT, and Sigfox) in combination with low-cost sensors, enable a system-wide inclusion of communicating items (Li *et al.* 2014). An exemplary application is a decentralised rainwater storage unit, which is capable to control outflow in real time. In this context, Xu *et al.* (2020) investigated the benefits of weather forecasts for real-time controlled storage tanks at catchment scale, showing that discharges – prior to precipitation events – reduced uncontrolled overflows. Additionally, Di Matteo *et al.* (2019) and Liang *et al.* (2019) demonstrated in a simulation-based approach, that a coordinated control between two storage units can reduce peak runoff rate of roof areas even for rare rain events. In contrast, Roman *et al.* (2017) also considered irrigation requirements in the control strategy, thus improving both, detention capacity and drinking water savings.

Previous studies have mainly focused on smart storage tanks greater than 1 m^3. In this context, Oberascher *et al.* (2021) introduced the smart rain barrel (SRB) concept as an IoT-based solution for micro storage with storage volumes between 200 and 500 L. The SRB is utilised for advanced rainwater harvesting and consists of a conventional RB available in normal hardware stores, which is extended by a remotely (and centrally) controllable discharge valve. To tackle the two contracting objectives, i.e. (1) discharge of rainwater to provide additional storage volume, and (2) detention of rainwater for irrigation purposes, high-resolution weather forecasts are added into the control strategy in that work. Measurement data (e.g., filling level) and control commands (e.g., open discharge valve) are exchanged via LoRaWAN, which allows an integration into a smart city development. The effectiveness of the SRB concept was demonstrated by a two-stage approach: (1) development and operation of a protype and (2) model-based investigation of retrofitting a real urban water infrastructure system with a large number of SRBs. The results showed that the SRBs can clearly improve overall system performance of urban drainage and water supply network by reducing combined sewer overflow volume and providing a sufficient amount of rainwater to substitute drinking water for irrigation purposes. However, a simplified control strategy for wet weather was utilised, and all discharge valves were opened simultaneously if precipitation was forecasted. Consequently, if sewer conditions were unfavourable, e.g., a partly filled combined sewer overflow (CSO) due to a previous rain event, the uncontrolled opening resulted in artificial CSO events and reduced the effectiveness of the SRB concept.

The aim of this work is to improve the control strategy for the SRB concept during wet weather. Therefore, different control strategies (e.g., grouped emptying, opening in combination with the (hydraulic) state of the sewer and model predictive control) are applied, and impacts are evaluated in terms of CSO events and flood volume. For a case study, the existing urban water infrastructure of an alpine municipality was hypothetically retrofitted with SRBs, providing an additional storage volume of 181 m^3.

METHODS

Integrated urban water management with micro storages – 'Smartin' tool box

The open-source software 'Smartin' (Oberascher *et al.* 2021), available under https://github.com/iut-ibk/Smartin-Toolbox/tree/master/smartin, was used for simulations. 'Smartin' is capable of modelling real-time controlled micro storages developed as IoT-based solutions in a coupled model of urban drainage and water supply network in very high spatial and temporal detail. The software is based on several Python packages, including PySWMM (McDonnell *et al.* 2020) as a Python wrapper for the hydrodynamic stormwater management model (SWMM5), and Python EPANET Toolkit provided by Open Water Analytics (https://github.com/OpenWaterAnalytics/epanetpython/tree/dev/epanet_python/epanet_python) for EPANET2.2 (Rossman *et al.* 2020).

In 'Smartin' the SRBs are implemented as low impact development (LID) type RB into SWMM5, and outflow is individually controlled by changing the drain coefficient. Additionally, high-resolution weather forecasts are applied to estimate future inflows into each of the implemented SRB, and, if the estimated inflow exceeds available storage volume, the discharge valve of the SRB is opened. In cases in which estimated inflow is lower than the total storage volume (equal to RB volume), the discharge valve is closed if the available detention volume matches exactly the estimated inflow to ensure a fully filled SRB at end of the forecast period. In contrast, if the estimated inflow exceeds the total storage volume, the discharge valves are closed before the period with expected peak intensity. During dry weather periods, the stored rainwater is used for irrigation and daily irrigation demand is calculated based on crop evapotranspiration. In this work, a forecast period (referred as accumulation time in the following) of the weather forecast of 4 h is assumed, whereas the update time step is 2 h. Originally, a simplified control strategy was implemented in 'Smartin', in which discharge valves of all implemented micro storages were opened simultaneously (hence denoted '**SRB all**' in the following). However, simultaneous opening could worsen system performance if sewer conditions were unfavourable. Consequently, 'Smartin' was extended here by three additional control rules to improve overall system performance during storm events. The control strategies are implemented as a heuristic controller (if-then based) to manage the additional storage volume provided by the SRB implemented and can be described as follows:

- **SRB grouped**: In this control strategy, the SRBs implemented are randomly subdivided into four groups, and the control groups are staggered emptied in 30 min steps.
- **SRB CSO depth**: The discharge valves of the implemented SRBs are opened simultaneously, but the opening is dependent on actual system states. Therefore, filling depth in the CSO structure (total depth of 2.3 m) is considered in the control strategy, and a threshold is defined. In this work, the threshold is set to be 1.0 m. Consequently, discharge valves are only opened if the actual filling depth in the CSO structure at the update time step is below this threshold ($<$1.0 m), whereas in the opposite case (filling depth $\geq$1.0 m), all discharge valves remain closed.
- **SRB MPC**: In the third control strategy, model predictive control (MPC) is applied to optimise future control (the handle variable is number of discharge valves opened in this work), and can be summarised as: (1) actual filling depth of SRBs and sewer is determined and based on future weather forecasts, a simplified SWMM5 model is created; (2) discharge valves of 100% of SRBs are opened, and CSO volume is evaluated; and (3) if there is no CSO event, settings are adopted into control strategy, whereas in the case of a CSO event, the number of SRBs is reduced by 20% randomly and step (2) is repeated.
- **Uncontrolled RBs**: Performance of conventional (equivalent to uncontrolled) RBs is used as a reference state in this work to investigate the impacts and effectiveness of different control strategies.

Performance evaluation

Flood volume and CSO performance are used as indicators to evaluate the effectiveness of control strategies applied for wet weather. For CSO performance, hydraulic stress and ammonia toxicity are commonly defined short-term impacts of CSO in technical regulations (Riechel *et al.* 2016). Therefore, overflow volume and ammonium (NH_4) concentration are chosen as performance indicators. Additionally, this approach is extended to include other harmful substances such as (heavy) metals, e.g., copper (Cu) and cadmium (Cd). Roof areas are a widespread source for copper, and as the SRBs concept aims to retain roof runoff, copper is considered as performance indicator too.

For the case study, no data about quality measurements are available. As stated in previous publications, event mean concentrations (EMCs) are associated with high uncertainties, but the approach is often used by practitioners and considered as usable in the lack of further data (Tuomela *et al.* 2019). Therefore, pollution wash-off is simulated by applying EMC during rain events, and the used pollution concentrations are summarised for different surface types and sewers in Table 1.

Case study

The different control strategies were tested by hypothetically retrofitting an existing urban drainage system of an alpine municipality located in Austria with SRBs. The municipality is drained by a combined sewer system, and network characteristics can be seen in Figure 1. Furthermore, the (in reality) overdesigned combined sewer overflow structure is re-dimensioned to meet minimum requirements of Austrian standards (new storage volume of 154 m^3). For simulations, the calibrated SWMM5 input file of Oberascher *et al.* (2021)

Table 1 | Mean pollution concentrations derived from publications for different surface types (Gobel *et al.* 2007; Riechel *et al.* 2020) and sewer flow (Gasperi *et al.* 2008)

Type	NH_4-N (mg/L)	Cu (μg/L)	Cd (μg/L)
Roof	3.39	153	0.8
Green area	0.8	11	0.7
Traffic (yard)	0.1	23	0.8
Traffic (yard industry)	0.1	80	1.2
Traffic (street)	0.1	86	1.6
Sewer	25	81	0.5

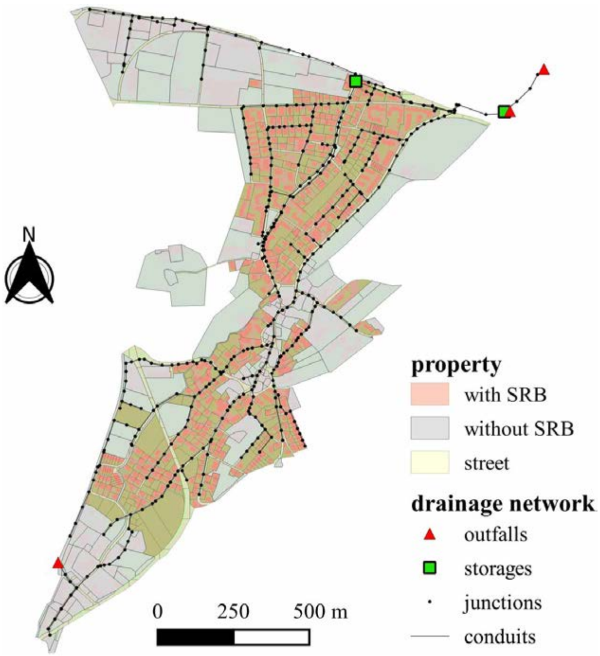

Figure 1 | Overview of the case study subdivided into properties with SRBs and without SRBs, and urban drainage network characteristics.

is used. The input file includes details on property level, and 630 properties with an area of 15.2 ha are connected to the urban drainage system. Properties in land classified as residential area, mixed-use area, and agricultural area are selected as installation places, as buildings in these areas have space for installation and green areas for irrigation. Therefore, 384 properties (roof area of 8.16 ha) are equipped with SRBs, whereas each property is further subdivided into green, traffic, and roof areas. For the SRBs, real RB sizes (200, 300, and 500 L) are chosen, which are available in normal hardware stores. The SRB size depends on the connected roof area, and a precipitation quantity of 6 mm is chosen as the reference value for choosing SRB size. In total, these SRBs provide an additional storage volume of 181 m^3. Additionally, properties with SRBs are highlighted in Figure 1. For more details on the case study, reference is made to Oberascher *et al.* (2021).

For the control strategy 'SRB MPC', a simplified SWMM5 model is created to predict future system states. The model consists of one big sub-catchment and the CSO structure, and the model is calibrated and validated with PCSWMM (CHI) based on data from a measurement campaign (rain data, and one flow measurement) between June and September 2017.

Climatology

Precipitation data available in 1 min time steps are extracted from a nearby weather station for 2018. In Austria, irrigation occurs mainly during the summer half-year (21 March to 23

September) (Neunteufel *et al.* 2014). Consequently, no rainwater is extracted from uncontrolled RBs outside this period and, therefore, no additional detention volume can be provided. In contrast, SRBs can be emptied automatically but, to compare results, the summer half-year 2018 was chosen as the simulation period. First, three characteristic rain events are extracted with total rain sum between 7.9 and 11.3 mm to test different control strategies, whereas maximum rain intensity is in the range of 0.1 and 1.3 mm/min (Table 2). The rain events cause a CSO volume of 210, 447, and 833 m^3, respectively, and the latter also had a flood volume of 3.9 m^3. Second, the total rain series of the summer half-year 2018 is applied for simulations to investigate the impact of different control strategies over a longer period. Precipitation data are available in 1 min steps and total precipitation amount is 424 mm for the summer half-year 2018, whereas daily precipitation varies between 0 and 32 mm/day (Figure 2). To model frequent extractions of rainwater for irrigation purposes, temperature data, available in a temporal resolution of 10 min, are utilised to calculate daily irrigation demand. Daily mean temperature ranges from −3 to 25 °C and temporal progression over the summer half-year is shown in Figure 2.

Table 2 | Rain characteristics of the investigated rain events and caused CSO and flood volume in the reference state without any SRBs

Rain	Day	Total rain sum (mm)	Max. rain intensity (mm/min)	CSO volume (m^3)	Flood volume (m^3)
Event 1	15 July 2018	7.9	0.8	210	0
Event 2	29 March 2018	12.9	0.1	447	0
Event 3	10 May 2018	11.3	1.3	833	3.9

Weather forecasts are one of the key elements of control, and are here integrated from the integrated nowcasting through a comprehensive analysis (INCA) system (Haiden *et al.* 2011). The INCA system is applied for mountain terrain and is based on 1 km grid cells, and supports numerical weather forecast models to represent the changing topography of the Alps. For the case study, weather forecasts are available for the next 24 h in 15 min steps for every 15 min.

RESULTS AND DISCUSSION

Illustration of CSO performance

Figure 3 illustrates the functionality of different control strategies for the SRBS applied to the real rain event 2 on 29 March 2018. As can be seen in Figure 3(a), the rain event is non-continuous and frequently interrupted with rain breaks. This effect is also reflected in filling of the CSO (Figure 3(b)), showing an increase during phases with precipitation and a decrease during rain breaks for the reference state without any RBs. However, a complete emptying of the CSO is not achieved during the investigated rain event. If the filling depth of the structure exceeds 2.3 m, an overflow occurs (Figure 3(d)), whereas two events can be identified during the investigated period. The total overflow volume is 447 m^3 for the reference state. Time series of pollution concentrations (NH_4-H, Cu, and Cd) are similar to the overflow volume as pollution wash-off is simulated with EMC, therefore reference is made to the results summarised in Table 3.

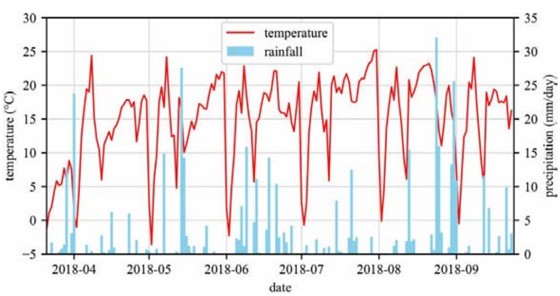

Figure 2 | Daily mean temperature and precipitation sum during the investigated summer half-year 2018.

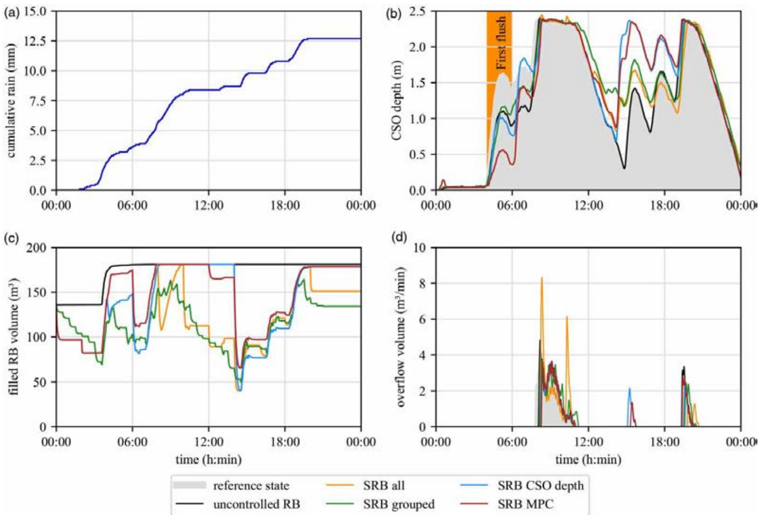

Figure 3 | Illustration of the functionality of different control strategies for the real rain event 2 on 29 March 2018: (a) cumulative rain sum, (b) CSO depth, (c) filled rain barrel volume, and (d) combined sewer overflow volume into receiving waters.

Table 3 | Results of performance indicators for a real rain event on 29 March 2018

Type	Overflow volume (m^3)	NH_4-N (kg)	Cu (g)	Cd (μg)
Reference	447.40	3.94	56.44	334
Uncontrolled	408.06	3.51	51.59	3,050
SRB all	377.05	3.30	47.04	281
SRB all (perfect)	315.80	3.04	35.35	214
SRB grouped	381.86	3.39	47.01	282
SRB grouped (perfect)	309.49	3.07	35.17	213
SRB CSO depth	362.47	3.29	41.81	253
SRB CSO depth (perfect)	294.17	2.87	35.40	216
SRB MPC	361.41	3.27	43.70	263
SRB MPC (perfect)	313.58	3.01	37.75	228

Figure 3(c) shows the filled RB volume over the duration of the rain event. Considering a longer event, the impact on the sewer increases with a higher initial volume, as less additional detention volume is available, and thus more stormwater is discharged before or during the rain event. Therefore, a very high initial volume of the RBs was assumed as the focus of this work was to improve wet weather control strategies including CSO performance for IoT-based micro storages. In this work, initial filling was randomly set between 50 and 100%, and filled RB volume is around 135 m^3 at the beginning of the investigated period (in contrast, total storage volume of the SRBs is 181 m^3). With first precipitation, the uncontrolled RBs are completely filled, and since no water is withdrawn for irrigation, the level remains constant for the rest of the period. However, despite the low empty storage volume (as the difference between total storage volume of 181 m^3 and filled RB volume) the uncontrolled RBs cause a reduced filling of the CSO at the beginning. Afterwards, filling depth and overflow volume correspond to the reference state. For the uncontrolled RBs, total overflow volume is 408 m^3 (39 m^3 less than the reference state).

In contrast, all SRBs are emptied at the beginning of the investigation period (as rain is forecasted) and filled RB volume decreases from 135 m^3 to approximately 80 m^3. Consequently, there is a small runoff peak noticeable

(Figure 3(b)), which is less obvious in cases of staggered emptying. Additionally, trajectories of the control strategies 'SRB all', 'SRB CSO depth' and 'SRB MPC' are equal at the beginning, and in the following, first differences occur when CSO event is expected in 'SRB MPC' or filling depth in the CSO structure is higher than 1.0 m. Afterwards, with start of precipitation, the SRBs begin to fill again and can thereby significantly reduce the first runoff peak in the sewer system. In this example, the first runoff peak induces no CSO overflow, but it highlights that the SRBs can postpone the start of CSO events which is important for first-flush phenomenon. However, due to different control aims, each SRB control strategy has a different pattern from that point on. For a better identification of the individual processes, reference is made to Figure 4, which shows a detailed section in the period from 06:00 to 12:00. Particularly noticeable are the overflow peaks of the control strategy 'SRB all', which are approximately twice as high as the reference state. In this control strategy, discharge valves of SRBs implemented are opened simultaneously, resulting in an artificial runoff wave in the sewer. Consequently, as conditions are unfavourable due to an already filled CSO structure and further precipitation at this time, peak overflow volume is increased rapidly. However, these simultaneous discharges have the advantage, that storage volume becomes more quickly available, and therefore, the second overflow event can be reduced significantly. Over the whole rainfall event, CSO overflow volume can be reduced by 70 m^3 compared to the reference state. Interestingly, the control strategy 'SRB grouped' has the least improvement compared to uncontrolled RBs (reduction of 65 m^3). In this control strategy the SRBs are divided into subgroups that are staggered emptied. Therefore, peak runoff rate in the sewer is decreased, which helps to avoid artificial CSO events. In contrast, decrease of filled RB volume is slower than with other control strategies. Consequently, a lower detention volume can be provided compared to the control strategy 'SRB all', which increases overflow volume.

