2nd International Joint Conference on Water Distribution Systems Analysis & Computing and Control in the Water Industry
Valencia (Spain), 18-22 July 2022
doi: https://doi.org/10.4995/WDSA-CCWI2022.202214441

LONG-TERM TRANSITIONING OF WATER DISTRIBUTION SYSTEMS: ERC WATER-FUTURES PROJECT

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Abstract

The percentage of the world population living in urban settlements is expected to increase to 70% of 9.7 billion by 2050. Historically, as cities grew, the development of new water infrastructures followed as needed. However, these developments had less to do with real planning than with reacting to crisis situations and urgent needs, due to the inability of urban water planners to consider long-term, deeply uncertain and ambiguous factors affecting urban development and water demand. The "Smart Water Futures: Designing the Next Generation of Urban Drinking Water Systems" or "Water-Futures" project, which was funded by the European Research Council (ERC), aims to develop a new theoretical framework for the allocation and development decisions on drinking water infrastructure systems so that they are: (i) socially equitable, (ii) economically efficient, and (iii) environmentally resilient, as advocated by the UN Agenda 2030, Sustainable Development Goals. The ERC Synergy grant project tackles the "wicked problem" of transitioning water distribution systems in a holistic manner, involving civil engineering, control engineering, machine learning, decision theory and environmental economics expertise. Developing a theoretical foundation for designing smart water systems that can deliver optimally robust and resilient decisions for short/long-term planning is one of the biggest challenges that future cities will be facing. This paper presents an overview of related past research on this topic, the knowledge gaps in terms of investigating the problem in a holistic manner, and the key early outcomes of the project.

Keywords

Drinking water networks, transitioning, real-time monitoring, long-term design, sustainability, deep uncertainty

1 INTRODUCTION

Nearly 80% of the world's population is exposed to high levels of threat to water security due to anthropogenic climate change [1]. Latest studies confirm that considerable changes in freshwater resources have been occurring across the globe, indicating a future in which already limited water resources will become even more precious [2]. On the other hand, the continuous expansion of the urban footprint means that an estimated 70% of the world's population will live in urban areas by 2050 [3]. The dramatically increased water demands resulting from this unprecedented urbanization, together with increasingly uncertain climate conditions indicate the need for a holistic, intelligent decision-making framework for managing water infrastructures in the cities of the future. This framework needs to ensure that allocation and development decisions on water infrastructure systems will be made in a socially equitable, economically efficient and environmentally resilient way as advocated by the UN Agenda 2030, Sustainable Development Goals, SDGs [4]. Consequently, there is a need for a new approach to designing the next generation of urban drinking water systems that applies not only to the planning and management of mature water infrastructure systems such as those found in developed countries, but also to developing countries where the fastest population growth is predicted over the next 50 years. We need a framework that can: (i) adapt to evolving urban water networks, new sensing technologies and consumer behaviours; (ii) integrate real-time monitoring and control with long-term planning and policy-making; (iii) assimilate water quality issues with water supply problems; and (iv) incorporate economic, social, ethical and environmental considerations. Moreover, the new framework needs to be human-centric so that intelligent algorithmic solutions are explainable and acceptable by human policymakers, managers, operators and consumers.

The "Smart Water Futures: Designing the Next Generation of Urban Drinking Water Systems" or "Water-Futures" project, which was funded by the European Research Council (ERC), aims to develop a new theoretical framework for the allocation and development decisions on drinking water infrastructure systems [5]. We consider four challenges for the development of the framework for drinking water systems: scenario-based staged development, real-time smart operation, explainable machine learning and economic considerations. This paper presents an overview of related past research on this topic, the knowledge gaps in terms of investigating the problem in a holistic manner, and the key early outcomes of the project.

2 SCENARIO-BASED STAGED DEVELOPMENT OF DRINKING WATER SYSTEMS

2.1 Staged development

World cities are facing crucial policy decisions about how to achieve long-term water security considering their ageing water infrastructures. The key challenges are based on whether cities: (i) can anticipate the future growth trends; (ii) will adopt a long-term perspective; (iii) will take into account decision robustness; (iv) will consider policy flexibility; and (v) are keen to develop strategic visions to support water infrastructure planning decisions [6]. Most of the early planning models were based on financial criteria and considered only pipes as network elements for replacement or renewal at a particular future time, i.e., a static, one-stage problem of deciding when it is economic to replace a pipe [7],[8],[9]. Engelhardt et al. [10]reviewed long-term planning strategies for water infrastructures and identified key advantages of implementing an optimisation-based, holistic approach to infrastructure planning. Several studies have since optimised mainly small benchmark systems considering one, or at most a limited number of the following issues: (i) a single-objective economic criterion; (ii) a static, one-stage problem; (iii) ideal foresight; i.e., the correct prediction of future; (iv) only pipes as decision variables; and (v) perfect rationality of decision-makers [11], as seen in Figure 1. What is currently missing, is extending the problem of planning and management into the more generalized problem of sustainable transitioning of urban water systems, considering multiple objectives and decision variables (e.g., pricing, investment, number of sensors to install), while considering both hydraulic and quality dynamics as well as deep uncertainties.

