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Do machine learning methods used in data mining enhance the potential of decision support systems? A review for the urban water sector

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Abstract. With sustainable development as their overarching goal, Urban Water System (UWS) managers need to take into account all social, economic, technical and environmental facets related to their decisions. Decision support systems (DSS) have been used widely for handling such complexity in water treatment, having a high level of popularity as academic exercises, although little validation and few full-scale implementations reported in practice. The objective of this paper is to review the application of artificial intelligence methods (mainly machine learning) to UWS and to investigate the integration of these methods into DSS. The results of the review suggest that artificial neural networks is the most popular method in the water and wastewater sectors followed by clustering. Bayesian networks and swarm intelligence/optimization have shown a spectacular increase in the water sector in the last 10 years, being the latest techniques to be incorporated but overtaking case-based reasoning. Whereas artificial intelligence applications to the water sector focus on modelling, optimization or data mining for knowledge generation, their encapsulation into functional DSS is not fully explored. Few academic applications have made it into decision making practice. We believe that the reason behind this misuse is not related to the methods themselves but rather to the disassociation between the fields of water and computer engineering, the limited practical experience of academics, and the great complexity inherently present.

Keywords: AI, decision support, review, urban water system

1. Introduction

1.1. The urban water system

The urban water system (UWS) constitutes part of the natural water cycle. Water is extracted from natural or artificial reservoirs (surface water, groundwater, etc.) and is treated for use and consumption. It is then transported to an urban agglomeration – an urban area where population and/or economic activities are sufficiently concentrated for water to be conducted to and collected from. After its various uses (municipal, industrial, agricultural), it is collected again through a system of conduits (sewer system) responsible for the transportation of wastewater to a treatment facility. At the wastewater treatment plant (WWTP) it is treated and then either reused or discharged back to the environment, most commonly a receiving water body. As [42,44] explain, and [30,40] exemplify, the primary concerns of UWS have evolved through the years. For example on the wastewater side, they evolved from being primarily about sanitation and hygiene (early 20th century) to focussing on water pollution and the removal of organic matter and nutrients (mid – late 20th century) to the removal of emerging pollutants and other concerns (late 20th – present). As we advance our understanding of the complicated interconnected relationships between society and environment the goals of water management also become more complex and multifaceted: for example, the goal of simply removing nutrients during wastewater treatment is now consid-

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ered out-dated, other environmental emissions of treatment are also now taken into account (e.g. greenhouse gas emissions) and the ecological status of water bodies is accounted for in more detail.

There is great eco-toxicological concern regarding the presence of various emerging pollutants, such as nanomaterials and persistent chemical compounds found at trace concentrations (namely micro-pollutants) in our water bodies. Excessive nutrient discharge is not only a main cause of eutrophication but also a waste of resources; especially with regards to phosphorus, as phosphate rock is a limited and critical raw material. Nutrient recovery is now more feasible with the development of new technologies that allow valuable products (such as fertilisers) to be generated from wastewater. Wastewater is also a source of organic matter, which can be used for the production of biogas, a potent renewable energy source. Efficient recovery of biogas is now possible for supplying energy to the WWTP or for other uses [10]. These opportunities are increasingly more important in the face of increased energy dependency on energy imports and scarce energy resources in Europe and beyond. Energy efficiency is a progressively important topic, including in the treatment of water and wastewater, in the process of reducing primary energy consumption and reducing greenhouse gas emissions. Water resource efficiency also comes in question, especially in the Mediterranean region facing dire climate change impacts. Water scarcity is reported in nearly all Mediterranean river basin districts. Institutions and governing bodies, including the European Union, encourage reclamation for various applications. Besides protecting the quantity and quality of water resources, the sustenance of the ecosystems they bear is also of increasing concern. A large number of factors put ecosystems at risk in the "anthropocene". Insufficiently treated discharges are only part of the damage, ever-increasing water needs, excessive use of fertilisers and pesticides in agriculture, diffuse pollution and urbanisation are some others. Around the world, societies aim to restore, maintain and improve ecological status of aquatic ecosystems to ensure the provision of goods and service that contribute to human well-being. Surface waters provide services for recreational activities (swimming, fishing, rowing and other water sports); agricultural practices, such as irrigation, benefit from good quality of surface and groundwater; the industrial sector also benefits from water of sufficient quality to be used for industrial practices. Healthy aquatic ecosystems do not only benefit the direct users of water services, but also everyone that uses a service indirectly (e.g. consumer of agricultural products) or merely values the existence of the service (e.g. knowing that beautiful natural environment is in proximity). Improved qualities for aquatic ecosystems and the associated increase of biodiversity and environmental assets could therefore have important socio-economic benefits, including for public health and resilience towards future environmental pressures [34].