Control strategies with the best improvements are 'SRB CSO depth' and 'SRB MPC', which reduce overflow volume by 85 and 86 m^3, respectively. Discharge valves of the SRBs are only opened if the filling level in the CSO is below a certain level or no CSO event is expected in the future, thereby reducing the risk of an artificial runoff wave. However, this example shows also that these two control strategies are strongly dependent on future weather development and

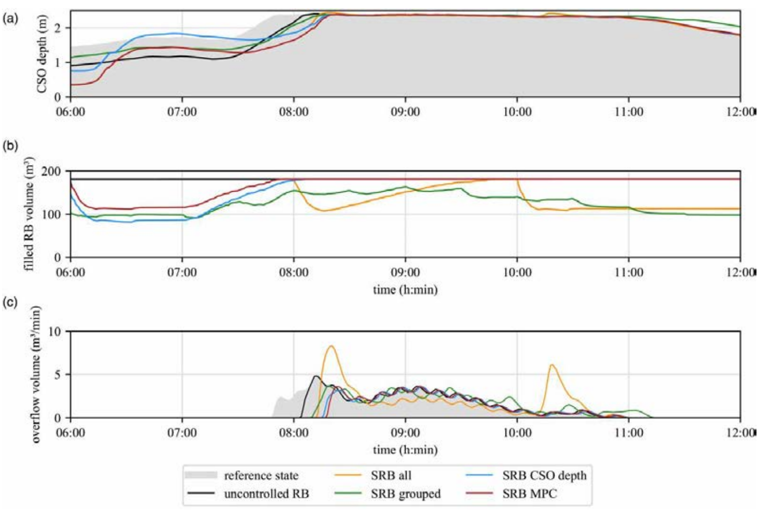

Figure 4 | Detailed section of the real rain event 2 on 29 March 2018: (a) CSO depth, (b) filled rain barrel volume, and (c) combined sewer overflow volume into receiving waters.

forecast quality. First, the SRBs are emptied continuously in the other control strategies during the investigated period, while in 'SRB CSO depth' and 'SRB MPC' the SRBs are emptied at a later time (14:00). Therefore, the SRBs are emptied by a rain volume of over 100 m^3, which causes a higher degree of filling of the CSO structure over the next hours. Consequently, these control strategies are more vulnerable to future precipitation, which is highlighted by an additional CSO event at 15:00 and higher duration and overflow volume at the second CSO event compared to the other control strategies. Second, for the model predictive control, the additional CSO event can be attributed to the forecast quality of the used weather forecasts. Additionally, Figure 5 shows the results of model predictive control applied with real weather forecasts in comparison to perfect weather forecasts, in which predicted amount and pattern illustrate exactly the real precipitation event. As can be seen in Figure 5(a), rain amount over the accumulation time of 4 h is nearly the same for real rain and real weather forecasts. However, there is a big difference in the time pattern noticeable. For the real weather forecasts, there is little precipitation predicted at the beginning, whereas the intensity is expected to increase strongly at the end of the forecast period. In contrast, the real event is divided into two precipitation periods with approximately equal amounts occurring in both first and second half of the forecast period. Consequently, if the control strategy 'SRB MPC' is tested with a perfect weather forecast, this additional CSO event can be avoided. In general, applying perfect weather forecasts further improves system performance as can also be seen in Table 3.

Illustration of flood performance

Figure 6 shows the performance for rain event 3 on 10 May 2018 in which the runoff exceeds the system capacity and flooding occurs. Total rain volume for this precipitation event amounts to 11.3 mm, whereas peak intensity is 1.3 mm/min at 15:24 (Figure 6(a)). In total, flood volume is 3.90 m^3 for the reference state without any RBs. As can be seen in Figure 6(b), nodes with flooding are mainly concentrated on one area in the middle of the sewer system,

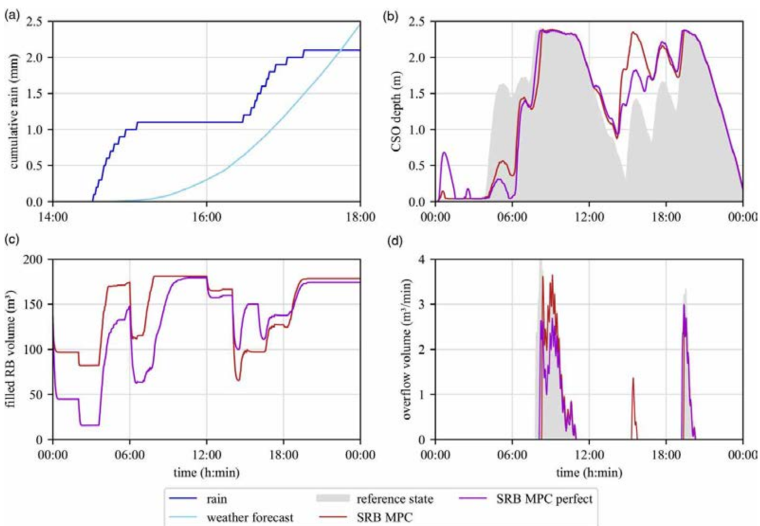

Figure 5 | Performance evaluation of 'SRB MPC' applied with perfect and real weather forecasts for the real rain event 2 on 29 March 2018.

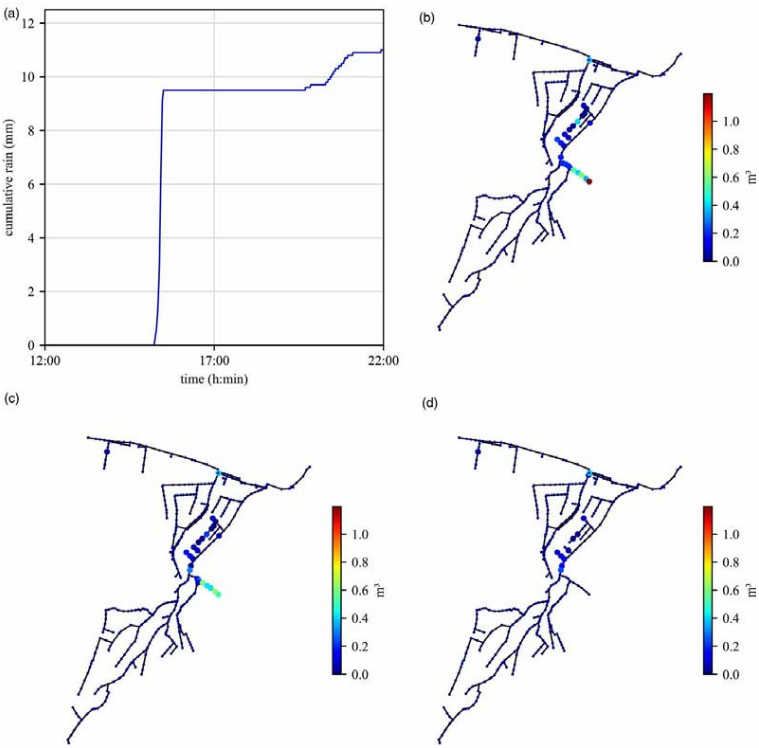

Figure 6 | Potential of the SRB concept to reduce flood volume for the real rain event 3 on 10 May 2018: (a) precipitation pattern, (b) flood volume of reference state without any RBs, (c) flood volume for control strategy 'SRB MPC' applied with real weather forecasts, and (d) flood volume for control strategy 'SRB MPC' tested with perfect weather forecasts.

which is characterised through low slopes in main and secondary pipes. In contrast, applying the SRB concept can reduce overflow volume. As an example, Figure 6(c) and 6(d) illustrate flood volume for the control strategy 'SRB MPC' applied with real and perfect weather forecasts, respectively. Therefore, real weather forecasts reduce mainly flood volume (reduction of 1.1 m^3), whereas perfect weather forecasts decrease both number of affected nodes and flood volume (reduction of 3.0 m^3).

Overall performance analysis

Figure 7 summarises the results of the investigated rain events including the summer half-year 2018 subdivided into the chosen performance indicators for wet weathers. As the results show, CSO reduction compared to the reference state without any RBs is between 7 and 67%. As expected, there is a difference between the applied control strategies noticeable. More advanced control strategies

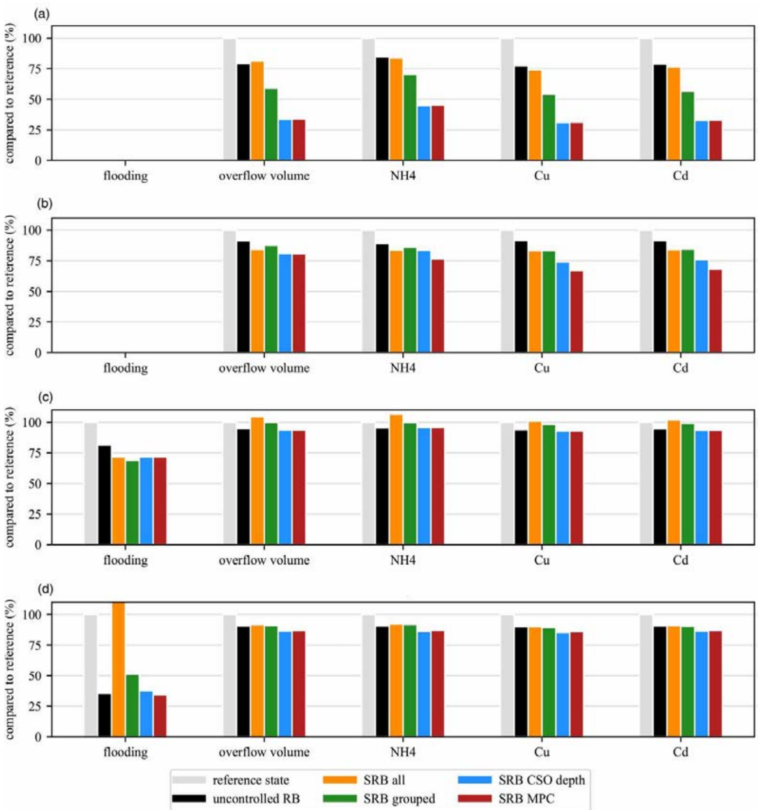

Figure 7 | Performance evaluation (reduction of volume/pollution mass) compared to the reference state of different control strategies for (a) rain event on 15 July 2018, (b) rain event on 29 March 2018, (c) rain event on 10 May 2018, and (d) summer half-year 2018.

including overall system states (e.g., 'SRB CSO depth' or 'SRB MPC') have a better performance than simpler strategies without considering sewer states for discharge events of the SRBs (e.g., 'SRB all' and 'SRB grouped'). Considering sewer states, e.g., filling depth of the CSO structure, prevents the SRBs from being emptied when conditions are unfavourable, thus reducing the risks of artificial CSO events. Additionally, in 'SRB MPC' number of discharge valves opened is optimised regarding CSO performance, therefore this control strategy achieves the highest CSO reduction of all investigated control strategies. In contrast, the control strategy 'SRB CSO depth' is based on a sensor measuring filling depth in the CSO structure. Interestingly, performance indicators show only minor differences to 'SRB MPC' for all investigated rain events. Consequently, by choosing a convenient threshold for discharge events of SRBs implemented, almost identical results can be achieved, while considerably less information (e.g., sewer network) is required for implementation.

As can be concluded from the results, effectiveness of the SRB concept is strongly dependent on characteristics of the rain events (e.g., amount of precipitation, rainfall pattern) and thereby caused CSO event. As the SRB concept implements micro storage, efficiency is particularly higher if CSO volume is in balance with implemented storage volume. However, the relationship between CSO volume and implemented additional storage volume decreases with higher overflow volumes, thereby reducing effectiveness. As can be seen from the investigated rain event 2 (Figures 3 and 7(b)), rain breaks during the rain event reduce the utilised system capacity (e.g., in this work filling depth of CSO structure), and can be used to empty the SRBs to provide additional storage volume. Consequently, the SRB concept is more effective than uncontrolled RBs if the SRBs implemented are already (partially) filled with rainwater due to previous precipitation.

As the EMC concept for predicting pollution loads is applied, reduction of pollution mass in CSO volume is strongly dependent on overflow volume. Interestingly, the effectiveness for Cu and Cd reduction is higher for the advanced control strategies compared to simpler strategies. For example, main sources for Cu are roof areas, which are also the catchment areas of the SRBs. Through a coordinated emptying of the SRBs based on sewer states, artificial CSO events caused by discharge of roof runoff can be avoided, which also decreases Cu mass in CSO overflow. In this context, a critical discussion about applied spatial and temporal resolution of pollution modelling cannot be missing. Due to the use of a finely subdivided simulation models, time and area type-dependent pollutant models are also required, however hardly any values (especially for heavy metals) at this level of detail are yet to be published. Therefore, using event mean-based concentration greatly simplifies data collection and allows a first assessment of the effects, but, conversely, also loses the dynamics of pollution wash-off (e.g., first flush effect). However, as the results indicated, the SRBs can postpone the start of a CSO event, thereby a further reduction of pollution mass is expected compared to EMC.

Further discussion and outlook

The main purpose of a rainwater harvesting system is to provide rainwater for non-potable water applications (e.g., irrigation, toilet flushing). The ability to release stormwater automatically can lead to a not fully filled RB at the end of each precipitation event in cases when more rainfall is forecasted that actually falls, thus decreasing the amount of substituted drinking water. Additionally, smart rainwater harvesting systems are strongly dependent on digital system components (e.g., accuracy of weather forecasts, reliability of data communication technology, effectiveness of control strategy), whereby disturbances can significantly impact the effectiveness in terms of stormwater detention and rainwater harvesting. Consequently, further analysis should pursue an integrated approach, including performance indicators of urban drainage network, rainwater harvesting systems and digitalisation. If all these factors are considered, the complexity of the control strategy is significantly increased, and opens up future research topics.

CONCLUSION

In this work, different control strategies for the SRB concept for wet weather are investigated. The SRBs are real-time controlled micro storages with a storage volume between 200 and 500 L and used for smart rainwater harvesting management. The SRBs are developed as an IoT-solution and can be emptied prior to rain events to increase detention volume. For the case study, a sewer system of an alpine municipality was utilised and 384 properties in land classified as residential area, mixed-use area, and agricultural area were hypothetically retrofitted with SRBs, providing an additional storage volume of 181 m^3. The simulations were performed with the open-source software 'Smartin', which can model micro storages developed as an IoT-based solution in a coupled model of urban drainage and water supply system.

Flood volume and combined sewer overflow (CSO) performance (e.g., overflow volume, ammonia (NH_4), copper (Cu), and cadmium (Cd) concentrations), are used as indicators to evaluate the effectiveness of control strategies applied for wet weather. The different control strategies are tested and evaluated by using three characteristic rain events of summer half-year 2018. Therefore, CSO volume and subsequently pollution mass is reduced between 7 and 67% depending on the control strategy and rain characteristics. As the results indicated, simpler control strategies (e.g., simultaneously or grouped opening of discharge valves of the SRBs implemented) create artificial runoff waves in the sewer and can therefore worsen system performance even above the reference state. It comes as no surprise, that more advanced control strategies (e.g., based on filling CSO, model predictive control), which take the actual sewer system into account, can better reduce the performance indicators and can thereby significantly improve system performance.

However, the effectiveness is strongly dependent on rain characteristics (e.g., rain pattern, amount of precipitation). For example, the tested control strategies are more effective with rain events interrupted with rain breaks. Rain breaks reduce the utilised system capacity and can therefore be used to empty the SRBs to provide additional detention volume. Consequently, the SRBs provide an advantage compared to uncontrolled RBs, if the storage volume is (partly) filled due to previous rain events. Additionally, the relationship between storage volume of the SRBs and CSO overflow volume is a major factor influencing effectiveness. As the SRBs provide only a limited additional detention volume, the effectiveness increases with lower CSO volume. If the available storage volume is filled with rainwater, no further improvements regarding CSO performance can be achieved. For higher CSO volume, the SRBs can postpone the start of an CSO event, which is important in the event of a first-flash phenomenon.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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4.2 Paper V

Oberascher, M., Dastgir, A., Li, J., Hesarkazzazi, S., Hajibabaei, M., Rauch, W., Sitzenfrei, R., 2021. Revealing the Challenges of Smart Rainwater Harvesting for Integrated and Digital Resilience of Urban Water Infrastructure. Water. 13(14). https://doi.org/10.3390/w13141902.

water MDPI

Article

Revealing the Challenges of Smart Rainwater Harvesting for Integrated and Digital Resilience of Urban Water Infrastructure

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Abstract: Smart rainwater harvesting (RWH) systems can automatically release stormwater prior to rainfall events to increase detention capacity on a household level. However, impacts and benefits of a widespread implementation of these systems are often unknown. This works aims to investigate the effect of a large-scale implementation of smart RWH systems on urban resilience by hypothetically retrofitting an Alpine municipality with smart rain barrels. Smart RWH systems represent dynamic systems, and therefore, the interaction between the coupled systems RWH units, an urban drainage network (UDN) and digital infrastructure is critical for evaluating resilience against system failures. In particular, digital parameters (e.g., accuracy of weather forecasts, or reliability of data communication) can differ from an ideal performance. Therefore, different digital parameters are varied to determine the range of uncertainties associated with smart RWH systems. As the results demonstrate, smart RWH systems can further increase integrated system resilience but require a coordinated integration into the overall system. Additionally, sufficient consideration of digital uncertainties is of great importance for smart water systems, as uncertainties can reduce/eliminate gained performance improvements. Moreover, a long-term simulation should be applied to investigate resilience with digital applications to reduce dependence on boundary conditions and rainfall patterns.

