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Review

Indicator based multi-criteria decision support systems for wastewater treatment plants

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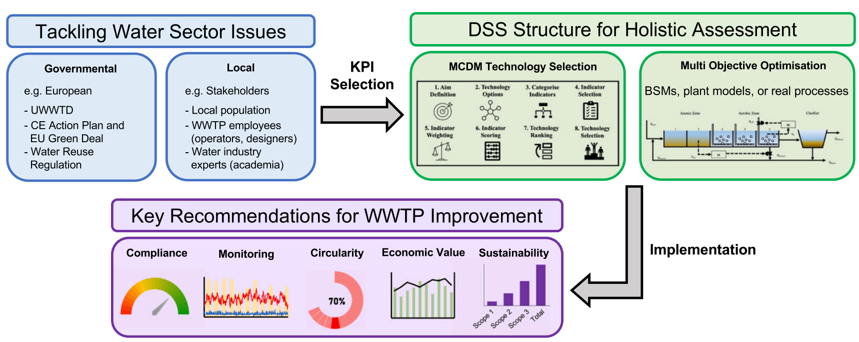
HIGHLIGHTS

- DSS indicators are not selected in line with water sector sustainability targets.
- Process optimisation DSSs state much clearer aims than technology selection DSSs.
- Inconsistent categorisation of environmental, social, and technical KPIs
- Fuzzy-AHP and -TOPSIS are commonly employed to reduce human error.
- Few examples of real-world WWTP process control optimisation due to reliance on BSM.

GRAPHICAL ABSTRACT



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ABSTRACT

Wastewater treatment plant decision makers face stricter regulations regarding human health protection, environmental preservation, and emissions reduction, meaning they must improve process sustainability and circularity, whilst maintaining economic performance. This creates complex multi-objective problems when operating and selecting technologies to meet these demands, resulting in the development of many decision support systems for the water sector. European Commission publications highlight their ambition for greater levels of sustainability, circularity, and environmental and human health protection, which decision support system implementation should align with to be successful in this region. Following the review of 57 wastewater treatment plant decision support systems, the main function of multi-criteria decision-making tools are technology selection and the optimisation of process operation. A large contrast regarding their aims is found, as process optimisation tools clearly define their goals and indicators used, whilst technology selection procedures often use vague language making it difficult for decision makers to connect selected indicators and resultant outcomes. Several recommendations are made to improve decision support system usage, such as more rigorous indicator selection protocols including participatory selection approaches and expansion of indicators sets, as well as more structured investigation of results including the use of sensitivity or uncertainty analysis, and error quantification.

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1. Introduction

The wastewater sector is faced with many challenges that result from ageing and inefficient processes, including substantial carbon emissions, high energy consumption, regulatory compliance failures, and loss of public trust (Borzooei et al., 2019). Unfortunately they are only being worsened by the impacts of climate change, urbanisation, and population growth (Haldar et al., 2022). Although a plethora of technologies have been developed in recent years to combat these issues at a wastewater treatment plant (WWTP) level by academia and industry (Kehrein et al., 2020), water utilities are unable to make the required investment decisions to shift towards sustainable wastewater treatment. Decision support systems (DSSs) have been used to support complex decision making in the water sector, including WWTPs with the aim of optimising technology selection procedures or process control to improve operational performance (Wardropper and Brookfield, 2022).

Wastewater decision makers have additional considerations compared with other industries, as on top of conventional technical, economic, and environmental issues, the social and regulatory implications of their actions must be considered (Ullah et al., 2020). Commonly public perception and social acceptance problems arise when utilising and recycling wastewater streams to generate resources (Kehrein et al., 2020). Water provision and sanitation services are also highly regulated and must be protected due to their importance for society, industry, and the environment (Preisner et al., 2022). Additionally, it is proving difficult to create markets for new products recovered from wastewater, such as tackling the end-of-waste status for their use in the European Union (Palmeros Parada et al., 2022). Therefore, water utility and WWTP decision makers are facing stricter regulations to improve operation regarding human health protection, environmental preservation, and emissions reduction (Mannina et al., 2019), whilst simultaneously pursuing greater circularity and revenue generation through resource recovery strategies to improve business performance. This creates complex multi-objective problems when operating and selecting technologies for improving WWTPs, which are traditionally labour intensive, trial-and-error experiments that rely on the judgement of operators (Ntalaperas et al., 2022; Sucu et al., 2021). To ensure that all relevant information, performance trade-offs, and cause and effect relationships are taken into consideration when dealing with complex problems, DSSs must be utilised by the water sector for more robust decision making (Ullah et al., 2020).

A DSS is a computational system that assists the user in choosing an optimal or consistent solution to a particular problem in a reduced timeframe, particularly when the solution is unclear, by aggregating often conflicting values or preferences to examine the trade-offs between solution objectives (Giupponi and Sgobbi, 2013; Mannina et al., 2019; Wardropper and Brookfield, 2022). A review by Mannina et al. (2019) classified wastewater DSS intentions as; design, energy consumption, operational optimisation, improvement of effluent quality, or environmental sustainability. Of course, decision makers may want to investigate a combination of or all of these goals at once, which can often be contradictory (Eseoglu et al., 2022). For example, WWTP direct emissions and electricity consumption typically increase when improving effluent quality, however, this action negatively impacts any net zero targets. Therefore, when using DSSs to solve multi-objective problems the goal of the study must be defined with clear constraints for optimisation, and an adequate number of relevant key performance indicators (KPIs) chosen, to ensure the resulting decision is a true reflection of the defined goals.

Multi-criteria decision-making (MCDM) tools for selecting the optimal technology for a specific scenario have been developed in literature (Eseoglu et al., 2022; Južnič-Zonta et al., 2022; Sucu et al., 2021). Depending on MCDM application, the goals of the assessment will impact the KPIs used to constrain the decision-making process and final outcome. Conventional WWTP operation is monitored using effluent quality and consequently controlled with a few key parameters, meaning process control is often intuitive with operators unable to understand the real time impacts of their decisions (Ntalaperas et al., 2022). Another key area for DSS use in the water sector is online process optimisation, however, it has not been widely applied in WWTPs as improvements to sensors, mathematical models (soft sensors), and data visualisation are needed for precise operational monitoring and control. However, a combination of data-driven models and artificial intelligence enables performance prediction that can be used to reduce energy demand, decrease costs, improve effluent quality, and lower emissions (Matheri et al., 2022).

Considering the transformation that WWTPs face to improve performance by reducing emissions, energy consumption, and operating costs whilst meeting stricter regulatory targets, water utilities are expected to become ever more reliant on DSSs to solve multi-objective problems for optimal selection and operation of sustainable technology. This study focuses on the use of multi-criteria DSSs to support these two functions for WWTP decision makers. Rather than focussing solely on their typology, analysis of the correct selection and utilisation of relevant KPIs during DSS application is prioritised, to ensure that outcomes fulfil decision maker requirements. This is a pertinent aspect of complex multi-objective decision-making and one which is often overlooked or undervalued by the methodologies in the literature.

2. Methodology

2.1. Wastewater sector goals

Currently, there is a mismatch in terms of the decision maker goals and the KPIs selected when utilising DSSs at a WWTP level. Therefore, this section maps the wastewater ambitions of the European Commission which can be used to direct the utilisation of DSSs to meet water sector targets.

The European Commission has directives which act as the framework for adequate wastewater treatment in the EU and are critical sources for understanding high-level water sector goals. However, in many cases they are decades old and do not reflect the regions recent sustainability ambitions (European Commission, 2022). The Urban Wastewater Treatment Directive (UWWTD) (91/271/EEC) published in 1991, acted as the basis for transforming European water systems by limiting pollutant levels in WWTP discharge. The Sewage Sludge Directive (86/278/EEC) was introduced for the correct use of sewage sludge in agriculture. It details the requirements in terms of heavy metal concentration, quantities of sludge applied per hectare, and the crops prohibited from application (Council of the European Union, 1986). Although the UWWTD and Sewage Sludge Directive have been successful in improving environmental and human health, as 92 % of wastewater is now treated satisfactorily (European Commission, 2022), the next generation of wastewater treatment must go beyond this to achieve the EU's sustainability goals, whilst ensuring this fundamental objective is still maintained.