1.2. UWS and the pillars of sustainability

These concerns and challenges are mirroring a general socio-political concern that took hold in the late 20th century. Various United Nations agencies, along with many individual nations, local governments and corporations have adopted sustainable development as an overarching goal of all economic and social development [32]. Decisions based on economic, social and environmental conditions of the present and the future will accordingly be necessary across sectors, including the UWS. A new metric – that of sustainable development – will need to be adopted [10] and the UWS will need to measure up to new standards of economic, social and environmental sustainability. This does not just entail impacts of the UWS to the three pillars of sustainability, but equally the impacts of changes in these three pillars to the system.

Article 9 of the Water Framework Directive (WFD) states that "*Member States shall take account of the principle of recovery of the costs of water services, including environmental and resource costs, [. . .] and in accordance in particular with the polluter pays principle.*" Full cost recovery of water and sanitation services is a major component of the strive towards improving UWSs and rehabilitating the receiving water bodies [31]. Full cost recovery implies the accounting of externalities such as water pollution and overextraction. Failure to recognise the total value of water assets has been identified as one of the factors that can set in motion a vicious cycle of underfunding in UWS infrastructure and management activities [33]. Besides full cost recovery, efficient use of resources is also necessary in times of economic instability, such as the economic crisis experienced in Europe since 2008. With limited financial resources, integrated system analyses are necessary to work out the UWS interventions that would offer the best "value-for-money".

The urban water cycle is large in many aspects, not least in terms of geography. Water sanitation, water supply and watershed authorities, environmental agencies, municipalities as well as the industrial and agricultural sectors all form a part of the urban water cycle. Involvement of these stakeholders and integration of their concerns and interests are necessities for a sustainable UWS management. The contrasting visions and priorities between these stakeholders make their integration into the decision-making process a complex endeavour. For example, public priorities might lie in other aspects of governance or other types of environmental pollution. How is the administration meant to allocate funds for UWS when budget is restricted and the local society would rather see other issues addressed?

Perhaps what really makes this situation an incredibly complicated problem is that there is no panacean answer; no solution can be the most socially acceptable, most environmentally beneficial and have the highest financial return. A trade-off is almost always established and some of the aspects need to be compromised – preferably with the end-goal of sustainable development. The trade-off relationships are certainly not linear and the variables are many. Dynamic elements of socio-ecological systems, such as biophysical relationships, human preferences and behaviour, and feedbacks between them are poorly understood [39]. There is no "one fits all" solution (or rather compromise) to be found either; each decision-making challenge is specific to its characteristics and concerns.

1.3. Uncertainty in UWSs

Uncertainty is one of the most important concerns in any type of decision-making. It affects UWSs in various ways and undermines their efficacy [45]. In UWS decision-making its presence may have formidable consequences when a wrong or simplified picture of the system is perceived. Alas, uncertainty is a fact of life and decision makers have indicated more willingness to trust models if they are presented to them accompanied by the appropriate uncertainty analyses [2]. This is largely due to the liability and responsibility they assume for their decisions. A better understanding of the types of uncertainty would also potentially lead to more trust in these tools [45].

