Decision support systems (DSS) for wastewater treatment plants – A review of the state of the art

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Abstract

The use of decision support systems (DSS) allows integrating all the issues related with sustainable development in view of providing a useful support to solve multi-scenario problems. In this work an extensive review on the DSSs applied to wastewater treatment plants (WWTPs) is presented. The main aim of the work is to provide an updated compendium on DSSs in view of supporting researchers and engineers on the selection of the most suitable method to address their management/operation/design problems. Results showed that DSSs were mostly used as a comprehensive tool that is capable of integrating several data and a multi-criteria perspective in order to provide more reliable results. Only one energy-focused DSS was found in literature, while DSSs based on quality and operational issues are very often applied to site-specific conditions. Finally, it would be important to encourage the development of more user-friendly DSSs to increase general interest and usability.

Keywords: Decision Support System (DSS), Wastewater Treatment Plant (WWTP), decision - making process; process optimization; mathematical modelling.

1. Introduction

Wastewater treatment plants (WWTPs) are studied worldwide in view of finding more sustainable solutions for their management. WWTPs have been traditionally evaluated by end-of-pipe approaches, i.e. removal of pollutants from a stream before being disposed of or delivered into the environment (Garrido-Baserba et al., 2014). The increase of the environmental issues related to the WWTPs (greenhouse gas – GHG emissions, stringent regulation for water quality effluent, etc.) impose to see the plants as a complex system within a complex environment (Brinkmann et al., 2016). According to the aforementioned approach WWTPs have to achieve at least three sustainability targets: environmental protection (low pollutants discharge), social acceptance (human sanitary protection) and economic development (feasible operational and construction costs) (Garrido-Baserba et al., 2012; Garrido-Baserba et al., 2014).

Therefore, design and operation of WWTPs have to assume various complex objectives, such as minimizing costs while creating safe and operative installations that provide completely reliable wastewater treatment (Poch et al, 2012; Rodriguez-Roda et al., 2000). WWTPs are also facing stricter regulations regarding environment and human health, and are also being considered as sources of material and/or energy, by recovering nutrients and through biogas production (Bisinella de Faria et al., 2015). In addition to the previous concerns, conventional controller design approaches do not provide objective ways of quantifying the risk involved in the decisions engineers take as they develop their designs (Benedetti et al., 2010). Consequently, it is important to integrate the cause-effect relationships in WWTP management actions and to effectively represent the knowledge in order to enable comprehensive reasoning (Aulinas et al., 2011; Cortés et al., 2001). With this regards the adoption of a decision support system (DSS) during the design/operation of a WWTP could provide a useful support (Cortés et al., 1999; Rodriguez-Roda et al., 2000; Poch et al., 2004; Bisinella de Faria et al., 2015).

A DSS is an information system that supports a user in choosing a consistent response for a particular problem in a reduced time frame (Hamouda, 2011), i.e. DSSs are computer-based systems, built in order to solve multi-scenario problems by analyzing the feasibility of each scenario in a short time in order to provide a near optimum solution among them. A DSS may also be applicable for multiple problems and the possible solutions may or may not integrate aspects of sustainable development.

The adoption of DSSs allows to select more reliable and sustainable solutions thanks to the application of an integrated approach to problem analysis (Hamouda, 2011). The DSSs often include mathematical models, design/operational standards, interactive graphic displays and user-friendly interfaces (Rodriguez-Roda et al., 2000; Sànchez-Marrè et al., 2004; Torregrossa et al., 2018). Therefore, DSSs applied to WWTPs represent valuable tool for selecting the most appropriate solutions (e.g., plant configuration, operational conditions, etc.) for a given situation (Rodríguez-Roda et al., 2002; Rodriguez-Roda et al., 2000). Over the last decade, several DSSs applications on WWTPs were published in literature and the main publications are summarized in Table 1. As mentioned before, Table 1 presents the DSSs that have been applied with focus on several scopes:

i. Design (D)
ii. Energy consumption (E)
iii. Operational optimization (O)
iv. Improvement of the effluent Quality (Q)
v. Environmental Sustainability (S).

On the basis of the main focus, four main approaches have been adopted by the DSSs:

- Life Cycle Assessment (LCA)
- Mathematical Model (MM)
- Multi Criteria Decision Making (MCDM)
- Intelligent DSS (IDSS)

These approaches have been also described in the table 1.

As far as the authors are aware, none of the studies has presented an updated compendium that classifies the DSSs in accordance to its main purposes. Thus, the main goal of this paper is to create an up to date database containing the novelties related to the application of DSSs in WWTPs. This paper also aims to help researchers and engineers on the selection of the most suitable method to address their management problems without recurring to an extensive research that takes time and financial investment.

This paper is divided into five main sections (Sections 2 to 7). Section 2 contains an historical overview of the DSS applied to WWTPs in order to better understand the past and current state of the art. Section 3 presents a conceptual review of the main types of DSS that are being used for researchers and engineers to address WWTP issues, aiming to classify these DSSs according to their main focus. Section 4 summarizes the main focus of DSSs when applied to the fundamental steps involving a WWTP, such as, design, operation, quality/energy aspects and sustainability. In Section 5, a review of the main DSS applications is reported. Section 6 summarizes the key elements, gaps and findings obtained from this work. Finally, Section 7 summarizes the main conclusion drawn from this review paper.

93 **Table 1.** Summary of the main Decision Support Systems found in literature during 2010-2019.

Reference	Type of DSS	Main Focus	Study Application
Molinos-Senante et al. (2014)	MCDM	S	Applied for two extensive technologies (constructed wetlands and pond systems; and five intensive technologies (extended aeration, membrane bioreactor (MBR), rotating biological contactor, trickling filter, sequencing batch reactor. No specific location was mentioned in the paper.
Yoshida et al. (2014)	LCA	S	Real WWTP located in Copenhagen, Denmark.
Bertanza et al. (2015)	MCDM	D	Applied to a laboratory scale municipal WWTPs.
Bisinella de Faria et al. (2015)	LCA / MM	Q	The plant under study was similar to that proposed in BSM2 (Jeppsson et al., 2006).
Garrido-Baserba et al. (2015)	MCDM	S	Large WWTP which serves 1,000,000 person equivalents, in order to enable the exploration of a wide variety of alternative.
Kyung et al. (2015)	MM	S	Real advanced hybrid WWTP.
Morera et al. (2015)	LCA / MCDM	D	Applied to two different WWTPs (La Garriga and Granollers), located in Spain.
Castillo et al. (2016)	LCA / MCDM	D	Scenario analysis. Scenario 1: retrofitting in a conceptual plant of Italy; Scenario 2: retrofitting in a real plant in the United States; Scenarios 3, 4 and 5, the installation of a new plant in the United States, in South America and in Europe, respectively.
Kalbar et al. (2016)	MCDM	S	Two case studies for the application of several scenarios: 1) selection of technology for an upcoming township project in Mumbai, Índia; 2) lake rejuvenation project in the suburbs of Thane, Índia.
Lorenzo-Toja et al. (2016)	LCA	O / S	Applied to Betanzos and Calafell WWTPs, both located in Spain.
Pintilie et al. (2016)	LCA	S	Applied to Tarragona WWTP, Spain
Saagi et al. (2016)	MM	O	Hypothetical structure as the catchment described in ATV A 128 (ATV, 1992).
Singh and Kansal (2016)	LCA / MM	E / S	Real wastewater infrastructure of Delhi, India
Chhipi-Shrestha et al. (2017)	MCDM	D	Presents a conceptual DSS to assess fit-for-purpose wastewater treatment and reuse and is applied to an hypothetic case study.
Torregrossa et al. (2017)	IDSS/MCDM	E	Two real conventional activated sludge system (CAS) WWTPs in Germany and in The Netherlands.
Zeng et al. (2017)	MM	O / Q	China's urban WWTPs**.**
Arroyo and Molinos-Senante (2018)	MCDM	D	Applied for two extensive technologies (constructed wetlands and pond systems; and five intensive technologies (extended aeration, membrane bioreactor, rotating biological contactor, trickling filter, sequencing batch reactor.
Chow et al. (2018)	MCDM	O	Real WWTP located in Whyalla, south of Australia**.**
Díaz-Madroñero et al. (2018)	MM	O	Real WWTP located in the province of Alicante, Spain.
Gémar et al. (2018)	MM	S	Thirty small WWTPs from Spain were sampled between 2014 and 2016, featuring three different secondary treatment technologies: CAS system, rotating biological contactors (RBC) and trickling filters (TF).

Reference	Type of DSS	Main Focus	Study Application
Jiang et al. (2018)	MM	S	Real data obtained from WWTP located in the Lake Taihu region, China
Jing et al. (2018)	MM	Q	Seawater obtained from a clean coastal site in Saint John's, Canada
Nadiri et al. (2018)	IDSS/MM	Q	Real WWTP of Tabriz, Iran.
Pascual-Pañach et al. (2018)	IDSS	O	Supervision of a WWTP located in the Barcelona region, Catalonia.
Torregrossa et al. (2018)	LCA / MM	O	Plant data were generated with the STOAT simulator, that has been set-up to replicate the operational conditions of the WWTP of Solingen-Burg, Germany.
Ye et al. (2019)	IDSS	D	Optimal design of WWTPs in view of reducing resources and operational costs.
Oprea (2018)	IDSS	S	The IDSS has been applied to Danube River, consequently the WWTPs effluent quality has been optimized by means of IDSS
Xin et al. (2018)	MCDM	D	Real WWTP of Minnesota, United States.

LCA = Life Cycle Assessment; MM = Mathematical Model; MCDM = Multi Criteria Decision Making; IDSS = Intelligent Decision Support System; D = design; E = energy consumption; O = operational optimization; Q = improvement of the effluent quality; S = environmental sustainability.

