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SMART DATA ANALYSIS FOR SMART WATER NETWORKS

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Abstract *Water is an indispensable resource for human and economical welfare, and modern society depends on complex, interconnected infrastructures to provide safe water to consumers. Given this complexity, efficient numerical techniques are needed to support optimal control and management of water distribution systems (WDSs). This document is intended to be a position paper on soft computing tools to suitably handle the huge amount of data generated by processes related to smart water applications. The paper is structured in two main parts: the first part reviews a number of state-of-the-art soft computing techniques for WDS management and gives a prospective on future research directions. The second part of the paper proposes a number of new hot topics coming up nowadays in the operation and management of smart water networks. These are Big Data, near real-time monitoring, epidemiology-based data analysis tools, uncertainty of asset states, and event-driven applications. This further research is essential to develop new algorithms to deal with the inherent volume and complexity of WDSs databases, able to exploit the information in advanced metering infrastructures as fully as possible. It also aims to contribute to water utilities decision support systems in both modelling extreme events and improving network resilience.*

1 INTRODUCTION

Soft computing is a family of algorithms that aims to solve complex problems for which more conventional methods are unable to provide a solution in polynomial time. Soft computing approximates the solution for these kind of problems, providing insight where there is not a feasible approach to have an exact solution. According to L.A. Zadeh, "the guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost". Soft computing methods are often also referred to as Computational Intelligence methods. These conform a set of algorithms that can be classified roughly into: fuzzy systems, neural networks, evolutionary computation, machine learning and probabilistic reasoning.

This work presents a position paper on soft computing tools to suitably handle the huge amount of data generated by processes related to smart water applications. This new approach is relatively recent, and one of the first works on water distribution systems (WDS) using advanced data analysis is the contribution by Savic and Walters, 1999 [1]. This paper formalised the concept of hydroinformatics as a discipline based on computational sciences and artificial intelligence, as a way to tackle water network management and maintenance, in particular. This paper represented an inspirational starting point on the use of geographic information systems and data mining in the water industry. The developed methods were mostly based on artificial neural networks (ANN) and genetic algorithms (GA). These authors and their group (based in Exeter, UK) have pioneered the application of evolutionary computing, in particular genetic algorithms, to the design [2], scheduling [3], and optimization [4] of water distribution networks. A second key contribution on this topic was made by Babovic et al. 2002 [5]. This work proposed using data mining methods to determine the risks of pipe bursts. For example, analysis of the database of already occurred bursts events can be used to establish a risk model as a function of associated characteristics of bursting pipes. The approach opened new avenues in that time for asset management by applying such methods as Bayesian networks and evolutionary algorithms.

It was 2003 when Bessler et al. [6] developed a data mining algorithm to generate a set of control rules that gave the best historical operating policy for water reservoir control. The data mining tool used in this work was based on decision trees (algorithm C5.0) and the obtained results were close to those obtained by applying optimization techniques. By that time, coinciding with the settle of data mining as a new data analysis trend, a range of data-driven methods were adopted to approach several topics in urban hydraulics. This is the case of proposing to use ANNs and fuzzy adaptive systems (FAS) to replicate the behaviour of an on-line deterministic model that controls a water system [7]. It also was in the early 2000s when comparisons on the performance of short-term water demand forecast models were approached. The aim was to compare classical approaches with those based on artificial intelligence (AI) such as expert systems and ANNs [8]. The result was that, among others, the new AI methods outperformed classical regression and time series analysis. Water quality analysis has also progressively adopted intelligent data analysis methods in that time. Chau, 2006 [9] reviewed AI techniques in water quality modelling. The survey included knowledge-based systems, GAs, ANNs, and fuzzy inference systems. It is in 2006 when Tzatchkov et al. [10] first introduced geographic information system (GIS) analysis and concepts inherited from graph theory to implement efficient algorithms for WDS division into district metered areas (DMAs).