Staged design of drinking water networks may be defined as the problem of identifying a sequence of design decisions that need to be taken over several consecutive stages during the planning horizon, to optimize benefits and costs, subject to specific constraints at each stage [12]. Optimization tools are often used to seek the best sequence of interrelated designs, which cannot be optimized individually as each of them encompasses the solutions from previous stages. The main advantage of staged development is the ability to use *an adaptive design strategy* to make decisions that adapt over time to changing circumstances rather than base them on a fixed design over the entire planning horizon. This is particularly important when decisions have to be made under deep uncertainty with multiple possible futures, such as in the case of increased climate variation.

	STANDARD APPROACH	WATER-FUTURES APPROACH
Multi-objective optimization	✗	✓
Multi-stage decisions	✗	✓
Deep uncertainty considered	✗	✓
All network elements	✗	✓
Perfect rationality of DM	✓	✗

Figure 1. Approaches to long-term planning strategies for water infrastructure, the standard approach vs. the approach taken by the Water-Futures project

With the realisation that climate change poses fundamental threats to infrastructures, people and urbanised areas, the last 20 years have witnessed an increase in research related to the impact of deep uncertainty on the long-term security of water infrastructure systems [13]. Combined with that, two key considerations have to be incorporated into the adaptive design of drinking water networks:

1) *Design flexibility* - the ability to implement the first-stage design while keeping a view of the long-term system development, and

2) *Design robustness* - the ability of a design to satisfy as many future scenarios as possible.

2.2 Long-term scenarios

While several researchers have developed approaches to introduce flexibility and/or robustness to infrastructure planning [14], [15], [16] [17], the ultimate goal of integrating short-term and long-term planning activities in a holistic theoretical decision-making framework under deep uncertainty (e.g., climate, demographic or economic projections) has not been addressed.

Engineers are accustomed to using historical data in the design of infrastructure. For example, demand projections based on past realisations are used to assess the need for new infrastructure. However, predicting the long-term future is extremely difficult and often ends up with wrong predictions. For example, when twenty-seven top US scientists in the sixties predicted what the world would look like in 20 years; out of 335 predictions, nearly all were wrong [18]. Multiple scenarios are used instead to provide a better understanding of the range of possible environments the water infrastructure system must contend with in the future. Using multiple scenarios avoids the situation when building a water infrastructure project specifically for one (wrong) scenario, but uses a diversity of scenarios over which the project should perform robustly and satisfactorily [13].

3 REAL-TIME SMART MANAGEMENT OF WATER DISTRIBUTION SYSTEMS

Decision making in urban water distribution networks can be viewed in terms of the long-term planning and management, discussed in the previous section, as well as in terms of the operational management of the water system, which is characterized by real-time and short-term decisions. Real-time decision making is typically implemented by automated systems or algorithms and supervised by water operators during the everyday monitoring and control of the system. In this section, we focus on some of the key issues that need to be addressed in real-time monitoring and control of urban drinking water distribution systems, especially in view of new technological advances that are starting to become widely available for the management of water distribution systems.

The objectives of monitoring and control of water systems include detecting and resolving unanticipated events in the system, controlling the system parameters to minimize losses and safeguard quality, optimising resource allocation and making sure the system works in the most efficient way (e.g., energy efficiency). On the other hand, real-time monitoring and control must be aligned with the long-term management and planning decisions, as well as the general high-level policies. This includes monitoring how the risk of abnormal events changes in time and how to reconfigure the system in order to mitigate extreme events, which may be of low probability but high impact. At the same time, it is crucial that future technology developments (e.g., new embedded sensors and actuators) will not increase risks to urban water systems (e.g., malicious attacks).

Various aspects of the real-time monitoring and control problem have been investigated in water systems [19]. In practice, usually, the system parameters are unknown, therefore the models need to be calibrated using an optimization method [20],[21]. Since water consumption affects the flows in a network, consumers play an important role in the dynamics of drinking water distribution systems, and their behaviour has been studied and modelled [22][23][24]. Moreover, placement problems have been studied, to determine where to optimally install water quality and hydraulic sensors, to improve event detectability [25],[26]. Using sensor information, various methods have been proposed for contamination diagnosis [27],[28],[29], as well as leakage detection and localization [30]. In parallel to monitoring, feedback control methods have been proposed for water quality control [31],[32], pump scheduling [33] and pressure valve control [34][35].

From a monitoring and control perspective, water distribution systems are cyber-physical-social systems [36] with multiple interactive dynamics and feedback loops:

- *Physical part* – this includes all the physical components that are required for the normal operation of a water distribution system, such as pipes, tanks, valves, etc
- *Cyber part* – this includes all the algorithms that are required for monitoring the operation of the water system and for autonomously controlling the behaviour of the physical system.
- *Social part* – this includes the human behaviour that influences the operation of the water system, such as the water demand of consumers, behaviour of operators and policy makers, etc.

The cyber-physical-social framework for the design and analysis of real-time monitoring and control methods for water distribution systems facilitates a holistic approach that takes into consideration the embedded nature of the cyber-physicals parts of the system, while at the same time incorporating human behaviour (social part), which is an integral part of the operation of water systems. The dynamics of drinking water distribution networks include the hydraulic dynamics (e.g., flows and pressures) and the water quality dynamics (concentration of various chemical substances and biological species). Due to the conventional decay of chemicals over time, the hydraulic dynamics affect the water quality dynamics.