2. Historical overview of DSS applied to WWTP

Figure 1 shows an overview of the evolution of DSSs applied to WWTPs related to the last six decades focusing the attention on the main DSS approach adopted.

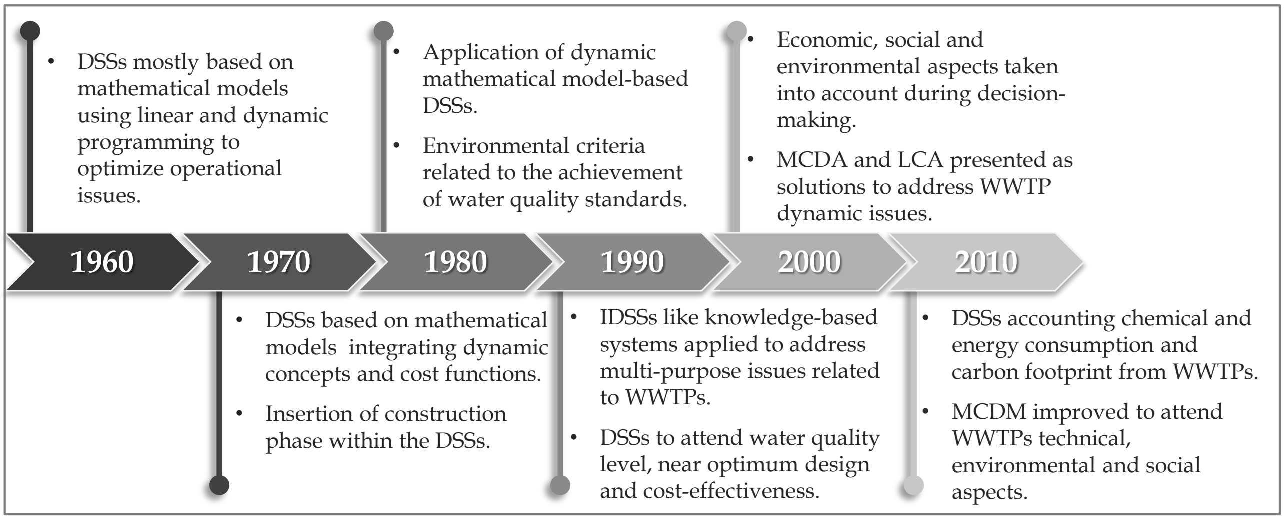

Figure 1. Overview of the evolution of DSSs applied to WWTPs.

While, Figure 2 shows the evolution over the time of DSS and IDSS on the basis of their main tasks.

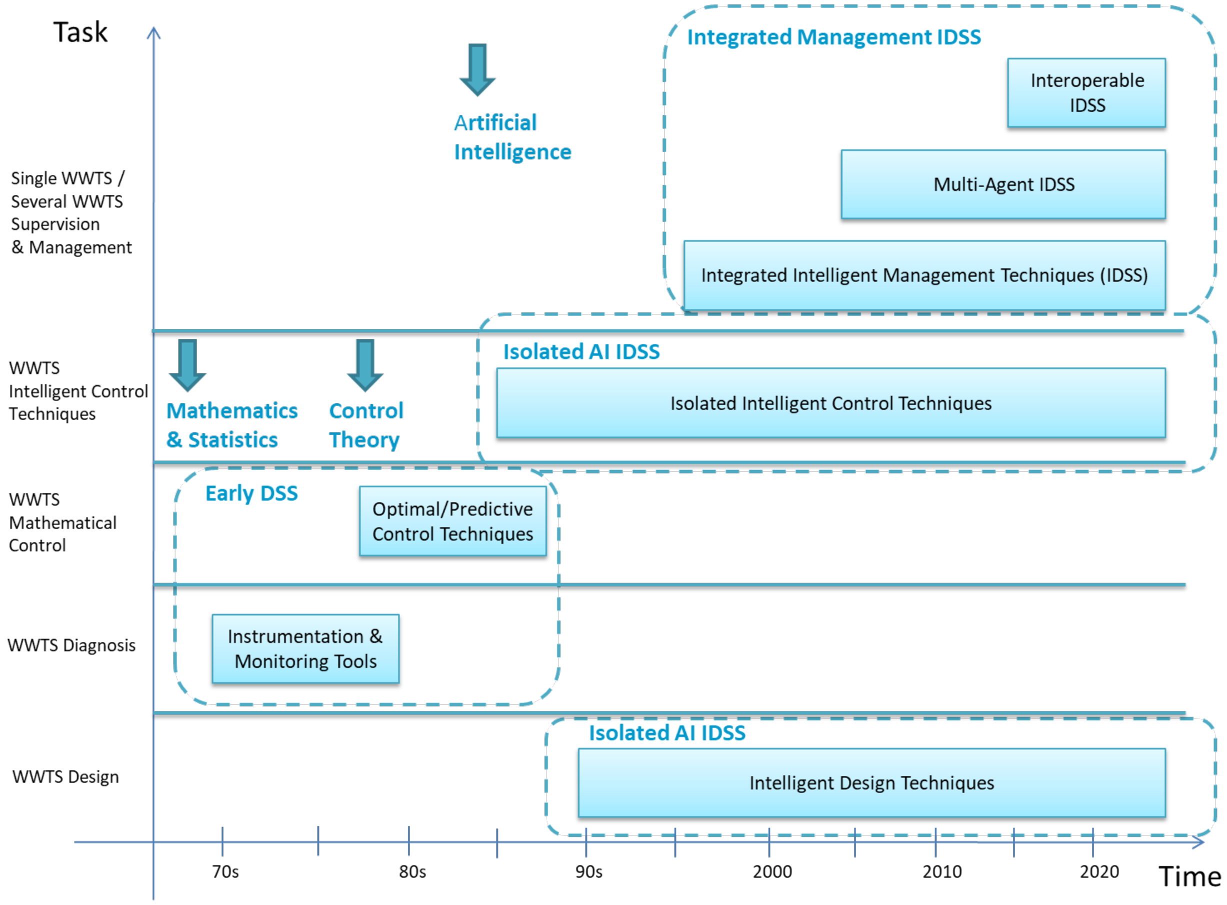

Figure 2. DSS and IDSS evolution for WasteWater Treatment Systems

2.1. From DSSs origin to their application as dynamic tools

The optimization of the wastewater treatments by using DSSs started since 1960s (Anzaldi et al., 2014). At this period, the availability of computer-based systems has increased and the scientific community started to have easier access to advanced computers. Since this period, WWTP major issues were reported as being related to its inherent complexity and dynamicity, which were hard to solve due to the lack of proper instruments, control and automation. Information technology has played an increasing role in the planning, design, and operation of water treatment systems (Hamouda, 2011). Thus, DSSs have being applied to solve WWTP related issues and their complexity.

In 1965, Deininger studied the ways to obtain high water quality levels by applying concepts of linear programming, i.e. when problems can be solved using linear equations or inequalities (Deininger, 1965).

The 1970s brought a more mature use of such DSSs due to the application of more dynamic concepts regarding the wastewater treatment, which includes transport systems and the integration of different treatment levels

(Converse, 1972; de Melo and Camara, 1994). Although this decade was important for the development of mathematical model-based DSSs, a certain difficulty in their application to real cases is reported (de Melo and Camara, 1994). The use of cost functions within the models is also reported (Hahn et al., 1973; Wanielista and Bauer, 1973) with the aim to integrate operational quality and cost optimization to more complex algorithms, e.g. convex, heuristic and geometric programming (Deininger and Su, 1973; McConagha and Converse, 1973), obtaining the best possible solutions among the alternatives provided by the DSSs at the time. Klemetson (1975) also used dynamic programming to select optimal solutions during the design phase.

From 1981, studies were published reporting the evolution of the DSSs going towards the consideration of state variables depending on the time, to ensure that results would include the dynamicity inherent to effluent quality in different periods (Klemetson and Grenney, 1985). The environmental criteria considered during decision-making were mostly based on deviations related to water quality standards (Joshi and Modak, 1989). Still in 1980s, the acquired knowledge regarding growth-based kinetics was combined with mathematical modeling and the Activated Sludge Model (ASM) No. 1 was published (Henze et al., 2000). In this period, the first IDSSs were developed. They were mainly isolated Artificial Intelligence (AI) techniques using a Knowledge-Based System (KBS) approach to mimic the experts reasoning process like the works of (Flanagan, 1980; Berthuex et al., 1987; Maeda, 1985; Maeda, 1989; Gall and Patry, 1989; Tzafestas and Ligeza, 1989), or some intelligent control approaches like using a Genetic Algorithm (GA) control approach (Karr, 1991) or a Fuzzy Logic (FL) control approach (Czoagala & Rawlik, 1989).

2.2. Intelligent DSSs spreading as design and operation tools

In the beginning of the 1990s, the design of a WWTP considered the need to follow a three-phase process, which included: i) list possible treatment processes; ii) perform bench-scale testing to acknowledge the applicability of the proposed treatment processes; and iii) select the best option among the tested processes and consider engineer quality (Evenson and Baetz, 1994). In the same period, what-if analysis and functions of utility including costs have been introduced in literature (Vanrolleghemet al., 1996; Maheepala et al., 2000). During this decade the need of real-time operational control and concerns about safety increased (Rodriguez-Roda et al., 2000), inciting the use of online systems (Metzger, 1995) to improve WWTP management and to prevent accidents. Details on the adoption of online systems are reported in the review paper proposed by Olsson et al. (2003).