Keywords: communication technology; digital resilience; smart rainwater harvesting; smart city; smartin toolbox; weather forecast

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1. Introduction

A way to evaluate the performance and functionality of urban water infrastructure including different extension strategies is by measuring the term resilience. In the literature, resilience can be considered as a form of robustness against system failures and is determined by evaluating the loss of system functionality [1–3]. For example, failure magnitude and duration are used to calculate the severity and to evaluate the resilience of urban drainage networks (UDNs) against structural failures [3]. For UDN, urban flooding, combined sewer overflows (CSOs) and inflow quantity to wastewater treatment plants are commonly used metrics to measure degree of resilience in UDNs [3,4]. Furthermore, Dong et al. (2017) applied this method to evaluate the impacts of a sustainable expansion of an UDN with green infrastructure (e.g., green roof, permeable pavement and storage tanks) to cope with future uncertainties (e.g., climate change, and urbanization) [4].

In contrast to other elements of green infrastructure, the main aim of rainwater harvesting (RWH) systems is to retain and store rainwater during precipitation events for usage in non-potable drinking water applications such as irrigation or toilet flushing during dry weather periods [5]. Additionally, RWH systems represent a temporary storage volume for rainwater, thereby influencing runoff behavior into UDN. Therefore, 'water supply efficiency' and 'detention/stormwater capture efficiency' are commonly applied as metrics for evaluation at the household scale [6–8]. In case of a large-scale implementation, RWH systems can improve water resource recovery due to the substitution of drinking water [9] and performance of UDN (e.g., reducing flood volume) due to the detention of rainwater [10]. However, detention efficiency is strongly dependent on user behavior and withdrawal quantities in relation to the detention volume. This can be a limitation especially for traditional systems, which are therefore referred to as uncontrolled RWH systems [6,11]. For example, higher withdrawal volumes empty RWH systems faster, therefore additional storage volumes can be provided for stormwater detention.

In this context, the Internet of Things (IoT) concept as part of smart cities assists the development of communicating 'items' integrated into the overall system [12]. Additionally, low-cost sensors combined with innovative communication technologies (e.g., NB-IoT, LoRaWAN, Sigfox) support a large-scale implementation too. Consequently, this development enables new possibilities for the management of urban water infrastructure in a smart city framework [13]. For example, this concept is being widely applied in the development of smart RWH systems [14–17]. In contrast to uncontrolled RWH systems, smart RWH systems are equipped with a remotely controllable discharge valve, which enables an automatic release of stored stormwater prior to rain events to provide additional detention volumes. Therefore, weather forecasts are commonly integrated into control strategy, and predicted amounts and patterns of rainfall are used to determine discharge volume and closing time, respectively. However, performance is strongly dependent on the quality of the weather forecast and the predicted amount of precipitation to ensure a fully filled RWH system is available at the end of the precipitation event. Therefore, applying smart RWH systems leads to a conflict between the two contrary objectives: (1) store as much rainwater as possible for irrigation purposes and (2) provide as much detention volume as possible for UDN performance.

While the potential for smart RWH systems has been well established at the household level, impacts of a widespread implementation are to a large extent unknown. In contrast to existing infrastructure, smart RWH systems represent dynamic systems, and urban resilience is influenced by the interaction of the coupled systems, RWH units and UDN, including performance of digital system components. In particular, digital parameters may differ from the perfect performance, whereas the performance is influenced by the accuracy of weather forecasts or reliability of data communications in the case of smart RWH. Consequently, digitized systems require new definitions of resilience [18], while the effects of deviations in digital parameters are largely unknown and hardly addressed in literature.

To fill this research gap, this work aims to investigate the impact of a large-scale implementation of smart RWH systems on the resilience of urban water infrastructure and to determine influences of deviations on digital parameters associated with smart RWH systems. First, an integrated resilience parameter is presented, in which digital parameters are considered as uncertainties for classic and quantifiable metrics from urban water infrastructure. In the second step, digital parameters are determined for smart RWH systems, which can also significantly influence the results in the case of deviations. Afterwards, an Alpine municipality is hypothetically retrofitted with smart rain barrels (SRBs) as representative of smart RWH systems, and finally the influence of different digital system configurations on resilience is compared.

2. Materials and Methods

2.1. Integrated Resilience Index for the Interlinked Systems Smart Rainwater Harvesting and UDN

For this work, a two-step approach was used to determine influences of digital uncertainties associated with smart RWH on resilience. First, classic and quantifiable metrics from urban water infrastructure were combined to calculate resilience for the interlinked systems RWH and UDN. For this work, combined sewer overflows (CSO) and empty

RWH system were investigated as system failures for UDN and RWH systems, respectively. Therefore, CSOs with discharged pollution load (m_{CSO}) divided by total quantity of tracer mass introduced into the system ($\underline{m_{total}}$) was used as a severity measurement for CSO (Sev_{CSO}). Furthermore, the amount of water demand that cannot be covered by the RWH system, expressed by the difference between the delivered rainwater (V_{RWH}) and total water demand for irrigation (V_{IRR}), divided by V_{IRR}, was used as the severity measurement for RWH (Sev_{RWH}). Subsequently, the resilience index (Res) was defined by:

$$\text{Res} = k_{CSO} \times \left(1 - \frac{m_{CSO}}{m_{total}}\right) + k_{RWH} \times \left(1 - \frac{V_{IRR} - V_{RWH}}{V_{IRR}}\right), \quad (1)$$

$$m_{CSO} = \sum_{i=1}^{N_{rain}} \int_{t_1}^{t_2} m_{tracer,CSO,i} \times dt, \quad (2)$$

$$m_{total} = \sum_{i=1}^{N_{rain}} \int_{1}^{t_2} m_{tracer,i} \times dt, \quad (3)$$

$$V_{RWH} = \int_{t_0}^{t_m} Q_{irr,need} \times dt - \int_{t_0}^{t_m} Q_{irr,,RWH} \times dt, \quad (4)$$

$$V_{IRR} = \int_{t_0}^{m} Q_{irr,need} \times d_t, \quad (5)$$

$$w_{CSO} + w_{RWH} = 1, \quad (6)$$

in which w_{CSO} and w_{RWH} are the weights for respective severities; N_{rain} is number of rain events; t_1 and t_2 are start and end time of rain events; $m_{tracer,CSO,i}$ and $m_{tracer,i}$ are tracer mass in CSO and total induced tracer mass; t_0 and t_m are start and end time of the irrigation period; $Q_{irr,need}$ and $Q_{irr,RWH}$ are the daily irrigation demand (based on daily evapotranspiration, for more information, refer to Section 2.2) and daily irrigation demand covered by RWH systems.

In the second step, possible deviations of perfect performance for digital system components were considered as uncertainties. For this purpose, the performance of different digital parameters was varied and applied to the system to determine the range of uncertainties associated with smart RWH systems.

As described above, smart RWH systems are characterized by their ability to automatically release stored rainwater prior to rain events based on weather forecasts. There-fore, with reference to smart RWH approaches [8–11], the following digital uncertainties could be identified:

- Accuracy of weather forecast: predicted rainfall and accuracy of weather forecasts in-fluence the (automatic) emptying of the smart RWH units and therefore the effectiveness of RWH and sewer performance,
- Reliability of data communication: communication technologies transmit measurement data and control commands, whereas transmission quality (e.g., number of successful transmissions) is dependent on chosen communication technology.

These uncertainties can show the ideal forms of behavior but may also differ from the ideal value or perfect performance and thus have an impact on the entire system. For example, data communication can be without packet losses, but may also imply major packet losses depending on the chosen communication technology. Therefore, the degree of these factors was varied and applied to the system in this work to determine the range of uncertainties associated with smart RWH systems.

2.2. Integrated Modeling of Urban Water Infrastructure

The open-source software "Smartin" [15] (available online https://github.com/iut-ibk/Smartin-Toolbox/tree/master/smartin, accessed on 22 February 2021) was utilized for simulations. "Smartin" is capable of modeling and simulating IoT-based RWH systems in a coupled model of a UDN and water distribution network (WDN) in real-time. The two main components of "Smartin" are the following Python packages: (1) PySWMM [19] as a Phyton wrapper for the hydrodynamic Storm Water Management Model (SWMM5) [20] to simulate run-off processes in UDN; and (2) Python Epanet Toolkit provided from Open Water Analytics (https://github.com/OpenWaterAnalytics/epanet-python/tree/dev/epanet_python/epanet_python, (accessed on 14 August 2019) for Epanet 2.2 [21] to analyze pressure and water quality in WDNs. Additionally, "Smartin" provides a very high spatial (property level) and temporal data resolution (seconds in UDN; hours in WDN) and supports individual control of each implemented RWH unit based on actual system states.

For UDN, the RWH systems were implemented as a low impact development (LID) type rain barrel. Each rain barrel implemented can be controlled individually by changing the drain coefficient. Based on high-resolution weather forecasts, future inflow to each implemented RWH unit was estimated, and discharge valve was opened in case the available detention volume was lower than the estimated inflow volume. Afterwards, the discharge valve was closed if either available detention volume was equal to the estimated inflow (if the rain barrel volume was greater than the estimated inflow) or before a period with a predicted peak intensity (if the rain barrel volume was lower than the estimated inflow). For dry weather, crop evapotranspiration was used as a reference value to determine irrigation demand, requiring temperature data as an input variable for an applied Hargreaves equation [22]. Afterwards, rainwater was extracted from the RWH system to satisfy irrigation demand, supplemented with drinking water in case stored rainwater could not meet irrigation demand.

When introducing "Smartin" [15], a simplified control strategy for wet weather was implemented and all discharge valves were opened simultaneously. However, in later work, "Smartin" was extended by more advanced control strategies based on sewer conditions [23]. These strategies were used for this work, and supplementary to these, "Smartin" was further extended by including uncertainties from data transmission losses for different communication technologies in the control strategy. Therefore, a random generator was implemented, which evaluates the successful digital transmission of each control command (e.g., opening discharge valve) depending on characteristics of chosen communication technology. Additionally, uncertainty in real weather forecasts was included in the control strategy.

2.3. Case Study

As a case study, an existing UDN of an Alpine municipality located in Austria was used. The UDN was designed as a combined sewer system with a general flow direction to north-east (Figure 1) and included an overdesigned CSO structure. According to Austrian standards, these structures should have a volume of 15 m^3 per hectare of immediate runoff area [24], requiring a total volume of 154 m^3 to fulfil current state of the art. However, CSO performance can only be improved slightly beyond this point, resulting in the influence of CSO metric on resilience index decreasing significantly beyond this point, whereas the impact of RWH performance increases substantially. Subsequently, uncontrolled RWH systems (with frequent use) represent the optimal extension solution, as most rainwater can be provided. Additionally, smart rain barrels are used to showcase smart RWH systems, which support an easy large-scale implementation of additional storage to improve the performance of existing and systems with an insufficient performance (e.g., under-designed due to increasing urbanization or climate change).

Therefore, the CSO structure was re-dimensioned to 60% of the required size (new storage volume of 91.5 m^3) to investigate the effects of different extension strategies for detention volumes (e.g., central enlargement of CSO structures or decentralized implementation of SRBs). Furthermore, the calibrated SWMM5 input file of Oberascher et al. [15] was used for simulations, which has a good level of detail at the property level. In total, 630 properties were connected to the drainage network, which were further subdivided into green, roof and traffic areas.

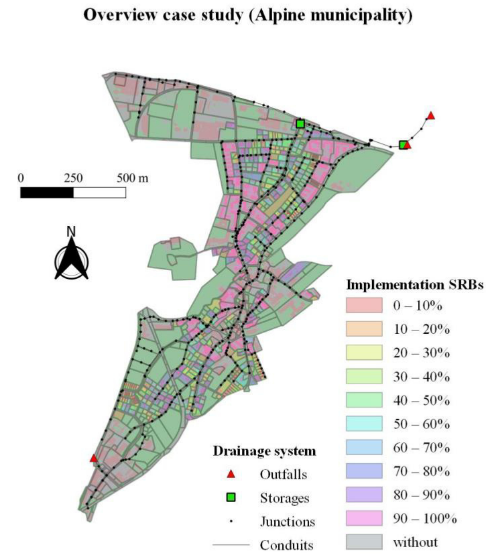

Figure 1. Overview of the Alpine municipality used as the case study with UDN and its associated implementation of SRBs based on roof sizes, starting with the smallest roof area.

For simplicity, CSO performance was evaluated by using a tracer for pollution loads. It was assumed that wastewater and rainwater have a concentration of 1 mg/L and 0 mg/L, respectively, for evaluations. Consequently, the concentration and quantity of discharged pollution loads depended on the dilution of wastewater with rainwater, which allowed a different assessment of small CSO events with low discharge volumes from large events with high dilution rates.

For simulations, precipitation and temperature data were extracted from a nearby weather station (distance of 6 km) for 2018. Precipitation data is available in a temporal resolution of 1 min, whereas temperature is measured in 10 min steps. Additionally, real high-resolution weather forecasts were extracted from the integrated nowcasting through a comprehensive analysis (INCA) system [25] for the weather station described above. The weather forecasts are available in 15 min time steps for the next 24 h every 15 min, whereas a weather forecast period (or accumulation period) and update time steps of 4 h and 2 h were assumed for simulations.

The presented approach was first tested under a single rain event with a rain sum of 12.9 mm (Table 1) and the severity of CSO events was illustrated for different digital parameters. In contrast, irrigation processes mainly take place in Austria during summer-half years (21 March—23 September) [26], therefore the summer-half year 2018 was chosen as an investigation period to determine the integrated resilience parameter. During this period, daily precipitation was between 0 and 32 mm/day with a total precipitation amount of 424 mm, whereas daily mean air temperature varied between −3 and +25 °C.

Table 1. Characteristics of the investigated rain events with caused tracer mass in CSO in the reference state without any rain barrels, including required irrigation demand for green areas during the summer-half year (21 March—23 September) 2018.

Rain	Observation Period	Precipitation Sum (mm)	Tracer CSO (kg)	Irrigation Demand (m^3)
Event 1	29 March 2018.	12.9	1.12	-
Summer half-year 2018	21 March— 23 September 2018.	424	208.33	8800

The smart rain barrel (SRB) concept presented in [15] was chosen as a representative of smart RWH systems. The SRB is an IoT-based micro storage with a storage volume between 200 and 500 L (for more details on dimensions, refer to [15]). Therefore, a conventional rain barrel available in hardware stores was extended by a remotely (and centrally) controllable discharge valve, whereas control commands (e.g., opening discharge valve) and measurement data (e.g., actual filling depth) were exchanged via LoRaWAN. The SRB was under operation during the summer months, whereas they are removed during the winter months due to frost in Austria. Additionally, precipitation volume was low in form of snow during the winter period. Therefore, usually no CSO or flooding events occurred in the winter period. The SRBs are intended for smart city developments including a multi-actor partnership between network operators (material costs) and property owners (e.g., installation and maintenance work).

2.4. Description of the Investigated Scenarios

For an overview of all investigated scenarios, refer to Table 2.

Table 2. Summary of considered scenarios and uncertainties for smart RWH systems.

Uncertainty Sources	Metric	Considered Factors	Defined Scenario (Name)
Distribution	Number	Degree of penetration	Degree of penetration between 10 and 100% in 10% steps
Weather forecast	Accuracy	Deviation amount of predicted rain	+25% rain quantity (high rain) real weather forecast (real rain) −25% rain quantity (low rain)
Data communication	Reliability	Connection quality Network load	1.5% packet losses (good quality—SF7) 28.3% packet losses (average quality) 81.9% packet losses (bad quality—SF12)
Control strategy	Effectiveness	controlled coordinated	Simultaneously opening discharge valves (RTC all) Based on sewer states (RTC CSO depth)

2.4.1. Scenarios and Uncertainties of Examination Parameters

The following parameters were used as boundary conditions for the analysis:

- For the SRBs, 384 properties could be identified as possible installation locations, as these properties were indicated as residential areas which have place for installation and green area for irrigation. To consider different degrees of implementations as uncertainty factors for the distribution, the properties were ordered by roof area size and varied in 10% steps between 0 and 100% beginning with the smallest roof areas. It was assumed that each property has a green area of 25 m^2 for irrigation.
- For control strategies of the SRBs, we distinguished between coordinated and uncoordinated strategies. Therefore, the control strategies 'RTC all', with a simultaneous opening of all discharge valves and 'RTC CSO depth' with an opening based on sewer states were investigated in more detail. For the control strategy 'RTC CSO depth', a CSO filling depth of 1.0 m was set as a threshold (with a discharge water level at 1.4 m). Consequently, all discharge valves were only opened if the filling depth in the

CSO structure was below 1.0 m at the update time step, while they remained closed if the filling depth was greater than 1.0 m.

2.4.2. Scenarios and Uncertainties of Digital Parameters

As described above, influences of the digital uncertainties, namely weather forecast and data communication, were considered in this work:

- For weather forecasts, a deviation of ±25% was assumed, therefore the predicted amount of rainfall was either reduced or increased by 25%, as illustrated in Figure 2b.
- The communication technology LoRaWAN operates in public frequency bands and can be used by anyone, therefore the amount of packet losses in LoRaWAN is strongly depending on network loads. Furthermore, LoRaWAN uses spreading factors (SF7 to SF12) to spread signals over channel bandwidths, whereas a higher spreading factor increases transmission distance and packet losses [27,28]. Consequently, three different scenarios were defined, namely good network quality (low packet losses with SF7 and low distribution with 1000 IoT-devices), average network quality (average packet losses and medium distribution with 5000 IoT-devices) and bad network quality (high packet losses with SF12 and high distribution with 8000 IoT-devices). Packet losses were calculated based on the findings of Blenn and Kuipers [27] and are highlighted in Figure 2a.