During the last few years, there have been significant advances in the development of new sensing devices that measure various hydraulic and quality parameters of water systems. These sensing devices are often deployed in an Internet-of-Things (IoT) setting, with the capability to be embedded and integrated with real-time decision and control algorithms.

It is anticipated that this technological trend will continue in the future with further proliferation of IoT technology and the advancement of information and communication technologies and data analytics. This will result in novel sensing devices for measuring water quality and hydraulic parameters, which are expected to be smaller, cheaper and possibly easier to install and maintain. Moreover, these devices will be connected to the internet, so the information will be available for processing in real-time, both to human operators as well as to algorithms for automated decision making. Other advances that are affecting the operation and smart management of water distribution systems are the development of virtual sensors, which are based on algorithmic methods for measuring parameters at certain locations (in contrast to hardware devices) [37], and IoT actuators, which are internet-enabled devices that can enhance the automation and supervision processes of water distribution systems.

While these technological advances provide the potential for significantly enhancing the capability for real-time smart management of water distribution systems, they also pose some key challenges and risks. For example, with the wide deployment of internet of things devices, there are risks associated with privacy issues, which need to be seriously addressed. Moreover, there are significant risks associated with the potential of malicious cyber-physical attacks. Since water systems are critical infrastructures (similar to energy and power grids, telecommunication networks, transportation systems, etc), it is crucial that they are protected against any potential cyber-physical attack that may compromise its smooth operation, or even worse, cause contamination of the drinking water. Therefore, in addition to handling normal operation, real-time monitoring and control algorithms are required to be able to detect malicious attacks and to be able to distinguish between normal or accidental faults (e.g., sensor faults, actuator faults) and malicious attacks (e.g., replay attacks).

4 EXPLAINABLE MACHINE LEARNING

Although hydraulic equations of water distribution systems (WDS) are well understood, and powerful simulation technologies of WDS exist [38], modelling of real networks is subject to severe uncertainties: More than 16% of water pipes have surpassed their useful lives and face serious ageing and deterioration challenges, where the exact state is usually unknown [39]. Moreover, optimal planning and control depend on expected future demand, a widely unknown quantity in particular in the light of yet unclear effects caused by global warming or growth of cities [40]. In such settings, data-driven modelling and prediction constitute one possibility to match formal models to reality.

The increase of digital information including historical data on water demand as well as real-time sensor information, which mirrors the current state of the network, has led to a rise of data-driven methods, in particular machine learning models, in WDS. These offer crucial technologies, which are capable of enhancing physical simulation and control by information relevant for decisions which depend on the specific network state **¡Error! No se encuentra el origen de la referencia.**. Tasks which have been addressed by machine learning in this context are widespread: estimating the condition of water pipelines, leakage detection and localization, prediction and management of pipe failures, modelling of water quality, demand prediction, optimization of water treatment plans, early warning systems, or efficient data-driven optimization, to name just a few [39],[40],[41],[42],[43],[44]. Besides classical machine learning methods such as Bayesian modelling, random forests, or kernel methods, recent approaches often rely on deep learning [45],[46],[47].

In the context of WDS, a number of specific challenges arise, which cause the need for adaptations of common workflows in machine learning:

1) Heterogeneous data format – while most machine learning technologies have been designed for homogeneous vectorial data, measurements in the domain of WDS include

heterogeneous sensor data, which are subject to spatial and temporal characteristics. Mixed real-valued and discrete representations can render optimization difficult, and data heterogeneity causes the need for data assimilation [48]. In recent years, dedicated models which can directly deal with temporal or spatial data such as deep recurrent and graph neural networks have led to promising results [48],[49], but it is yet unclear how to best represent digital information in the light of underlying domain knowledge in WDS [58].

2) Imbalanced data and changing distribution – the frequency of observed phenomena does not necessarily scale with their relevance in WDS. As an example in the context of prediction and management, pipe failures are observed much less frequently than normal behaviour, hence the data distribution is skewed. As a consequence, machine learning models need to correct for such biases and deal with imbalanced data [43]. In real-time dynamic systems, another challenge is given by data drift, i.e., the fact that the data-generating process might change over time, caused by sensor fatigue or changing demands in developing cities, for example. Such phenomena lead to a violation of one of the fundamental assumptions of classical machine learning, the assumption that data are identically distributed and representative of the underlying regularity. Here special care has to be taken to continuously adapt machine learning models to possibly changing demands using online learning technologies [51][52][53].

3) Necessity of human-centred design – WDS as critical infrastructure directly affect humans in their daily life. Thereby, humans have different roles: (i) as customers to whom service is provided, (ii) as actors who determine the development of WDS via their behaviour (e.g. exhaustive consumption of water) and decisions (e.g. price policy), and (iii) as engineers who need to guarantee a sustainable quality of service. Human-centred design in WDS needs to take these roles into account to achieve robust functionality and sustainability of WDS [54]. While machine learning technologies can help in short-term control and long-term planning of WDS, the black-box nature of modern technologies such as deep networks adds a possible complication here: humans might be incapable of understanding the rationale behind decisions made by ML technologies, and human intention and objectives implemented in ML systems might be severely misaligned [55]. Hence human-centred design in WDS faces the challenge to make ML technologies transparent to humans.