1.4. Adaptive management – A new decision-making paradigm

Authors have remarked on the fact that stationarity and its associated implications for UWS management are dwindled under the weight of rapid and unpredictable changes [6,29]. This suggests that current static design and upgrading practice is unsuitable as it is based on the premise that the future can be effectively predicted [6,12]. Unless current management regimes undergo a transition towards a more adaptive approach sustainable management of water and wastewater resources cannot be realised [22,25,36]. Adaptive management relies strongly on a decision-making process that is participatory and has active stakeholder involvement. Stakeholder participation allows for the inclusion of a wide range of different perspectives rather than decision-making by specialists and experts in isolation – something that is particularly important in early design and planning stages [35]. There is also an apparent gap between experts and/or researchers and stakeholders and/or policy makers, which often leads to an inadequate application of models and other support tools in the decision-making process [23]. Early involvement of stakeholders in the development and application of support tools can help bridge that gap and spread the application of model-based tools in the decision-making process [5]. In terms of the adaptive capacity of a system, a broad range of perspectives can facilitate adaptation by recognising new challenges and needs for institutional change [35]. For these reasons, the European Water Framework Directive encourages that "*stakeholders are invited to contribute actively to the process and thus play a role in advising the competent authorities*" [14].

Sections 1.2–1.4 have described a situation of daunting complexity for UWS decision makers. The decision making methods necessary should be able to: incorporate various tools and criteria; include stakeholder and expert input/knowledge; address uncertainty and decision robustness; and help to better understand and predict the behaviour of the system and its processes when deterministic modelling is insufficient. Artificial Intelligence (AI) methods present a valuable option in that respect and can be coupled with decision support systems (DSS) to help in handling the high level of complexity that UWS management requires. The objective of this paper is to review of AI methods applied to UWSs and to investigate the integration of these methods into DSS.

2. Transforming data to knowledge in the water sector

Technologies are now available for the conservation of water resources; reduction of water consumption, reclamation and reuse of wastewater; the management and extraction of energy from the wastewater stream; the recovery of nutrients; the separation of wastewater sources; and not least in instrumentation, control and automation. At the same time methods for data processing, information processing and decision have advanced significantly [37]. Three main computer science research fields are dedicated to the transformation of data to usable knowledge and support decisions: (i) artificial intelligence (AI), which is a broad term for using either data or knowledge to offer solutions to existing problems that require some search or reasoning, (ii) machine learning (ML), which is a specific area from AI that offers procedures learning from data, and (iii) data mining (DM), which is an interdisciplinary field to discover patterns in large data sets and subsumes both ML, statistical modelling, or visualization disciplines. This review paper focuses on the ML methods that are shared between AI and DM research fields (black circle in Fig. 1). We found 16074 papers on ML applied to water and 1394 applied to wastewater published in the period between 1935 and August 2016.

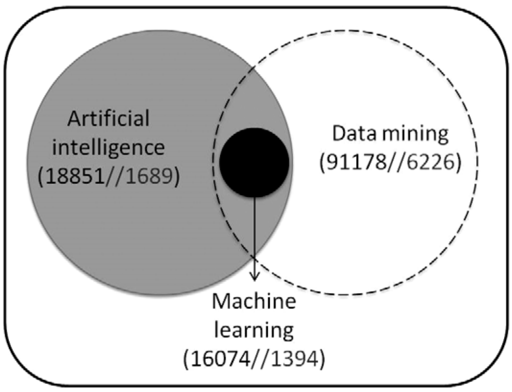

Fig. 1. Number of papers dealing with data mining (DM), artificial intelligence (AI) and machine learning (ML) within the water (left part of the bracket) and wastewater sectors (right part of the bracket). Based on SCOPUS search (see Appendix).

The reviewed ML methods are the most popular in the data mining context [18,19], and include clustering, artificial neural networks, decision trees & classifiers, swarm intelligence, case-based and Bayesian networks (BNs). When looking into the specific methods for ML we see that artificial neural networks (ANN) is the most popular method in the water and wastewater sectors followed by clustering (Fig. 2). Clustering was first applied to the water sector in the late 60s to enhance process understanding; ANN overtook clustering within five years of its first application as there was increasing interest in predicting process behaviour (Fig. 3). ANN is the most widely accepted DM method and is widely used in various areas of water-related research. One of the most widespread applications of neutral networks is the modelling of natural and man-made water systems [1]. Traditional deterministic models used to enhance process understanding are often over-parameterized which make them computationally demanding. ANN (together with other data-driven models) emerged as an attractive option for prediction and classification in water systems. ANN are normally very effective to capture the non-linear relationships that exist between variables in complex systems, and can also be applied in situations where insufficient process knowledge is available to construct a deterministic model of the system [16]. The principal benefits of such methods are their fast execution time (once the ANN has been trained) as compared to traditional deterministic dynamic models implemented with ordinary differential equations, and their small requirement of prior knowledge. Within the water sec-