To instigate further change to WWTPs, a proposal to update the UWWTD was published in October 2022 with the aim of introducing new rules up to the year 2040 (European Commission, 2022). This update will be key for delivering the European Green Deal's zero pollution target and highlights many water sector goals that decision makers will need to adopt in Europe. It expands regulatory compliance to smaller plants and introduces binding energy neutrality targets for the sector, polluter pays for the treatment of toxic micropollutants, and minimum recovery rates for phosphorus. Additionally, improved data monitoring and usage are required for measuring and mitigating greenhouse gas (GHG) emissions and micropollutants, and making KPIs public to improve benchmarking and transparency (European Commission, 2022).

The European Commission is pursuing a CE to facilitate many of its sustainability targets, therefore, it published the CE Action Plan in 2020 (European Commission, 2020). As part of this, the European

Commission aims to intensify nutrient recovery from wastewater by establishing Integrated Nutrient Management Plans (Radini et al., 2023). Another key element is the development of Water Reuse Regulation (2020/741) to facilitate the circular use of wastewater effluents. The document provides a classification system regarding the technology required to achieve the contaminant levels for application to specific crop grades (European Parliament, 2020), relying on the use of Water Reuse Risk Management plans to ensure public and environmental health (Radini et al., 2023). WWTPs should improve effluent quality for the circular use of water, also reducing the quantity of raw water abstracted. Therefore, it is clear that for a sustainable and circular transition, WWTPs must focus on emissions reduction, resource recovery, and water reuse, and acknowledge the importance of proper data usage, to align with water sector goals at a European level.

Analysis of regional government wastewater strategies is vital for creating useful DSSs. However, their it remains challenging to implement tangible decisions at WWTP level, as individual utilities have their own priorities based on local facets. Considering legislative constraints, sector-wide ambitions, and local factors can make the identification of priorities at a WWTP-scale challenging for decision makers. Therefore, rigorous indicator selection and usage is needed to ensure DSS KPIs align with stakeholder goals at every level of decision making, or else WWTPs are at risk of undesirable future impacts and events.

2.2. *Article collection method*

2.2.1. *Research question*

There have been recent publications which discuss multi-criteria analysis (MCA) DSSs for the wastewater sector (Ddiba et al., 2023; Mannina et al., 2019), however they allude to issues that exist for the assessment and selection of technologies. Mannina et al. (2019) states that '*sustainable aspects are incorporated in accordance to DSS developers, as there is no standard that can be applied while developing the systems*', whilst Ddiba et al. (2023) concludes that some sustainability implications are not adequately covered by decision support tools. This shows that a lack of standardisation has resulted in the development of indicator-based methodologies that do not fully consider the sector's sustainability goals. However, the wastewater sector must meet the requirements set out in Section 2.1 in the coming years, therefore, this review systematically analyses the specific indicators selected, and how they are used by DSSs, to understand the impact on WWTP outcomes. This results in the research question of *how are indicators selected and utilised in decision support tools for technology selection and process optimisation at WWTPs, and to what extent are sustainability and circularity pillars harmonised to meet decision maker goals?* Additionally, the need to construct standardised DSS procedures to facilitate sustainability outcomes is highlighted, thus following literature review recommendations are provided to act as the starting point for this. The types of MCA used to facilitate complex decision making have already been the subject of systematic reviews (Kozłowska, 2022), meaning the methods available in literature have already established. Therefore, they do not require further generalised study and is why the focus of this review is on DSSs implemented for wastewater technology assessment to understand current practices and provide recommendations for improvement.

2.2.2. *Search strategy*

The evaluation of WWTP DSSs was completed using systematic review, following the guidelines of the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) method (Page et al., 2021). Articles describing multi-criteria, indicator-based DSSs for WWTP technology selection and process optimisation were collected from Scopus (www.scopus.com) and Web of Science (www.webofscience.com) databases. The configuration of this review required two independent searches to collect data using a combination of Boolean connectors, and a previous review in the area by Mannina et al. (2019) established the time series of 2018–2022. MCDM technology selection DSSs were found using the search term *("wastewater treatment"* OR WWT OR *WWTP* OR *sludge)* AND (*DSS* OR "decision support system" OR MCA OR "multi criteria" OR MCDM OR "multi-criteria") AND (selection OR identification OR KPI). Whilst the multi-objective optimisation DSS search used (WWTP OR "wastewater treatment plant" OR "wastewater treatment process") AND (control OR operation OR monitoring OR optimisation OR optimization) AND multi AND (criteria OR objective) terms.

2.2.3. *Selection of studies*

Fig. 1 shows the steps taken to screen initial search results and collect articles used for review (Page et al., 2021). Results were exported to Mendeley reference management software for processing, and after removing duplicates 127 articles and 144 articles related to technology selection and process optimisation DSSs were identified respectively. They were then analysed to ensure the inclusion of only high-quality, peer-reviewed, original articles, thereby removing non-English, conference proceedings, book chapter, and review paper sources. Next, sources were primarily screened based on their title, and subsequently using the abstract and content in full, to establish the final list of articles. Technology selection DSSs were excluded if used for geographic location planning, source selection, resource allocation, performance assessment, or operation monitoring, and did not utilise multiple indicators for decision making. Process optimisation DSSs were excluded if only used for performance monitoring, fault-detection, visualisation tasks, load prediction, or sensor utilisation, and did not use multiple indicators to optimise control parameters. An additional six relevant articles were collected from a review paper by Mannina et al. (2019) investigating DSSs for WWTPs, to incorporate appropriate literature from outside the search time series.

3. Technology selection DSSs

The decision to invest in new technology at a WWTP is a complex and multi-faceted decision to fulfil business, sustainability, and regulatory targets. MCDM tools have been developed for this purpose, however, there is often little emphasis on linking the goals of the assessment with indicator selection, weighting, and scoring methods. This potentially leads to outcomes that do not truly satisfy all stakeholder and decision maker goals at regional, national, utility, community, or WWTP scales. Literature collected in Section 2 is reviewed to understand conventional methods and highlight good practices regarding alignment of KPIs with DSS goals. Table 1 summarises the MCDM WWTP technology selection DSSs collected from literature, resulting in a total of thirty-one articles.

Table 1 summarises DSS properties namely the technologies selected, aim, case study of application, and categories used to group assessment indicators. The four main technology groups selected using MCDM DSSs are; wastewater treatment (WWT), sewage sludge treatment (SST), water reuse (WR) and resource recovery (RR), or a combination thereof. Since 2018, the development of DSSs for the selection of RR technologies has emerged as a priority for decision makers. The aim of each DSS has been directly quoted from the source, as this is key to understanding specific goals of the DSS when selecting appropriate indicators to facilitate desired outcomes. Lastly, the categories defined when selecting indicators are provided, which is important for relating DSS goals to selected KPIs for technology assessment. The assessment category column in Table 1 highlights the popularity of using economic, environmental, social, and technical sustainability dimensions to group indicators. Steps of the reviewed MCDM DSSs are summarised in Fig. 2, including examples at each stage from the reviewed literature.

The thirty-one papers developing MCDM technology selection DSSs were categorised in Table 1 based on the type of technology being assessed. Selection of WWT technologies is the most common with fifteen DSSs, as WWT decision making is complex so selection of treatment methods is challenging. RR is the second most common focus, which can be attributed to the emphasis placed on selecting sludge