4.1 Explainable AI (XAI)

Explainable AI (XAI) or, more specifically, explainable machine learning refers to methods which substantiate black box technologies with components which can be understood by humans [56]. Commonly, one distinguished global XAI methods, which provide insight into the global function of a model (such as the most relevant rules which characterize a leakage), and local XAI methods, which explain a single decision only (such as an explanation of why a specific sensor signal should be interpreted as a leakage rather than normal behaviour). In recent years, a variety of different technologies have been proposed, whereby they differ w.r.t the form of explanation (such as feature-based versus exemplar-based methods), the algorithmic choices used to compute the explanation (such as post-hoc methods versus embedded methods), and the objective of the explanation (such as proposing actions how to repair an observed fault versus explanations which specify who should be held liable for an observed failure).

Most local XAI technologies for deep models have been proposed in the last few years only; hence, in WDS, existing XAI approaches mostly focus on global models: as an example, natively interpretable global XAI methods have been proposed in the form of neuro-fuzzy-systems [41], i.e., extensions of logical rules to continuous measurements, which characterize conditions of water pipelines. Global hybrid explanation methods are presented in the work [58]: more specifically, leakage detection methods combine hydraulic transient modelling and machine learning technologies to extract the most relevant features based on which to design the model. Post-hoc technologies, which determine the most relevant features to decide the water quality in the context of Algal bloom for trained machine learning models, have been proposed in the work [57]. These latter methodologies belong to the class of feature-relevance-determination methods, using different principles to account for possible redundancies and correlations of the information which is contained in diverse sets of features.

In a recent approach, local explanation technologies have successfully been used to explain sensor failures in spatio-temporal networked data in WDS [59]: Here time series models predict local sensor values based on the neighbourhood, and a threshold strategy is used to indicate deviations of sensor measurements from expected behaviour. Afterwards, so-called counterfactual explanations are used to explain why the deviation takes place. Counterfactual explanations provide the information on what needs to be changed in the input to obtain the desired output change. They can be computed particularly efficient for specific models [60]. In the work [59], local counterfactual explanations are coordinated within the WDS in such a way that it becomes possible to identify the global source of the sensor fault as a `consensus' of all local explanations. The results demonstrate the benefit which arises when harvesting on the network structure in WDS for XAI methods, yet it still deals with a comparably simple setup. Recent advances in XAI technologies for deep graph neural networks [61] or distributional changes [60] offer promising starting points to explore the capabilities offered by XAI technologies for complex spatio-temporal systems as present in WDS.

4.2 Fairness and trust

Since XAI technologies provide insight into the mechanism based on which automatic decisions are taken, they offer a convenient possibility to inspect the objectives implemented by an AI model in an explicit form. In particularly, XAI methodologies enable humans to identify deviations of an AI model from the desired functional and non-functional goals set by a human partner. Here, two crucial objectives are fairness and trust.

The notion of `fairness' formalizes the intuition that an AI model treats individuals or groups similarly unless there are valid reasons not to do so. As an example, the outcome of a recidivism decision should be independent of a person's ethnicity, hence the latter should constitute a `protected' feature which does not influence the final outcome [63]. XAI methods can uncover violations of this objective, since they are capable of explaining the dependency of decision outcomes and such protected attributes. Indeed, it has been shown that there exist popular AI models used in practice which display a severe bias in diverse areas including automated hiring, recidivism assessment, or language models [63],[65]. In WDS, however, the notion of fairness is yet widely unexplored, albeit highly relevant. Here fairness refers to the question of whether access and quality of WDS are evenly distributed among all customers of a WDS unless prohibited by unavoidable physical constraints. In the light of long-term developments, fairness in WDS also refers to differences in costs, quality, and services of WDS over several generations.

The notion of `trust' summarizes the prerequisites which are required such that a human is willing to use an offered AI system. In the first place, this notion refers to the trust that the objectives aimed for by a human are met by the system, including non-functional ones such as fairness; beyond this alignment, it includes the trust that the AI model does so robustly and in possibly changing or adversarial realistic environments. Hence a second crucial demand to establish trust are guarantees for the security and safety of WDS in realistic and possibly changing environments [64]. Partially, robustness against attacks can be guaranteed by mathematical properties [62]. XAI technologies offer an additional avenue based on which to inspect, which attacks and changes can be harmful to a system – an opportunity which is yet widely unexplored in the domain of WDS.

5 ECONOMIC CONSIDERATIONS FOR LONG-TERM TRANSITIONING OF WATER DISTRIBUTION SYSTEMS

The Water-Futures human-centric approach aspires to develop a methodology that integrates economic, social, ethical and environmental considerations, with direct relevance to UN Agenda 2030, into an interdisciplinary decision-support framework that will allow agent-based societal welfare maximization in the short, medium and long-run, under deep uncertainty. In doing so our research focuses on five central unresolved scientific questions, challenging the traditional paradigm of Neoclassical Economics. These questions will drive our investigations for an alternative, deeper, more mature understanding of the structure of human preferences and the decision-making process.