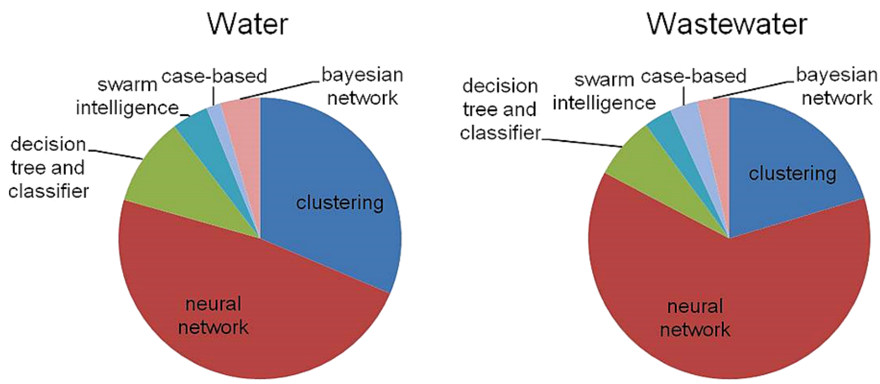

Fig. 2. Number of papers using machine learning (ML) techniques within the water (left) and wastewater sectors (right). Based on SCOPUS search.

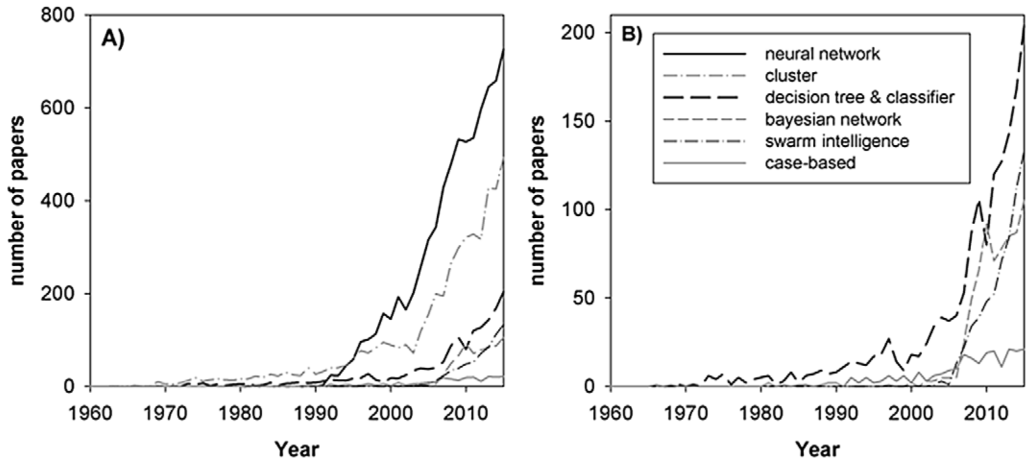

Fig. 3. Evolution of reviewed techniques applied to the water sector. (A) all methods reviewed together; (B) only methods with less than 200 papers.

tor ANN have been applied to model systems, to optimise process performance, for data reconciliation and for uncertainty assessment.

Besides clustering and ANN, classifiers were already applied in the 70s and showed an exponential increase after 2000. Decision trees were applied in the early 90s and also increased their visibility in the water sector after 2000. BNs and swarm intelligence/optimisation have shown a spectacular increase in the water sector, being the latest techniques to be incorporated but overtaking case-based reasoning. BNs are an increasingly popular method of modelling uncertain and complex domains such as ecosystems and environmental management. Bayesian modelling techniques have several features that make them useful in many real-life data analysis and management questions [43], being the most relevant ones the fact that provide a natural way to handle missing data and that they facilitate learning about causal relationships between variables. The reasons behind the rapid penetration of BNs into the water sector is their simplicity to build (users are the designers), the fact that they are diagrammatically based (which facilitates communication to people without technical abilities) and their relatively simple adaptation to new situations. BNs have been applied to water resources management (e.g. [24]), ecological modelling (e.g. [3]), public participation in the management of water resources (e.g. [21]), urban drainage water quality and quantity modelling (e.g. [13]), and wastewater treatment process performance prediction (e.g. [26]).