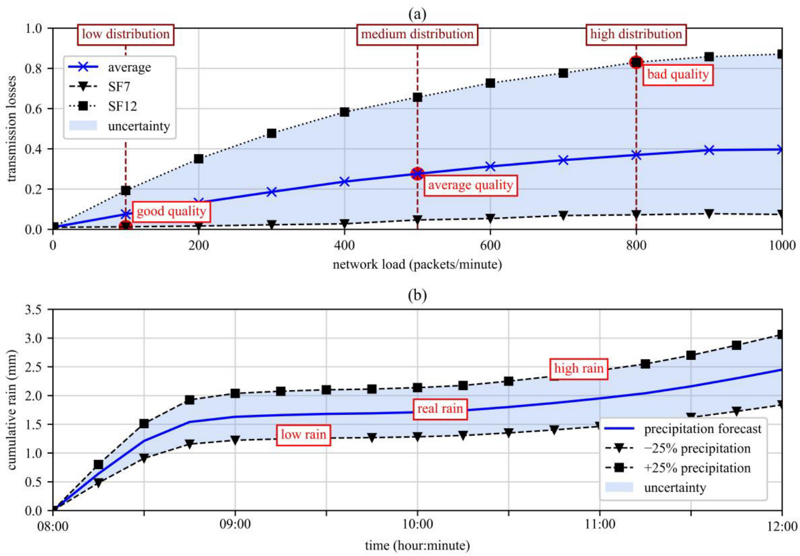

Figure 2. Illustration of considered digital uncertainty scenarios for smart RWH systems (**a**) for different connection quality and network loads for the communication technology LoRaWAN based on the results of [27]; and (**b**) real rainfall forecasts including a deviation of ±25% illustrated for a real rain event.

2.4.3. Scenario Combinations

For resilience analysis, each defined scenario was combined with each other, resulting in 180 scenario combinations. This simplified approach was chosen because simulation times for the summer-half year are up to three days (depending on the degree of penetration). The investigated scenario combinations were compared with uncontrolled RWH systems and an expansion of the existing CSO structure to the state of the art. As performance of uncontrolled RWH systems is strongly dependent on acceptance probability and user behavior, it was assumed that rainwater is extracted for irrigation purposes from the RWH system every second time. Additionally, the existing UDN (without any RWH systems) was utilized as a reference state. In total, 192 simulations were carried out.

3. Results and Discussion

3.1. Influences of Digital Uncertainties on Performance

3.1.1. Single Rain Event

The single rain event was used to show the impact of smart RWH systems and assigned uncertainties on tracer load in CSO events over time, while also allowing a comprehensive discussion about associated challenges and difficulties in detail. Therefore, a penetration rate of 100% (corresponding to 384 smart rain barrels with a total storage volume of 181 m^3) was assumed.

The single rain event showed a total amount of precipitation of 12.9 mm but was characterized through frequent rain breaks during the event (Figure 3a). Furthermore, two CSO events were apparent for the reference state without any RWH systems, causing a total tracer load in CSO overflow of 0.151 kg. At the beginning of the event, a partial filling of each RWH system implemented was assumed. Therefore, the start of a CSO event was slightly delayed for uncontrolled RWH systems as additional detention volumes were provided, which then followed the pattern of the reference state. In contrast, smart RWH systems could be emptied prior to rain events. Consequently, more additional detention volume was available and the start of the CSO event could be further postponed. However, afterwards each investigated scenario had a different pattern.

Figure 3b shows influences of deviations assigned with weather forecast, whereas for simulations, an average network quality for data communication was assumed (i.e., packet losses 28.3%). For the first CSO event, two behaviors were particularly noticeable: (1) an increase of the predicted amount of precipitation can provide more detention volume and thus reduce CSO volumes and subsequently tracer mass; and (2) a simultaneous opening of all discharge valves (as applied in the control strategy 'RTC all') sharply increases m_{CSO} at the end of the first CSO event. This can be explained by the fact that the smart RWH system is fully filled at the update time step at 10:00, and all discharge valves are opened as further precipitation is forecasted for the next 4 h. Consequently, this process creates an artificial CSO event. In contrast, the control strategy 'RTC CSO depths' considers system states, and as CSO depth is higher than 1.0 m at 10:00, this discharge process is avoided/postponed. The intermediate results at 12:00 show that a coordinated strategy ('RTC CSO depths') clearly results in a more significant improvement compared to an uncoordinated strategy ('RTC all'). Additionally, an overestimation of forecasted precipitation amount has a positive effect on stormwater performance.

However, afterwards, this exemplary evaluation also shows the complexity of rain events with longer durations and frequent rain breaks. At 14:00, CSO depth is below 1.0 m and discharge valves of smart RWH systems are opened in the control strategy 'SRB CSO depth', as further precipitation is forecasted. Therefore, the filling depth of CSO structure is higher for this control strategy from that time onwards. Consequently, this situation causes a significant increase in m_{CSO} in the second CSO event and therefore, decreases efficiency compared to the control strategy 'RTC CSO depth' (although better adapted to the overall system).

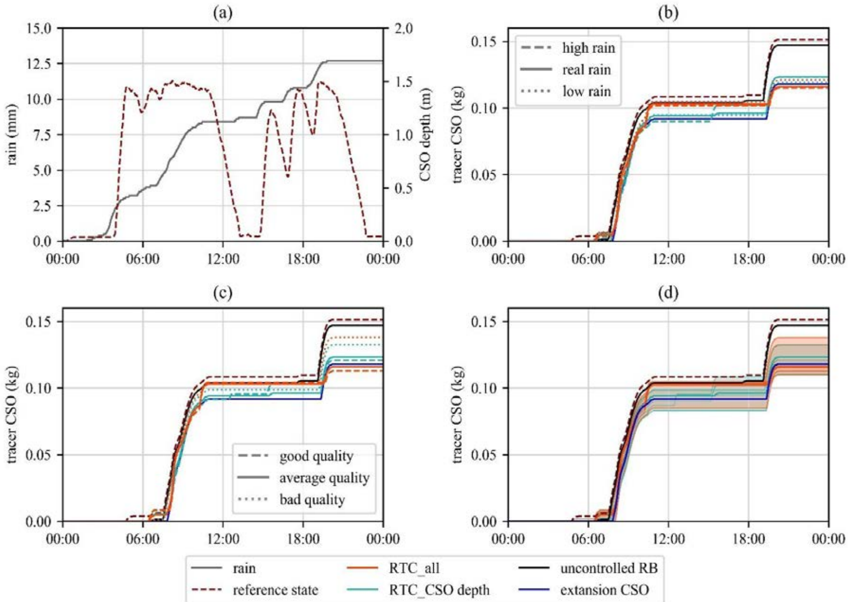

Figure 3. Performance evaluation for a real rain event on 29 March 2018 subdivided into the control strategies 'RTC all' and 'RTC CSO depth' compared with the reference state without any RBs and uncontrolled RBs; (**a**) temporal pattern of precipitation and CSO depth for the reference state; (**b**) effects of uncertainties in weather forecasts with the scenario 'average quality' of data communication on tracer load in CSO; (**c**) effects of uncertainties at data communication with the scenario 'rail rain' on tracer load in CSO; and (**d**) illustration of all investigated scenarios highlighting the range of uncertainties associated with smart RWH systems.

This pattern is also noticeable in Figure 3c, which shows different scenarios for data communication with real weather forecasts (no deviation of predicted amount of precipitation). The communication network with higher quality has lower packet losses, resulting in more control commands (e.g., open discharge valves) that can be successfully transmitted. Consequently, a higher number of discharge valves were opened, and thus additional detention volumes could be provided. As before, two different trends could be distinguished. For the control strategy 'RTC CSO depth', a higher quality of communication network clearly reduces m_{CSO} for the first CSO event. However, due to the high number of smart RWH systems discharged, it subsequently causes a higher degree of filling in the CSO structure and has therefore a negative effect on the second CSO event. In contrast, the opposite case is noticeable for the control strategy 'RTC all'. First, a good quality communication network leads to a higher increase of m_{CSO} at the end of the first CSO event. Second, through this additional CSO discharge, system capacity used is lower and thereby causes the smallest increase in m_{CSO} in the second CSO event.

Finally, Figure 3d summarizes all investigated scenario combinations and highlights the range of uncertainties associated with smart RWH scenarios.

As a central conclusion, it can be summarized that the effectiveness of smart RWH systems is highly dependent on boundary conditions and precipitation patterns for single rain events. For example, scenario-combinations, which show the best improvements for the first CSO event (e.g., a control strategy based on actual sewer performance, an overestimation of amount of precipitation and a good network quality) lead to a noticeable worsening of system performance for the second CSO event compared to other smart RWHs scenario combinations.

3.1.2. Long-Term Simulation (Summer-Half Year 2018)

For scenario combinations with any kind of RWH system, the number of RWH systems varies between 38 and 384 units, corresponding to a degree of penetration of 10% and 100%, respectively. Therefore, additional storage volume is in the range of 10.3 and 181.0 m^3. The results for investigated scenario combinations vary between 2.514 and 2.843 kg for m_{CSO} and 121 and 308 m^3 for V_{RWH}. In contrast to the presented single rain event above, dependence on selected boundary conditions at the beginning of simulation decreases through considering a longer time period. Therefore, results of the complete summer half-year 2018 allow a clear distinction in effectiveness of different control strategies. As the results show, each investigated scenario combination achieves an improvement compared to the reference state, whereby the effectiveness is influenced by the three following factors.

First, there is a strong dependence between effectiveness and degree of penetration for all investigated scenarios. As expected, a higher number of any kind of RWH systems implemented improves system improvements more. Additionally, the spreading of associated uncertainties is increasing with degree of penetration, as highlighted for m_{CSO} and V_{RWH} in Figure 4. This can be explained by the fact that a higher number of RWH systems has more potential for improvements and consequently, uncertainties also have a higher impact. In this context, a coordinated control strategy based on sewer conditions ('RTC CSO depth') shows lower variation in results than an uncoordinated control strategy ('RTC all').

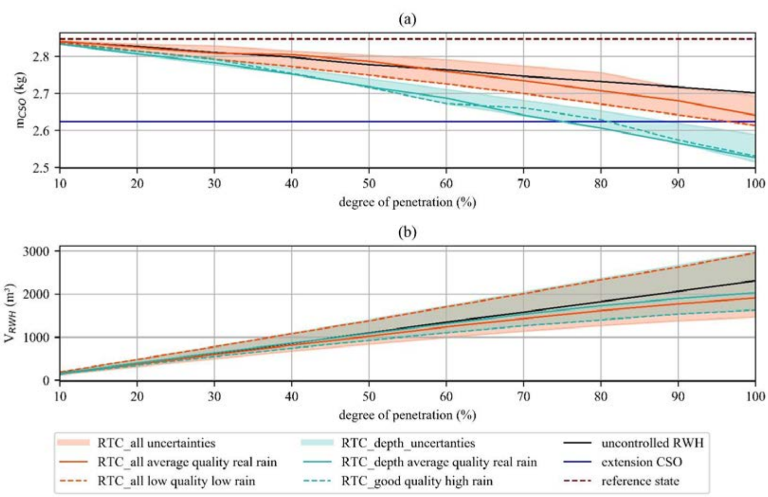

Figure 4. Performance evaluation based on (**a**) m_{CSO} and (**b**) V_{RWH} resulting from control strategies 'RTC all' and 'RTC CSO depth' and compared with uncontrolled RWH systems for different degrees of penetration. Additionally, the range of digital uncertainties associated with any kind of RWH systems is highlighted.

Second, the effectiveness of smart RWH systems depends on applied control strategy. As can be seen in Figure 4, there is a clear distinction between a coordinated control strategy and an uncoordinated control strategy for stormwater performance. For example, each scenario combination of the control strategy 'RTC CSO depth' provides better results for m_{CSO} than 'RTC all'. In contrast, there are only small differences in V_{RWH} that are noticeable. Interestingly, uncontrolled RWH shows only marginal differences in terms of m_{CSO} compared to the control strategy 'RTC all', although a reduced abstraction of rainwater was assumed. In contrast, uncontrolled RWH systems still represent an optimum scenario for V_{RWH}, suggesting that the RWH systems were implemented to provide a volume which is too small to satisfy all irrigation requirements. Additionally, an overestimation of precipitation in weather forecasts results in not fully filled smart RWH systems at the end of the rain event and therefore reduces the amount of usable rainwater for irrigation.

Third, the efficiency of smart RWH systems implemented is dependent on investigated uncertainty and differ between the applied control strategy and considered subsystem (e.g., RWH and UDN). For example, uncertainties, providing more additional detention volume (e.g., increasing amount of precipitation, low packet losses) cause an increase of m_{CSO}, but decrease V_{RWH} for control strategy 'RTC CSO depth'. Conversely, uncertainties providing less additional detention volume (e.g., a decreasing amount of precipitation forecasted, high packet losses) achieve the opposite result, namely a worsening of m_{CSO} and an increasing of V_{RWH}. Therefore, a scenario combination of 'high rain' and 'good network quality' illustrates this effect in Figure 4. Interestingly, a decreasing amount of precipitation forecasted and/or high packet losses improve both m_{CSO} and V_{RWH} for the control strategy 'RTC all'. If less rainwater is simultaneously discharged from the smart RWH systems, the probability of artificial CSO events is reduced. As a result, less tracer mass is discharged and subsequently, m_{CSO} is improved. Furthermore, this approach also causes an improvement of V_{RWH}, as the discharge volume of the SRBs is lower, and therefore, more rainwater can be provided for irrigation. To display this effect, the scenario combination 'low rain' with 'bad quality' has been marked in Figure 4.

In summary, effectiveness is strongly dependent on the additional volume implemented (e.g., increases occur with the degree of penetration), whereby the control strategy applied has a significant influence on efficiency (e.g., coordinated strategy performs better than uncoordinated strategy). Subsequently, effectiveness is also influenced by digital parameters (e.g., deviations in weather forecasts, packet losses in data communication), whereby these influences differ for the control strategy applied and the considered subsystem (e.g., RWH or UDN).

3.2. Integrated Resilience Analysis

The Resilience index (Res) was calculated for the summer half-year 2018. Total irrigation demand was estimated based on the model of Oberascher et al. (2021) [15] and was 8800 m^3 in total (V_{IRR}), which corresponds to approximately 10 days of average water consumption for the case study. Furthermore, induction of tracer mass into the system was only considered for wet weather and was found to be 13.078 kg (m_{total}). The weighting were are chosen to be 0.8 and 0.2 for w_{CSO} and w_{RWH}, respectively, considering local preferences to improve CSO performance. Then, these values were used to calculate the integrated resilience index (Res) for all investigated scenarios, as shown in Figure 5.

The reference state (CSO volume of 91.5 m^3) and the extension of the CSO structure to fulfil current regulations (new CSO volume of 154 m^3) are only influenced by CSO performance, and Res was calculated to be 0.626 and 0.640, respectively. In contrast, Res is based on CSO and RWH performances for all scenario combinations with any kind of RWH and depends on the degree of penetration. Therefore, Res ranges between 0.630 and 0.687 for uncontrolled RWH systems, whereas it varies between 0.629 and 0.701 for smart RWH systems.

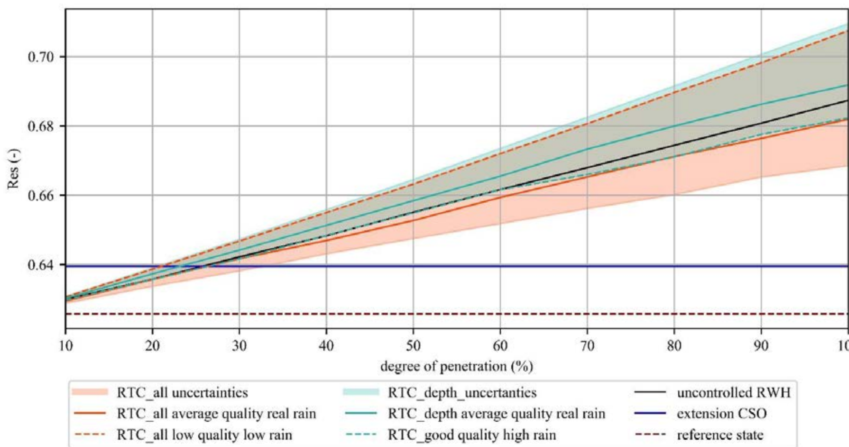

Figure 5. Resilience index (Res) subdivided into control strategies 'RTC all' and 'RTC CSO depth' and compared with uncontrolled RWH systems for different degrees of penetration. Additionally, a range of digital uncertainties associated with smart RWH systems is highlighted.

The extension of the CSO structure by 62.5 m^3 corresponds to an additional storage volume of approximately 135 rain barrels and thus a penetration rate of 35%. As can be seen in Figure 5, all scenario combinations with RWH systems show an improvement in Res at this degree of penetration, which is mainly due to drinking water savings. Therefore, RWH systems represent a good alternative for necessary extensions of existing urban water infrastructure. With a higher degree of penetration, the influence of CSO performance on Res increases.

Additionally, smart RWH systems have the ability to further improve Res, but the range of uncertainties associated with a smart RWH system increases with a higher degree of penetration. Interestingly, however, an unfavorable scenario combination for digital parameters can also significantly reduce system resilience compared to uncontrolled RWH systems.

Furthermore, achievable results are strongly influenced by current conditions (e.g., existing infrastructure) and desired requirements for optimization (in this work improving RWH and/or UDN) and can therefore not be predicted easily. For example, an increase in precipitation does not always improve CSO performance, as shown by the control strategy 'RTC all'. Consequently, considering uncertainties of digital parameters is of the greatest importance for successfully realizing smart water systems.

Finally, the recommended extension strategy is strongly related on preferred performance improvements. In this context, the achievable results are between the two extreme cases: (1) CSO extension shows a clearly better improvement if the focus is only on CSO performance (e.g., a degree of penetration of 80% (approximately 150 m^3) and advanced RTC has the same impact on CSO performance as an CSO extension (65 m^3)); and (2) smart RWH systems use rainwater for irrigation processes reducing drinking water demand, which is not the case with CSO extension. Therefore, the resilience index is strongly influenced by the weighting factors chosen, which subsequently influences the best extension strategy.