Along with the advance on intelligent data analysis methods new approaches have been tailored to their application to WDSs. It can be highlighted the introduction of particle swarm optimization (PSO) algorithms and its comparison to GAs for the analysis and design of water networks [11, 12]. The use of PSO to support the design of WDSs has been improved from the standard approach and other evolutionary algorithms to a self-adaptive version of PSO [13]. The methodology avoids this way all the process of localizing and fine-tuning suitable parameter values for WDS design.

Machine learning methods have had a key role regarding predictive models for water demand. In the first decade of this century, ANNs were used with the back-propagation algorithm for several Civil Engineering applications [14]. Zhou et al. [15] developed time series models for daily water consumption in Melbourne, Australia. ANN models have also been used to model weekly peak demand [16]. Shrestha and Solomatine [17] presented in 2006 a regression methodology based on fuzzy clusters applied to estimate hydrological data sets. Optimization of pump-scheduling based on forecasting urban water demand for the city of Seoul was proposed by Kim in 2007 [18]. It was in 2010, when Herrera et al. [19] presented a comprehensive study where compared several machine learning models for predicting hourly water demand. The set of models analysed was composed by ANNs, projection pursuit regression, multivariate adaptive regression splines, random forests, and support vector regression.

The issue of detecting and locating leaks in pipes was also addressed by intelligent data analysis. One can find several approaches in the literature. Among them, the work by Poulakis et al. [20], who developed a Bayesian system identification methodology for leakage detection in WDSs, is worth mentioning. The methodology was suitable to handle the associated uncertainties when modelling leakage events. This ultimately provided estimates of the most likely leakage events. Izquierdo et al. [21] investigated a neuro-fuzzy approach for estimating different anomalous states in WDSs. Years later, Candelieri et al. [22] used hydraulic simulation along with data analysis techniques, based on Supervisory Control And Data Acquisition (SCADA) systems, Customer Information Systems (CISs) and GIS, for improving leakage management processes.

Traditionally, leakage location has been the starting point when proposing a WDS division into DMAs. Nowadays several methods adapted from heuristics processes and machine learning tools have been developed. The most studied works on water network division are based on variations of graph clustering [23, 24, 25], spectral clustering [26, 27, 28], community detection [29], multi-agent systems [30, 31], breadth and depth first search [32, 33] or multilevel partitioning [34]. The work by [35] is the first to propose a sectorisation approach for large-scale water networks. A water network division into DMAs can also be used for handling several operational and managerial issues in WDSs [34, 36, 37, 38, 39].

New trends in leakage location make use of new approaches such as ground penetrating radar and data-driven analyses to identify pipes and locate potential pipe bursts [40]. Instances of these analyses can be found in various of Ayala-Cabrera's key works. These works range from the study of wave amplitudes together with an intensive matrix manipulation [41], to combining

the use of multi-agent and clustering approaches [42]. The analysis of the raw georradar images based on multi-agent systems brings the possibility to accurately locate even such GPR-non-friendly elements as plastic pipes [43].
Soft computing techniques used to approach these processes are expected to be robust and efficient. However, despite some of the elements integrated in these issues are quantifiable, others may be classified as intangible. As a consequence, suitable techniques to treat information that is plagued with uncertainty and subjectivity are also needed. For example, works such as [44, 45], have used AHP, a multi-criteria decision-making technique. Their aim is to to prioritize leak management policies in the decision-making process to design the transition from intermittent to continuous supply in third-world water distribution systems [46, 47].

2 SOFT COMPUTING TECHNIQUES FOR WDS MANAGEMENT

This section reviews a number of state-of-the-art soft computing techniques for WDS management and gives a prospective on future research directions.