3. Decision support tools for improved UWS management

In this seemingly dire decision-making setting, one must not overlook the fact that the tools and methods made available by research and technology are now more advanced and all encompassing than ever. The focus of research and technology development to support in the challenges described in Section 1 is demonstrated by the ever-increasing literature addressing these issues. Figure 4(a) presents the number of documents published per year containing each of the terms along with the terms “wastewater” or “water” in the title, abstract and keywords.

The complexity of the UWSs decision-making however requires more elaborate approaches than the mere application of conventional numerical models [15]. For this purpose integrative approaches of expert systems, rule-based systems and other tools also started appearing, giving rise to advanced tools (such as environmental decision support systems) for multi-criteria decision-making [20,37,41]. There has been an increased application of DSS in UWS literature: Fig. 4(a) presents the results of a search in the Scopus database for articles published per year containing the term “decision support” along with the terms “wastewater” or “water” in their title, abstract or keywords. Their increased application can be attributed to the multiple benefits they appear to offer for UWS management. At higher levels of executive decision-making, DSS offer the ability to incorporate qualitative knowledge from different agents; the ability to integrate various tools, analyses and metrics; can summarise expertise from

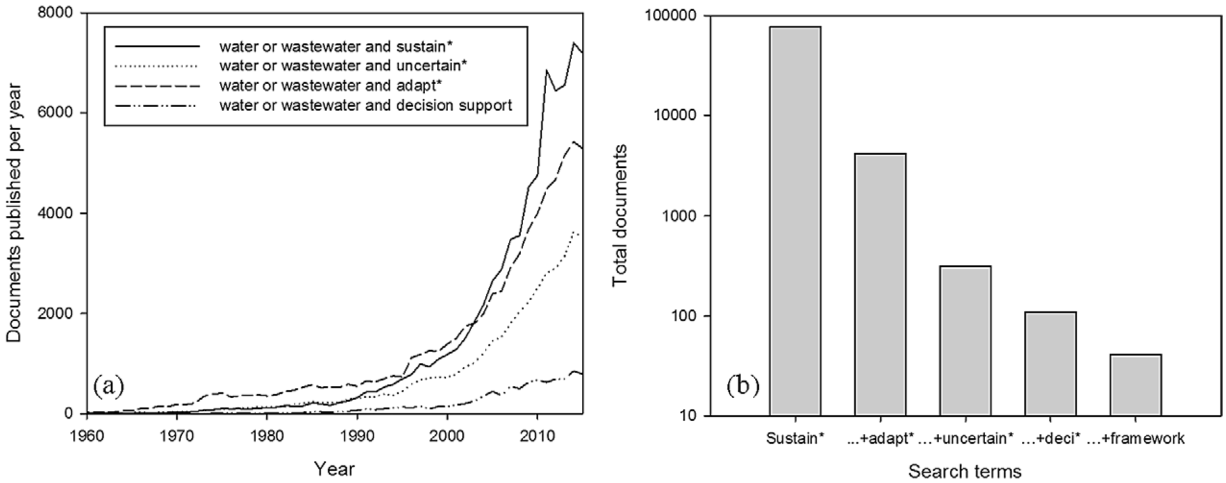

Fig. 4. Results of search through the Scopus database for (a) number of documents published for each search term per year; and (b) number of documents published for combinations of terms.

different fields (ecology, hydrology, engineering and others); facilitate in the communication between scientific outcomes and decision-making; and provide easily communicable outcomes. For technical, mid and low level management, DSS can support decision-making by incorporating various monitoring technologies (e.g. data acquisition, data validation and analysis); integrating expert knowledge with models and other tools; providing both online and offline responses; helping the user to formulate and diagnose the problem. Given this magnitude of abilities, DSS can solve problems of high complexity; can cope with situations where experience is essential for finding a solution; reduce the time needed to identify the problem and make a decision; and improve the consistency, quality and argumentation of decisions [38]. This approach to decision support is conducive to effective decision-making for sustainable development as advocated by authors [4,10,11] due to the complexity and multi-disciplinary nature of the issues (e.g. society, policy, operation, environment, finance) (as detailed in Section 1.2).