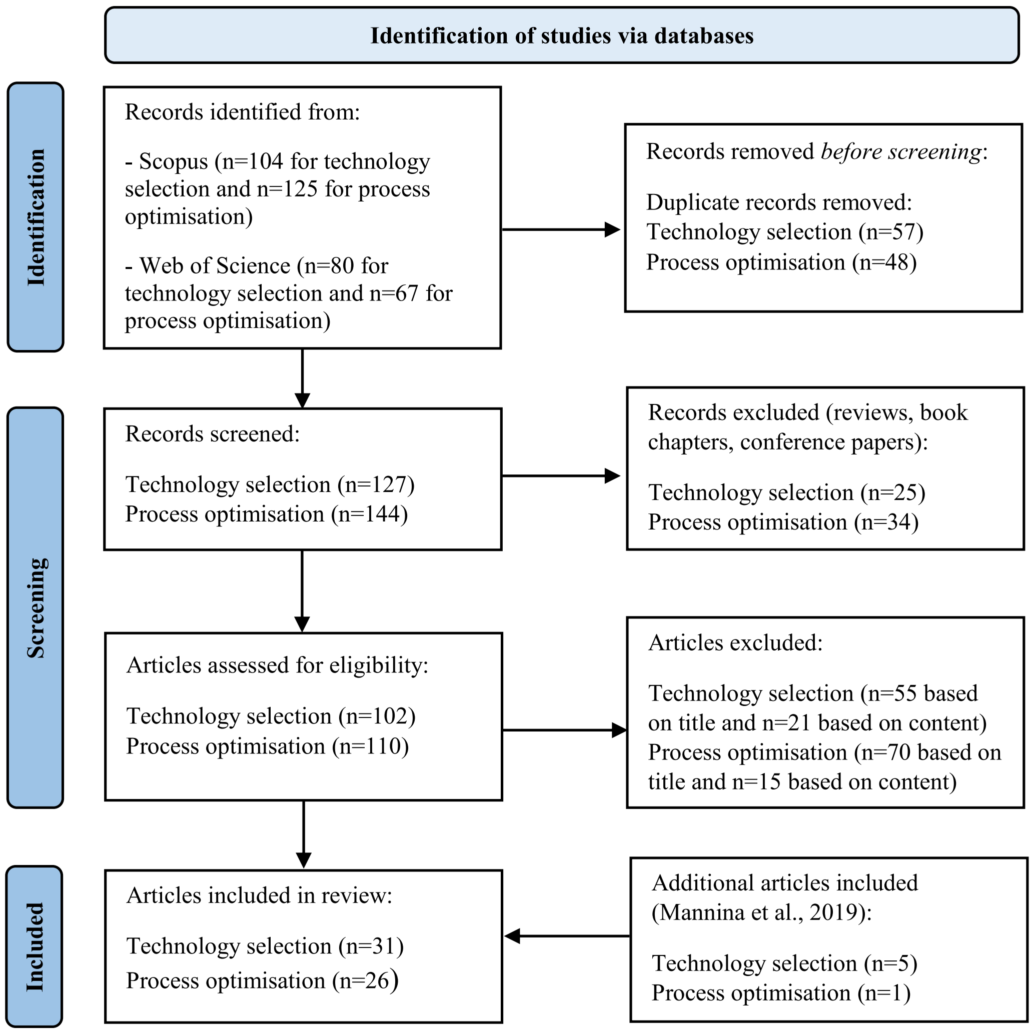

Fig. 1. Flowchart of the steps taken during the article selection procedure (Page et al., 2021).

treatment technologies for recovery purposes (usually energy). This highlights the desire of decision makers to make use of a resource that was previously considered a waste during WWT, reflecting the modern objective to enhance circularity of the sector. Four DSSs for WR technology selection have been developed, acknowledging that due to global warming, water stress is being exacerbated for many people, requiring more efficient use of water by decision makers. Lastly, two DSSs focused solely on the selection of technologies for SST, whilst only one was developed that combined technology selection for WWT and SST. It is critical to list the type of technologies being selected by a DSS so that the correct assessment criteria or indicators can be integrated. This is reflected by the low number of WWT/SST DSSs, as it is difficult to select criteria that are suitable for the assessment of both treatment technologies since their goals and expected outcomes differ.

3.1. DSS goals

To ensure that selected technologies will result in the benefits expected by stakeholders and decision makers, the aim of DSS application must be clearly defined. As shown in Table 1, the most common aims used vague and generic language for the selection of the most *suitable/appropriate/viable/best-fitting* technology in ten DSSs. Although this reveals the intention of the DSS, rarely are these terms explained in a way that enables the user to understand what these 'suitable' technologies may look like considering the scenario of application. This lack of direction limits wider utilisation of developed DSSs and could explain why most are not used across multiple case studies. Next, nine DSSs aim for the *identification/selection/prioritisation/recommendation* of technologies for a specific function, including non-potable water reuse or resource recovery strategies. Although this instructs the user with regards to the expected function of selected technologies, it does not provide any justification as to the reasoning for their selection. Third, the aim of seven DSSs is to select sustainable or assess the sustainability of alternatives. This is not useful unless a vision of sustainable wastewater treatment is defined by the DSS developers, as users cannot fully understand how to assess and compare the sustainability of alternatives (targets summarised in Section 2.1 are useful here). *Evaluation/analysis* of technologies utilising specified criteria, such as environmental or economic aspects is another common DSS aim, with three identified from the collated list. These highlight the assessment criteria used to select technologies but does not provide the user with adequate reasoning of why they should implement the technologies. Finally, two DSSs aim to *optimise* or *find the optimum* solution, which is difficult to comprehend unless the objectives being optimised are explicitly defined. Without a clear definition of DSS aims, there is a disconnect in user knowledge, as the aim is key for understanding why a DSS is implemented and selecting the correct indicators to facilitate desired outcomes or water sector targets. Therefore, vague language must be mitigated, and complete definition of aims is encouraged from DSS developers to help users implement technology selection tools correctly.

Table 1
Summary of wastewater treatment MCDM technology selection DSSs.

Author	Year	Group	Aim	Case study	Assessment categories	Weighting method	KPIs selected
Molinos-Senante et al.	2014	WWT	*Assess the sustainability of WWT technologies*	1500 PE WWTP	Economic, Environmental, Social	AHP	CAPEX, OPEX, removal efficiency, energy consumption, land use, sludge production, potential for RR and WR, reliability, odours, noise, visual impact, public acceptance, complexity
Garrido-Baserba et al.	2015	SST	*Identification and assessment of the most appropriate sludge treatment technologies*	1,000,000 PE WWTP	Economic, Environmental	Fixed	Annual cash flow, annual income, total annual equivalent costs, GWP
Castillo et al.	2016	WWT	*Analysis of the alternatives through a multi-criteria approach, considering operational, economic, and environmental criteria*	Retrofit vs construction of WWTP in Italy	Economic, Environmental, Operational	User Defined	Nitrogen removal, CAPEX, OPEX, CBA, LCA, noise, visual impact, need for specialised staff, flexibility
Chhipi-Shrestha et al.	2017	WR	*Evaluating the potentiality of fit-for-purpose wastewater treatment and specific reuse for a community*	Comparing non-potable water uses for 10,000 PE community	Economic, Environmental	User Defined	Microbial concentration, quantitative microbial risk assessment, development of alternative treatment trains, estimation of reclaimed water quantity and its distribution, LCC, energy use, carbon emissions
An et al.	2018	SST	*Helping the decision- makers/ stakeholders to select the most sustainable technology among multiple scenarios*	Three sludge management strategies	Economic, Environmental, Social, Technical	AHP	CAPEX, OPEX, land use, environmental risk, resource utilisation efficiency, operability, site selection, applicability, and management level requirement
Arroyo and Molinos-Senante	2018	WWT	*Choice of the most sustainable WWT alternative*	Seven small-scale WWT technologies	Economic, Environmental, Social	CBA	CAPEX, OPEX, removal efficiency, energy consumption, land use, sludge production, potential for RR and WR, reliability, odours, noise, visual impact, public acceptance, complexity
Sadr et al.	2018	WR	*Selection of WWT technologies for non-potable water reuse applications in different contexts*	Large WWTPs in Brazil and Greece	Economic, Environmental, Social, Technical	AHP	CAPEX, OPEX, energy consumption, environmental impact, community acceptance, adaptability, ease of construction and deployment, land requirement, complexity, water quality
Oertlé et al.	2019	WR	*Promote water reuse in regions where it is still an emerging concept*	Thirteen treatment trains in different locations	Economic, Technical, Requirements and Impacts	User Defined	CAPEX, OPEX, distribution costs, energy demand, chemical demand, odour generation, sludge production, land required, groundwater impact, reliability, ease of upgrade, adaptability, ease of operation/ construction/ demonstration
Đurđević et al.	2020	SST/ RR	*Technology selection for sewage sludge energy recovery*	WWTP planned for Rijeka, Croatia	Socio-economic, Environmental, Technical	AHP	Material stabilisation, energy reuse, nutrient recovery, commercial acceptance, product transport/ storage, GHG reduction, pre-treatment requirements, hazardous by-products, heavy metal content, public acceptance, OPEX, CAPEX, labour requirements, energy savings, societal contribution
Ali et al.	2020	WWT	*Evaluate and prioritise different wastewater treatment technologies used in Pakistan*	Five WWT alternatives in Pakistan	Undefined	VIKOR	Cost, land requirement, processing time, manpower requirement, efficiency, environmental impact, energy consumption, sludge production, safety, chemical requirement
Gherghel et al.	2020	WWT/ SST	*Identify the most suitable treatment scheme for the management of wastewater and sludge*	Large WWTP of 720,000 PE in Italy	Economic, Environmental, Energy, Land Use	AHP	GHG emissions, running costs, service landfill surface, electricity consumption, planimetric size, biorefinery capabilities, landfill requirements
Chrispim et al.	2020	RR	*Support decision-making on resource recovery strategies; to recommend operational and technological strategies*	WWTP in Sao Paulo serving 1.4 million PE	Economic, Social, Environmental and Technical, Political	N/A	Recovery potential, maturity, resource utilisation, skilled labour requirements, product quality, positive environmental impact, CAPEX, OPEX, revenue, logistics, acceptance, accordance with policy and legislation