Regarding the IDSS approach, during this period there was a great explosion on generating Intelligent DSS. There was a generalization in the use of Knowledge-Based Systems which was reported in view to address multi-purpose demands, such as diagnosis of an activated sludge WWTP (Sànchez-Marrè, 1991; Serra et al., 1994), water quality within legal requirements, near optimum design (Krovvidy et al., 1991; Krovvidy and Wee, 1993) and cost-effective technologies for WWTP operation and control (Beck et al., 1990). Some other intelligent control techniques based on Artificial Neural Network (ANN) approaches were applied (Capodaglio et al., 1991; Kosko, 1992; Côte et al., 1995; Syu et al., 1998), or using fuzzy rule generation approach like in (Wang et al., 1997). Furthermore, in this decade some work proposed to apply Case-Based Reasoning (CBR) to the supervision of a WWTP (Sànchez-Marrè et al., 1997). In addition, a multi-agent distributed and integrated management architecture for supervising a WWTP was proposed in literature (Sànchez-Marrè et al., 1996) to use more than one AI technique. In this decade, the use of AI in DSS for environmental systems was generalized as detailed in (Cortés et al., 2000), where a general architecture for IDSS suitable for WWTP was presented. This initial proposal was refined in a later study (Poch 2004).

The 2000s brought up concerns regarding the three main elements of sustainable development: economy, social aspects and environment (Afgan et al., 1999). For this reason, comprehensive planning tools were developed in order to address the growing sustainability demand, without, however, completely attend social aspects. During this period, European Council established a framework of community actions in the field of water policy (including wastewater treatment) in view of achieving good qualitative and quantitative status of all water bodies (Directive 2000/60/EC). This Directive favored the adoption of DSS in WWTP field in view of reducing the mass of pollutants discharged into the environment.

Nevertheless, the multi-purpose demand was specifically managed with the use of IDSS. Some new expert systems (ES) in which the logic of the system bears a resemblance to human reasoning (Ahmed et al., 2002) were continued to be developed. Models based on the concept of artificial neural networks (ANN) were reportedly used in view of predicting the interlinkage among the processes involved in WWTPs/society/economy (Hamed et al., 2004). In the mid 2000 simulation and benchmarks appear to be the main sources of evidence to support decisions in WWTP (Jeppsson et al 2006; Vrecko et al 2006). In (Roehl et al 2006) strategies to decrease the enormous costs of simulations are addressed. Some new intelligent techniques were proposed in the literature like the use of Multi-Agent Systems (MAS) for the operation and management of a WWTP (Riaño et al., 2001; Borrell et al., 2002) and the use of MAS for water management using the simulation of scenarios in decision-making for a river basin (Rendón-Sallard et al., 2006). An extensive survey on the use of Agent Technology in environmental processes was done in (Aulinas et al., 2009). In addition, the data-driven approach to build IDSS was started to be considered as in (Comas et al., 2001), and the need for standardizing the terminology and using a background knowledge in WWTPs was implemented with the use of ontologies (Ceccaroni et al., 2004). The application of CBR was consolidated with some works like (R-Roda et al., 2001; Sànchez-Marrè et al., 2004). Finally, researchers in IDSS field started to be aware of the increasing need for setting some general framework for the development of IDSS (Sànchez-Marrè et al., 2008). The MCDM approach was presented as a friendly solution that takes into consideration technology and cost information for the selection of the most appropriate treatment system, weighting of other important indicators with the aim to present a final ranking of possible solutions to a specific problem (Hidalgo et al., 2007). LCA was also applied as a credible "cradle-to-grave" evaluation of the environmental impacts of a wastewater treatment plant (Renou et al., 2007).

2.3. DSS impoving to consider environmental and social aspects including climate change

During the 2010s the increase on the environmental and social emphasis to all types of industrial process occurred. Further, the needs for economic efficiency (e.g. minimizing energy and chemicals consumption and plant footprint) and operational reliability (Comas et al 2010; Hakanen et al., 2011; Carburenau et al 2013) faced with even more stricter environmental requirements. In addition, climate change issues have also acquired a notable role in WWTPs' decision support systems. In this matter, GHG are being more commonly assessed due to the relevance that WWTPs have on the emissions of methane (CH_4) and nitrous oxide (N_2O) (among others, Kampschreur et al., 2009; Ahn et al., 2010; Caniani et al., 2015; Lorenzo-Toja et al., 2016). The increase of DSSs with the aim to quantify GHGs from WWTPs is related to the fact that environmental cost-benefit ratio is representing an unacceptable business risk (Foley et al., 2010) and GHGs are being considered as an undesirable treatment output (Zeng et al., 2017; Gémar et al., 2018). For the abovementioned reasons, IDSS (Poch et al., 2017) and MCDMs (Bertanza, 2015; Arroyo and Molinos-Senante, 2018) have been evolving to support decision makers in choosing the most suitable technology among all the alternatives that were developed along the past years. IDSSs have evolved in the direction of using extensively the data-driven approaches, appearing a subfield named Enviromental Data Mining born in 2006 (Gibert et al. 2008) and reviewed in literature (Gibert et al., 2012), and using the MAS approach (Polakóv and Metzger, 2012). In addition, the characterization of IDSS for environmental systems was increasing (Sànchez-Marrè et al., 2012). Furthermore, the concept of IDSS interoperation (Sànchez-Marrè, 2014) appeared during this period.

With the appearance of IoT and development of smart sensors, distributed real time computing and real-scale Artificial Intelligence, new generations of IDSS rely on intensive multimodal data and the new field of Environmental Data Science approaches (Gibert et al 2018). In Corominas et al. (2018) a nice review of the data science techniques used in water management systems to transform data into relevant knowledge for decision support is provided. Quality of sensor data is object of attention (Alferes et al., 2016), removal of emergent pollutants (pharmacy, pesticides, micro-pollutants...) become more and more important (Hadjimichael et al., 2016; Fisher et al., 2017; Kim et al., 2017) and participation of end-users seem to gain importance for a design of effective systems at real full-scale (Corominas et al. 2018). The concept of workflow-based operation systems in WWTPs, and in general, environmental systems points towards this direction (Pascual-Pañach et al., 2018). Nowadays, DSS become central elements to support new designs of adaptive water management systems required for the rapid and unpredictable changes occurring in the context, that precludes the assumption of stationarity announced in literature (Domínguez et al., 2006; Milli et al., 2008; Torregrossa et al., 2018).

More details of DSS's evolution during the last decade are presented in the following sections where the systems were categorized in accordance to their main characteristics.

3. Main types of DSS applied to WWTP issues

Four main types of DSSs have been found in literature: i. Life Cycle Assessment (LCA) based; ii. mathematical models (MM) based; iii. Multi-Criteria Decision Making (MCDM) based; iv. Intelligent Decision Support Systems (IDSS) based (see Figure 3). A summarized discussion regarding these four types of DSS is presented in this section in order to provide the reader an overview of their application to WWTPs.

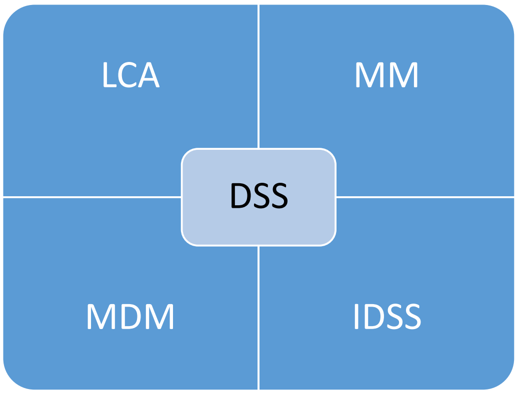

Figure 3. Main DSS existing in literature

3.1. Life Cycle Assessment DSS for WWTP

LCA is applied to WWTPs in order to evaluate the environmental profile of every aspect from the beginning to the end, including WWTP's processes efficiency and services (Pasqualino et al., 2009). LCA methodology allows computing all environmental emissions (solid, liquid and gaseous) generated from all the involved processes in view of converting them into environmental impacts and impact indicators looking to the environment, social and economic aspects (Yoshida et al., 2014). The core idea behind the LCA applications on WWTPs is to elaborate/quantify indicators for assessing the global environmental impacts of WWTPs. The main contributors to the environmental profile provided by a WWTP are energy consumption, wastewater discharge, sludge disposal/reuse and land occupation (among others, Hospido et al., 2004; Lassaux et al., 2007). Sludge reuse, for example, is very often considered during the LCA due to its potential applicability to industrial symbiosis as agronomical fertilizer (Pasqualino et al., 2009) or fuel recovery (Zarkadas et al., 2016). Another example is the current discussion regarding the reuse of the treated wastewater, which could be applied to agriculture irrigation, urban routines, groundwater recharge, recreation, among others (Pintille et al., 2016).

Despite of the sustainable approach presented by these kind of reuses, environmental regulations require restrictive targets, which are hard to achieve due to several management questions. For this reasons, during the last decade, LCA has gained particular interest from the WWTP sector, as its features have encountered the urgent need of researchers/scientists/operators of WWTPs to better quantify the environmental impact of plants, reduce the operational costs, reduce the mass of pollutants discharged, facilitate the wastewater recycling and reuse recovery materials or energy (Yoshida et al., 2014).

Several applications and review papers on LCA of WWTPs have been published in the literature (among others, Friedrich et al., 2007; Ahmed, 2011; Corominas et al., 2013a). Researchers have applied LCA for several scopes: i. evaluate the environmental impact of specific WWTPs case studies (Venkatesh and Brattebø, 2011; Pintile et al., 2016); ii. set-up control strategies for improving WWTPs operations as pure LCA (Yoshida et al., 2014) or coupled with mathematical models (Flores-Alsina et al., 2010; Bisinella de Faria et al., 2015); iii. design in view of comparing different plant configurations or non-conventional (e.g. MBR) versus conventional technologies (e.g. CAS) (Clauson-Kaas et al., 2004; Morera et al., 2015). The evolution of LCA applications can also be found in the literature depending on the scope and the WWTPs technology applied. Examples of recent applications, main purposes and achieved results are presented in section 5 of this work.