ML methods can be used to build DSS. Figure 5 shows that out of all journal papers in the water sector that deal with ML methods (almost 50,000) only about 2,500 (a 5%) also deal with decision or planning. Going into detail to different research fields related to water (wastewater, drinking water, urban drainage, rivers, and agriculture), the same observation applies. In the specific case of wastewater treatment only 209 papers link ML methods with DSS. Whereas ML applications to the water sector focus on modelling, optimization or knowledge generation, their encapsulation into functional DSS is not fully explored and DSS full potential is not being used. Looking at the literature on these terms (and their variations) in the fields of water and wastewater, the extensive focus placed on them individually is clearly apparent (Fig. 4(b)). Studies looking at combinations of the terms are reduced, despite the strong interrelations of the terms for water and wastewater management (as previously elaborated). Searching the Scopus database with all the terms ("(water or wastewater") and sustain* and adapt* and uncertain* and deci* and framework") results in 41 documents of which 27 are research articles. None of these 27 articles providing frameworks highlight the importance of ML techniques to help developing more robust DSS that can provide more qualified decisions.

We believe that the reason behind the misuse of ML methods in DSS is not related to the methods themselves; there are enough methods in the computer engineering field that have shown excellent performance to solve environmental problems. This is demonstrated by their ever-increasing use (Fig. 3). However, most of the methods remain at the academic level and have not made it into decision support tools (Fig. 5). This would suggest that the limitations are not pertinent to the nature of ML methods per se, but rather to how they are incorporated in DSS for non-academic applications. Examples of successful methods that made it into practice are ANN and decision trees. Non-academic applications rarely provide methodological contributions or are published in research journals making it difficult to obtain information about them [17]. On the other hand, most AI techniques have been adopted by academics who have limited practical experience (mostly using toy or benchmark examples). Another

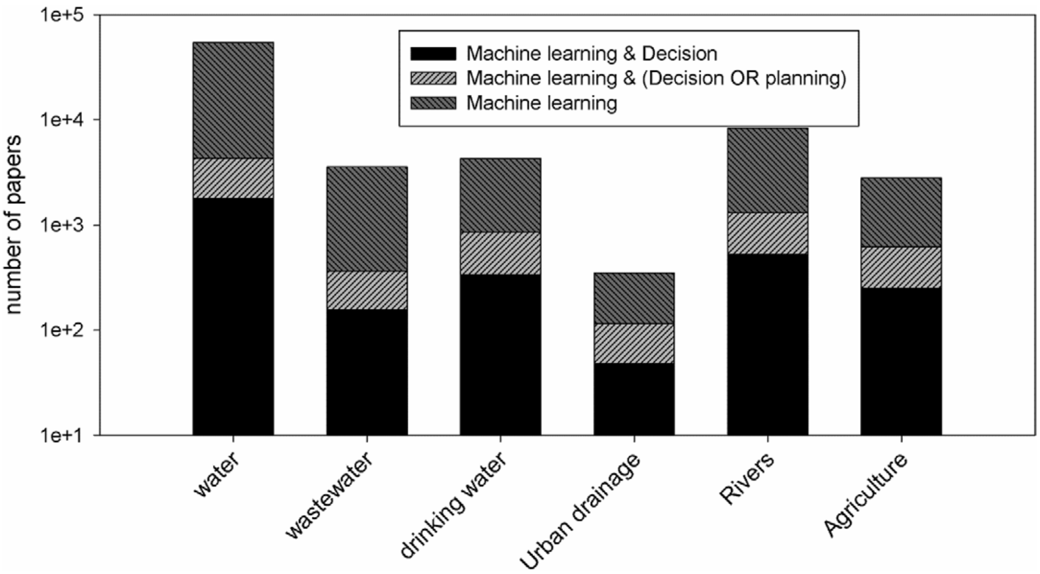

Fig. 5. Number of papers dealing with water per sector that incorporated machine learning (ML) methods, with a differentiation on the number of papers that supported decision-making or planning.