(*continued on next page*)

Table 1 (*continued*)

Author	Year	Group	Aim	Case study	Assessment categories	Weighting method	KPIs selected
Liu et al.	2020	WWT	*Optimise the sewage treatment technologies and their combination technologies*	Town in Liao River Basin, China	Economic, Environmental, Social	AHP	Construction cost, land cost, OPEX, removal rate, life expectancy, stability, resource recovery, simplicity, ecological values, risk assessment
Ullah et al.	2020	WWT	*Assist decision-makers to select suitable WWTTs from a set of alternatives*	Two sources of wastewater in Islamabad, Pakistan	Undefined	N/A	Odour, removal efficiency, land use, manpower, financial resources, time availability, chemical availability, oxygen requirement, sludge management and disposal
Palma-Heredia et al.	2020	SST/RR	*Selection of the best-fitting sewage sludge valorisation strategies*	WWTP in Spain	Regional Level, Plant Level, Process Level	Fixed	Viability, material circularity, self-sufficiency, risk assessment, NPV, removal efficiency, sludge production, biogas production, efficiency, CAPEX, OPEX
Ling et al.	2021	WWT	*Assess and compare the sustainability of different wastewater treatment options*	Seven WWT options in UK	Economic, Environmental, Social, Resilience	AHP	Energy requirement, land use, pollutant removal, sludge production, RR potential, GHG emissions, public acceptance, odour, noise, visual impact, reliability, complexity, CAPEX, OPEX
Fetanat et al.	2021	WWT/RR	*Prioritise energy recovery from wastewater treatment technologies*	WW management in Behbahan City, Iran	Water Security, Energy Security, Food Security	LAM	Water security (access, safety, and affordability), energy security (availability, accessibility, affordability, acceptability, applicability, and adaptability), food security (availability, access, utilisation, and stability)
Büyüközkan and Tüfekçi	2021	WWT	*Evaluate the most suitable WWT decision system*	WWT selection for a company in Istanbul, Turkey	Economic, Environmental, Technical, Administrative, Management	AHP	Water/energy/discharge/chemical costs, monitoring, waste production, environmental benefits, facility management, NPV, volumetric capacity, water quality, applicability and performance, reliability and sustainability
Lizot et al.	2021	WWT	*Evaluation of WWT systems considering relevant economic, social, technical, and environmental criteria*	Twenty WWT options for a sanitation company in Brazil	Economic, Environmental, Social, Technical	AHP	CAPEX, OPEX, NPV, Land, manpower, reliability, replicability, complexity, removal efficiency, sludge production, GWP, acceptance
Sucu et al.	2021	RR	*Find the optimum treatment train consisting of compatible unit processes which can recover water, energy and/or nutrients*	Large and small WWTP recovering irrigation water	Economic, Environmental, Social, Technical	User Defined	Annual cost, potential income, acceptability, affordability, land area, odour, noise, flexibility
de Almeida et al.	2021	WWT	*Develop and apply a methodology for sewage treatment systems selection*	Benevente River watershed in Brazil	Operational, Technical, Environmental, Social	Multi Attribute Utility Theory	Removal efficiency, energy demand, land use, CAPEX, OPEX, sludge treated, sludge disposed, reliability, simplicity, resistance, odour, noise, aerosol generation, insect attraction
Eseoglu et al.	2022	WWT	*Technology selection problem for wastewater treatment that integrates all aspects of sustainability with the behavioural characteristics of decision makers*	Four WWTPs >100,000 m^3/d Istanbul, Turkey	Economic, Environmental, Social, Technical	AHP	Energy consumption, sludge production, reuse of treated water, capital cost, land required, OM cost, energy saving, sludge disposal cost, removal eff, maturity, simplicity, applicability, replicability, flexibility, reliability, odour, manpower needed, social acceptance, social benefit, aesthetic
Leoneti et al.	2022	WWT	*Choosing a WWTP for a municipality*	Six 40,000 PE WWTP alternatives in Brazil	Economic, Social, Environmental	Game Theory (rank order centroid)	Cost, effluent quality, land area, sludge production
Liu and Ren	2022	SST/RR	*Promote the sustainable decision-making process of sludge management*	Four sludge-to-energy options	Economic, Environmental, Social, Technical	BWM	Climate change, acidification, eutrophication, net cost, social acceptance, governmental support, educational significance, odour, complexity, maturity, accessibility
Attri et al.	2022	WWT	*Sustainability assessment of wastewater treatment technologies*	Six alternatives for secondary WWT	Economic, Environmental, Social, Functional	Fuzzy Stepwise Weighted Assignment Ratio Analysis	Removal efficiency, effluent DO and coliform, NP removal capabilities, area, power requirement, OPEX, CPAEX, odour, noise, visual impact, flexibility, reliability, ease of operation, FOG tolerance, waste sludge production

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Table 1 (*continued*)

Author	Year	Group	Aim	Case study	Assessment categories	Weighting method	KPIs selected
Renfrew et al.	2022	RR	*Identification of strategies for resource recovery from wastewater*	Priority resource identification for UK water sector	Recovery, Market, Cost, Carbon, Treatment Impacts, 6 Capitals	User Defined	RR potential, market, treatment, cost, carbon, 6 capitals
Nkuna et al.	2022	SST/ RR	*Selection of the most viable thermochemical technology to handle municipal WWS for energy recovery*	Three technologies converting WW sludge to energy	Economic, Technical	AHP	Dependability, maturity, sludge use, energy production, energy consumption, CAPEX, OPEX
Južnič-Zonta et al.	2022	RR	*Given a set of resource recovery and wastewater treatment process units, quickly determine the best plant configuration*	Medium size WWTP in Manresa, Spain	Economic, Environmental, Technical	User Defined	Effluent quality, costs, maturity, GHG emissions, area
Silva Junior et al.	2022	WWT	*Select the most appropriate technologies for wastewater treatment*	WWT in urban and rural municipalities in Brazil	Economic, Socio-Environmental, Technical	User Defined	Area demand, quality performance, mechanisation rates, electric power consumption, CAPEX, OPEX, operational complexity, BOD removal
Srivastava and Singh	2022	WR	*Selection of an appropriate wastewater treatment chain that produces effluent suitable for the defined reuse*	WWT technologies for water reuse in Kanpur, India	Economic, Environmental, Technical	Full Consistency Method	CAPEX, OPEX, land use, energy consumption
Salamirad et al.	2023	WWT	*Select the most appropriate municipal WWT technology*	Seven WWTP alternatives in Iran	Economic, Social, Environmental	BWM	Investment cost, reliability, efficiency, volume dependency, requirement for additional treatment, energy consumption, sludge production, odour, workforce requirement, law and regulation compliance, salinity removal, bacteria removal