3.2. Mathematical Model-based DSS for WWTP

The oldest DSSs found in literature are based on mathematical models. This type of DSS is the more developed since the knowledge required for their application is already widespread. MM based DSSs represent powerful tool to obtain a comprehensive understanding of WWTP features since do not require a high costs to be implemented (Mannina et al., 2016). Their application may seek the assessment of biological carbon, phosphorus and ammonia removal (Henze et al., 2000; Zuthi et al., 2012), with the aim to predict the effluent quality. In addition, biomass metabolism can be evaluated in view of understanding excess sludge production, oxygen consumption rates (Fenu et al., 2010) and direct GHG emissions (Sweetapple et al., 2014).

MMs may differ each other on the basis of their level of details and complexity. Literature often report simplified models in view of having rapid responses (among others, Kyung et al., 2015; Zeng et al., 2017; Nadiri et al., 2018). These simplified models often include the direct and indirect GHG emissions quantification (e.g., Kyung et al., 2015) coupled with the economic/social indicators (e.g., Gémar et al., 2018;

Jiang et al., 2018). The simplified models adopted are commonly based on the mass balance and/or on the emission factors established in the literature. For example, Kyung et al. (2015) quantified the on-site GHG emissions from a five-stage Bardenpho WWTP on the basis of the emission factors established by experimental data.

Detailed type of model can be adopted when a more reliable representation of reality is required. However, the adoption of mechanistic mathematical models (e.g. the activated sludge model - ASM family) is rare since they are complex and require detailed dataset to be adopted (Henze et al., 2000). Some attempt of establishing a DSS based on mechanistic mathematical models (often coupled with LCA) exist in the literature (among others, Foley et al., 2010; Flores-Alsina et al., 2010; Corominas et al., 2013b, Boiocchi et al., 2017). For example, Boiocchi et al. (2017) applied a dynamic model to a WWTP with the aim of assessing the nitrous oxide emissions related to the metabolism of the ammonia oxidizing bacteria (AOB). This application demonstrates that dynamic models are used when researchers are seeking for specific answers that may enhance the plant's performance. MMs have also been applied to WWTPs inclusing membrane bioreactors with the aim to prevent their known limitations (e.g., membrane fouling, higher energy requirement and higher GHG emissions) from affecting the scattering and viability of the technology (Zuthi et al., 2013).

Several advantages can be listed concerning this kind of DSS. For example, the use of MMs may proportionate the validation of lab-scale results and provide credible estimations for full-scale facilities (Zuthi et al., 2012), offering a wide range of possible solutions to be considered during a decision-making process (Mannina & Cosenza, 2013). Their main liability is related to the lack of default values for several crucial information (e.g., biomass growth and decay rates, formation/degradation coefficients, among others), which may reduce its accuracy (Zuthi et al., 2012). For this reason, some MMs are applied for specific WWTP and must suffer somes changes for the application to other sites (Ni and Yuan, 2015).

From the abovementioned considerations, it is possible to conclude that DSSs based on mathematical modelling can allow stakeholders to explore a variety of possible solutions for an issue of interest prior to their application on-site, which may allow saving time and money while solving a determined problem.

3.3. Multicriteria Decision Making based DSS for WWTP

The MCDM based DSS represent the combination of different criteria/methods established with the aim of optimizing the behavior of a WWTP in which several technologies are applied focusing the attention towards several optimization targets (e.g. reducing emissions, reducing operational costs) (among others, Torregrossa et al. 2017; Chow et al., 2018). MCDM based DSS application to the WWTP context is suggested when multi-objective responses are required in order to pursue a more efficient management of the whole facility (Zeng et al., 2017; Jiang et al., 2018). In particular, the MCDM approach is one of the most reliable DSSs when it comes to pursue the optimization of WWTPs.

MCDM based DSS application are still under careful studies since an MCDM may require developed systems and complex software with the aim to obtain faster responses. Literature shows that the use of MCDM may lead to more sustainable wastewater treatment, as they can include several environmental issues (e.g., GHG emissions and resources consumption) with a similar weight as operating features and effluent quality (Mannina et al., 2019). Indeed, MCDMs are often coupled with other types of DSSs in view of providing a more comprehensive response to the treatment issues (Bisinella de Faria et al., 2015). For example, Castillo et al. (2016) coupled a multi-criteria analysis to an integrated mathematical model with the aim of generating a ranked short-list of feasible treatments for three different scenarios (which included different types of wastewater treatment), obtaining the optimal type of treatment and the most robust solution under influent uncertainties and tighter effluent limits. Mannina et al. (2019) coupled an integrated mathematical model to an optimization technique named Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in order to optimize the bahaviour of a membrane bioreactor pilot-plant. Multiple criteria were assessed during the work (e.g., operating aspects and costs, emissions of liquids and gases, energy demand, among others) considering the influence of the main operating parameters (e.g., sludge retention time – SRT, recycle ratio and air flow rate) of a benchmark scenario, which was used as reference for the optimization. Results provided an optimal set of parameter to ensure 48% reduction in terms of operating costs and a 10% reduction in terms of direct emissions. From both previous examples, one can see that DSSs based on MCDM have a great potential to improve the work of managers and researchers regarding the wastewater treatment.

3.4. Intelligent Decision Support Systems for WWTP

Finally, the IDSS based propose the integration of several techniques, some coming from the Artificial Intelligence (AI) and others coming from Statistics or Control Theory field, to improve the complex decisions made by the final users of a WWTP. The reader may refer to Sànchez-Marrè and Cortés (2011) for a further review of the application of AI tools to WWT systems. Both data-driven methods induced from historical data, and model-driven techniques obtained from experts or from first-principle models, are integrated into these systems to improve the performance and reliability of these operation, control, management or design systems. In the last years, some researchers have been studying a more complex WWT system, formed not only by one WWTP, but a whole River Basin (RB) composed by several WWTPs, the corresponding water connections and the receiving water body of the river (Oliva-Felipe et al., 2017). New generations of IDSS based on AI represent the current state of the art. Indeed, they allow establishing a dependence between data (acquired by means of AI systems), focus and actions (Gibert et al 2018).

3.5. Main software tools available for the various DSS

In this section, the software mostly adopted, as authors are aware, for each type of DSS will be briefly presented.

Regarding the LCA, the software mostly adopted WWTP filed is the Superpro/Envrio Pro Designer commercialized by Intelligen, Inc. This software allows handling the wastewater processes (coupled with tens of other processes). This tool is quite simple to be adopted since include an intuitive graphical and user interface. Another LCA software is GaBi life cycle assessment software, commercialized by GaBi solutions. This latter can be adopted as a tool for a sustainable WWTP design. Further, it includes the tools for calculating the carbon, ecological, environmental and water footprint of the WWTP, coupled with the tool for evaluating the resource recovery efficiency.

Regarding the MM and MCDM advanced software are available in the market as support for plant design, diagnostic, optimization, operation. Among these tools, the mostly adopted are WEST, produced by MIKE Powered by DHI, and GPS-X, produced by Hydromantis Environmental Software Solutions, Inc. Both of these software algorithms are based on the ASM proposed by the International Water Association (Henze et al., 2000). WEST and GPS-X allow to simulate the WWTP at plant scale and the integration with other software systems in view of selecting the best option for an optimal plant design or operation.

Since IDSS are often the integration of different decision support techniques, it is hard to find a single software that can be declared as specifically applicable for WWTPs. Indeed, literature shows that different existing systems can be joined to support intelligent decision-making. The Environmental Problem Solving Interface LOgic Nonmonotonic (EPSILoN) is an example of an IDSS based on expert knowledge system that works in a two-step process. The first step regards the insertion of the process knowledge into the platform by the user, so EPSILoN can obtain the information needed for the decision-making process. Then, as a second step, EPSILoN must be able to understand user's request so it can provide the results of the reasoning.

GESCONDA (Sànchez-Marrè et al., 2010) was a tool conceived as a system for knowledge discovery and Data Mining, but currently, the system supports additional functionalities. A case-based reasoning engine and a rule-based reasoning shell are provided. Those skills of GESCONDA makes it a suitable prototype tool for the deployment of IDSSs, including all main steps like data preparation and filtering, data mining, model validation, reasoning abilities to generate solutions, and predictive models to support final users.

Oprea (2018) introduced a knowledge-based modelling framework for IDSS that can be applied to several environmental issues, which had coupled ontological approach with data mining and Bayesian networks. By means of these three approaches, the IDSS is capable of store knowledge regarding the environmental issue, to perform specific analysis on the basis of inductive learning techniques (decision trees and rules algorithms), and to represent the dependences between different parameters defined by the problem.

4. Main focus of DSS application in WWTPS

In Figure 4 the DSS working principle in WWTP field is summarized on the basis of the key focuses linked to its adoption (Figure 4). According to the relevant literature, the key focuses of applying a DSS in WWTP field are: design new plants, reduce energy consumption, improve effluent quality, making WWPTs sustainable, improve plants operation and, their combination (among them, Yoshida et al., 2014; Pintilie et al., 2016; Gémar et al., 2018; Jiang et al., 2018). The DSS can be adopted in literature as a closed loop, depending on the main focus imposed (Figure 4). On the basis of the imposed focus, a collection of a database is first required to run models or software used as support. The results allow to improve experts' knowledge. Then, the results interpretation provides information and potential advises for decision making. Consequently, the actions to undertake in view of obtaining the established focus can be identified (Figure 4).