2.1 Agent Swarm Optimization for WDS design

Agent Swarm Optimization (ASO) [48] is a novel paradigm that combines several ways to approach general purpose optimization problems by using various swarm-based algorithms. The ensemble of these swarms follows the way in which multi-agent systems are organised into various schedules (negotiation, cooperation, and competition) to reach the optimal solution or the Pareto front of the multi-objective optimization problem in hand. This way, ASO offers robustness through a framework where various population-based algorithms coexist: different agent breeds (PSO and ant colony optimization, among others; but also including human input). A key for successfully developing ASO is to approach a suitable interaction among the different swarms involved on solving the problem. ASO dynamically combines the strengths of multiple meta-heuristics and demonstrates good performance to support decision-making processes by solving multi-objective optimization problems, especially in the field of WDS design, calibration, etc.

2.2 Hybrid models for water demand forecasting

Hybrid models for time series analysis were initially designed to use traditional methods, such as autoregressive moving average (ARIMA) models. A more complex method was proposed to modelling the residuals of the base process [49]. By combining the two models it is possible to have the best of both worlds: the reasonable explanation of the process thanks to ARIMA and the extraordinary accuracy of a neural network. This approach has shown to be specially suitable on processes of time series with intervention. For instance, it is a step forward on predicting water demand time series of sudden modification of their behaviour given valve manoeuvres or disruption events.
The above explained classical trend has evolved to giving response to obtain the highest accuracy in the predictions and being able to be easily adapted to the challenges coming from its further on-line development. This is the basis for the work of Brentan et al. in 2017 [50]

who propose applying support vector regression, as one of the currently better machine learning options for short-term water demand forecasting, to build a base prediction. In this model, a Fourier time series process is built over it to improve the base prediction. This addition produces a tool able to eliminate many of the errors and much of the bias inherent in a fixed regression structure when responding to new incoming time series data.

2.3 Social network community detection for WDS sectorization

In the computer domain, social networks are graphs intended to represent relations among social actors through a set of dyadic ties. Water supply networks can be thus represented and, therefore, it is possible to implement over them, algorithms/concepts from the graph theory and from the social network theory. As in a social network, the importance of each element of a WDS depends on the interrelation degree with other elements. In a WDS, the interrelation depends on the topological and hydraulic features but, essentially, on the topological and energy redundancy that have a different influence on each network element [51]. Social networks applies useful concepts of density and centrality as measures of importance which can be ultimately useful for ranking the relative importance of pipes or also can be a guide for further WDS division into DMAs [52, 53]. For instance, graph-theoretical indices, such as node betweenness, are often applied to the individuals of a social network. In a WDS it is possible to use the edge betweenness associated to a link which is now a water pipe. Edge betweenness measures the amount of paths that connect two given nodes and that pass through that pipe. Another measures coming from social networks which are useful to work with WDSs are those measuring modularity, that is to say, how well a group of individuals (or nodes) is connected in a network. Community detection algorithms measure how well the individuals or nodes are represented in one community, thus providing insight for further WDS division into DMAs.

3 FURTHER RESEARCH AVENUES

This section proposes a number of new hot topics coming up nowadays in the operation and management of smart water networks. These are Big Data, near real-time monitoring, epidemiology based data analysis tools, uncertainty of asset states, and event-driven applications. This further research is essential to develop new algorithms to deal with the inherent volume and complexity of WDS databases, able to exploit the information in advanced metering infrastructures as fully as possible. It also aims to contribute to water utility decision support systems in both modelling extreme events and improving network resilience.

3.1 Big data

Big data is defined in the Gartner's IT Glossary as "high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization". This definition is also known as the 3V's, making reference to the 3 key challenges in which big data is involved: volume, velocity, and variety. Some researchers also view big data as a problem of high complexity. Big data is strongly related to the topic of Urban Informatics, which analyses the high complexity, hetero-

geneity, and volume of data generated in urban environments.
In the WDS field, big data issues arise from high rate data streams acquired through smart sensors and automatic metering readers. Even for small water utilities these may produce a huge amount of data to be stored and further analysed [54]. Despite to be a certainly unexplored topic for WDSs, there have been some first approaches for analysing near real-time water consumption and developing leakage simulation varying in the flow and pressure provided by the demand time series [55].
The use of graph databases to manage the huge volume of data that is processed nowadays by water utilities is another promising tool that deserves further development and research. Graph databases use graph structures for semantic queries with nodes, edges and properties to represent and store data. The performance of graph databases naturally engage with both the spatially distributed customer information and the physical topology of water networks.