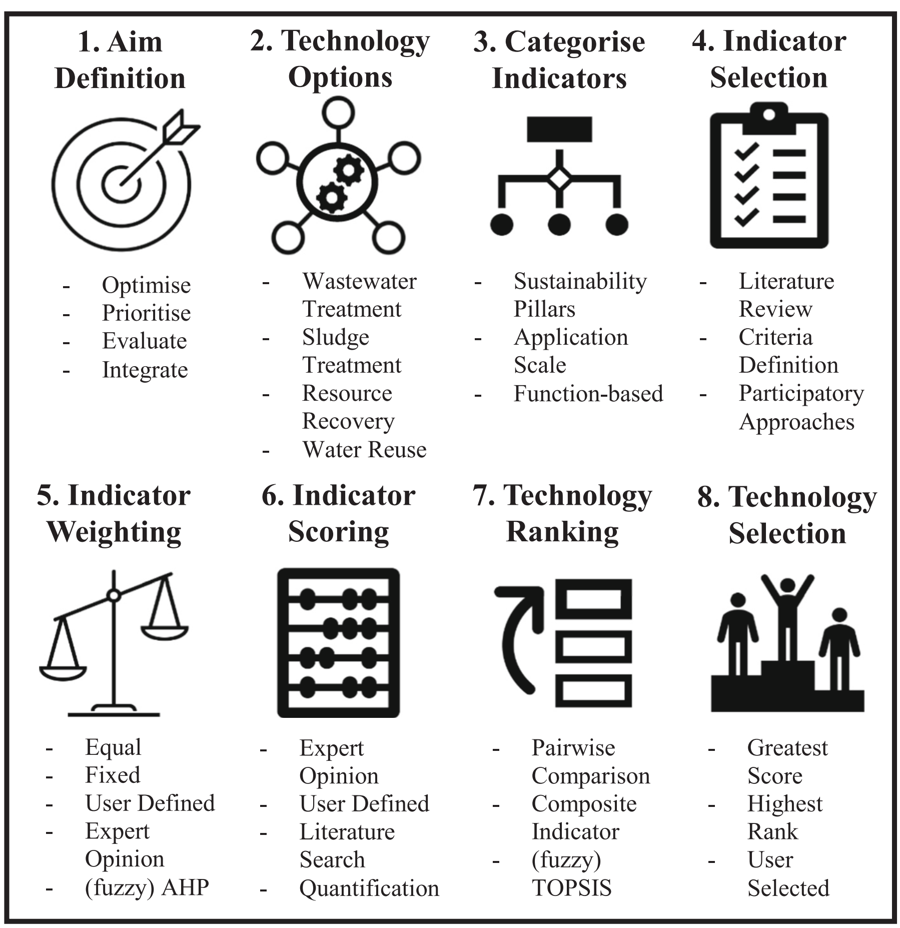

Fig. 2. Generic steps of MCDM technology selection DSSs, including examples and techniques available for use at each stage.

3.2. Indicator selection

As discussed, selection of assessment indicators or criteria when using any WWTP DSS is crucial to ensure the chosen technology fulfils decision maker and stakeholder goals. Therefore, methodologies implemented for indicator selection by DSSs are scrutinised and summarised in Fig. 3.

Fig. 3 shows that it is common for DSS developers to self-select indicators or provide a list from which users can choose indicators, with little methodological explanation given (An et al., 2018; Castillo et al., 2016; Chhipi-Shrestha et al., 2017; Chrispim et al., 2020; Fetanat et al., 2021; Garrido-Baserba et al., 2015; Gherghel et al., 2020; Južnič-Zonta et al., 2022; Renfrew et al., 2022; Srivastava and Singh, 2022; Sucu et al., 2021). This results in a significant gap in DSS user knowledge, as they are unable to reason whether the selected indicators are relevant to their scenario of application. Data availability can be used to guide indicator selection, relying on primary data where possible or secondary data acquired through reasonable effort, such as modelling, whilst meeting data quality requirements. To improve the robustness of indicator selection, some authors define criteria or provide additional justifications to choose appropriate indicators from literature (Arroyo and Molinos-Senante, 2018; Attri et al., 2022; Liu and Ren, 2022; Molinos-Senante et al., 2014; Nkuna et al., 2022; Palma-Heredia et al., 2020; Sadr et al., 2018). For example, Molinos-Senante et al. (2014) reasons indicator selection using *transparent, representative, relevant and quantifiable* evaluation criteria, however, definitions of these terms are not provided potentially resulting in ambiguity for the user.

More complete approaches conducted structured literature reviews for indicator selection (da Silva Junior et al., 2022; Leoneti et al., 2022; Lizot et al., 2021). Lizot et al. (2021) describes the terms entered into literature search engines to collect assessment criteria utilised by other WWT MCDM tools, and then lists specific information and data availability requirements applied to create indicator shortlists. However, only a short description of shortlisting steps is given which focuses on technical aspects (such as plant load, location, or size), rather than sustainability goals. Alternatively authors used knowledge of local factors to select appropriate DSS indicators from literature (de Almeida et al., 2022; Oertlé et al., 2019). Đurđević et al. (2020) utilised their own judgement to select DSS indicators considering the state of wastewater and sewage sludge management, socio-economic standards, and available data (from national databases) in the local area. Liu et al. (2020) provides an explanation of the local context for each indicator provided, such as using economic costs as the project may *need some financial support from the community* or process simplicity *due to the lack of professionals* for operation. This strategy encourages the DSS user to consider local factors during decision making, however, a more robust approach is to use local stakeholder perspectives as well.

Some DSS developers recognise the importance of rigorous indicator selection to achieve desired outcomes by utilising external expert or stakeholder opinions, for example to screen assessment criteria from a longlist identified during literature review (Ali et al., 2020; Salamirad et al., 2023). Ling et al. (2021a, 2021b) developed a method starting with a round of literature review to collate indicators previously used to evaluate WWT performance. The list is then refined based on key terminology mentioned during interviews (thematic analysis using Nviva software) with water company employees utilising the DSS. Eseoglu et al. (2022) employs the use of a questionnaire study by experts from across many roles in WWTPs from design to operation, and combines this with other information including effluent discharge regulation, environmental impacts, and design parameters. These DSSs acknowledge that indicator selection is an important part of strategic MCDM, and the combination of stakeholder views with technical appraisal of local factors enables the user to select indicators which adequately reflect their goals. Fig. 3 highlights that these more robust indicator selection methods are less popular, helping to answer the research question by reporting a lack of robust methods for indicator selection in most of the DSSs developed for WWTPs.

The specific indictors selected showed that only two DSSs did not utilise economic indicators (Chrispim et al., 2020; Fetanat et al., 2021), with most the common being capital and operating expenditure, whilst others chose life cycle costing (LCC) (Chhipi-Shrestha et al., 2017) and net present value analysis (Lizot et al., 2021). Removal efficiencies of regulated wastewater constituents, including total suspended solids (TSS), chemical oxygen demand (COD), biological oxygen demand (BOD), nitrogen, and phosphorus, were commonly selected to determine treatment performance (Arroyo and Molinos-Senante, 2018; Eseoglu et al., 2022; J Ling et al., 2021b; Liu et al., 2020; Molinos-Senante et al., 2015; Silva Junior et al., 2022). Indicators of environmental performance covered GHG emission (Gherghel et al., 2020; Južnič-Zonta et al., 2022; Jiean Ling et al., 2021a), carbon footprint (Chhipi-Shrestha et al., 2017; Renfrew et al., 2022), and life cycle assessment (LCA) (usually eutrophication, climate change, and acidification) impacts (Castillo et al., 2016; Lizot et al., 2021). Effort was made to consider the social impacts of technologies, commonly their odour and noise aspects (Eseoglu et al., 2022; Oertlé et al., 2019; Sucu et al., 2021), whilst some quantified microbial (Chhipi-Shrestha et al., 2017) and ecological risks (Liu et al., 2020). In most cases, circularity indicators were combined with environmental KPI sets, including water reuse (Eseoglu et al., 2022; Lizot et al., 2021), resource or product recovery potential (Chrispim et al., 2020; Renfrew et al., 2022), and material circularity (Palma-Heredia et al., 2020). Lastly, technology energy consumption was one of the most commonly selected indicators, however, only a few DSSs consider renewable energy (Lizot et al., 2021), energy reduction (Durdević et al., 2020), or self-sufficiency (Palma-Heredia et al., 2020) dimensions.

From this it is clear that DSS developers select indicators from across the triple bottom line to support sustainable performance, but there is a gap in terms of facilitating sustainability targets and circularity assessments. Few KPIs are explicitly selected to quantify progress towards the high-level water sector targets of Section 2.1 by failing to link indicator selection with targets such as GHG reduction, phosphorus recovery, or energy neutrality. This even includes those DSSs with the aim of selecting technologies for sustainable and circular actions, such as water reuse or energy recovery.

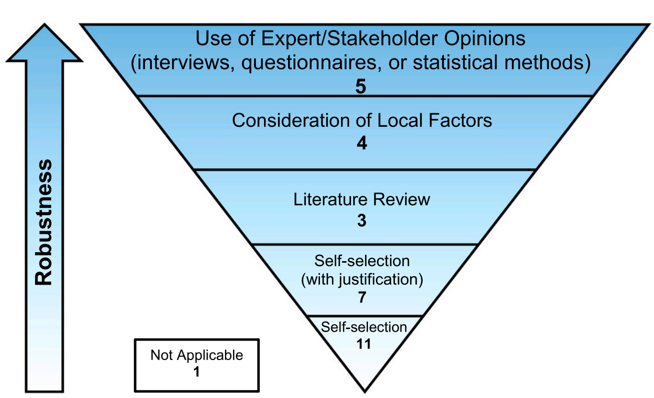

Fig. 3. Methods of indicator selection used by MCDM technology selection DSSs, with the number DSSs using each method in bold.