3.3. Further Discussion and Outlook

In the chosen approach, resilience is determined based on classic definitions of resilience, and additionally, deviations of digital parameters from perfect performance are considered as uncertainties in the inputs. Although this approach highlights the importance of considering digital resilience, it poses a challenge for interpretating the results. For example, it is not easy to determine which digital uncertainty causes the decrease in resilience. Therefore, a more straightforward method is required in future work to facilitate the interpretation of the impact of individual digital uncertainties associated with smart RWH systems. For example, these requirements can be met by defining a new (digital) resilience metric, which includes the performance curves of digital components.

Additionally, the performance of UDN was evaluated based on tracer mass in CSO events, assuming that the tracer is only induced in wastewater. This resulted in a certain dilution effect, and therefore, lower CSO events had a higher impact. However, as the results demonstrated, improvements are strongly dependent on the current situation (e.g., in this case existing infrastructure). Therefore, further work should use real pollution loads instead of tracer mass. Additionally, the method used herein did not consider wash-off processes of different surfaces, meaning that the 'first flush' effect was mimicked inadequately. For the hydraulic-dynamic simulation, a high-resolution model at the subcatchment level subdivided by different surface types was used to investigate the effects of IoT-based micro reservoirs on UDN. Consequently, future work should also include time and area-dependent pollution models for adequate simulation of pollution loads.

4. Conclusions

In this work, the impact of a large-scale implementation of smart rainwater harvesting (RWH) systems on resilience of urban water infrastructure was analyzed. Smart RWH systems are characterized by automatically releasing stored rainwater based on weather forecasts prior to rain events to increase detention capacity, therefore influencing both the RWH unit and urban drainage network (UDN). Additionally, digital parameters (e.g., weather forecasts, data communication and applied control strategies) may differ from the perfect performance and thus influence overall system performance. To evaluate these impacts, classic and quantifiable metrics of UDN and RWH systems for resilience were combined by using uncertainty assessments caused through digital parameters (e.g., source of uncertainties are deviations in predicted amount of precipitation and packet losses of control commands). Afterwards, an Alpine municipality was hypothetically retrofitted with smart rain barrels as an IoT-based solution for smart RWH.

Based on the obtained results, the following main conclusions can be drawn for large-scale implementation of smart RWH systems:

- To evaluate the resilience of digital systems, a longer period should be considered, as the performance during single events is very dependent on boundary conditions and rainfall patterns.
- Smart RWH systems provide the opportunity to automatically release stormwater prior to rain events and can thereby further increase integrated system resilience (e.g., reducing combined sewer overflow events while providing a sufficient amount of rainwater for non-potable usages). Therefore, a large-scale decentralized retrofitting of existing infrastructure with smart RWH systems represents a good alternative for required extensions of existing and under-designed urban water infrastructure.
- However, results of the integrated resilience index are influenced by weighting factors chosen. Therefore, recommended extension strategies were strongly related on preferred performance improvements (e.g., CSO and/or RHW optimization).
- Additionally, the importance of a coordinated integration and real-time control increases with number of smart RWH units implemented, as the potential for improvements (or degradation) of system performance largely depends on the storage volume added.

- Furthermore, a sufficient consideration of digital uncertainties (e.g., reliability of data transmission, accuracy of weather forecasts) is of the greatest importance for smart water systems, as associated uncertainties can reduce/eliminate otherwise obtained performance improvements.

Author Contributions: Conceptualization and methodology, M.O. and R.S.; software, M.O.; writing—original draft preparation, A.D. and M.O.; writing—review and editing, J.L., M.H., R.S., S.H. and W.R. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The code used for the simulations is publicly available in the GitHub repository (https://github.com/iut-ibk/Smartin-Toolbox/tree/master/smartin, accessed on 22 February 2021), whereas case study data is not publicity available because it contains existing infrastructure data of water distribution and urban drainage network including personalized water consumption data.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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5 Smart applications in real-world experiences

5.1 Smart Campus - Paper VI

Essential for smart water city and digitalisation projects is a functional measurement and control network. To gain real experiences with information- and communication technologies (ICT), the Campus Technik of the University of Innsbruck has been comprehensively equipped with a variety of low-cost sensors for quantitative and qualitative measurements in the field of urban water infrastructure (UWI) over the last years. Additionally, different communication technologies have been tested. In previous work, installation of a measuring network in the field of UWI was started and included water meters and weather stations. In course of this dissertation, the existing measuring system was maintained and continuously extended with different measurement devices. Figure 5.1 gives an overview over the installed measurement devices including used communication technology. The campus area, called “Smart Campus”, is part of a pilot project for smart water cities integrating water distribution and urban drainage network including nature-based solutions into one overall monitored system.

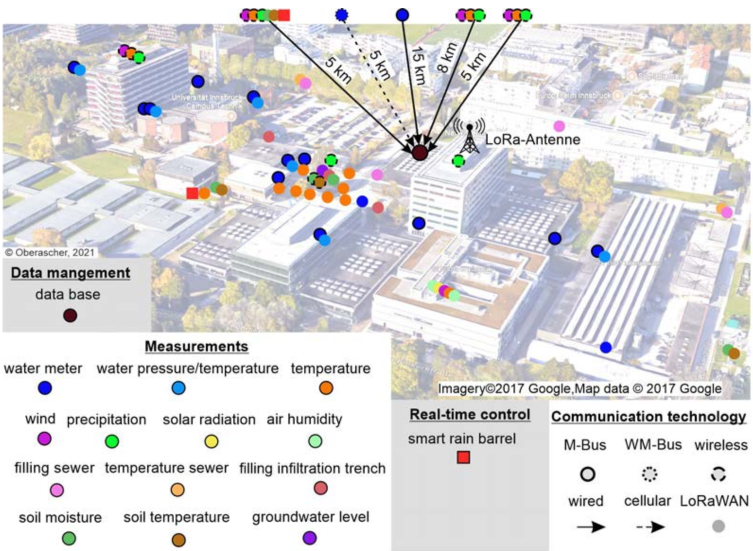

Figure 5.1: Overview over the monitoring and controlling network at the "Smart Campus" showing measurement parameters including used communication technology.

Thereby, a multitude of parameters (e.g., soil moisture, water level, surface temperature, water pressure, water consumption, climate data, ...) are measured and transmitted in high resolution in intervals of 1 - 15 min. In total, the measuring network currently includes 12 water meters and six pressure sensors for the water supply; in addition, two combined weather stations with precipitation, wind, air temperature and humidity as well as two stations with precipitation measurement are installed on the campus grounds. For urban drainage, five stations with soil moisture and soil temperature sensors, seven level sensors as well as one pressure sensor for sewer and green infrastructure and two temperature sensors for wastewater are installed. The measuring station network in this design has been in operation since end of 2020. Non-sensitive data (everything except water distribution network) is freely available under https://umwelttechnik-swc.uibk.ac.at. Through this high-resolution data, the system conditions in water distribution, in wastewater and drainage infrastructure are known in real time. Consequently, the smart campus represents an ideal test bed for innovative applications in the field of UWI. An exemplary application therefore is the smart rain barrel (SRB) and a prototype is under operation during the summer months. The following sub-chapters show selected evaluations of the measurement data to demonstrate the potential of applications based on high-resolution data.

5.1.1 Evaluation Data of Water Distribution Network

Water loss management is one of the objectives at the smart campus, including a detection of unwanted water losses in buildings and water distribution network. First, measured water consumption at one building at the smart campus can be seen in Figure 5.2. Thereby, water consumption is decreasing at the beginning and follows the pattern of working days. However, a pipe came loose from a pump in a laboratory during the night hours, resulting in an additional water loss of around 6 m^3 before the event was detected in the morning. In this case, there was luckily a drain in the floor next to the pump, keeping the damage to a minimum.

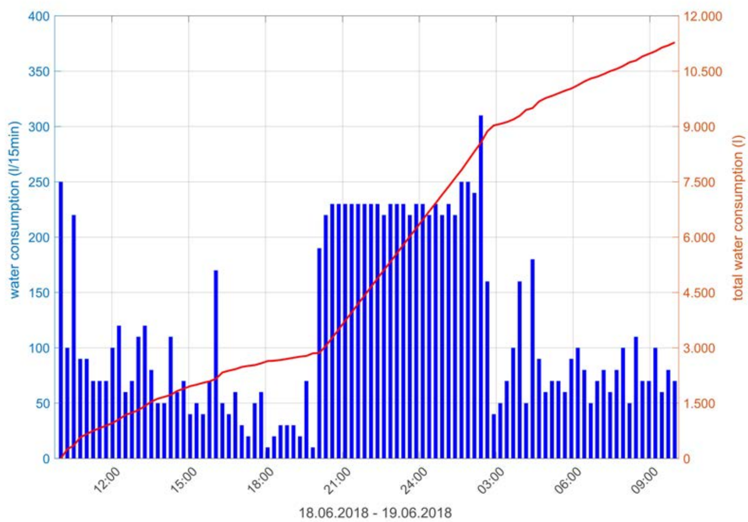

Figure 5.2: Water loss in a building at the smart campus.

However, unwanted loss of drinking water cause a damage over € 450 million alone in Austria every year (Verband der Versicherungsunternehmen Österreichs, 2020). As shown in the example, high-resolution measurements of water consumption can be used to detect leaks in buildings at an early stage. Thereby, digital water meters represent smart measures to minimise these water damages.

Figure 5.3 shows a documented real pipe burst in the water distribution network at the smart campus. Therefore, difference between measured inflow and consumption can be an indication of possible leaks in the network. As not all buildings are equipped with a water meter, there is always a difference between inflow and consumption noticeable. However, a sudden increase in both inflow and difference quantity can be seen very clearly on 03.03.2020. Normally, such an incident can be only discovered after occurrence of a local damage (e.g., undermining of streets) or increased water quantities for billing. Additionally, water pressure sensors installed at the campus showed a significant reduction in water pressure during the pipe burst due to additional pipe friction losses. The pipe burst was finally repaired 3 days later by installing a temporarily bypass pipe. The total water loss in this case was estimated to be approx. 1.000 m^3, whereas no further damage was caused, e.g., by penetration of water into surrounding buildings.

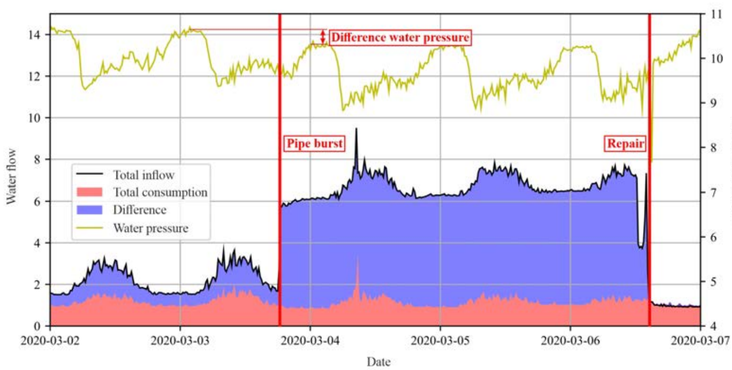

Figure 5.3: Water leakage in the water distribution network at the smart campus.

Another interesting evaluation in Figure 5.4 shows drinking water temperature during the exit restrictions in spring 2020. The combination of low withdrawal quantities and an unfavourable pipe installation in a boiler room resulted in drinking water temperatures between 26 and 30°C. According to valid standards, e.g., ÖNORM EN 806-2 (2005), cold water temperature should not exceed 25°C after 30 s after full opening of taps, as hot water favours the formation of germs, e.g., legionella bacteria. In this context, smart systems represents also an possible measure to tackle this issue. For example, smart devices (e.g., smart toilet flushes, smart faucets) can be automatically opened to release drinking water in case of high drinking water temperatures. Subsequently, residence time in house pipes is reduced, which increases the drinking water quality.

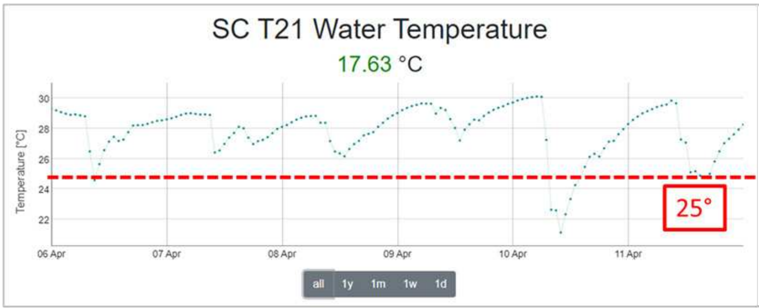

Figure 5.4: Drinking water temperature during the exit restrictions in spring 2020.

5.1.2 Evaluation Temperature Data

Figure 5.5 illustrates surface and air temperatures for different installation locations during a hot period in September 2020, extended by solar radiation and precipitation data. As can be seen, there is a clear correlation between solar radiation and measured temperature, resulting a clear distinction between day and night hours. Furthermore, cloudy (07.09.) and sunny days (08 - 10.09) can be distinguished very well. As expected, impermeable surfaces have a higher maximum temperature as green areas, e.g., maximum temperature of bitumen roofs, stone pavings, and green areas are 70°C, 36°C, and 26°C, respectively, during the observation period. Interestingly, minimum temperature during the night hours is partly the opposite and bitumen roofs have a lower temperature than green areas (e.g., 8°C compared to 12°C). Consequently, impermeable surfaces have a higher difference between day and night hours (e.g., up to 60°C), whereas variations are much lower for green areas (e.g., up to 15°C).

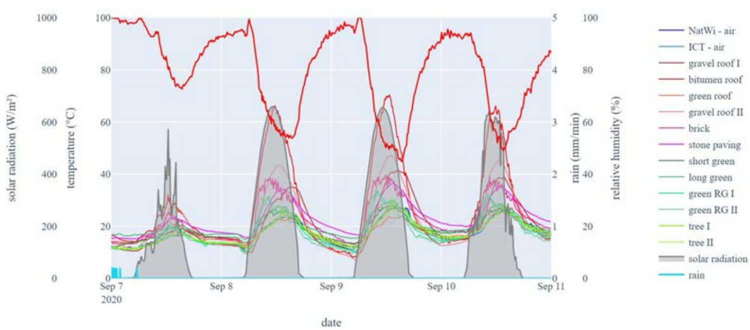

Figure 5.5: Temperature for different surface areas and installation places during a sunny period in autumn 2020.

Urban growth cause an increase of impervious surfaces, thereby effecting local micro climate. Especially, impervious and dark surfaces have higher temperatures due to reduced evaporation and higher absorption of solar radiation, which can lead to urban heat island effects in cities (Deilami et al., 2018). Subsequently, nature-based solutions (NBS) are frequently used as countermeasure, as NBS have positive effects on urban micro climate through increasing shading, evapotranspirations, and water storage (Norton et al., 2015; Ruangpan et al., 2020). In this context, the exemplary comparison between different surface types showed very well the potential for green infrastructure for improving ambient temperature in urban areas.

5.1.3 Paper VI

Oberascher, M., Kinzel, C., Rauch, W., Sitzenfrei, R., 2020. Einblicke in eine „Smart Water City“ - ein Projekt der Universität Innsbruck (insights into a "Smart Water City" - a research project of the University of Innsbruck - only available in German). WWT - Wasserwirtschaft Wassertechnik: Das Praxismagazin fuer das Trink- und Altwassermanagement. 11/12, 13-16. Reprinted with Permission of Publisher.

Martin Oberascher; Dr. Carolina Kinzel; Prof. Dr. Wolfgang Rauch; Prof. Dr. Robert Sitzenfrei

Einblicke in eine „Smart Water City“

Der Campus Technik der Universität Innsbruck erhielt in den letzten Jahren intelligente Mess- und Steuerungssensorik. Dank dieser Basis wurde eine „Smart Water City" entwickelt. Dadurch können neue technologische Lösungen in Zusammenarbeit mit lokalen Akteuren intensiv getestet werden.

Ein modernes Konzept für die urbane Wasserinfrastruktur beinhaltet, neben zentralen Bestandteilen wie der Kanalisation und das Wasserversorgungsnetz, auch vermehrt dezentrale Anlagen für eine Bereitstellung bzw. Behandlung von Regenwasser vor Ort. Die stetige Weiterentwicklung des Internet of Things (IoT)-Konzeptes hat die Entstehung von kostengünstigen Sensoren in Kombination mit innovativer Datenübertragung begünstigt /1/. Dadurch können bestehende Systeme relativ einfach mit Mess- und Steuerungssensorik ausgestattet werden /2/. Zudem ermöglicht das IoT-Konzept auch die Einbindung einer Vielzahl von dezentralen Anlagenteilen in ein gemeinsam gesteuertes Gesamtsystem.

Zusammen mit der Einbindung der Bevölkerung ergeben sich dadurch neue Möglichkeiten für Betrieb und Wartung. Ziel des Forschungsprojekts „Smart Water City“ ist es, innovative Dienstleistungen für verschwiedene Akteure der urbanen Wasserinfrastruktur zu erproben sowie deren kommunalen Mehrwert zu bestimmen.

Smarter Campus

Ein umfangreiches Mess- und Steuerungsnetz stellt die Basis für die Umsetzung einer „Smart Water City“ dar. Dazu wurde der Campus Technik der Universität Innsbruck über die letzten Jahre hinweg umfassend mit intelligenter Mess- und Steuerungssensorik zum „Smart Campus“ ausgestattet (Bild 2).