The traditional paradigm in Neoclassical Economics toward welfare maximization passes through rationality. A rational agent is assumed to seek to maximize utility given information and geographical boundaries. However, research has shown that rationality is a situation that is relative and under (deep) uncertainty it is violated. Moreover, different definitions of rationality exist and each produces different results. Time and uncertainty are correlated, while uncertainty often takes the form of ambiguity (when probabilities of uncertain events are unknown). The term risk refers to situations in which the probabilities of events' occurrence are known, while the notion of uncertainty is broader and refers to situations in which this may not be the case [66]. Most decisions indeed must be made in situations in which some events do not have an obvious, unanimously agreed-on probability assignment. This might be because too little information is available or because different predictions exist, resulting from different models or datasets or different experts' opinions. Currently, the evaluation of climate policy is generally performed using models that do not distinguish between risk and uncertainty but actually reduce any kind of uncertainty to risk. In this task we will augment the mathematical decision-making framework towards treating deep uncertainty, enabling robust decision making with regard to the short, medium and long-run development of urban water systems under climate change, as short and long-run decisions should be dynamically consistent and integrated into a unifying framework.

People do not only differ in their tastes for goods and services, but also with regard to how selfish or fair-minded they are, which has important economic consequences. This also highlights the ethical dimension of welfare maximization, the concept of eudaimonia which has been neglected so far [67]. We will develop a mathematical decision framework for the allocation of urban water (over time and space, and between societal layers) and the development of the systems technology and infrastructure that supports this allocation, which will augment the current neoclassical paradigm to internalize the ethical dimension in decision making that lead societies to eudaimonia. The suggested augmentation builds on the literature on “Subjective Well-Being”, which has produced remarkable results over the last years on determinants of happiness, consequences of happiness, causality, integration into standard economics and policy consequences.

“Subjective Well-Being” entails a deeper understanding of human preferences with regard to public goods, such as water infrastructure and related environmental concerns. These preferences are not documented in any markets and as a result, we need to infer them from other choices people make, or to directly elicit them via field or laboratory experiments. Water-Futures will use non-market valuation experimental methods [68] aided by virtual reality experiences (to the best of our knowledge this is the first attempt for this integration) to elicit willingness to pay and welfare benefits for exciting, or planned water infrastructures. People's preferences and valuation are dynamic and are shaped by available information and people’s ability to understand this information -which is multidisciplinary and science hectic. Water-Futures search for responses to these challenges will build on a novel combination of the literature on “Subjective Well-Being” and “Experimental Behavioural Economics” for developing a new mathematical decision-making framework, integrated with the water systems engineering, optimal control and machine learning algorithms, that can support the design of smart urban water systems in a way that leads societies to eudaimonia (happiness via preference satisfaction). As far as implementation is concerned Water-Futures aims to use the systems innovation approach to co-design the future vision for urban water systems and co-develop the technological, policy, and financial pathways towards achieving this future vision, by engaging through living labs, all relevant stakeholders from different countries across the world.

In a response to United Nations Secretary-General Antonio Guterres' call for action: "Today, Sustainable Development Goal 6 is badly off track" and it "is hindering progress on the 2030 Agenda, the realization of human rights and the achievement of peace and security around the world", our endeavour is to support and accelerate the implementation of SDG6 for the people, the planet and their prosperity.

6 SUMMARY AND CONCLUSIONS

The dramatic rise in water demand resulting from unprecedented urbanization, together with increasingly uncertain climate conditions indicates the need for a holistic, intelligent decision-making framework for managing water infrastructures in the cities of the future. This framework needs to ensure that allocation and development decisions on water infrastructure systems will be made in a socially equitable, economically efficient and environmentally resilient way as advocated by the UN Agenda 2030, Sustainable Development Goals. Consequently, there is a need for a new approach to designing the next generation of urban drinking water systems that applies not only to the planning and management of mature water infrastructure systems such as those found in developed countries but also to developing countries where the fastest population growth is predicted over the next 50 years.

The new design approach needs to: (i) be adaptable to evolving urban water networks (in stages), new sensing technologies and consumer behaviours; (ii) be able to integrate real-time monitoring and control with long-term planning and policy making; (iii) be able to assimilate water quality issues with water supply problems; and (iv) incorporate economic, social, ethical and environmental considerations. Moreover, the new framework needs to be human-centric so that intelligent algorithmic solutions are explainable and acceptable by human policymakers, managers, operators and consumers. Due to its complexity and many interdependent factors, this challenge is a typical 'wicked problem', which seems impossible to solve [69].

The success of the Water-Futures project depends on inter- and trans-disciplinary synergies, which combine and transcend the different expertise and methodologies (Sections 2-5) into a holistic design framework. As an example, scenario generation constitutes a key factor to enable decision-making under deep uncertainties, yet it requires socio-economic insights into the rationality of human decision making and machine technologies to uncover homogeneous clusters and critical transitions in long-term dynamics. Conversely, a valid quantitative evaluation of the explainability of machine learning models is impossible without a reference to expert knowledge and human perception, hence vocabulary and validity need insights from control theory and socio-economics. Short- and long-term objectives of control and decision making of smart water systems are closely interrelated, yielding a strong interdependency of technical as well as societal modelling objectives, at the same time requiring machine learning technologies to tame the involved combinatorial complexity. Integrating ethics and fairness in control systems requires socio-economics expertise. Conversely, integrating physical feedback loops and the different social dynamics requires deep collaboration between systems and control theory as well as water engineering. Although only in its first year this six-year project has already identified the key areas of research and addressed some of the fundamental elements of the Water-Futures framework for long-term transitioning of water distribution systems.