3.3. Indicator categorisation

Often criteria or indicators are categorised to show user assessment priorities and indicate potential benefits or impacts of selected technologies. Table 1 defines the DSSs categories employed to separate indicators and shows that twenty of the thirty-one DSSs utilise discrete sustainability pillars. The most popular combination uses four environmental, economic, social, and technical (assumed interchangeable with *functional, operational,* or *resilience*) categories. Nine DSSs used a combination of other categories defined by the developers, and some did use sustainability pillars, however, they were combined to create hybrid socio-economic or -environmental categories. Many DSSs also utilise circularity KPIs, however, as mentioned in Section 3.2 they are categorised as environmental indicators. This is worrying as enhancing the circularity of wastewater resources does not directly correspond to improved environmental performance. This leads to a significant gap in decision maker knowledge as circularity indicators are being used to as a substitute for sustainability impacts. Therefore, DSSs with circularity objectives, such as resource recovery, need standardised assessments that use CE indicators to evidence enhanced resource circularity, supported by sustainability analysis to quantify wider benefits. This will facilitate technology selection that simultaneously meet the water sector sustainability and circularity targets detailed in the European Green Deal and CEAP.

Some DSS developers created hybrid categories including socio-economic (Đurđević et al., 2020) and socio-environmental (Silva Junior et al., 2022), or combined environmental and technical categories together (Chrispim et al., 2020). This suggests authors may be unsure as to which categories some indicators belong. This is further perpetuated by authors placing the same indicators in different sustainability pillar categories. For example, WWT technology removal efficiencies have been placed in environmental sustainability (Liu et al., 2020; Lizot et al., 2021; Molinos-Senante et al., 2014) and technical categories (Eseoglu et al., 2022; Silva Junior et al., 2022). This may explain the increase in popularity of using the four pillars of sustainability for categorisation in recent years, as it enables delineation of operational and environmental KPIs, highlighting the desire of decision makers to understand the environmental impacts of potential technologies more clearly. However, this seems to result in some confusion regarding the objectives of certain indicators, such as GHG/carbon footprint, as Đurđević et al. (2020) defines this as a technical indicator, whereas Lizot et al. (2021) utilises it as an indicator of environmental performance. Similarly, odour and noise indicators are placed in both environmental (Sucu et al., 2021) and more commonly social categories (Eseoglu et al., 2022; Lizot et al., 2021; Molinos-Senante et al., 2014). These differences evidence the need to enhance sustainability/circularity assessment knowledge and develop standardised methods for KPI selection and categorisation.

The popularity of indicator categorisation using sustainability pillars has led to some DSS developers using this method even when their defined aims do not refer to sustainable technology selection. To combat this, some authors generated their own indicator categorisation strategies. Fetanat et al. (2021) developed indicator categories using the water-energy-food nexus framework to view wastewater as a renewable energy source, which aligns with the DSS goal to prioritise energy recovery from WWT. Palma-Heredia et al. (2020) created an indicator hierarchy depending on the scale of the application, therefore allowing decision makers at regional, WWTP, and operational levels to prioritise certain indicators. Although these categorisation methods are not as established in literature as sustainability pillars, developing indicator categories which consider DSS goals may be a more effective way for users to understand the indicators required to achieve their aims, especially whenever sustainable technology selection is not the objective. However, it can be concluded there is confusion when categorising selected indicators and how this activity aligns DSS outcomes with decision maker goals.

3.4. Indicator weighting

Weighting of indicators is a critical stage for DSS users, as it enables them to prioritise or mitigate criteria depending on their objectives. Therefore, the frequency of each technique used by DSS developers for indicator weighting is provided in Fig. 4. The MCA discussed are those currently employed by water sector DSSs and does not reflect best practices for multi-attribute decision making.

It is common for indicators to be weighted according to the DSS user,

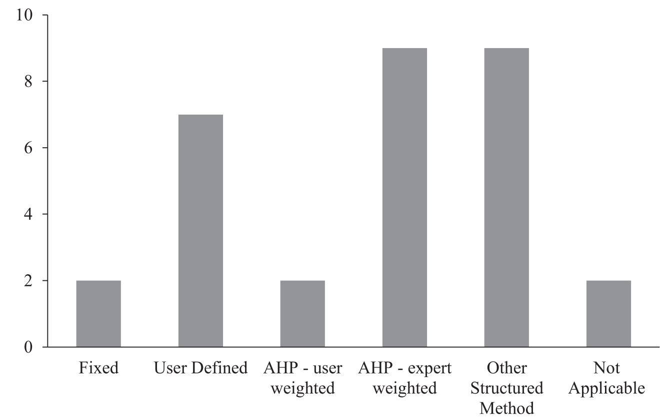

Fig. 4. Methods used to weight indicators for MCDM technology selection DSSs.

and then a weighted summation is simply calculated to create a composite indicator used to analyse technologies. Garrido-Baserba et al. (2015) and Palma-Heredia et al. (2020) develop DSS weights for indicators that are predetermined and fixed, and given equal weighting respectively. Although this simplifies DSS usage, this weighting system is not recommended as it does not provide users with the ability to tailor KPI impacts to reflect their goals, which can be viewed as undermining the principles of MCDM. Another method commonly employed by DSS developers is to allow users to define weights themselves, (Castillo et al., 2016; Chhipi-Shrestha et al., 2017; Južnič-Zonta et al., 2022; Oertlé et al., 2019; Renfrew et al., 2022; Silva Junior et al., 2022; Sucu et al., 2021), however, DSS users can be faced with >20 indicators so assigning weights without a structured methodology of comparing indicators can lead to inconsistencies during analysis. This can result in indicator weightings that do not align adequately with aims and lead to bias in the assessment. Therefore, techniques are employed by DSS developers enabling structured analysis of indicators using opinions of experts and stakeholders.

The analytical hierarchy process (AHP) is the most common weighting method used by reviewed DSSs with eleven. AHP was proposed by Saaty (1987) for decision making influenced by multiple independent factors (Liu et al., 2020). It investigates the relationship between criteria to create a hierarchy from which they can be prioritised (Eseoglu et al., 2022), often utilising external experts and stakeholders to create pair-wise comparisons. Therefore, many DSSs reviewed use standard AHP for weighting indicators (Đurđević et al., 2020; Gherghel et al., 2020; Jiean Ling et al., 2021a; Lizot et al., 2021; Molinos-Senante et al., 2014; Nkuna et al., 2022). However, Ling et al. (2021a, 2021b) reported rarely seeing extreme scores on the judgement scale, and when the full scale was used the threshold consistency ratio (compares the weighting matrix against a random matrix, acceptable value of ≤ 0.1) is often not achieved. To overcome the uncertainty due to imprecise human judgements or ambiguity, fuzzy logic is implemented (Eseoglu et al., 2022). Many DSSs employ fuzzy-AHP weighting (An et al., 2018; Büyüközkan and Tüfekçi, 2021; Eseoglu et al., 2022; Liu et al., 2020; Sadr et al., 2018), providing a structured method of indicator weighting whilst mitigating inconsistencies of human thinking.

Apart from AHP, DSS developers integrated a variety of weighting methods (Ali et al., 2020; Attri et al., 2022; de Almeida et al., 2022; Fetanat et al., 2021; Leoneti et al., 2022). Arroyo and Molinos-Senante (2018) implement Choosing-By-Advantages (CBA), citing several improvements over AHP including that it does not assume linear trade-offs between criteria. CBA encourages DSS users to understand the differences between criteria and assesses the importance of these differences, as supposed to AHP which can create conflicting questions. The Best-Worst Method (BWM) used by Liu and Ren (2022) and Salamirad et al. (2023) provides a simpler weighting step for decision makers as the number of comparisons is reduced, improving the consistency ratio of results and removing much of the uncertainty during pairwise comparisons. Srivastava and Singh (2022) simplify weighting even further by employing the Full Consistency Method, minimising the number of comparisons to achieve consistent results.

Lastly, some DSS developers recommend the use of 'experts' without actually defining whom this might include (Attri et al., 2022; Liu et al., 2020), collecting opinions from stakeholders with little knowledge of the investigated system or local area, leading to inconsistent results. Whereas Eseoglu et al. (2022) utilises expert opinions from every stage of WWT including design, construction and operation engineers, and Gherghel et al. (2020) acknowledges the viewpoints of stakeholders from six different specialities, such as political, environmental, and plant operator stakeholders to ensure the holistic collection of viewpoints. Therefore, stakeholders with a range of expertise that understand local factors for indicator weighting should be used to reduce bias and inconsistency.