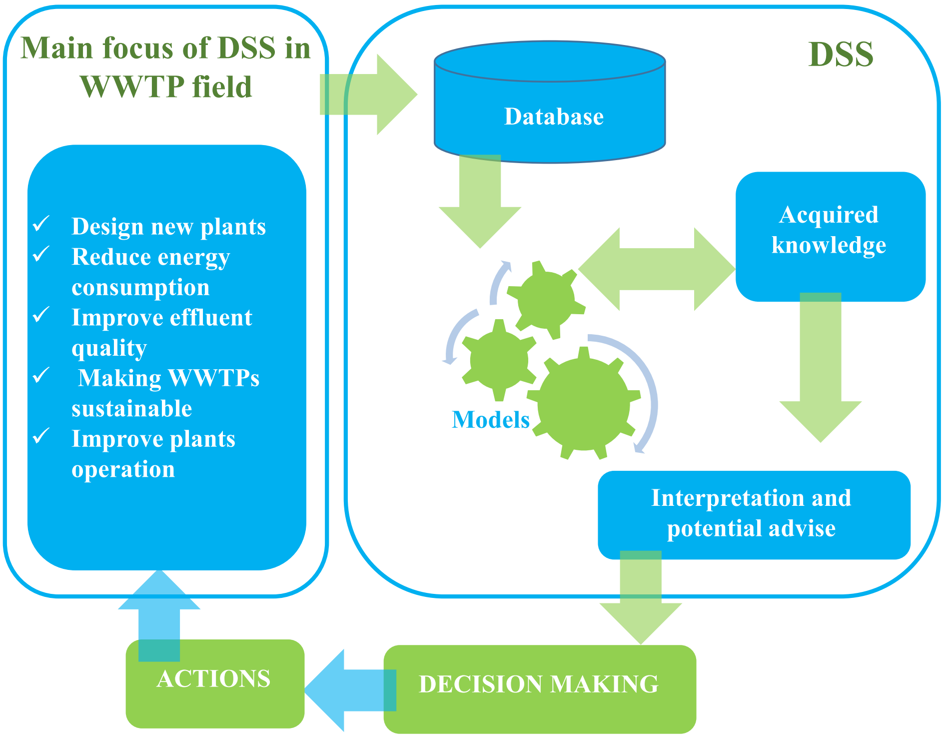

Figure 4. Main focus of DSS application in WWTP field

In the following sub-sections some details about each focus and the main DSS applications found in literature related to each focus wil be discussed.

4.1 DSS focused on design

Currently, two different scenarios can be find in the world regarding the design of WWTPs (Castillo et al., 2016): i) establish a wastewater treatment program (e.g. United States and Europe), seeking to retrofit existing facilities in order to attend more stringent water quality regulations; ii) implement new wastewater treatment plants, such as India, Latin America and Africa, aiming to meet health and ecological standards.

Finding a proper DSS for design purposes is a challenging since WWTPs usually have remarkably site-specific conditions, which makes difficult the adoption of DSSs for all WWTPs. Several DSSs focused on design aspects were found in literature with the scope of upgrading (Bertanza et al., 2015) and retrofitting (Morera et al., 2015; Castillo et al. 2016). DSS developers are also having trouble to keep up with the rapid growth of innovations that is currently happening. Thus, it is hard to find a system that comprises a considerable amount of new technologies and an integration among them to address the whole wastewater treatment (Comas et al 2010; Castillo et al., 2016; Poch et al, 2017).

Despite of the aforementioned challenges, DSSs are able to guide the decision makers into a more rational decision as they consider several aspects at the same time to provide the most suitable solutions. Considering design purposes, for example, the selection of a treatment train on current days does not considers only technological aspects, but also environmental regulations, economic feasibility and stakeholders appreciation, and DSSs are able to present the integrated evaluation within minutes, while a decision maker would need months to present a similar result.

Castillo et al (2016) have presented a detailed study discussing the capability of DSSs as tools to support the designing of new WWTPs. The study of Castillo et al (2016) can be used as a good example of “DSS for design” since three case studies (in United States, South America and Europe) of real projects were adopted by the authors and compared to the results obtained with a DSS. With this regards, they applied the Novedar_EDSS tool which allows to compare different designing scenarios (adoption of different processes technologies, treatment of wastewater having different qualitative and quantitative features, etc…) thanks to its two main sub-units linked each other (specific knowledge base, Skb-units and compatibility knowledge base, Ckb-units). After defining the scenario to be analyzed, during the diagnosis step the Novedar_EDSS allows to compare different technologies (by means of Skb-units) and to identify the appropriate process flow diagrams to be adopted (by means of Ckb-units). The designing alternatives are compared during the last step of Novedar_EDSS by using a multi criteria analysis. The findings obtained by Castillo et al (2016) show that by using the Novedar_EDSS tool the same treatment processes of the real project have been selected, thus showing that this tool represents an excellent decision-makers to support the choice of best technology and treatment processes to be adopted.

4.2 DSS focused on energy aspects

WWTPs are strongly dependent on energy to be operated (Akhoundi and Nazif, 2018). Despite of this dependence, plant managers usually access energy data with a low frequency which provides a long time gap between the occurrence of problems regarding energy aspects and its detection (Torregrossa et al., 2017). Energy is currently measured by automatic sensors that gather the data to feed enormous databases, from which is hard to retrieve information to support the decision-making process. Along with this scenario, it is possible to find studies mentioning process inefficiency as one of the causes for increasing energy consumption within a WWTP (Akhoundi and Nazif, 2018; Torregrossa et al. 2018), which directly affects plant costs. Both situations highlight the importance of a DSS focused on energy demands.

Torregrossa et al. (2017) affirmed that a DSS specially focused on energy aspects of WWTP management does not exist. It is, however, possible to find studies using decision support tools accounting energy consumption and converting this results in terms of indirect GHG emissions (Singh and Kansal, 2016; Tomei et al., 2016; Zeng et al., 2017). The main problem of this approach is that energy is usually considered by DSSs as an input data collected from plant's measurements and not as a result from the decision-making process, i.e., while evaluating plant's performance, managers do not directly seek for mitigating energy consumption, as its consumption appears to be a result of other performance indicators.

One of the first attempt of applying a DSS with the aim to selct strategies for reducing energy consumption and GHG emissions from WWTPs was proposed by Singh and Kansal (2016). Specifically, they combined different simple mathematical models and an LCA to evaluate the total energy consumption and the GHG footprint of WWTPs. The simple mathematical model adopted by Singh and Kansal (2016) were based on mass balance and described th energy consumption and the direct GHG emissions due to: mechanical devices (for example, mixer, pump, aerators), construction materials, diesel used for sludge transportation from the plant to the final destination (e.g., landfill, composting plant etc…) and chemicals used during the plant operation (e.g., disinfectants or flocculants). The energy consumption and GHG emissions of twelve WWTPs in Delhi was assessed in view of understanding the key factors influencing their values in the centralized (the whole catchment area wastewater treated in a large WWTP) and decentralized (several small households treatment systems treating the wastewater produced inside the catchment area) systems. The study of Singh and Kansal (2016) showed the trade-offs between pollution reduction, energy savings, and GHG emissions reduction, which may influence in the decision-making concerning infrastructure's choices. Thus, according to the authors, the choice between centralized and decentralized systems depends on the aim, i.e. if the goal is to lower the degree of pollution, then centralized systems offer more energy savings; if, however, urban wastewater infrastructure is to be designed for recycling and reuse locally, decentralized systems are more energy efficient.

4.3 DSS focused on quality aspects

DSSs can be applied to WWTPs in order to predict the effluent quality under known WWTP operational conditions (Nadiri et al., 2018). For example, it is possible to adopt DSSs in view of calculating treatment efficiency and evaluating the removal of substances even prior to initiate the treatment under different operational conditions, implemented processes and influent features (Hamed et al., 2004; Sonaje and Berlekar, 2015).

One of the most representative example of DSS focused on quality aspects was presented by Jing et al (2018), who introduced a novel probabilistic agent-based modelling approach for simulating the marine oily wastewater treatment process. The agent-based modelling approach has the particularity of describing each component of the system under study at micro scale, thus allowing to predicting the behavior of bulk liquid (e.g., interface between water and oil) that cannot be appreciate at macro scale. Specifically, Jing et al (2018) adopted this approach to evaluate the removal efficiency of naphthalene (NAP) from marine oily wastewater by using the ultra violet (UV) process. They found an excellent capability of the proposed modelling approach to describe the treatment process under study. Indeed, the calibrated model provided predicted results which have a root mean square error quite low (11.03%) compared to the measured data.

A discussion on some DSSs related to quality aspects will be presented in the following sections with the aim of emphasizing the structure of the adopted DSS (e.g., IDSS adopted by Nadiri et al. (2018).

4.4 DSS focused on sustainability aspects

The current goal of WWTPs is the improvement of wastewater treatment's sustainability (Gémar et al., 2018), i.e. treat an higher amount of water as possible, with less cost associated to the treatment and causing less environmental impacts. Considering sustainability as a multiple-aspect issue, it can be said that its assessment is a complex problem (Molinos-Senante et al., 2014).

Some DSSs were developed in order to provide an integration of techno-economic, environmental and social aspects, permitting a more complete evaluation of a WWTP when decision-making is needed (among others, Tomei et al., 2016; Xin et al., 2018). In order to assess the sustainable aspects of a WWTP, the opportunities for its improvement and prioritize actions have to be identified.

Recently, Oprea (2018) have proposed an environmental knowledge based IDSS able to solve different environmental issues (at water, economic or other levels) in view of creating a sustainable WWTP. The advantage of such approach is to dealing and solving complex environmental issues in a modular way.

Other DSSs related to sustainability, will be discussed in section 5 as examples of the DSS types application.