7 ACKNOWLEDGEMENTS

This paper is a result of the project Water-Futures which has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (Grant agreement No. 951424).

8 REFERENCES

[1] Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Liermann, C.R. and Davies, P.M., 2010. Global threats to human water security and river biodiversity. *Nature*, 467(7315), p.555.

[2] Rodell, M., Famiglietti, J.S., Wiese, D.N., Reager, J.T., Beaudoing, H.K., Landerer, F.W. and Lo, M.H., 2018. Emerging trends in global freshwater availability. *Nature*, *557*(7707), p.651.

[3] United Nations (UN), the Department of Economic and Social Affairs, 2018. World Urbanization Prospects: The 2018 Revision, Key Facts. *United Nations Department of Economics and Social Affairs, Population Division: New York, NY, USA*.

[4] United Nations (UN), 2015. Transforming Our World, the 2030 Agenda for Sustainable Development. *General Assembly Resolution A/RES/70/1*.

[5] The website of the Water-Futures ERC Synergy Project: https://waterfutures.eu/ (last accessed on 02/05/2022).

[6] Pot, W., 2019. Anticipating the Future in Urban Water Management: an Assessment of Municipal Investment Decisions. *Water Resources Management*, *33*(4), pp.1297-1313.

[7] Shamir, U. and Howard, C.D., 1979. An analytic approach to scheduling pipe replacement. *Journal AWWA*, *71*(5), pp.248-258.

[8] Walski, T.M., 1982. Economic analysis of rehabilitation of water mains. *Journal of the Water Resources Planning and Management Division*, *108*(3), pp.296-308.

[9] Walski, T.M. and Pelliccia, A., 1982. Economic analysis of water main breaks. *Journal AWWA*, *74*(3), pp.140-147.

[10] Engelhardt, M.O., Skipworth, P.J., Savic, D.A., Saul, A.J. and Walters, G.A., 2000. Rehabilitation strategies for water distribution networks: a literature review with a UK perspective. *Urban Water*, *2*(2), pp.153-170.

[11] Mala-Jetmarova, H., Sultanova, N. and Savic, D., 2018. Lost in optimisation of water distribution systems? A literature review of system design. *Water*, *10*(3), p.307.

[12] Tsiami, L. et al., 2022, A review of staged design of water distribution networks. *2nd WDSA/CCWI Joint Conference*, Valencia, Spain.

[13] Cunha, M., Marques, J., Creaco, E. and Savić, D., 2019. A Dynamic Adaptive Approach for Water Distribution Network Design. *Journal of Water Resources Planning and Management*, *145*(7), p.04019026.

[14] Lansey, K.E., Basnet, C., Mays, L.W. and Woodburn, J., 1992. Optimal maintenance scheduling for water distribution systems. *Civil Engineering Systems*, *9*(3), pp.211-226.

[15] Basupi, I. and Kapelan, Z., 2015. Flexible water distribution system design under future demand uncertainty. *Journal of Water Resources Planning and Management*, *141*(4), p.04014067.

[16] Creaco, E., Franchini, M. and Walski, T.M., 2014. Accounting for phasing of construction within the design of water distribution networks. *Journal of Water Resources Planning and Management*, *140*(5), pp.598-606.

[17] Marques, J., Cunha, M. and Savić, D.A., 2015. Multi-objective optimization of water distribution systems based on a real options approach. *Environmental Modelling & Software*, *63*, pp.1-13.

[18] Schnaars, S.P., 1989. *Megamistakes*. Collier Macmillan.

[19] Cantoni, M., Weyer, E., Li, Y., Ooi, S.K., Mareels, I. and Ryan, M., 2007. Control of large-scale irrigation networks. Proceedings of the IEEE, 95(1), pp.75-91.

[20] Savic, D.A., Kapelan, Z.S. and Jonkergouw, P.M., 2009. Quo vadis water distribution model calibration?. *Urban Water Journal*, *6*(1), pp.3-22.

[21] Zierolf, M.L., Polycarpou, M.M. and Uber, J.G., 1998. Development and autocalibration of an input-output model of chlorine transport in drinking water distribution systems. *IEEE Transactions on Control Systems Technology*, *6*(4), pp.543-553.

[22] Alvisi, S., Franchini, M. and Marinelli, A., 2007. A short-term, pattern-based model for water-demand forecasting. *Journal of Hydroinformatics*, *9*(1), pp.39-50.