Generally, the majority of DSSs in this study rely on AHP to weight criteria, which is corroborated by other reviews in the area (Kozłowska, 2022; Zolghadr-Asli et al., 2021), potentially incorporating high levels of uncertainty. Therefore, to ensure better indicator utilisation fuzzification and consultation of relevant experts can be used to reduce uncertainty. Additionally, methods recommended in literature, not utilised by the water sector DSSs reviewed, to mitigate weighting procedure errors are the entropy method for objective weight assignment or analytical network process (ANP) to account for correlations between criteria (Zolghadr-Asli et al., 2021).

3.5. Indicator scoring

A range of methods to score assessment indicators have been utilised due to the variety of scales and units of indicator results, and often the mix of quantitative and qualitative indicators selected. Linguistic (such as very bad to very good) or numerical (can be from 0 up to 10) series are commonly integrated to normalise results enabling their combination. Several DSSs rely on the experts used for indicator weighting to assign numerical ratings directly based on their opinion (Đurđević et al., 2020; Jiean Ling et al., 2021a; Renfrew et al., 2022), usually when there is lack of empirical data (Jiean Ling et al., 2021a). Alternatively, Fetanat et al. (2021) relied on linguistic terms to rate technology alternatives as the indicators selected were immeasurable (such as energy security availability).

Literature searches were used to establish numeric ranges of indicator results for each technology assessed (Attri et al., 2022). Silva Junior et al. (2022) collected data from technical-scientific literature relevant to case study location and assigned the final result by calculating the mean of the data range found. Before combination of indicator results, they were normalised to a value between 0 and 1 using the lowest and highest value observed for each parameter. Rather than quantitatively normalising values collected from literature, Liu and Ren (2022) utilised a linguistic scale of five from *very good to very poor*, whilst Lizot et al. (2021) created ranges for each indicator to assign a numeric value to normalise quantitative indicator scores.

Lastly, a common method for assigning scores to indicators is to directly quantify results (except for the indicators which are inherently qualitative). It was observed that most environmental and economic indicators were quantifiable, whilst technical and social indicators were qualitatively scored (Castillo et al., 2016; Leoneti et al., 2022; Liu and Ren, 2022; Molinos-Senante et al., 2014). Quantitative calculation of each indicator investigating technology performance is recommended, as it incorporates specific details and local factors of the case study. Relying on the judgement of DSS users or external experts enables uncertainty through the ambiguity or bias of human decision making to incorrectly score technologies. Furthermore, the use of values extracted from literature can mitigate the influence of local factors which can be pertinent for economic and technical indicators. Of course, when using qualitative indicators to investigate social aspects, local stakeholder views should be used to score technologies, due to their greater understanding of potential impacts in a given region.

3.6. Ranking

The final step is to rank technologies for selecting the technology which supposedly best meets user requirements. Palma-Heredia et al. (2020) presents KPI results and recommends the DSS user to complete pairwise comparisons for technology selection. Although this is a simple method of completing the final ranking, extensive indicator lists create complexity and inconsistencies in user judgement. Therefore, the most common method of technology ranking employed by DSS developers is to create a composite indicator using the weighted sum method (Castillo et al., 2016; de Almeida et al., 2022; Garrido-Baserba et al., 2015; Gherghel et al., 2020; Liu and Ren, 2022; Molinos-Senante et al., 2014). This synthesises indicator scores and their corresponding weights into a single performance index used to rank and select technologies (Jiean Ling et al., 2021a).

In the cases where multiple experts or stakeholders are used to weight or score assessment indicators, systematic analysis of results is needed to rank and select technologies. The technique for order of preference by similarity to ideal solution (TOPSIS) is commonly coupled with AHP. TOPSIS selects the best alternative based on the shortest distance to the ideal solution and the farthest distance from the negative-ideal solution in geometric terms (Južnič-Zonta et al., 2022), to intensify the correctness and validate selection of the most appropriate technology (Nkuna et al., 2022). When fuzzification of data has occurred during indicator weighting, to improve the robustness of outcomes, this can be continued to complete fuzzy-TOPSIS (Attri et al., 2022; Büyüközkan and Tüfekçi, 2021; Eseoglu et al., 2022; Liu et al., 2020; Sadr et al., 2018). Another method employed to overcome the uncertainty of comparative analysis, is fuzzy-VIKOR as used by Ali et al. (2020), which utilises positive and negative characteristics to define compromises when conflicting views cause issues with decision making. This is achieved by calculating three variables to establish the summation and maximum distance from the best value, which are then combined to calculate an overall score.

Alternatively, Leoneti et al. (2022) implements game theory to determine the preferred option from the list of acceptable outcomes, selecting the technology that maximises the Nash equilibria social welfare function. Lastly, Fetanat et al. (2021) utilised the linear assignment method (LAM) to rank technologies for energy recovery from WWTs. This method is chosen as it ranks alternatives according to conflicting criteria, by analysing the trade-offs between the ranking of each indicator for each technology. Therefore, LAM may be beneficial as wastewater and sewage sludge treatment shifts to prioritise other functions, such as resource recovery or water reuse. Studies in this area agree that TOPSIS is the most common ranking procedure (Štilić and Puška, 2023), however, best practice depends on the scenario of application. Methods such as PROMETHEE and ELECTRE are suited to handle conflicting stakeholder priorities (Štilić and Puška, 2023), whereas fuzzy logic and use of experts from as many specialities as possible should be used to tackle subjective ranking issues (Garcia-Garcia, 2022).

3.7. Uncertainty

There are various types of uncertainty that exist in MCDM that can arise at each step of DSS utilisation resulting from: variation, ambiguity, and incomplete preferences of human inputs; lack of system, parameter, data, external factor, or model knowledge; and prediction of outcomes or future events (climatic or socio-economic changes) (Walling and Vaneeckhaute, 2020). There are many methods to deal with MCDM uncertainty, one being fuzzification of scoring, weighting, and ranking procedures reliant on human judgement, as previously discussed in Sections 3.4, 3.5, and 3.6. Alternatively, sensitivity analysis is able to provide decision makers with insights into the uncertainty resulting from erroneous modelling of the assessed system or potential/future scenarios.

Scenario investigation is a widely applied method of sensitivity analysis, in which MCDM indicator weighting is altered to reflect different viewpoints or future situations. For example, Molinos-Senante et al. (2014) and Salamirad et al. (2023) conducted scenario analysis by favourably weighting environmental, economic, and social KPIs in turn, validating the selected technology (constructed wetlands and integrated fixed-film activated sludge respectively) still ranked highest under alternative weighting schemes. Alternatively, Renfrew et al. (2022) improved the robustness of technology selection by weighting KPIs based on potential future scenarios, including legislative changes for emissions compliance and carbon footprint reduction, and selecting technologies based on their average performance across the scenarios. Furthermore, global sensitivity analysis (GSA) was utilised to verify that technology ranking is robust to fluctuating inputs over a ± 10 % range and investigate which parameter's uncertainty have the largest impact on MCDM outcomes, educating future assessments (Renfrew et al., 2022). Lastly, Južnič-Zonta et al. (2022) aimed to use Monte-Carlo (MC) simulations to overcome probabilistic uncertainty of bio-chemical modelling processes to configure design parameters, before technology ranking is calculated and verified over each iteration (however this was not included in case study). Therefore, if potential errors are likely to be introduced by MCDM structure or case study that impact outcomes, then sensitivity analysis (scenario or global) should be used to validate the robustness of DSS results.

3.8. Recommendations

As discussed, there are already many reviews of DSS typologies in the literature, therefore, the review focuses on how indicator usage can be improved based on the methods currently implemented for WWTP technology selection. Therefore, following the review of thirty-one MCDM DSSs final recommendations and comments are provided in Table 2. Unfortunately, Sections 3.2 and 3.3 highlight the significant gap related to the utilisation of circularity and sustainability indicators, mainly that circularity aspects are used to investigate environmental performance and the lack of alignment with water sector goals reported as part of European Green Deal and CEAP. Additionally, WWTP DSSs still rely on user defined weighting, scoring, and ranking procedures, or structured methods, such as AHP and TOPSIS, which have issues with introducing uncertainty to the assessment. Generally, decision making in the water sector is still some distance from standardisation and harmonisation of sustainability and circularity assessments.