4.5 DSS focused on operational aspects

The DSS focused on operational aspects have the main aim to help WWTPs operators suggesting the best and fastest operational solutions in view of improving cost-benefit relations focusing on several aspects, including quality, energy and sustainability (Torregrossa et al., 2018). The system presented in (Sànchez-Marrè et al., 2004) is currently working as a real intelligent supervisor in many real WWTP. The setting-up and the adoption of DSS focused on operational aspect requires an extensive database (influent flow rate, air flow rate, influent features, etc.). Therefore, it is suggested to equip WWTPs with sensors able to deliver high-frequency data (Torregrossa et al., 2018).

The DSSs focused on operational aspects mentioned in this work as being the ones addressing management issues, e.g. optimization of control parameters (Díaz-Madroñero et al., 2018), and processing of plant report data (Torregrossa et al., 2018). Another important group of DSS are the IDSS focused on the supervision and general management of WWTPs which have been mentioned before. Currently, most of the efforts in IDSSs are focused on model interoperability (Sànchez-Marrè, 2014), and in scalable and automatic building of IDSS, independently from the location-site specific conditions (Pascual-Pañach et al., 2018).

5. Application of DSSs to full-scale WWTPs

This section presents the remarks of peer-reviewed international publications (source Science Direct) dealing with DSSs applied to WWTPs (adopted keywords “decision support systems” and “wastewater treatment”).

The period between 2010 and 2018 was considered in order to illustrate how the DSSs application to WWTPs evolved during the last decade. Most of the papers published from 2010 to 2013 presented the adoption of new approaches (Hernandez-Sancho et al., 2011) or similar types of DSSs (Li et al., 2013) in comparison to the following years. Thus, here the remarks of papers published in most recent years (from 2014 to 2018) are discussed.

The papers found in literature were classified in accordance to the type of DSS applied (LCA, MM, MCDM, IDSS or a hybrid DSS, i.e. comprising the previous types) and their main focus regarding WWTPs needs (design, energy, operation, quality and sustainability). In this period (2010-2018), the efforts on the IDSS type of DSS have been focused more on the proposal of general frameworks (Sànchez-Marrè, 2014), methodological approaches to generate reliable and useful IDSS for WWT systems (Pascual-Pañach et al., 2018), characterization of the environmental data mining subfield (Gibert and Sànchez-Marrè, 2012), and open challenges in the field of IDSS (Sànchez-Marrè et al., 2008), than in deploying applications for concrete WWTP installations. From the 28 papers considered in this review, three were related to LCA, seven to MCDM, eight to MM, three to IDSS, and seven were related to what this paper is calling as "hybrid DSSs", of which three used LCA+MM, two used LCA+MCDM, one IDSS + MM and one IDSS + MCDM (see Figure 5).

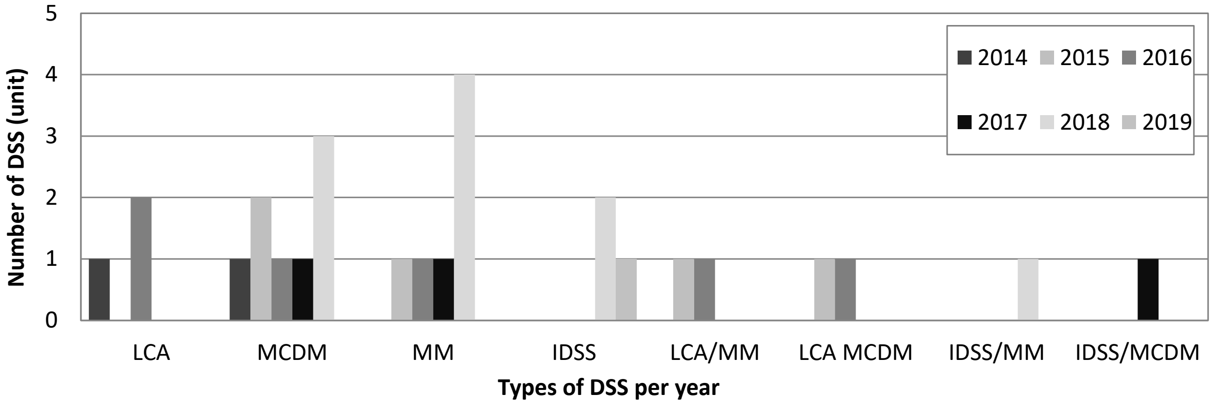

Figure 5. Main types of DSSs applied to WWTPs from 2014 to 2018 (source Science Direct), where: LCA = Life Cycle Assessment; MCDM = Multi-criteria decision making; MM = Mathematical modelling; IDSS = Intelligent DSS; LCA/MM = Life Cycle Assessment and Mathematical modelling; LCA/MCDM = Life Cycle Assessment and Multi-

criteria decision making; IDSS/MM = Intelligent DSS and Mathematical modelling; IDSS/ MCDM = Intelligent DSS and Multi-criteria decision making.

As for the main focus of the DSSs while applied to WWTPs, from the same 28 papers previously mentioned, nine were related to improvements during the design phase, one to improvements concerning energy aspects, five to provide solutions for the operational phase, three seeking to enhance effluent's quality, eight to better understand sustainable aspects, two integrated operations with i) design phase and ii) sustainability aspects, and one integrated energy with sustainability (see Figure 6).

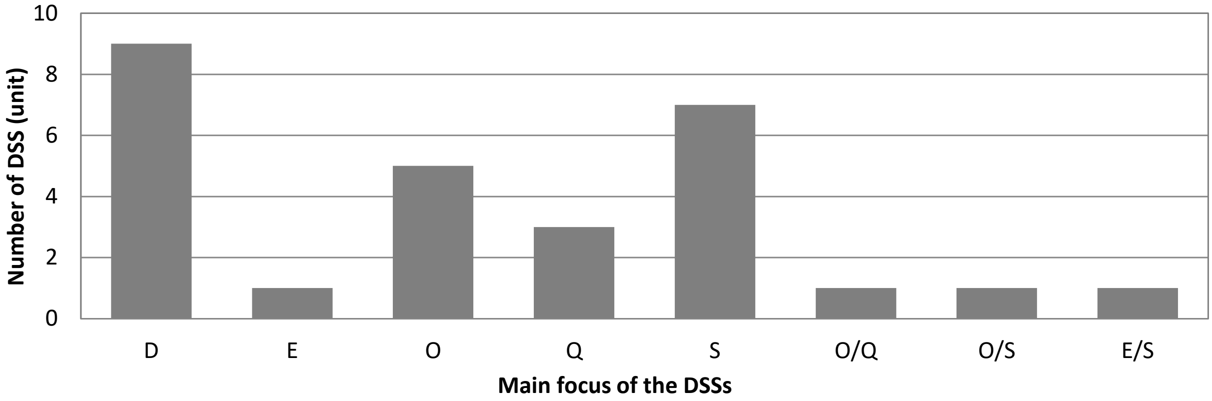

Figure 6. Main focus of DSSs applied to WWTPs from 2014 to 2018, where: D = Design; E = Energy; O = Operation; Q = Quality; S = Sustainability; O/Q = Operation and Quality; O/S = Operation and Sustainability; and E/S = Energy and Sustainability.

A brief description and the main features of the DSSs found in literature are presented in the following sections.

5.1 Life Cycle Assessment

Yoshida et al. (2014) and Pintilie et al. (2016) used LCA in view of assessing issues related to WWTP's sustainability. Yoshida et al. (2014) have emphasized the need of having good quality data. Indeed, Yoshida et al. (2014) have demonstrated that the use of overestimated data (e.g. emission inventory) during the LCA application may result in gross underestimation of environmental impacts associated with the WWTP. With this regard, authors suggested the inclusion of operational data and background emissions.

Pintilie et al. (2016) presented an extensive data collection and a Life Cycle Inventory (LCI) build-up. Two case studies from different climatic regions of Spain were taken into account for assessing water quality, direct (from carbon dioxide - CO_2, N_2O and CH_4) and indirect (from energy consumption) GHG emissions and toxicity coming from pharmaceutical and personal care products (PPCPs). From the extended LCI application, Pintilie et al. (2016) found that the WWTP construction phase is the least environmentally impacting, while the operation phase is the most impacting one. Pintilie et al. (2016) also emphasized that the removal of PPCPs could have strong environmental benefit when compared to non-treatment scenario underlying the key role played by non-conventional pollutants. Pintilie et al. (2016) also underlined the need of adopting measured GHG emissions data, since they are soften higher than the emissions factors; the use of emission factor could underestimate the total GHG emissions in almost 62%.

Lorenzo-Toja et al. (2016) applied an LCA to Spanish urban wastewater and water reclamation opportunities in order to identify and quantify its main environmental contributors. Authors found that energy demand was more environmentally impacting due to the large amount of energy required for the advanced treatment. They also found that non-potable use of reclaimed water could reduce the stress of fresh water supply in Spain.

5.2 Mathematical Models

Some of the DSSs found in literature based on mathematical models will be here discussed.

Gémar et al. (2018) assessed dynamic eco-efficiency (i.e. changes in eco-productivity over time) of WWTPs using the dynamic weighted Russell directional distance model (WRDDM). The WRDDM is a non-radial data envelopment analysis (DEA), and the authors used the approach aiming to obtain an eco-productivity change index for each major component of the WRDDM model, such as costs, pollutants removal, and greenhouse gas emissions. The results were quantified in terms of total factor eco-productivity (TFEPC) and the relative contributions of inputs (e.g. economic costs) and outputs (desirable, e.g. pollutants removal efficiency, and undesirable, e.g. environmental impacts). Results illustrated that although eco-productivity improved in half of the WWTPs assessed, there was still potential for improving some eco-efficiency components. Moreover, operational costs and GHG emissions were the main drivers reducing eco-productivity. The results also highlighted the importance of evaluating change in eco-productivity over time and in identifying the drivers associated with those changes, both of which can be used to support decision-making focused on the sustainability of WWTPs.