[23] Blokker, E.J.M., Vreeburg, J.H.G. and Van Dijk, J.C., 2009. Simulating residential water demand with a stochastic end-use model. *Journal of Water Resources Planning and Management*, *136*(1), pp.19-26.
[24] Donkor, E.A., Mazzuchi, T.A., Soyer, R. and Alan Roberson, J., 2012. Urban water demand forecasting: review of methods and models. *Journal of Water Resources Planning and Management, 140*(2), pp.146-159.
[25] Krause, A., Leskovec, J., Guestrin, C., VanBriesen, J. and Faloutsos, C., 2008. Efficient sensor placement optimization for securing large water distribution networks. *Journal of Water Resources Planning and Management, 134*(6), pp.516-526.
[26] Ostfeld, A., Uber, J. G., Salomons, E., Berry, J. W., Hart, W. E., Phillips, C. A., Watson, J.-P., Dorini, G., Jonkergouw, P., Kapelan, Z., Pierro, F. d., Khu, S.-T., Savic, D., Eliades, D., Polycarpou, M., Ghimire, S. R., Barkdoll, B. D., Gueli, R., Huang, J. J., McBean, E. A., James, W., Krause, A., Leskovec, J., Isovitsch, S., Xu, J., Guestrin, C., VanBriesen, J., Small, M., Fischbeck, P., Preis, A., Propato, M., Piller, O., Trachtman, G. B., Wu, Z. Y. & Walski, T., 2008. The battle of the water sensor networks (BWSN): A design challenge for engineers and algorithms. *Journal of Water Resources Planning and Management, 134*(6), pp.556-568.
[27] Perelman, L., Arad, J., Housh, M. and Ostfeld, A., 2012. Event detection in water distribution systems from multivariate water quality time series. *Environmental Science & Technology, 46*(15), pp.8212-8219.
[28] Eliades, D.G., Stavrou, D., Vrachimis, S.G., Panayiotou, C.G. and Polycarpou, M.M., 2015. Contamination event detection using multi-level thresholds. In Proc. of Computing and Control for the Water Industry (CCWI), *119*, pp.1429-1438.
[29] Afshar, A. and Najafi, E., 2014. Consequence management of chemical intrusion in water distribution networks under inexact scenarios. *Journal of Hydroinformatics*, 16(1), pp.178-188.
[30] Mounce, S.R., Mounce, R.B. and Boxall, J.B., 2011. Novelty detection for time series data analysis in water distribution systems using support vector machines. *Journal of Hydroinformatics*, *13*(4), pp.672-686.
[31] Polycarpou, M.M., Uber, J.G., Wang, Z., Shang, F. and Brdys, M., 2002. Feedback control of water quality. IEEE Control Sys*tems Magazine*, 22(3), pp.68-87.
[32] Wang, Z., Polycarpou, M.M., Uber, J.G. and Shang, F., 2005. Adaptive control of water quality in water distribution networks. *IEEE Transactions on Control Systems Technology, 14*(1), pp.149-156.
[33] Wang, Y., Ocampo-Martinez, C. and Puig, V., 2016. Stochastic model predictive control based on Gaussian processes applied to drinking water networks. *IET Control Theory & Applications, 10*(8), pp.947-955.
[34] Creaco, E. and Franchini, M., 2013. A new algorithm for real-time pressure control in water distribution networks. *Water Science and Technology: Water Supply*, *13*(4), pp.875-882.
[35] Wright, R., Stoianov, I., Parpas, P., Henderson, K. and King, J., 2014. Adaptive water distribution networks with dynamically reconfigurable topology. *Journal of Hydroinformatics, 16*(6), pp.1280-1301.
[36] Zhou, Y., Yu, Richard F., Chen, J., and Kuo, Y., 2020. Cyber-physical-social systems: a state-of-the-art survey, challenges and opportunities. *IEEE Communications Surveys & Tutorials*, 22(1), pp. 389-425.
[37] Vrachimis, S.G., Timotheou, S., Eliades, D.G., and Polycarpou, M., 2019. Iterative hydraulic interval state estimation for water distribution networks. *Journal of Water Resources Planning and Management*, 145(1), p. 04018087.
[38] Paluszczyszyn, D., Skworcow, P., & Ulanicki, B. (2015). Modelling and Simulation of Water Distribution Systems with Quantised State System Methods. *Procedia Engineering*, *119*, 554–563.
[39] Fan, X., Zhang, X., & Yu, X. (2021). Machine learning model and strategy for fast and accurate detection of leaks in water supply network. *Journal of Infrastructure Preservation and Resilience*, 2(1), 10.
[40] Elshaboury, N., & Marzouk, M. (2022). Prioritizing water distribution pipelines rehabilitation using machine learning algorithms. *Soft Computing*. doi:10.1007/s00500-022-06970-8
[41] Savić, D. ed., 2013. *Machine Learning in Water Systems: Proceedings of the AISB Convention 2013, Exeter, UK, 3.-5. April 2013*. University of Exeter.
[42] Zukang Hu, Beiqing Chen, Wenlong Chen, Debao Tan, Dingtao Shen; Review of model-based and data-driven approaches for leak detection and location in water distribution systems. *Water Supply* 1 November 2021; 21 (7): 3282–3306.
[43] Robles Velasco, A., Muñuzuri, J., Onieva, L., & Rodríguez Palero, M. (2021). Trends and applications of machine learning in water supply networks management. *Journal of Industrial Engineering and Management*, *14*(1), 45-54.
[44] Candelieri A, Ponti A, Giordani I, Archetti F. Lost in Optimization of Water Distribution Systems: Better Call Bayes. *Water*. 2022; 14(5):800.
[45] Wu, Z. Y., & Rahman, A. (2017). Optimized Deep Learning Framework for Water Distribution Data-Driven Modeling. *Procedia Engineering*, *186*, 261–268.
[46] Qian, K, Jiang, J., Ding, Y., Yang, S. "Deep Learning Based Anomaly Detection in Water Distribution

Systems," *2020 IEEE International Conference on Networking, Sensing and Control (ICNSC)*, 2020, pp. 1-6.