limitation that we identified is the lack of an association between the fields of water engineering and computer engineering. AI techniques are inherently multidisciplinary; they require numerous often incompatible and non-commensurate pieces of information from various sources to be brought together [9]. Combined with the intricate issues facing water and wastewater systems (explained in Section 1.2), the application presents a problem of formidable complexity. In terms of tool development, authors have suggested that better and more user-friendly interfaces, along with simpler tools and more support after product delivery would increase the use of AI methods in industry applications [8,28].

There is a need for more in-depth interactions between water and computer engineers when developing methods to guarantee their successful application. It is of paramount importance to train researchers and practitioners in both skills. In addition, there multiple techniques and there is little guidance for selection of the most appropriate AI method for a particular application. It is not always clear which methods will perform best in different settings, and how choices made will influence performance. Moreover, guidance on good practice for utilisation of AI methods for the water sector is needed as for instance the guidelines proposed for BNs in [7]. Finally, increasing computational power is required and as more high-resolution data become available, it is necessary to develop and use big data tools (such as distributed databases, massively parallel processing, and cloud computing) for effective and efficient searching, retrieving, analysis, and integration [27].

4. Conclusions

All social, economic, technical and environmental facets related to UWS management need to be taken into account by decision-makers. DSS can be major aids when handling such complexity. In this study we looked into the extent of the application of artificial intelligence methods applied to UWSs and their integration into DSS.

- When looking into the specific methods for machine learning used in data mining we see that artificial neural networks is the most popular method in the water and wastewater sectors followed by clustering;
- Only 5% of the journal papers in the water sector that deal with machine learning methods also deal with decision or planning;
- The encapsulation of machine learning methods into functional DSS is not fully explored;
- We believe that the reason behind the misuse of machine learning methods in practical applications of DSS is not pertinent to the nature of the methods per se, but because of the following reasons:

- o the lack of an association between the fields of water engineering and computer engineering;
- o most machine learning techniques have been adopted by academics with limited practical experience;
- o machine learning techniques are inherently multi-disciplinary and combined with the intricate issues facing water and wastewater systems the applications present problems of great complexity;
- o better and more user-friendly interfaces, simpler tools and more support after product delivery are necessary.

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Appendix

SCOPUS research queries to build Fig. 1.

(A) To build Fig. 1 (left part of the bracket)

(TITLE-ABS-KEY(water) OR TITLE-ABS-KEY(wastewater)) AND (TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("neural network") OR TITLE-ABS-KEY(clustering) OR TITLE-ABS-KEY("decision tree") OR TITLE-ABS-KEY(classifier) OR TITLE-ABS-KEY("swarm intelligence") OR TITLE-ABS-KEY("swarm optimization") OR TITLE-ABS-KEY("case-based") OR TITLE-ABS-KEY("bayesian network")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"re") OR LIMIT-TO(DOCTYPE,"ip"))

(TITLE-ABS-KEY(water) OR TITLE-ABS-KEY(wastewater)) AND (TITLE-ABS-KEY("generalized linear models") OR TITLE-ABS-KEY("ANCOVA") OR TITLE-ABS-KEY("ANOVA") OR TITLE-ABS-KEY("time series") OR TITLE-ABS-KEY("discriminant analysis") OR TITLE-ABS-KEY("regression") OR TITLE-ABS-KEY("principal component") OR TITLE-ABS-KEY("correspondence analysis") OR TITLE-ABS-KEY("factorial method") OR TITLE-ABS-KEY("data mining") OR TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("multi agent") OR TITLE-ABS-KEY("knowledge-based") OR TITLE-ABS-KEY("neural network") OR TITLE-ABS-KEY(clustering) OR TITLE-ABS-KEY("decision tree") OR TITLE-ABS-KEY(classifier) OR TITLE-ABS-KEY("swarm intelligence") OR TITLE-ABS-KEY("swarm optimization") OR TITLE-ABS-KEY("case-based") OR TITLE-ABS-KEY("bayesian network")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"re") OR LIMIT-TO(DOCTYPE,"ip"))