Jiang et al. (2018) presented the application of a social optimization model considering both wastewater treatment costs and valuation of ecosystem damage in view of finding the optimal solution for pollutant control levels. Results presented by Jiang et al (2018) showed that the integration between the treatment cost decision and the ecological damage in one model allows improving the policy-makers′ capability of identifying the trade-off for socially optimal solutions under various conditions.

A benchmark simulation model was developed by Saagi et al. (2016) to evaluate control strategies for the urban catchment and sewer network. The model can be integrated with existing/standard wastewater treatment models, such as ASMs. The presented model was able to describe the dynamic conditions related to wastewater generation and to provide an assessment of control strategies and structural modifications to be applied for the catchment and sewer system. On the other hand, further studies must be made in order to guarantee that the model can be applied to different site conditions.

Zeng et al. (2017) used a distance function approach to comprehensively assess the performance of 1079 urban WWTPs throughout China. The main aim of the study was to minimize the capital cost and energy consumption during the removal of conventional pollutants (COD, BOD; TSS, total nitrogen - TN, total phosphorus - TP). The co-benefit of controlling water pollution and mitigating climate change was also taken into account. Zeng et al. (2017) found that GHG emissions could decrease by 32.2% if all plants worked efficiently and that the parameterized distance function presented by the study showed to be useful in explaining the differences among WWTPs and their potential for performance improvement.

5.3 Multi-Criteria Decision Making

Bertanza et al. (2015) have developed a DSS procedure which allows the rating of several technical factors (system reliability, complexity, safety aspects, modularity, etc.) and estimating capital and operating costs in case of WWTP upgrading is needed. The main goal of Bertanza et al. (2015) was to use the DSS in order to evaluate different upgrading scenarios for existing WWTPs. The DSS revealed to be flexible and capable of providing a detailed assessment that emphasizes techno-economic, environmental and social aspects in order to help stakehoders on finding a most suitable solution for sludge management.

Chhipi-Shrestha et al. (2017) developed a DSS for evaluating the potentiality of fit-for-purpose (FFP) wastewater treatment and specific reuse for a community. FFP wastewater treatment simultaneously considers intended and economic viability, use, and environmental sustainability. The DSS considers as state variables the amount of reclaimed water production, the health risk of water reuse, the cost, the energy use and the carbon emissions. From the use of the proposed DSS, Chhipi-Shrestha et al. (2017) conclude that the quality of reclaimed water varies with different reuse applications which affects the types of treatment required. Treatment requirements may reflect on different cost, energy use, health risk and carbon emissions for each WWTP.

Molinos-Senante et al. (2014) presented an innovative methodology to assess the sustainability of WWTPs. Specifically, Molinos-Senante et al. (2014) have proposed a composite indicator embracing economic, environmental and social issues. The Analytical Hierarchical Process (AHP) (Saaty, 1986) is also used to assign the weights to each indicator based on expert knowledge. The methodology proposed by Molinos-Senante et al. (2014) was applied to seven wastewater treatment technologies for secondary treatment in small communities. The results showed that intensive technologies are the cheapest but have the lowest environmental sustainability, whereas the membrane bioreactor presents a contrary behavior. Indeed, the adoption of membrane bioreactors entails high operating costs (additional energy is required for membrane aeration and for permeate pump extraction), thus making this solution low economically sustainable. On the other hand, membrane bioreactors allow to achieve excellent effluent quality since the membrane physical barrier retains all the suspended (and a great part) of the dissolved pollutants, thus making this solution high environmentally sustainable.

5.4 Intelligent Decision Support Systems

Some of the works found in the literature are discussed below.

The PSARU IDSS (Poch et al., 2017) was commissioned by the Catalan Water Agency to a consortium of research groups with the objective of selecting the most appropriate wastewater treatment and disposal system for 3500 communities with less than 2000 inhabitants in Catalonia. A consortium of four environmental engineering research groups from different universities, an artificial intelligence research group and the Spanish Scientific Council led by the University of Girona was established to acquire and systematize the required knowledge and develop a system capable of reproducing the reasoning process of a group of experts facing the complex situation in question. A rule-based system was used as the main reasoning tool.

The IDSS for energy saving within WWTPs proposed by Torregrossa et al. (2017) has the novelty of considering the DSS as a combination of key performance indicators, expert knowledge, daily benchmarking, fuzzy logic, scenario analysis and shared knowledge. With this regards, the Shared Knowledge Decision Support System (SK-DSS) concept was adopted. The structure of SK-DSS is very complex and complete of informatin. SK-DSS includes several tools for data management, for evaluating key performance indicators (KPI calculator), for assessing the benchmark conditions, for analysing the role of different technologies adopted (rule generator), for the comparison of different technical and operating solutions for energy saving and selecting the optimal one (fuzzy logic engin, solution engine and knowledge discovery tools). The IDSS uses the on-line sensors and SCADA systems in view of pregressively find the most appropriate solution for energy saving. The IDSS proposed by Torregrossa et al. (2017) provides useful information to quickly find deficiencies and propose solutions to increase the energy performance.

Nadiri et al. (2018) proposed an IDSS that adopted a supervised committee of fuzzy logic (SCFL) models as surrogates for the WWTP modelling in view of avoiding the adoption of complex physical, chemical and biological models. The fuzzy logic (FL) model predicts water quality parameters using the measurements obtained from influent quality data, such as pH, temperature, chemical oxygen demand (COD), biochemical oxygen demand (BOD), and total suspended solids (TSS). The SCFL model uses an ANN to combine forecasted results of water quality from individual FL models. Three FL models were used as surrogates proposed by Takagi-Sugeno (1985), Mamdani (1977), and Larsen (1980). The comparison between the SCFL results and the three surrogate models showed that the first one increased model's accuracy in approximately 30% for BOD, 31% for COD and 23% for TSS. Authors also recommended to perform future researches to focus on quality data considering time variation.

The atl_EDAR system described in (Sànchez-Marrè et al., 2004) is the real and successful implementation of an IDSS for the supervision and management of WWTPs, proposed some years ago in (Sànchez-Marrè, 1996). The atl_EDAR system is currently implemented and, during the period 2010-2018, it is running in near twenty WWTPs both in Europe and South America. It is especially remarkable the application of the system to the El Prat de Llobregat WWTP which manages 420.000 m^3/day, with an energy saving of 8,000 kWh/day. The system integrated both a rule-based system, a case-based reasoning system, and some fuzzy control algorithms, which made it very reliable and powerful.

5.5 Hybrid DSSs

The denomination "hybrid DSSs" is being used to represent the DSS that presented an association of more than one type of the DSSs previously classified in this work. A brief discussion on the most recently published studies will be provided in the following.

One of the first example of hybrid DSSs, discussed above in terms of DSS focused on energy aspects, has been presented by Singh and Kansal (2016). As discussed above, the DSS of Singh and Kansal (2016) combines simple mathematical models with the LCA approach. Despite the results obtained by Singh and Kansal (2016) showed realistic energy consumption and GHG emissions values, the adoption of simplified models have limited the possibility to widen the analysis in terms of operating factors or treatment processes affecting their values. For example, the adoption of resource recovery strategies in WWTPs may reduce significantly the energy and GHG footprints. With this regards, current literature suggests to combine new generation of simulation with intensive data-driven tween models based for example on IoT, 5G distributed computing and IDSS in view of supporting the WWTP design and the technology development concerning more sustainable water management according to the Directive 2000/60/EC (Gibert et al., 2018; Corominas et al., 2018).

The first attempt of combining innovative approaches was recently presented by Torregrossa et al. (2018). Specifically, Torregrossa et al. (2018) presented an approach that consists of combining the LCA, the DEA, the time series analysis and the statistical tests. The main aim of Torregrossa et al. (2018) was to monitor the potential deterioration of the eco-efficiency (energy and environmental performance) occurred during the modifications in processes behavior within a WWTP. The main innovation in DEA algorithm is based on the set of decision-making units (DMUs), which was represented as 1-day operation datasets of a single WWTP.

The results showed that the methodology was able to identify the modifications in processes behavior and their causes and provide solutions for the process improvement.

6. Discussions on DSS review

The optimal design/operation of WWTPs requires the integration among several factors having different nature techno-economic, environmental, health-hygiene and social-cultural (Díaz-Madroñero et al., 2018) making this issue very challenging. With this regards DSSs could represent a valid tool to address all the aforementioned factors and find a trad-off among them.

Considering the types of DSSs used, the studies presented by this work are following the current trend of applying more comprehensive tools to address WWTPs daily problems. The use of complex tools, such as LCA, MM, MCDM and IDSS, shows that the knowledge acquired so far concerning wastewater treatment has significantly grown with the years and more complex parts of the process become nowadays suitable for automatization to support the complex decisions underlying water management. The field is still in constant improvement and the results retrieved from these studies may provide even more opportunities so the scientific community can find innovative and more general solutions for WWTP issues, encompassing more and more aspects of the process, from safety to sustainability, including efficient operation, optimization of costs, treatment of emergent pollutants, reduction of emissions and other byproducts, in a way flexible enough to be adaptable to the rapid changing contextual conditions in which current WWTP have to perform

In a more specific way, *LCAs* was shown as an important tool to assess environmental contributors and hotspots, due to its extended scope (Pintille et al., 2016). Specifically, literature shows that LCAs present more reliable results while using more precise data as input, as the use of underestimated data may lead to a gross result regarding the environmental outputs (Yoshida et al., 2014). Additionally, as the LCA is mainly applied to environmental issues, it uses is constantly associated with sustainable aspects, but is not restricted to this type of use. Lorenzo-Toja et al. (2016) showed that the association of the LCA with operational and sustainable aspects led to an important result.