Dabei wird eine Vielzahl an Parametern (z. B. Bodenfeuchte, Wasserstand, Oberflächentemperatur, Wasserdruck, Wasserver-

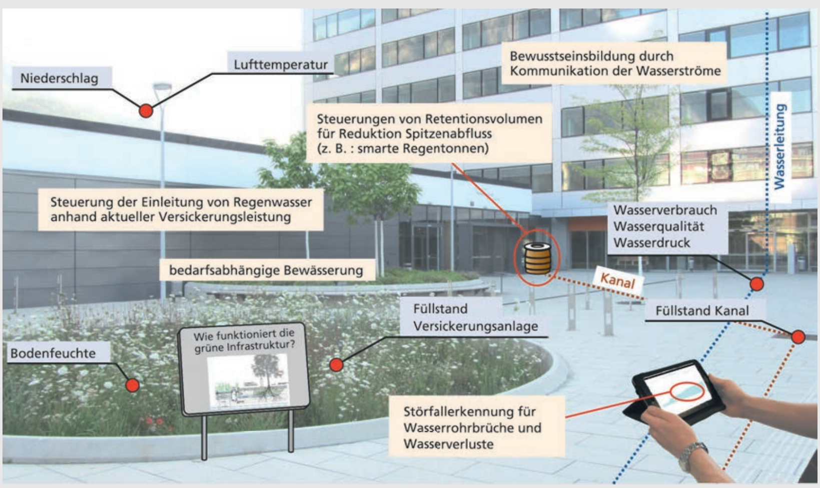

Bild 1 Der Campus Technik an der Universität Innsbruck – bestückt mit intelligenter Mess- und Steuerungstechnik

Quelle: Universität Innsbruck

Special: Regenwasser

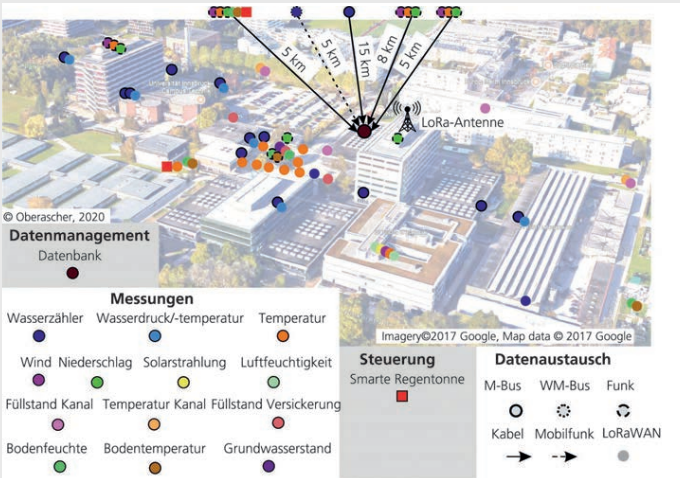

Bild 2 Mess- und Steuerungsnetzwerk am Campus Technik der Universität Innsbruck (Stand 2020)

Quelle: Universität Innsbruck

brauch, Klimadaten etc.) hochaufgelöst in Intervallen von 1 bis 15 Minuten gemessen und übertragen (Informationen zum Messstellennetz: https://umwelttechnik-swc.uibk.ac.at/, unsensible Daten frei zugänglich). Durch diese hochaufgelösten Daten sind die Systemzustände in der Wasserversorgung und in der Abwasser- und Entwässerungsinfrastruktur in Echtzeit bekannt. Der „Smart Campus" stellt dadurch einen idealen Testraum für innovative Dienstleistungen im Bereich der urbanen Wasserinfrastruktur dar. Nachfolgend werden die smarte Regentonne und ein Frühwarnsystem für Wasserverluste als beispielhafte smarte Anwendungen näher vorgestellt.

Smarte Regentonne (SRT)

Regentonnen sammeln Regenwasser, das bei Bedarf zur Bewässerung verwendet werden kann und dadurch den Trinkwasserbedarf reduziert. Einzelne Regentonnen weisen bezogen auf das Gesamtvolumen der Entwässerungsinfrastruktur ein kleines Retentionsvolumen auf, jedoch kann die Summe aller Regentonnen auch für die Regenwasserbewirtschaftung ein bedeutungsvolles Volumen darstellen. Die Retentionswirkung von herkömmlichen Regentonnen ist sehr stark von der individuellen Regenwasserentnahme abhängig (Vorfüllung bei Regenereignis). Um Regentonnen optimal zu nutzen, wurde das Konzept der smarten Regentonne als eine in Echtzeit kontrollierbare Speichereinheit entwickelt (Bild 3). Dazu wurde eine herkömmliche Regentonne mit einem automatisch steuerbaren Ventil sowie einem Füllstandsensor ausgestattet. Die Regentonne wird über einen Regensammler an das Fallrohr der Dachentwässerung angeschlossen. Der Austausch von Daten (aktueller Füllungsgrad) als auch von Steuerungsbefehlen erfolgt über das Niedrigenergiefunknetz LoRaWAN. LoRaWAN hat einen niedrigen Energieverbrauch bei hohen Übertragungsreichweiten und stellt dadurch eine Grundvoraussetzung für den Einsatz der smarten Regentonne in Smart Cities dar.

Ein wichtiges Element der Kontrollstrategie sind hochaufgelöste Wettervorhersagen, mit denen das benötigte Speichervolumen berechnet wird. Die SRT wird vor einem Regenereignis, falls der prognostizierte Abfluss das aktuell vorhandene Speichervolumen überschreitet, so weit entleert, dass bei Regenende die Tonne wieder vollgefüllt ist. Bild 4 zeigt beispielhaft für ein reales

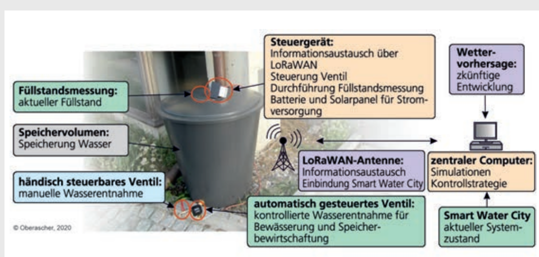

Bild 3 Übersicht über die Bestandteile der Smarten Regenwassertonne (SRT)

Quelle: adaptiert nach /4/

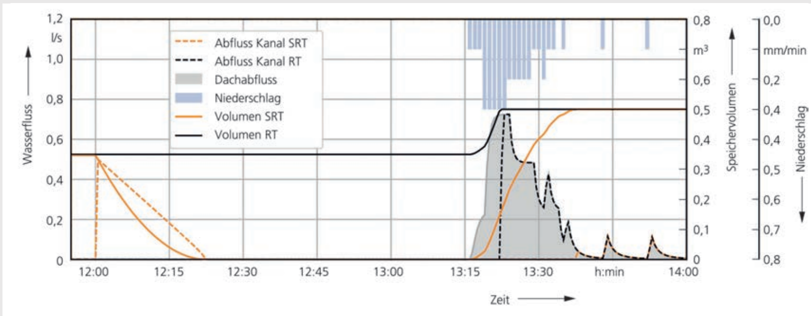

Bild 4 Beispielhafte Funktionsweise der SRT gegenüber einer herkömmlichen (ungesteuerten) Regentonne

Quelle: adaptiert nach /4/

Regenereignis die ideale Funktionsweise einer SRT im Vergleich zu einer herkömmlichen (ungesteuerten) Regentonne (RT). Das Beispiel verdeutlicht, dass eine SRT trotz ihres kleinen Volumens den Spitzenabfluss auch bei stärkeren Regenereignissen deutlich reduzieren kann. Im Vergleich zur ungesteuerten Regentonne kann die SRT den Spitzenabfluss in diesem Beispiel um ca. 80 % reduzieren. Gleichzeitig wird nach dem Regenereignis eine möglichst vollgefüllte Regentonne zur weiteren Verwendung des Regenwassers bereitgestellt.

Wie durch Simulationen festgestellt /3/, ist die Wirksamkeit einer einzelnen SRT besonders gegeben, wenn die Regentonne teilweise oder vollständig gefüllt ist und die Trockenperiode zwischen Regenereignissen kurz ist (kein Bewässerungsbedarf). Die Einsparung von Trinkwasser für Bewässerungszwecke ist bei der ungesteuerten Regentonne jedoch geringfügig höher als bei der SRT, da Unsicherheiten bei der Wettervorhersage dazu führen können, dass die Regenmenge überschätzt wird und somit die Regentonne bei Ereignisende nicht vollgefüllt ist. Um die Auswirkungen einer großflächigen Installation von SRT auf die urbane Wasserinfrastruktur zu untersuchen, wurde die open-source Software „Smartin“ entwickelt /4/. Durch „Smartin“ können eine Vielzahl von SRT individuell in einem gekoppelten Modell aus Wasserversorgung und Siedlungsentwässerung (Software EPANET2 and SWMM5) in Echtzeit gesteuert werden. Zur Veranschaulichung wurde eine reale urbane Wasserinfrastruktur einer alpinen Gemeinde mit ca. 2.500 Einwohner modellbasiert mit SRT ausgestattet. Für die Simulationen wurde die Anzahl der SRT variiert (Gesamtvolumen von 45 – 180 m³) sowie unterschiedliche Prognosezeiträume der Wettervorhersage untersucht. Obwohl eine einfache Kontrollstrategie verwendet wurde, konnte eine deutliche Verbesserung des Gesamtsystems durch eine Reduktion von Mischwasserüberlauf- und Überflutungsvolumina (bis zu 14 bzw. 40 %) sowie der Bereitstellung von Regenwasser für Bewässerungszwecke (bis zu 9 m³ pro Regentonne im Jahr) erzielt werden.

Die Materialkosten für eine SRT (Regentonne mit 500 l Volumen, elektrisches Kugelhahnventil, Steuerungseinrichtung, LoRaWAN Antenne) belaufen sich auf ca. 475 €. Als Vergleichswert betragen die Investitionskosten für ein zentrales Mischwasserüberlaufbecken zwischen 600 und 3.600 € pro m³ /5/. Im Unterschied zu zentralen Bauwerken mit einer Lebensdauer von Jahrzehnten, unterstützen die SRT einen einfachen Einbau in die bestehende Infrastruktur. Dadurch unterstützen die smarten Regentonnen ein flexibles Design (sowohl räumlich als auch mengenmäßig) und stellen eine ideale Erweiterung der bestehenden Infrastruktur gegenüber wechselnden Einflüssen (z. B. Klimawandel, Zunahme Versiegelung) dar. Dabei sind die SRT als Partnerschaftsmodell zwischen Entwässerungsbetreiber und Regentonnenbesitzer angedacht. Zum Beispiel kann der Entwässerungsbetreiber die Kosten für die Steuerung und Einbindung in ein zentrales Kontrollsystem übernehmen (Vorteil von zusätzlichem Speichervolumen im System). Der Regentonnenbesitzer kann dagegen die Aufstellung und Wartung übernehmen (Vorteile: Regenwassernutzung, Messwerte für Bewusstseinsbildung und Systemverständnis; Einbindung in Smart Home Umgebung zur automatischen Bewässerung).

Frühwarnsystem für Wasserverluste

Einen zentralen Punkt in „Smart Water City“ stellt auch das Wasserverlustmanagement im Trinkwassernetz dar. In Bild 5 ist ein dokumentierter realer Rohrbruch am Campus Technik dargestellt. Die Differenz aus Zufluss zum Campus Technik und Verbrauch (digitale Wasserzähler) stellt eine Indikation auf mögliche Undichtheiten und Leckagen im Versorgungsnetz dar. Obwohl durch die Gebäude ohne Wasserzähler immer eine Differenz zwischen Zufluss und Verbrauch gegeben ist, ist sehr gut eine sprunghafte Zunahme sowohl des Zuflusses als auch der Differenzmenge am 03.03.2020 ersichtlich. Oftmals wird eine solche Fehlstelle erst nach Auftreten von lokalen Schäden (z. B. Unterspülungen) oder erhöhten Wassermengen bei der Abrechnung entdeckt. Am Campus wurden Wasserdrucksensoren mit LoRaWAN Übertragung installiert. Sie zeigten während des Rohrbruchs eine deutliche Reduktion des vorhandenen Wasserdruckes durch die zusätzlichen Rohrreibungsverluste. Den Rohrbruch behob man schließlich 3 Tage später durch die Errichtung einer Bypassleitung (temporär). Der gesamte Wasserverlust wurde in diesem Fall aufgrund der relativ kurzen Laufzeit mit insgesamt ca. 1.000 m³ abgeschätzt. Es entstan-

Special: Regenwasser

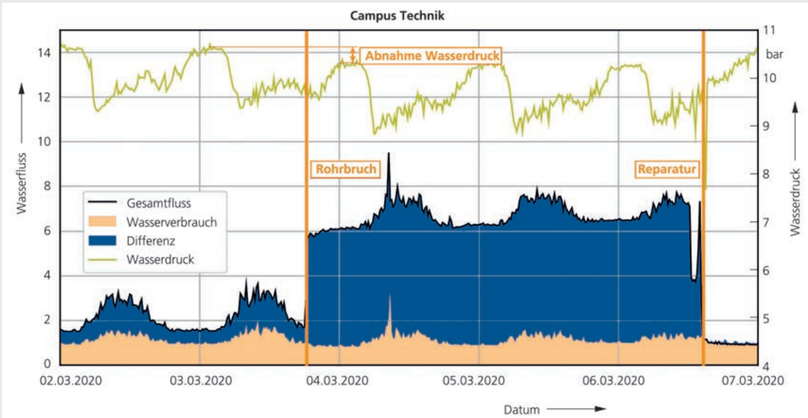

Bild 5 Anwendungsbeispiel eines Frühwarnsystems für Wasserverluste

Quelle: Universität Innsbruck

den keinerlei weitere Schäden, z. B. durch Eindringen von Wasser in Gebäuden.

Ausblick

Bestehende Infrastruktur aus Smart Cities Implementierungen sowie kostengünstige Sensorik ermöglichen eine verbesserte sowie räumlich verteilte Erfassung von Systemzuständen auch in der Wasserinfrastruktur. Diese Informationen können anschließend für eine integrative Betrachtung sowie smarte Bewirtschaftung verwendet werden. Werden mehr Sensoren räumlich verteilt installiert, können Systemzustände besser bestimmt und Optimierungspotenziale verlässlich aufgezeigt werden. Jedoch werden für Messgeräte in der urbanen Wasserinfrastruktur vorwiegend batteriebetriebene Sensoren eingesetzt, wodurch auch der Ressourceneinsatz ansteigt. Zudem bewirkt die Umsetzung einer fixen Messinfrastruktur primär Investitions- und Betriebskosten, wobei ein möglicher Mehrwert nur durch die aktive Nutzung der Messwerte erzielt werden kann. Im Forschungsprojekt sollen daher weitere Optimierungspotenziale untersucht und eine umfangreiche Analyse der ökologischen und ökonomischen Auswirkungen durchgeführt werden, um den kommunalen Mehrwert einer „Smart Water City" bestimmen zu können.

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5.2 Paper VII

Oberascher, M., Möderl, M., Sitzenfrei, R., 2020. Water Loss Management in Small Municipalities: The Situation in Tyrol. Water. 12(12). https://doi.org/10.3390/w12123446.

The smart applications presented so far in this dissertation are intended to improve system operation, but are based on a large-scale implementation of ICT in the field of UWI. The implementation and maintenance of such a high-resolution measurement network is time-consuming and requires sufficient expertise, which will make it a major challenge for small municipalities and network operators (in Austria).

Therefore, the next chapter highlights that an improvement in the system can be achieved even with a small use of ICT and digitalisation efforts. The analysis of water loss management shows that simple performance indicators based on mass balance can be used for evaluation, whereas a combination of different measures (e.g., performance indicator, online-measurement of inflow, or state funding) can help to reduce water losses in the network. Advantages are an easy usage, making the presented methods interesting for small municipalities, and an increase in sustainability (e.g., decrease of water losses), as one of the main objectives of smart cities.

water

MDPI

Article

Water Loss Management in Small Municipalities: The Situation in Tyrol

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Abstract: Water losses in water distribution networks (WDNs) are unavoidable. Water losses are evaluated based on performance indicators (PIs) and used for future recommendations for network operators to take measures against water losses. However, these evaluations primarily focus on large and medium sized WDN and do not deal with the challenges of small WDNs (e.g., technical, and financial limitations, missing data). Therefore, an appropriate water loss management is a major challenge for operators in the federal state of Tyrol (Austria) due to the high number of small WDNs, e.g., low income in combination with long network lengths. In this regard, this work specifies and discusses state funding in Austria to support network operators to reduce water losses. To assess the impacts on management strategies, 40 WDNs, supplying 200 to 16,000 inhabitants, are investigated in detail. As the comparison of different PIs shows, a volume related PI (e.g., water loss volume divided by total water demand) is recommend as the decision criterion for local authorities due to minimal efforts and its easy calculation. Moreover, public funding helps to significantly reduce water losses in individual systems, but countermeasures should be different for small and larger WDNs. For example, leakage detection campaigns and rehabilitation planning based on pipe age should be established in future for larger WDNs in Tyrol. In contrast, an online flow metering system to monitor system inflows is suggested for small WDNs. Based on measurement data, leakages and burst can be detected and repaired swiftly.

Keywords: state funding; performance indicators; practical experiences; small municipalities; leakage

1. Introduction

Water loss in water distribution networks (WDNs) can be defined as the difference between the quantity of drinking water fed to the system and the metered and billed water consumption [1,2]. These losses, called non-revenue water (NRW), consist of unbilled but authorized water consumption (e.g., extractions from hydrants), apparent losses (e.g., unauthorized water extractions or meter inaccuracies), and real losses caused by leakages [1,2], whereby the greatest influence on water balance is from real losses [3]. Water losses in WDNs vary widely depending on the maintenance efforts. In this context, water losses can be as high as 40% and 80% of system inputs in Europe [4] and developing countries [5], respectively, while being on average between 16% and 30% [4–6]. Apart from financial costs, water losses cause ecological issues too, for example, drinking water that has to be treated and pumped more than once [7,8] and water losses can increase stress on water resources in countries with water scarcity [9]. Additionally, leakages represent a major challenge in sustainable agriculture and food growing, whereas water losses reduce the amount of available water and further increase the resource conflict between agriculture and domestic water

Water **2020**, *12*, 3446

usage [10–12]. In total, global water losses in WDNs are estimated to be 126 billion cubic meters per year, corresponding to a total value of USD 39 billion [13].