(TITLE-ABS-KEY(water) OR TITLE-ABS-KEY(wastewater)) AND (TITLE-ABS-KEY("automatic reasoning") OR TITLE-ABS-KEY("wet semantics") OR TITLE-ABS-KEY("sentiment analysis") OR TITLE-ABS-KEY("natural language processing") OR TITLE-ABS-KEY("agent-based") OR TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("multi agent") OR TITLE-ABS-KEY("artificial intelligence") OR TITLE-ABS-KEY("knowledge-based") OR TITLE-ABS-KEY("neural network") OR TITLE-ABS-KEY(clustering) OR TITLE-ABS-KEY("decision tree") OR TITLE-ABS-KEY(classifier) OR TITLE-ABS-KEY("swarm intelligence") OR TITLE-ABS-KEY("swarm optimization") OR TITLE-ABS-KEY("case-based") OR TITLE-ABS-KEY("bayesian network")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"re") OR LIMIT-TO(DOCTYPE, "ip"))

(B) To build Fig. 1 (right part of the bracket)

(TITLE-ABS-KEY(sewer) OR TITLE-ABS-KEY(wastewater) OR TITLE-ABS-KEY("waste water") OR TITLE-ABS-KEY(sewage)) AND (TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("neural network") OR TITLE-ABS-KEY(clustering) OR TITLE-ABS-KEY("decision tree") OR TITLE-ABS-KEY(classifier) OR TITLE-ABS-KEY("swarm intelligence") OR TITLE-ABS-KEY("swarm optimization") OR TITLE-ABS-KEY("case-based") OR TITLE-ABS-KEY("bayesian network")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"re") OR LIMIT-TO(DOCTYPE,"ip"))

(TITLE-ABS-KEY(sewer) OR TITLE-ABS-KEY(wastewater) OR TITLE-ABS-KEY("waste water") OR TITLE-ABS-KEY(sewage)) AND (TITLE-ABS-KEY("generalized linear models") OR TITLE-ABS-KEY("ANCOVA") OR TITLE-ABS-KEY("ANOVA") OR TITLE-ABS-KEY("time series") OR TITLE-ABS-KEY("discriminant analysis") OR TITLE-ABS-KEY("regression") OR TITLE-ABS-KEY("principal component") OR TITLE-ABS-KEY("correspondence analysis") OR TITLE-ABS-KEY("factorial method") OR TITLE-ABS-KEY("data mining") OR TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("multi agent") OR TITLE-ABS-KEY("knowledge-based") OR TITLE-ABS-KEY("neural network") OR TITLE-ABS-KEY(clustering) OR TITLE-ABS-KEY("decision tree") OR TITLE-ABS-KEY(classifier) OR TITLE-ABS-KEY("swarm intelligence") OR TITLE-ABS-KEY("swarm optimization") OR TITLE-ABS-KEY("case-based") OR TITLE-ABS-KEY("bayesian network")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"re") OR LIMIT-TO(DOCTYPE,"ip"))

(TITLE-ABS-KEY(sewer) OR TITLE-ABS-KEY(wastewater) OR TITLE-ABS-KEY("waste water") OR TITLE-ABS-KEY(sewage)) AND (TITLE-ABS-KEY("automatic reasoning") OR TITLE-ABS-KEY("wet semantics") OR TITLE-ABS-KEY("sentiment analysis") OR TITLE-ABS-KEY("natural language processing") OR TITLE-ABS-KEY("agent-based") OR TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("multi agent") OR TITLE-ABS-KEY("artificial intelligence") OR TITLE-ABS-KEY("knowledge-based") OR TITLE-ABS-KEY("neural network") OR TITLE-ABS-KEY(clustering) OR TITLE-ABS-KEY("decision tree") OR TITLE-ABS-KEY(classifier) OR TITLE-ABS-KEY("swarm intelligence") OR TITLE-ABS-KEY("swarm optimization") OR TITLE-ABS-KEY("case-based") OR TITLE-ABS-KEY("bayesian network")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"re") OR LIMIT-TO(DOCTYPE, "ip"))

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