[47] Hajgató Gergely, Paál György, & Gyires-Tóth Bálint. (2020). Deep Reinforcement Learning for Real-Time Optimization of Pumps in Water Distribution Systems. *Journal of Water Resources Planning and Management*, *146*(11), 04020079.

[48] Bragalli, C., Fortini, M., & Todini, E. (2017). Data Assimilation in Water Distribution Systems. *Procedia Engineering*, 186(C), 506–513.

[49] Xing Lu, & Sela Lina. (2022). Graph Neural Networks for State Estimation in Water Distribution Systems: Application of Supervised and Semisupervised Learning. *Journal of Water Resources Planning and Management*, 148(5), 04022018.

[50] Candelieri, A., Conti, D., & Archetti, F. (2014). A Graph based Analysis of Leak Localization in Urban Water Networks. *Procedia Engineering, 70,* 228–237. doi:10.1016/j.proeng.2014.02.026

[51] Jakob, J., Artelt, A., Hasenjäger, M., & Hammer, B. (2022). SAM-kNN Regressor for Online Learning in Water Distribution Networks. *CoRR*. doi:10.48550/arXiv.2204.01436

[52] Losing, V., Hammer, B., & Wersing, H. (2018). Incremental on-line learning: A review and comparison of state of the art algorithms. *Neurocomputing*, 275, 1261–1274. doi:10.1016/j.neucom.2017.06.084

[53] Malialis, K., Panayiotou, C. G., & Polycarpou, M. M. (2021). Online Learning With Adaptive Rebalancing in Nonstationary Environments. *IEEE Trans. Neural Networks Learn. Syst*., 32(10), 4445–4459. doi:10.1109/TNNLS.2020.3017863

[54] Ganji, A., & Miles, S.B. (2018). Toward Human-Centered Simulation Modeling for Critical Infrastructure Disaster Recovery Planning. *2018 IEEE Global Humanitarian Technology Conference (GHTC)*, 1-8.

[55] Christian, B. (2020). *The Alignment Problem*. W. W. Norton & Company, ISBN-10: 0393635821

[56] Molnar C. *Interpretable Machine Learning*. Leanpub, ISBN 978-0-244-76852-2.

[57] Park J, Lee WH, Kim KT, Park CY, Lee S, Heo TY. Interpretation of ensemble learning to predict water quality using explainable artificial intelligence. *Sci Total Environ*. 2022 Apr 6;832:155070. doi: 10.1016/j.scitotenv.2022.155070. Epub ahead of print. PMID: 35398119

[58] Ayati Amir Houshang, Haghighi Ali, & Ghafouri Hamid Reza. (2022). Machine Learning–Assisted Model for Leak Detection in Water Distribution Networks Using Hydraulic Transient Flows. *Journal of Water Resources Planning and Management*, 148(2), 04021104. doi:10.1061/(ASCE)WR.1943-5452.0001508

[59] Artelt A, Vrachimis S, Eliades D, Polycarpou M, Hammer B. One Explanation to Rule them All — Ensemble Consistent Explanations. Bielefeld University 2022.

[60] Artelt, A., & Hammer, B. (2022). Efficient computation of counterfactual explanations and counterfactual metrics of prototype-based classifiers. *Neurocomputing*, 470, 304–317. doi:10.1016/j.neucom.2021.04.129

[61] Ying, R., Bourgeois, D., You, J., Zitnik, M., & Leskovec, J. GNNExplainer: Generating Explanations for Graph Neural Networks. *Advances in neural information processing systems*, 2019.

[62] Zhang, K., Keliris, C., Polycarpou, M. M., & Parisini, T. (2021). Discrimination between replay attacks and sensor faults for cyber-physical systems via event-triggered communication. *Eur. J. Control*, 62, 47–56. doi:10.1016/j.ejcon.2021.06.026

[63] Mehrabi, N., Morstatter, F., Saxena, N.,Lerman, K. Galstyan, A. . 2021. A Survey on Bias and Fairness in Machine Learning. *ACM Comput. Surv*. 54, 6, Article 115 (July 2022), 35 pages.

[64] Chakraborty, A., Alam, M., Dey, V., Chattopadhyay, A., & Mukhopadhyay, D. (2018). Adversarial Attacks and Defences: A Survey. *CoRR*. http://arxiv.org/abs/1810.00069

[65] Schröder, S., Schulz, A., Kenneweg, P., Feldhans, R., Hinder, F., & Hammer, B. (2022). The SAME score: Improved cosine based bias score for word embeddings. *CoRR*. doi:10.48550/arXiv.2203.14603

[66] Koundouri, P., N. Pittis, P. Samartzis, N. Englezos, A. Papandreou. (2021). Ambiguity Aversion, Modern Bayesianism and Small Worlds, *Open Research Europe*, Vol1, Issue 13, Pages 13, F1000 Research Limited.

[67] Pugno M. (2016). On The Foundations of Happiness in Economics. London: Routledge.

[68] Koundouri, P., 2009. 'The Use of Economic Valuation in Environmental Policy: Providing Research Support for the Implementation of EU Water Policy under AquaStress'. Routledge, Taylor and Francis Group. Series: Routledge Explorations in Environmental Economics. ISBN: 978-0-415-45323-3.

[69] Rittel, H.W. and Webber, M.M., 1974. Wicked problems. *Man-made Futures*, *26*(1), pp.272-280.