Water losses in individual WDNs are evaluated and compared by using technical performance indicators (*PI*s) as described by the International Water Association (IWA) [1,14]. Basically, *PI*s relate water losses to system parameters, where a higher value corresponds to an increased amount of water losses. However, a correct assessment is important as recommendations for network operators are based on these indicators [1]. For example, these measures can include leakage detection approaches [15–22] or rehabilitation planning [23–25] to reduce water losses in WDNs. According to the literature, simple *PI*s (e.g., NRW compared to total system input) are too dependent on current withdrawal quantities and should not be used [14,26]. Therefore, the infrastructure leakage index (PI_{ILI}) as the ratio between real losses and real losses reduced to a technically unavoidable level is recommended as the input value in the literature [26,27]. The determination of PI_{ILI} as an input parameter for future measures requires a large amount of data and is therefore time-consuming. In this regard, water loss management is, particularly for very small municipalities (<5000 inhabitants), a major challenge [28,29]. Additionally, network operators of small WDNs (common in Austria) have to deal with the following problems: (1) long total network length due to distributed settlement area; and (2) low income due to low number of inhabitants supplied with drinking water. Consequently, advanced water loss strategies and qualified manpower are too expensive, and an appropriate water loss management is a major challenge. This work presents and discusses experiences and influences of state funding on water loss management for small municipalities in the federal state of Tyrol (Austria).

The detailed objective of this work is to support network operators of small municipalities and local authorities for a goal-oriented tackling of water loss management. Our goals can be summarized as follows:

- Identify a usable performance indicator (*PI*) for water loss management that is especially suitable for challenges of very small municipalities.
- Present common sources of water loss in small water distribution networks (WDNs).
- Describe influences of state funding and rehabilitation planning on performance of WDNs (e.g., improving water loss management).
- Discuss additional problems faced by operators of small WDNs.

In this context, the article is structured as follows: Section 2 reviews state-of-the-art *PI*s for WDNs, including an insight into Austrian regulations and state funding. Furthermore, characteristics of the 40 investigated WDNs are described in this section. In Section 3, results regarding different areas of water loss management (water loss assessment, identification of locations of water loss, and rehabilitation planning) are presented and discussed, supplemented by additional problems faced by network operators. Finally, Section 4 provides the conclusions and give guidance how to apply goal-oriented water loss management in small municipalities.

2. Materials and Methods

2.1. Technical Performance Indicators for WDNs

One of the simplest *PI*s is the volume related *PI* (PI_V), calculated by the following equation:

$$PI_V(\%) = \frac{100 * Q_L}{Q_D}, \quad (1)$$

where Q_L is the estimated water loss volume (m^3/a) and Q_D is the water demand volume (m^3/a). The literature recommends total system input as the reference value [26,27]. In contrast, Austrian water law specifies that water demand should be used for comparison and therefore that is what was used as the basis in this work. The key advantage of PI_V is that this *PI* can be easily calculated and is therefore often used, but according to recommendations of the IWA, it is not suitable for determining the effectiveness of measures in regard to real water losses [14,26].

Other simple *PI*s are PI_L (m^3/h/km) and PI_C (litre/day/service connection), which include basic network characteristics in the calculation. For example, PI_L relates water losses to network length, whereas PI_C establishes a relationship between water losses and number of service connections. PI_L and PI_C are calculated by the following equations:

$$PI_L = \frac{Q_L}{L_m * 8760} \ \ldots \ldots \ \frac{N_C}{L_m} \leq 20 \quad (2)$$

$$PI_C = \frac{Q_L * 1000}{N_c * 365} \ \ldots \ldots \ \frac{N_C}{L_m} \geq 20 \quad (3)$$

where L_m is the total length of the network (km) and N_C the total number of service connections. Equation (2) is limited to not more than 20 service connections per kilometer of main pipe as the amount of water loss of service connections are not considered explicitly. In contrast, Equation (3) relates water losses to the number of service connections and should be used with more than 20 service connections per kilometer of main pipe. According to the literature, application of a *PI* related to network design is limited and more suitable for target settings as it does not take operating characteristics (e.g., water pressure, seasonality) into account [23].

In this regard, the infrastructure leakage index (PI_{ILI}) is the most used and recommended *PI*:

$$PI_{ILI}(-) = \frac{\frac{Q_L * 1000}{N_c * 365}}{\left(\frac{18 * L_m}{N_c} + 0.8 + \frac{25 * L_p}{1000 * N_c}\right) * P} \ \ldots \ldots \ N_c \geq 3000, \quad (4)$$

where L_p is the average length of service connections (m) and *P* is the average operating pressure (m). PI_{ILI} was specifically designed to compare real losses between different systems, including local conditions like the operating pressure [26]. Additionally, PI_{ILI} provides an indication of the minimum possible water loss that can be achieved by the existing infrastructure [23,26]. However, disadvantages of PI_{ILI} are the high number of input parameters and that the results of the equation are not particularly understandable for non-technicians [23]. At first, usage of PI_{ILI} was limited to larger networks (more than 5000 or 3000 service connections depending on the literature), but recent literature [30,31] concluded that PI_{ILI} can be used for smaller WDNs.

2.2. Overview of Austrian Standards and State Funding Related to WDNs

The Austrian water law (Wasserrechtsgesetz—WRG, 1959) specifies an efficient use of drinking water [32], inducing network operators to maintain the WDN. The law obliges network operators to engage external consultants to technically and hygienically assess the state of the investigated WDN. This process includes the use of state-of-the-art technologies to quantify water losses, to calculate a water balance, and to identify and localize leakages. Subsequently, the network operators have to repair and renew the system and submit a report to the competent authority. This process is repeated every five years to maintain the WDNs at a high standard. Furthermore, the law regulates that in case of intentionally wrong reports, the network operator has to compensate for the damages caused.

Additionally, the Austrian government funds various measures that ensure problem-free operation and a reduction of water consumption. To specifically support operators of small WDNs, development of a pipe information systems and leakage detection campaigns were funded with a maximum of 50% and 62.5% of the total cost since 2007 and 2016, respectively. The development of a pipe information system includes a survey of location and properties (e.g., diameter, material, construction year) of various network elements and a creation of a digital image of the network. When water losses are higher than 20% of the total system input, leakage detection is mandatory to obtain governmental funding.

2.3. Case Study

In this study, the performances of different WDNs located in the federal state of Tyrol (Austria) were investigated. Tyrol is a federal state with 757,850 inhabitants and an area of 12,640 km^2, subdivided into 279 municipalities. Only 24 municipalities have an official population of more than 5000 persons, and 150 municipalities have less than 1500 inhabitants. In total there are 760 public drinking water facilities, which are mostly operated by municipalities, with a degree of connection to about 96% of the population [33]. Additionally, tourism accounts for a significant share of water consumption due to the Alpine location of Tyrol, and in winter, water is used for artificial snow production too. The federal state of Tyrol is located in the Dfb climate cone, where D, f, and b, refer to cold climate, without dry season, and warm summer, respectively [34]. Average domestic water consumption is 135 L per capita per day. Additionally, there is a clear distinction between winter (120 L per capita per day) and summer (150 L per capita per day), mainly caused through increased outdoor applications (e.g., garden irrigation, filling of private swimming pools) [35].

The evaluations of the WDNs were based on using the above-mentioned reports according to the Austrian water law (11 available supervision reports) and funding reports (23 available reports). Additionally, a network survey was conducted in 2012 and the results were included in this work (40 available reports).

2.3.1. Network Characteristics

In total, 40 WDNs were investigated with a supply area ranging from 0.36–120 km^2. However, WDNs located in Tyrol are subject of the critical infrastructure protection (CIP) of Austria [36], including the regulation of usage of WDNs data. Therefore, the data presented should not give any indication of the location of the WDNs and, consequently, detailed information on the water infrastructure itself cannot be provided. To overcome this limitation, Table 1 shows characteristic system variables using statistical parameters (e.g., minimum, mean, and maximum) to provide certain details relevant for calculation of *PI*s. Network data was extracted from funding reports, including average length and number of service connections, and afterwards was analyzed with a geographical information system (GIS). The average total network length was 25.6 km and the average number of service connections was 642, with 16.8 m length each. In this context, Figure 1 shows the connection density between total inhabitants and total network length. As can be seen, connection density is in the range of 22 to 210 connected inhabitants per km network pipes and increases slightly with increased network length. Sources of drinking water are mostly springs; groundwater wells are additionally used in five WDNs. In all investigated cases, drinking water is supplied fully gravity driven. System pressure was estimated based on the difference between tank height and the center the of supplied area, considering pressure reduction valves (if known). As the evaluations have shown, average network pressure was in the range of 50 to 110 m. Average network age was calculated as a weighted average of all pipes being between 1962 and 2002.

Table 1. Primary characteristics of the 40 investigated water distribution networks (WDNs).

Property	Minimum	Average	Maximum
Connected inhabitants (-)	224	2951	15,747
Total network length (km)	7.0	25.6	103.0
Number of connections (-)	40.0	642.0	2945.0
Average connection length (m)	7.8	16.8	29.0
Network pressure (m)	50.0	79.2	110.0
Year of construction	1962	1987	2002

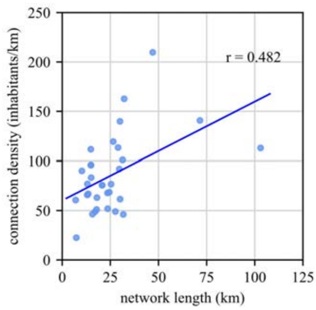

Figure 1. Correlation between total network length and connected inhabitants for the investigated WDNs.

2.3.2. Missing Data

In 29 reports water demand was missing and in 11 reports number of service connections was missing. In the literature [37–39], the following approaches to handle incomplete data sets and missing data are described: (1) complete case analysis: deleting all cases with missing data and investigating only complete datasets; (2) single imputation: replacing missing values with methods that allow for a good estimation of the values, and (3) multiple imputation: 3-step procedure (imputation, analysis, and pooling) to determine missing values including uncertainty analysis. As the probability of missing values (demand and/or service connections) is equal for all investigated WDNs, single imputation is a possible approach [40] and was chosen as the method to handle missing values in this work. Additionally, estimations with single imputations are based on simpler relationships, therefore promoting practical application for local authorities and network operators of small WDNs. For calculations, official and free available governmental data (e.g., number of inhabitants, overnight stays, and number of buildings) were used as input parameters to estimate assumed missing values. The estimated (assumed missing) data can then be validated with actual available data.

A water consumption of 250 L per inhabitant per day, including domestic, agriculture, and industrial use, and a water usage of 200 L per overnight stay was assumed to calculate annual water demand. Figure 2a shows a comparison between calculated water demand and measured network inflow from supervision reports reduced by estimated water losses. One municipality has a high amount of water demand for snow making, and was therefore not considered further [28]. In the case of a missing number of service connections, this value was estimated by using the number of buildings in a municipality. Figure 2b shows the correlation between number of buildings and number of service connections. In two municipalities, consumers are only partially supplied with drinking water from the public WDNs, therefore, these municipalities were not considered further for evaluations.

A correlation analysis revealed that both correlation coefficients (r) are higher than 0.9, indicating a good correlation between measured and estimated values. Consequently, number of inhabitants and overnight stays allow for a good assumption of annual water demand, and number of buildings allows for a conclusion of service connections in the case of missing data. In the case of missing length, length of service connections was assumed to be 15 m.

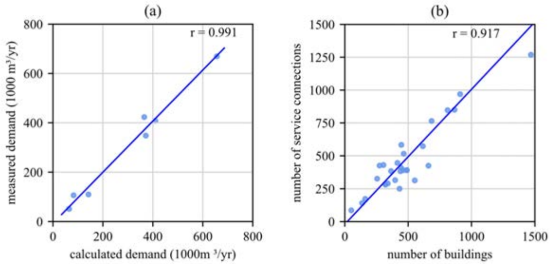

Figure 2. Correlation between (**a**) calculated water demand based on water assumptions per inhabitant and overnight stays and measured water demand as a total inflow reduced by estimated water losses and (**b**) number of service connections and number of buildings.

3. Results and Discussion

3.1. Evaluation of Water Loss Performance

The infrastructure leakage index PI_{ILI} was applied to evaluate and compare the performance of the 40 WDNs. As shown in Figure 3a, the PI_{ILI} ranged from 0.15 to 12 for the investigated WDNs. In particular, smaller systems with low water demands had a wide variation of that *PI*. Consequently, there was no correlation between water demand (as an indicator for population size) and PI_{ILI}, which was indicated by a pearson correlation coefficient of 0.24. In total, 9 WDNs, having a water demand less than 0.4 million m^3 (corresponding to 300–7000 inhabitants), had a value less than 1.0. These results are in accordance with the findings of a recent study, in which 24 of 54 investigated WDNs in Austria had a PI_{ILI} lower than 1.0 [31]. As described by the authors, there are two possible explanations for such low values. Basically, PI_{ILI} is calculated as a ratio between real losses and real losses reduced to technically unavoidable levels. First, continuous night flow measurements allow for a rapid identification of leakages in small WDNs, therefore, real losses can be decreased significantly. Secondly, design, installation, and maintenance efforts are high in Austria due to local standards and guidelines for reducing the reported number of failures and water losses. Consequently, the number of failures in Austria is lower than assumed in the calculation of technically unavoidable losses, supporting lower PI_{ILI} values. Another explanation is that water losses in small WDNs can be too low to measure. In this case, water losses are often underestimated, resulting in lower PI_{ILI} values.

Another disadvantage of PI_{ILI} is the large number of network parameters required for calculation. In this context, Figure 3b–d compare the simpler PI_V (ranging from 3 to 104%), PI_L (ranging from 0.02 to 1.15 m^3/h/km), and PI_C (ranging from 25 to 1290 L/day/service connection) with PI_{ILI}. Since water consumption instead of system input was used as a comparative value for calculation of these *PI*s, values above 100% are possible (occurring in one investigated WDN). In this case, (estimated) water losses were higher than water consumption of all consumers. As can be seen, the pearson correlation coefficient is for all configurations was very high (above 0.95), indicating that all simpler *PI*s are a good substitution for PI_{ILI} in smaller WDNs. However, only PI_V has the advantage of a practical evaluation. The advantage of PI_V is that it can be easily calculated, whereas PI_L and PI_C can be used only for parts of the WDNs due to limitations regarding service connections. We suggest using PI_V for small WDNs (less than 10,000 inhabitants) and PI_{ILI} for medium networks (greater than 10,000 inhabitants) in Tyrol.

To test the robustness of the chosen approach (estimation of missing demand and number of service connections based on number of inhabitants, overnight stays, and number of buildings), Table 2 shows correlation coefficients between the investigated *PI*s with $PI_{ILI.}$ for different missing data techniques (complete datasets, available datasets, or estimation of missing values). Although different missing data techniques were applied, the correlation coefficients did not change significantly, and, therefore, the obtained relations are robust in terms of data availability. Additionally, complete, and missing datasets are color-coded in Figures 3–5. However, simplified missing data techniques (e.g., single imputation) imply that uncertainties of variables affect the results and robustness of the chosen approach. In contrast, more complex procedures, such as multiple imputation, include uncertainty analysis by generating multiple datasets with plausible values [39–41]. Moreover, uncertainty and sensitivity analyses can be carried out to investigate the influence of uncertain input parameters [42]. However, these tools are time-consuming, and are, therefore, in conflict with the requirements of *PI*s for small municipalities and local authorities, which have to deal with limited time and human resources for goal-oriented water loss management. In this context, the *PI*s and also the data collection should be as simple as possible for a practical application. Consequently, detailed and time-consuming uncertainty and robustness analyses are not the focus of this work. Therefore, the results are subject to statistical fluctuations, but, as can be seen from the figures, this simple approach can compensate very well for a lack of basic data.

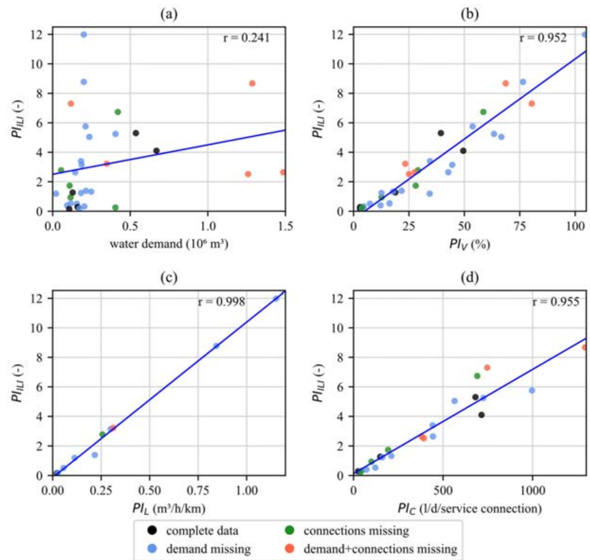

Figure 3. Correlation of infrastructure leakage index (PI_{ILI}) with (**a**) total annual water demand, (**b**) volume related *PI* (PI_V), (**c**) PI_L, and (**d**) PI_C.

Table 2. Correlations between different *PI*s with PI_{ILI}.

	PI_V	PI_L	PI_C
Complete dataset	0.931	- [1]	0.969
Available datasets (connections missing)	0.952	1.000 [2]	0.952
Available datasets (demand missing)	0.954	0.998	0.965
Estimation missing data (used approach)	0.952	0.998	0.955

[1] only one value; [2] two values.

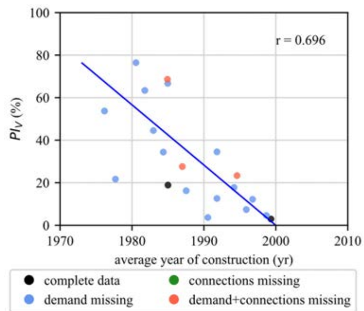

Figure 4. Correlation of volume related *PI* (PI_V) with average year of construction.

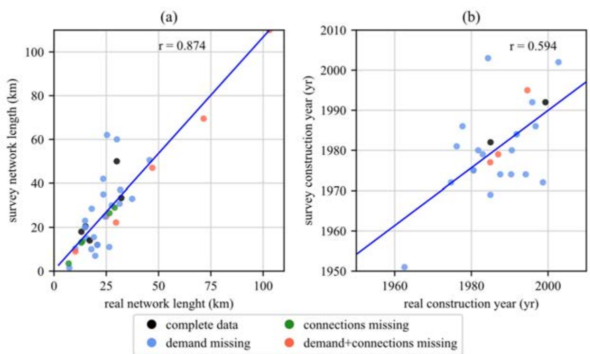

Figure 5. Correlation of (**a**) real network length from the pipe information system and estimated network length form the survey and (**b**) real construction year from the pipe information system and estimated construction year from the survey.