Mathematical models allow the investigation of how individual behavior could affect population dynamics while avoid the complex simulation of physical, chemical, and biological treatment processes (Jing et al., 2018). The application of MM can also provide more accurate results than the use of less complex tools, which would help on the reduction GHG emissions (Kyung et al., 2015) and operational costs, while maintaining effluent quality. Mathematical models also permit the assessment of dynamic conditions, which is why they can be applied to address several kinds of focuses. For example, Gémar et al. (2018) assessed the operational costs and the strategies for pollutants removal (both liquid and gaseous). The adoption of a dynamic MM has the great advantage of assessing dynamic conditions focused on sustainability. Jiang et al. (2018) also proved that MMs can be used in order to identify the optimal trade-off for socially solutions under various operational conditions. The operational conditions of WWTPs are very often assessed by mathematical models (Saagi et al., 2016; Díaz-Madroñero et al., 2018) due to the possibility of integrating existing wastewater treatment models (e.g. ASM) with the site-specific conditions in order to obtain more comprehensive results.

The *MCDMs* were used when a multi-criteria assessment was needed to support the decision-making process. The literature review presented here shows that MCDMs were never adopted for quality scopes. This is mainly due to the fact that MCDMs are more complex approaches than others. Comprehensive assessments to address design issues were found in literature, e.g. i. considering several system aspects (such as reliability, complexity, safety aspects, modularity, etc.) and estimating capital and operating costs for plant upgrading (Bertanza et al., 2015); ii. using comprehensive techno-economic analysis (TEA) to evaluate the technology and economic feasibility of the integrated system (Xin et al., 2018); iii. integrating the stakeholders interest in view of selecting the most suitable WWT technology to be adopted (Chhipi-Shrestha et al., 2017; Arroyo and Molinos-Senante, 2018). Web-based initiatives were seen only for MCDMs based on scenario-based analysis (Kalbar et al., 2016) and on online monitoring (Chow et al., 2018). The first one incorporated multiple scenario analysis to assess new treatment technologies, and environmental, social and economic aspects. As for the DSS presented by Chow et al. (2018), its main goal was to use real-time data in order to provide faster answers for the operators while handling the vast amount of data generated from online instruments.

The integration of different type of DSSs was presented in this work as being related to the need for a multi-criteria perspective and for an interconnection between different methodologies that are suitable for the different nature of the assessed data. It was also possible to see that hybrid DSSs have the capability to assess multiple WWTP issues and provide extensive results to help decision-makers. For example, the integration among LCA, data envelopment analysis, time series analysis and statistical tests presented by Torregrossa et al. (2018) allowed to analyze plant's global performance and to suggest improvement measures for the site operation. The same result was obtained by Bisinella de Faria et al. (2015) while applying LCA and a dynamic MM in order to assess effluent's quality after urine source-separation (USS). Hybrid DSSs were also used for assessing pollution reduction, energy savings and GHG emissions reduction (Singh and Kansal, 2016), local and global environmental and economic evaluations (Morera et al., 2015), and for plant retrofitting (Castillo et al., 2016).

The application of AI techniques in DSS created a new type of DSS: the so-called Intelligent Decision Support Systems (IDSS). IDSS, in general, used several models and methods, which were integrated to get more reliable and powerful DSS to provide support to the final users. The atl_EDAR IDSS proposed in (Sànchez-Marrè et al., 2004) integrated both a rule-based system, a case-based reasoning system, and some fuzzy control algorithms for the management, operation and supervision of WWTPs. Torregrossa et al. (2017) proposed an integration of some expert knowledge (inference rules) and fuzzy logic models to improve the operation of the WWTPs. Regarding the design of the best treatment systems, the PSARU IDSS (Poch et al., 2017) aimed at selecting the most appropriate wastewater treatment and disposal system for communities with less than 2000 inhabitants. It used the expert knowledge integrated in expert-based models and used a rule-based tool. Nadiri et al. (2018) proposed the use of an ensemble of fuzzy logic models, which predict some water quality parameters. These fuzzy model outputs are combined through the use of an ANN to get a final parameter prediction in a more accurate way. Pascual-Pañach et al. (2018) proposed the use of visual workflows, to enable the automation of the design task and the implementation of Intelligent Process Control Systems. The resulting framework can automatically generate both simulation models of the process and programming code to control and supervise the process, using workflows designed for each particular installation. The case study is focused on the supervision of a WWTP.

The abundant literature on DSSs oriented to WWTPs design, reflects the urgent need worldwide to upgrade existing plants or construct new plants able to achieve stringent effluent quality limits.

The adoption of DSS studies dealing with energy aspects (e.g., Torregrossa et al., 2017; Singh and Kansal, 2016) have underlined the high potential of using DSS in view od reducing the energy consumption within the

WWTP. In particular, the adoption of an energy-dedicated DSS or the improvement of DSSs based only on accounting energy consumption, can provide predictive solutions to reduce energy consumption.

Quality aspects are more easily assessed by the application of mathematical modelling, which allows to calculate the efficiency of the wastewater treatment. DSSs focused on quality aspects are often site-specifics and therefore to replicate its results for other plants the new tred of research is to correct/upda prior to its application. Among the DSSs focused on quality the study presented by Bisinella de Faria et al. (2015) have the innovative aspect of integrating MM with LCA, while the others used only MM. The integration presented by Bisinella de Faria et al. (2015) has the advantage of providing a complete impact assessment.

Regarding the DSS applied to operate WWTPs, literature shows that the proper operation in view of obtaining an excellent effluent quality is a well-known subject, but it is not easy to get an optimal, on-line and reliable operation of a WWTP. Therefore, the main current challenge of operators and managers is how to optimize operation obtaining excellent effluent quality with the minimum impacts (economic, environmental and social). As for the DSSs focused on quality aspects, operation-related DSSs are very often developed to attend a site-specific condition.

Literature shows that the integration of techno-economic, environmental and social aspects in most of the DSSs presented by this work could allow to better understanding the several complex aspects of a WWTP. However, the major limitation of this approach is the lack of consensus on the definition of sustainability in the framework of WWT (Hoffmann et al., 2000; Molinos-Senante et al., 2014), i.e. sustainable aspects are incorporated in accordance to DSS developers, as there is no standard that can be applied while developing the systems (Balkema et al., 2002; Molinos-Senante et al., 2014). This issue implies that sustainability results may assume different interpretations comparing different DSSs. On the other hand, DSSs based on sustainability aspects may have presented the most complete assessment in terms of integrated analysis, but this does not means that they presented the most reliable DSS. Each case scenario, methodology and result must be separatedly evaluated to understand which DSS could be replicated in another cases. Further, current knowledge suggests that the adoption of IDSSs represent a relevant research frontier since they have the capability to interlink the knowledge on the process (to be optimized or designed…) with the data acquired by using AI.

Further, this work has repeatedly mentioned that site-specific conditions are one of the major challenges while applying a DSS found in literature to an existing scenario. Indeed, the development of a DSS to address specific situation is a cost and time demanding task that sometimes prevents managers from pursue this kind of solution. However, following this line of research, there is the recent work of Pascual-Pañach et al. (2018), where they propose an interoperable workflow-based framework for the automation of building Intelligent Process Supervision Systems for WWTPs, and other environmental systems.

None of the presented DSSs integrated all five focuses investigated (i.e. operational, design, energy, quality and sustainability), which means that, so far, a comprehensive tool to address all WWTP management issues is not yet available.

Another aspect must be cited while evaluating DSSs application to WWTPs. Datasets are, very often, unavailable to help users on the application of DSSs and only a couple of DSSs (Chhipi-Shrestha et al. 2017; Kalbar et al. 2016) was declared as having a user-friendly interface. Also, only one DSS (Chow et al. 2018) were completely web-based. Despite of the fact that none of the DSSs can be considered unreliable based on these aspects, it would be important to stimulate the development of more user-friendly tools in order to increase general interest in use and test the systems. Web-based DSSs could also stimulate group decision-making, as the systems would be available to a higher number of persons. Furthermore, some tools for the development of integrated management and operation IDSS must be deployed.

8. DSS advantages against previous existing techniques for WWTP management

Before the deployment and use of DSS, the existing techniques for WWTP management showed several drawbacks:

- Difficulties to manage the high complexity of WWTPs due to the interaction of heterogeneus components and elements (biological, chemical, physical, mechanical, etc.)
- Lack of control, automation and instrumentation in WWTPs to cope with the dynamicity of WWTPs
- No exhaustive alternative decision analysis support
- No prognosis capabilities for possible alternative decision assessment
- No wide data-based models use

Literature review showed that LCA, MM, MCDM or IDSS are used to support the decision-making process regarding quality, operational, design, energy and sustanability aspects. The use of DSS shows several advantages against previous existing techniques for WWTPs management. These advantages are listed in the table 2, and it is marked in which type of DSSs system these advantages are shown with a greatest impact.

Table 2. Advantages of DSSs techniques for WWTPs

Concept	LCA	MM	MCDM	IDSS
Systematic alternative formation	x	x	x	x
Prognostic capabilities for alternative analysis	x	x	x	x
Evaluation of environmental impact	x			
Comparing designs of different plant alternatives	x			
Optimization of cost and/or emissions		x		
Economic efficiency			x	
Validation of lab-scale results			x	
Usee of data-driven techniques				x
Use of model-driven techniques				x
Integration of AI / Statistical / Control models				x

7. Conclusions

Based on this review, and taking into account the advantages of these techniques described in table 2, it would be important to encourage the adoption of innovative solutions for WWTP including sustainability, treatment of emergent pollutants, reduction of emissions and operational costs. The development of more user-friendly and web-based DSSs is also encouraged to increase general interest. In addition, some works are outlining the gap between the development of environmental IDSS and the actual implementation to the water market. This challenge should be more deeply explored in the future.

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