3.2 Near real-time monitoring

New paradigms introduced in data management within the smart city framework make that the model can take into consideration all the available information, and can be efficiently updated in near real-time [56]. The new paradigm of on-line modelling in WDSs is a topic of growing interest given the high amount of data information with which water utilities operate nowadays, aiming at making decisions in a very short time. On-line predictive models for water demand forecasting [57] emerge to bridge the gap between this constant flow of available information and off-line models, which are not optimized to be updated in near real-time. Through on-line models for water demand, it is possible to improve predictions of water demand and to have better control of such system state variables as flow and pressure, by suitable valve operation. In the work of Brentan et al., 2017 [50] an off-line base model is coupled with a lighter-to-run on-line process able to be adapted to any novelty. This work also proposes an optimal cycle after which the base off-line model should be up-dated to guarantee maximum accuracy on water demand predictions.

3.3 Epidemiology-based data analysis tools

Epidemiological data analysis applied to water engineering can be understood as whole-system approaches that focus on empirical research and provide a multidisciplinary framework to better study and understand customer water demand behaviour together with new capabilities to analyse various risks and vulnerabilities related to water distribution [58]. The classical approaches on epidemiological studies are associated with health-related states or events in specified populations, and applications on control of the different problems that arise in such a context. However, recent advances in Energy on Buildings [59] and also in Hydraulics [60] point to epidemiology as a promising data analysis tool-set with several concepts that can be adapted to other engineering applications.

3.4 Soft computing methods for asset management

Asset management is a process water utilities can use to make sure that planned maintenance can be conducted and capital assets (such as pumps, valves, and pipes, among others) can be repaired, replaced, or upgraded on time [61, 62]. There are two main research subjects directly related to asset management:

Uncertainty of asset states: The current asset attributes states on age, condition, and criticality have associated an essential uncertainty regarding their complete knowledge. This opens a proper research avenue on applying Soft computing methods, mostly some of those related to probabilistic reasoning and Bayesian analysis. Another related topics to further research are the optimal sustainable level of service, assets criticality, or minimising assets life-cycle cost. Heuristic model strategies for optimisation and ranking algorithms might be applied aiming to approach these objectives.

Event-driven applications: Montalvo et al., 2015 [63] proposed not to restrict analyses in WDSs to just using traditional hydraulic simulations. In their paper, they propose a holistic view of processes actually affecting a WDS with the aim of enhancing its performance. Event detection for an adaptive management of contamination threats and asset vulnerabilities [64] or on-line source identification of contamination events by dynamic optimization procedures [65], are instances of the processes considered as part of a global water network analysis. In all cases, soft computing methods play a key role for approaching the best practices on WDS event-driven management.

The benefits of a suitable asset management range from improving asset rehabilitation and replacement to optimising the return of investment by reducing cost of operations and capital expenditures. In addition, it improves responses to emergencies related to assets' security.

4 DISCUSSION

There has been a long way from the first intelligent data analyses that approached urban water issues. After a hard start in which these other engineering branches had the initiative on applying these concepts and methodologies, urban water management represents nowadays one of the most active fields of applications of soft computing in Civil Engineering. So, model development has grown fast in the last few years. New challenges have naturally arisen by attending the needs of both the research community (Academia) and water utilities (Industry) which have become interested in this area.

This paper, a position paper on computational issues for the Technical Session ST36: Soft computing for smarter operation management in water distribution systems of CMN2017, has a vocation of contributing to highlight just some of the future approaches and research avenues in this flourishing field. However, many more are near to come with the huge advance of computational models and the enormous talent and determined will of many professionals working in the field of urban hydraulics.

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