3.2. *Identification of Water Losses*

Leakage detection campaigns were utilized in 9 WDNs to detect and localize network failures. The results were divided into different network elements, namely: main pipes, service connections, hydrants, and valves; these are summarized in Table 3. As can be seen, failures were the most frequent at service connections with an average value of 4.5 failures per WDN. One reason for this can be retrofitting of existing WDNs with house connections, whereby for this process the main network is usually subsequently bored. In total, an average of 1.8 L/s (or 6.5 m^3/h) of drinking water is lost through faulty service connections. The second most common failure was found in hydrants, with an average of 1.9 hydrants per WDN showing a leakage. Interestingly, an average water loss of 0.2 L/s (or 0.7 m^3/h) is the lowest for faulty hydrants compared that of to other network elements. In contrast, failures in the main pipes occur on average 1.6 times per WDN, causing drinking water losses of 1.2 L/s (or 4.3 m^3/h). For the last investigated network element, the valves, a total of 0.6 faulty valves per network were detected, corresponding to an average additional water loss of 0.4 L/s (or 1.5 m^3/h). For the total network, water losses were on average 3.8 L/s (or 13.7 m^3/h), with a peak value of 13.0 L/s (or 46.8 m^3/h).

Table 3. Results of the leakage detection campaigns.

Property	Network Elements	Minimum	Average	Maximum
Failures (-)	Main pipes	0.0	1.6	4.0
	Service connections	0.0	4.5	14.0
	Hydrants	0.0	1.9	5.0
	Valves	0.0	0.6	2.0
Water losses (l/s)	Main pipes	0.0	1.2	4.2
	Service connections	0.0	1.8	6.1
	Hydrants	0.0	0.2	0.8
	Valves	0.0	0.4	1.7
	Total network	0.0	3.8	13.0

3.3. Experiences Regarding Rehabilitation

As shown before, the volume-related PI_V represents a good substitution of the complex leakage infrastructure index PI_{ILI} for smaller WDNs and is therefore used to discuss experiences with rehabilitation measures in Tyrol. As expected, water losses show a clear correlation with average year of construction, as can be seen in Figure 4. The investigated WDNs were constructed on average between 1962 and 1999. With increasing age, water losses increase sharply, whereas on average younger WDNs show significantly lower water losses.

Further important findings are:

- Rehabilitation: Although one WDN was very old, it has the lowest PI (PI_V is 7%). The initial WDN was constructed in the 1930s with first extensions and then renovations in the 1940s and 1950s, respectively. In the last few years, the network operators have put a lot of effort into renewing the system, reducing both average year of construction (now 1999) and water losses.
- Rehabilitation planning using survival curves: Only one of the investigated WDNs documented repair work due to bursts and leaks in a detailed way such that they could be used for estimating expected service life of pipes with the same construction year. Consequently, rehabilitation planning using survival curves does not provide statistically relevant information for network renewal as the data base is too small in small WDNs.
- On-line hydraulic monitoring: One WDN with less than 1,000 connected inhabitants had water losses of 3% of the total water demand. To achieve such a low value, the network operator installed an online monitoring system several years ago. By continuously measuring the system inputs, irregularities and anomalies can be detected, and bursts and leaks can be repaired relatively quickly. In contrast, none of the investigated WDNs used pressure sensors for leakage detection as pressure fluctuation are low due to overdesigned pipes (e.g., regulations about fire flow and minimum pipe diameter) and low water extractions (e.g., distributed system with a low number of connected inhabitants).
- Leakage detection campaigns: Two larger WDNs had a PI_V between 20 and 30%, corresponding to a PI_{ILI} between 2 and 3, although one of them had a very complex network structure with different pressure zones. To obtain these relatively low levels, leakage detection campaigns were carried out every year to detect failures in the WDNs. As reports from the network operators indicate, lower values of water losses were hard to achieve, but could be maintained through annual inspection. Additionally, repairing bursts and leakages, which are detected by applying leakage detection campaigns, can reduce water losses significantly. For example, a WDN with approximately 1500 inhabitants could reduce water losses from 45 to 7% within two months.

Figure 5a,b show the correlation of real network length and construction year from the pipe information system with results of the network survey in 2012. Interestingly, there is a difference between the level of knowledge of network operators and the actual WDN characteristics. For example, differences regarding network length were up to 36 km, whereas there was a considerable discrepancy in age of up to 18 years. As discussed above, average construction year can be related to amount of water losses, whereby older construction usually correlates with high water loss. Failure rates and associated leakages increase with pipe age [43] raising the amount of water loss. Consequently, values of *PI*s (e.g., PI_{ILI}, or PI_V) also increase, showing a worsening of system performance. Therefore, the promotion of pipe information systems should be expanded further in future to obtain a conclusion on actual age and to implement appropriate measures.

3.4. Additional Problems Faced by Network Operators of Small Municipalities

Additionally, the network operators described the following problems in their reports, which they have to deal with during operation:

- Private swimming pools: One of the main stresses affecting small WDNs is the high increase of private swimming pools and the filling of them with drinking water in spring and refilling in summer, which increases required drinking water demand considerably. As mentioned above, online monitoring systems are used to monitor system performance, where an increase of system input can indicate leakages in the system. Therefore, it is difficult to distinguish pool fillings from real leakages, though the period for pool filling can be limited to warm weekends in spring and summer.
- Conflict between settlement expansion and source protection areas: In Tyrol, protection zones have been established for many drinking water sources, in which handling of harmful substances and constructions are restricted. Additionally, settlement area is increasing due to constant expansion. Consequently, an increased potential for conflict between protection of drinking water resources and urban use of the landscape has been identified, and this conflict will increase further in future.
- Limits of harmful substances: At this state of legislation, expansive countermeasures are needed to reduce harmful substances in drinking water. Currently, there is a discussion about decreasing the limits of harmful substances, mainly focusing on arsenic, antimony, and uranium. These substances can be of natural origin (e.g., granite and gneiss are sources of uranium and were common in the case study), but human influences, e.g., contaminated sites in the form of former landfills, can also be identified as possible causes. In this context, this ongoing process may help the water utilities.

4. Summary and Conclusions

In this work, experiences of water loss management in small water distribution networks (WDNs) located in the federal state of Tyrol (Austria) were presented. Tyrol has in total 279 municipalities with 757,850 inhabitants, and 150 municipalities have less than 1500 inhabitants. In this context, water loss management, with the key steps of water loss assessment, identification of the locations of water loss, and rehabilitation planning, is a major challenge for such small systems. In this regard, 40 WDNs with a supply area ranging from 0.36–120 km^2 were investigated in detail, combined with a comprehensive discussion about Austrian standards and state funding regarding water loss management with a special focus on offerings and their practical applicability to small WDNs.

The results of water loss performance indicators (*PI*) (e.g., based on water loss volume, network characteristics (network length, number of service connection), or infrastructure leakage index) show a good correlation to each other. We therefore recommend the usage of water loss divided by water demand as a simple *PI* for small WDNs in Tyrol. The advantage is that this indicator is easier to determine than is the infrastructure leakage index recommended in the literature, but provides more or less the same evaluation criteria for local authorities. However, for larger systems (more than 10,000 inhabitants) the infrastructure leakage index should be additionally considered.

As the evaluation indicates, public funding helps to significantly reduce water losses in individual systems. Examples of state funding are leakage detection campaigns in combination with repair strategies or rehabilitation planning based on development of a pipe information systems. As the experiences demonstrate, these measurements should be established in future for larger WDNs in Tyrol.

However, without appropriate state funding, these measurements to reduce water losses in WDNs would not have been such successful. In contrast, there is a lack of reliable data for rehabilitation planning for small WDNs. Additionally, small WDNs have neither enough qualified employees nor investment resources to carry out advanced water loss strategies. Therefore, we suggest an online flow metering system to monitor system inflows for small WDNs. Based on the measurement data, leakages and bursts can be detected and repaired swiftly.

The evaluations were carried out for a limited number of small WDNs in Austria. However, it is expected that results can generally be transferred to small WDNs in other countries in the case of similar initial conditions (large WDNs length compared to supplied inhabitants and low revenues). Additionally, upcoming digitization (e.g., digital water meters and daily water consumption data at household scale) and increasing citizen engagement (e.g., reporting of failures) can be used to develop and implement new operational approaches in urban water infrastructure. Consequently, water loss management can be improved too, and makes room for future research activities in the smart cities concept.

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6 Conclusion and Outlook

6.1 Summary of conclusions

Due to the Internet of Things (IoT) concept, measurement and control equipment can be implemented even at underground and remote structure, allowing new possibilities in the management of network-based urban water infrastructure (UWI), e.g., water distribution and urban drainage network, and nature-based solutions. Additionally, system-wide management in interaction with urban population and other infrastructure is gaining in importance. Therefore, the main aim of this doctoral dissertation was to develop and analyse innovative concepts in the field of network-based UWI to contribute to this ongoing development. The main steps and conclusions for each research objective described at the beginning of this work are summarised below.

Objective 1: Literature review: data requirements and communication technologies for network-based UWI

- Existing and new applications in the field of network-based UWI are characterised by different requirements on spatial (household to city scale) and temporal (seconds to months) resolution of measurement and control data.
- Measurement and control data can be transmitted via wired and wireless (short and medium ranges, cellular, and low power wide area networks) communication technologies, whereas each communication technology has different features (e.g., data rate, transmission range) and limitations (e.g., number of data packets per day, energy consumption).
- Consequently, an efficient monitoring and control network requires a coordination between usable communication technology and intended application, which is not sufficiently considered by existing frameworks.
- To overcome this limitation, a detailed framework was presented which can be used as a decision making-tool by researchers, network operators and stakeholders. This framework is intended (1) to identify suitable communication technologies for different applications or (2) to define applications for an existing communication network.
- However, a combination of different communication technologies will be required to satisfy all specifications for integrated system-wide management or smart water city developments.

Objective 2: Proposing the smart rain barrel (SRB) concept

- The concept of the smart rain barrel (SRB) was introduced as an IoT-based micro storage for advanced rainwater harvesting (RWH). The SRB consists of a conventional rain barrel available in normal hardware stores, which is extended by a remotely controllable discharge valve. Measurement data and control commands are exchanged via LoRaWAN, which allows an integration into a smart city environment.

- The SRB can be emptied before rain events based on high-resolution weather forecasts. As simulation results at household level show, detention volume can be increased considerable, whereas the impact is most significantly in case of a (partially) filled rain barrel.
- Furthermore, the open-source simulation tool "Smartin" was developed, which is capable to model and simulate IoT-based micro storages in a coupled model of urban drainage and water distribution network in real-time. The software is based on SWMM5 and EPANET2.2, thereby enabling a very high spatial (at household scale) and temporal detail.
- The functionality of "Smartin" was tested by hypothetically retrofitting an existing infrastructure of an Alpine municipality with a large number of IoT-based micro storages (more detailed, SRBs).
- As results show, a large-scale implementation of SRBs can improve overall system performance by reducing combined sewer overflow (CSO) and substituting drinking water demand with rain water.

Objective 3: Performance optimisation of a large-scale implementation of SRBs as IoT-based micro storages

- In case of a large-scale implementation, an uncoordinated emptying (e.g., simultaneously opening discharge valves) can create an artificial CSO event in case of unfavourable conditions (e.g., partially filled CSO structure due to previous rain events).
- Therefore, control strategies including data of sewer states should be preferred. Additionally, importance of coordinated control strategies increases with storage volume added.
- However, effectiveness is strongly related on rain characteristics (e.g., amount of precipitation, rain pattern) and increases with lower CSO volume as SRBs provide limited additional detention volume.
- Furthermore, digital uncertainties (e.g., accuracy of weather forecasts, reliability of data transmission) can reduce/eliminate performance improvement, therefore an sufficient consideration of these parameters is of greatest importance.
- Subsequently, a large-scale implementation of SRBs can provide a good alternative for required system extensions in case of integrated performance improvements. However, recommendations are strongly related on preferred performance improvements (CSO and/or RWH optimisation).

Objective 4: Smart applications in real-world implementation

- To gain real experiences with high-resolution data, a university campus of Innsbruck, called "Smart Campus", was equipped with measurement and control devices. Therefore, a variety of parameters (e.g. soil moisture, water level, surface temperature, water pressure, water consumption, and climate data) are measured and transmitted in high resolution at intervals of 1 to 15 minutes.
- These data provide detail insights into system conditions, and therefore, the "Smart Campus" represents an ideal testing place for innovative concepts in the field of network-based UWI.

- In this context, a prototype of the SRBs, which is under operation at the "Smart Campus" during the summer months, and a warning system for water losses were presented as exemplary applications.
- The implementation of a high-resolution measurement network and smart applications (e.g., SRBs) are also associated with several challenges, requiring corresponding expertise and installation and maintenance are time-consuming. In contrast, the analysis of water losses in small municipalities in Tyrol (Austria) has shown that also "simpler measures" can contribute to a more sustainable operation as one of the main aims of smart cities.
- For example, state funding (e.g., leakage detection campaign) and online flow metering (e.g., monitoring inflow to detect detect leakages and bust) can help to significantly reduce water losses.
- Additionally, a volume related performance indicator (e.g., water loss volume divided by total water demand) can be used to evaluate water loss in small water distribution networks, which has the advantage of minimal efforts (e.g., data availability) and easy calculation.

6.2 Critical Discussion

The results of this doctoral dissertation show, that smart applications can (significantly) improve performance of existing systems. This potential is also well documented in literature, and smart applications can therefore be possible measures for future challenges caused by climate change, urbanisation, and maintenance in UWI.

However, digitalisation and smart city projects imply also new challenges for implementation and operation, raising security and privacy issues, and subsequently an critical discussion is essential. As these issues are already discussed in detailed in relevant literature (Ahad et al., 2020; Balogun et al., 2020; Bibri and Krogstie, 2017; Silva et al., 2018), this dissertation provides a short description with special emphasis to UWI.

First, the installation and operation of a ICT requires investment costs and resources as well as maintenance work to uphold the functionality. Additionally, battery-powered measurement devices will be significant for monitoring UWI, as remote and underground structures usually do not have a connection to the power grid. Consequently, the realisation of a measurement and control network will raise economic and ecological questions, which are currently not sufficient meet by literature (including this doctoral dissertation). In contrast, one of the main objectives of smart cities is to achieve economic and ecological sustainability. Therefore, a balance between deployed measurement sensor technology, intended use and prognostic effectiveness is required to fulfil this objective.

Second, management of UWI can benefit from increased data availability in terms of real-time operation and fault management. However, digital applications and access points also increase the vulnerability of the entire systems to cyber-physical attacks (e.g. hacking of critical system points) (Housh and Ohar, 2018; Rasekh et al., 2016). As number of participants is experted to increase in future (also as result of smart cities), this development may be further intensified. Additionally, high-resolution measurements of water consumption at household level are subject to applicable laws, e.g., the European General Data Protection Regulation (GDPR), as these data provide insight into personal lifestyle. Subsequently, dealing with these issues in an appropriate way will be an important factor for the future success of digitalisation research in the field of UWI (Moy de Vitry et al., 2019).

Third, the transformation of applications from purely technical to integration of a wide range of participants also implies in new requirements for the project team and the realisation. Additionally, realisation of an efficient monitoring and control network at high spatial and temporal resolution will require the involvement of the public. Following, importance of content communication increases to integrate different participants into the project, requiring interdisciplinary approaches. In contrast, functions of UWI are often unknown to the public as in case with positive effects of nature-based solutions on urban environment (Derkzen et al., 2017), whereas willingness of network operators to implement new technologies is also limited as stated by Yuan et al. (2019). Consequently, future research needs to investigate how to overcome these barriers caused by economic, human, technical, and regulatory reasons.

Finally, it is important to mention, that smart system components modify the previous behaviour of UWI and can also lead to a deterioration of system performance in cause of unfavourable conditions and/or inappropriate control strategies. For example, this effect was observed in Paper III and IV investigating the impacts of a large-scale implementation. In this context, an uncoordinated and simultaneously opening of the discharge valves of SRBs implemented could create an artificial combined sewer overflow (CSO) event in case of a partially filled CSO structure due to previous rainfalls. Furthermore, as shown by Paper III, uncertainties of digital parameters (e.g., accuracy of weather forecasts and reliability of data communication) have the potential to reduce/eliminate gained improvements. Therefore, the implementation of any kind of smart applications in large-scale requires a sufficient coordination between existing UWI infrastructure, smart applications, and communication networks.

From the author's view, a sufficient consideration of these factors is therefore a decisive criterion for the future success of the digitalisation and smart water cities development. Subsequently, addressing these factors properly before and during projects will enable the full potential of these systems.

6.3 Outlook

As the development of smart water cities is in its early stages, there is a wide range of future research topics to explore. Following, exemplary research topics are given, which can be seen as an extension to this dissertation:

- First, very much related to this dissertation, a detailed description and writing of a publication of the Smart Campus is still missing to share and disseminate the experiences made to the public and scientific community.
- The smart rain barrel presents an exemplary application for smart nature-based solution. This approach can be applied to other types of nature-based solutions (e.g., smart green roofs), whereby a main focus can also be on intelligent and coordinated control strategies between a variety of smart network elements.
- Great potential is also seen in an accurate emergency and crisis management of water supply systems, for example in detecting and localisation of leakage (Sanz et al., 2016; Sophocleous et al., 2019) and contamination events (He et al., 2018; Krause et al., 2008), and the identification of cyber-physical attacks (Housh and

Ohar, 2018; Taormina et al., 2017). However, these approaches are hardly tested in a real environment and due to lack of real-time data, available data (e.g., annual water consumption data of water meters) is mostly scaled down to simulation steps.

- Furthermore, new incidents can be defined due to the global Covid-19 crisis (e.g, pathogens transmissible via waste water and/or drinking water or uncoordinated withdrawal of drinking water for storage purposes (similar to hoarding purchases of toilet paper)), opening up future research topics.
- Additionally, applications are transforming from purely technological solutions to smart city approaches based on involvement of urban population. Subsequently, there is a need to also address social science (e.g., how to involve and communicate with the public) to support implementation and effectiveness of the intended applications.
- Finally, the installation and operation of a measurement and control network requires investment costs and resources, and battery-powered measurement devices are commonly used. Therefore, future research need to investigate ecological and economical impacts of digital water systems in more detail to achieve sustainability.

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