It is worth noting that analysis of DSS case studies showed that economic indicators were commonly prioritised during the weighting stages (Eseoglu et al., 2022; Liu et al., 2020; Lizot et al., 2021; Sadr et al., 2018). The CBA method employed by Arroyo and Molinos-Senante (2018) excluded economic indicators during the initial assessment, prioritising environmental and social factors, as monetary resources available are usually the constraint for any project. Environmental and social indicator results are then plotted against cost to facilitate the selection of the best technology option. Authors highlight the impacts of this by comparing AHP with CBA and showed that by considering economic factors alongside environmental and social indicators, unfavourable impacts were offset by low capital and operating costs. Therefore, as governments demand improved environmental and social performance of WWT in the coming years, to achieve targets such as net zero, the exclusion of economic indicators from initial assessment may be favoured.

Table 2
Summary of issues, recommendations, and beneficial outcomes related to the reviewed MCDM technology selection DSSs.

Issue	Recommendation	Outcome
Few DSSs provide a clear definition of aims or goals	Defining the goal and scope of the assessment should become common practice, as the first step of DSS development or application	Help decision makers understand the desired outcome of DSS utilisation
Rigorous indicator selection is often overlooked by DSS developers and do not consider high level water sector goals	Utilise participatory methods to incorporate local stakeholder, business (water utility), and regional/governmental objectives	Technology selection using KPIs that adequately reflects desired results and facilitate sector transformation
Indicator categorisation is often unclear resulting in inconsistencies across DSSs, mitigating circularity objectives	Use categorises that reflect the intentions of the DSS, helping to create more robust weighting strategies and consider CE targets of the water sector	Help to select and group relevant indicators, such as using sustainability pillars when selecting sustainable technologies, and mitigate the alignment of CE metrics with sustainability impacts
Expert or user defined weighting schemes can lead to a lack of local factor consideration	Stakeholders with an understanding of the local area from a range of job roles should be used for indicator weighting	Ensures that DSSs select technology that will meet the local demands in each scenario of application and reduce uncertainty of results
Unstructured or subjective weighting and ranking methods can lead to uncertain outcomes	Consider the specific issues of each DSS application to decide which method should be used to reduce uncertainty, such as entropy methods to enhance the objectivity of weighting, and either fuzzy logic to reduce human error or PROMETHEE/ELECTRE to overcome conflicting priorities during ranking	Remove the inconsistency and reduce uncertainty that can arise when human inputs are used to weight and rank indicators
There is little critical analysis of final technology selection in relation to decision maker goals	Techniques such as sensitivity analysis should be applied to investigate DSS outcomes	Ensure that the method is consistent across alternative scenarios, enhancing robustness of final technology selection

4. Multi-objective optimisation control

Following the selection of technologies, another type of DSS is needed for multi-objective optimisation of WWTP process operation and control. It is necessary to conduct distinct analysis of these DSS types as they are utilised differently by decision makers. Therefore, alternative methods and indicators are required, as it was seen that technology selection DSSs focus on sustainability KPIs whereas operational optimisation DSSs target cost and regulatory (effluent quality) aspects. Table 3 summarises the multi-objective process optimisation WWTP DSSs collected from literature, resulting in the review of twenty-six articles.

Table 3 shows an increase in the number of publications in this area, growing from four in 2018 to seven in 2022 which coincides with the availability of Benchmark Simulation Model (BSM) 1 and BSM2 (IWA, 2018) for testing WWTP control strategies. Some authors have recently published multiple papers in this area, testing different algorithms to find the optimal control strategy on the same simulation platform. DSSs were categorised depending on their ability to optimise the control of process operation dynamically (respond to changes in real-time) or statically (user defined inputs followed by KPI calculation). Most DSSs are dynamic, which corresponds with use of BSMs as time series data across three weather conditions is available for simulation testing (IWA, 2018). Generally, DSS aims were stated in clearer terms than those for technology selection, often stating which performance parameters or KPIs are targeted for optimisation. Most DSSs were not applied to real

Table 3
Summary of multi-objective DSSs for optimisation of WWTP operation.

Author	Year	Control	Aim	Application	Objective function
Qiao et al.	2018	Dynamic	*Achieving the effluent quality (EQ) requirements and minimizing the energy consumption (EC)*	BSM1	EC and EQI
Díaz-Madroñero et al.	2018	Static	*Develop more sustainable water systems*	2500 PE WWTP in Alicante, Spain	Total connections costs, total freshwater use, and total regenerated freshwater use
Han et al.	2018	Dynamic	*Optimal control operation with EC reduction while retaining standard EQ*	BSM1	EC and EQI
Qiao and Zhou	2018	Dynamic	*Acquire the balance between EC and EQ with the usage of the best set points*	BSM1	EC and EQI
Qiao et al.	2019	Dynamic	*Suitable set-points to balance the treatment performance and the operational costs*	BSM1	EQI and EC
Zhou and Qiao	2019	Dynamic	*Optimal control strategy is designed to reduce EC without violating effluent standards*	BSM1	EQI and OCI
Pisa et al.	2019	Dynamic	*Reduction of the number of violations as well as the improvement of WWTP's EQI and OCI metrics*	BSM2	EQI and OCI
Dai et al.	2019	Dynamic	*Optimal modification of an anaerobic–anoxic/nitrifying/ induced crystallization (A2N-IC) process*	ASM-2D	EQ, operating cost, and total volume
Borzooei et al.	2019	Static	*Evaluate and improve existing process performance in addition to optimise the production of renewable energy*	2 million PE Castiglione Torinese WWTP, Italy	EQI and ECI
Mannina et al.	2020	Static	*Optimization … in terms of operational costs and direct greenhouse gases emissions.*	Pilot plant MBR	Effluent Fine, EQI (liquid and gas), oxygen-to-total-Kjeldahl-nitrogen ratio, ratio nitrate-ammonia, CO_2 and N_2O emissions, and direct and indirect GHG emissions.
Revollar et al.	2021	Static	*Improving the eco-efficiency of WWTPs*	BSM2	EQI, OCI, Net energy, Excess heating energy, Electricity consumption, Energy/Pollution removed, Energy net/Pollution removed, Violations of the permit limits of effluent N, NH_4 and COD
Heo et al.	2021	Dynamic	*Operate at cost-efficient and sustainable WWTP*	BSM2	EQI, OCI, CH_4 reutilised as energy source
Ortiz-Martínez et al.	2021	Dynamic	*Optimise an economic cost term and an effluent quality index*	BSM1	EQI and economic cost
Han et al.	2021	Dynamic	*Achieve excellent treatment performance for a WWTP*	BSM1 and 10,000 m^3/d WWTP Beijing, China	EC and EQI
Tejaswini et al.	2021	Dynamic	*Enhance the performance of the WWTP by optimising the parameters of the default control strategy*	BSM1	EQI and OCI
Chen et al.	2021	Static	*Obtain sustainable control strategies*	10,000 PE WWTP Jiangsu Province, China	LCC and three LCA impact indicators (energy consumption, eutrophication, GHGs)
Campana et al.	2021	Static	*Reduce WWTP operating costs, improving at the same time treated effluent quality*	86,400 PE WWTP, Italy	Self-sufficiency ratio and net present cost
Li et al.	2021	Dynamic	*Meet the requirements of effluent quality and maintain sustainable operation with the lowest energy cost*	BSM1	EC and EQI
Fox et al.	2022	Dynamic	*Best setup that can enable optimal operational, environmental and energy performance*	Residential development SBR	NH_4 removal, prediction error, treatment time reduction
Xie et al.	2022	Dynamic	*Achieve tracking control of the main operating variables of the WWTP*	BSM1	EC and EQI
Niu et al.	2022	Dynamic	*Optimise EQ and EC in wastewater treatment process*	BSM1	EC and EQI
Han et al.	2022	Dynamic	*Optimal control strategy is proposed to improve the performance of WWTP*	BSM1	EQI, pumping energy, aeration energy
Caligan et al.	2022	Static	*Minimise the system's overall economic costs and environmental greenhouse gas emissions*	Wastewater sludge to bioenergy park	Cost and GHG emissions
F. Li et al.	2022	Dynamic	*Optimise the control of WWTPs*	BSM1	EC and EQI
Han et al.	2022	Dynamic	*Guarantee satisfactory EQ and EC with the excellent control accuracy of WWTP*	BSM1	EC and EQI
Du and Peng	2023	Dynamic	*Optimal control of wastewater treatment process*	BSM1	EC and EQI

case studies and instead utilised BSMs due to the complexity and non-linearity of WWTP modelling. This reliance results in little variation of KPIs selected (type or number), as BSMs have predefined indicators related to effluent quality and energy consumption/cost.

As shown in Fig. 5, the BSM1 plant is a 5-compartment activated sludge reactor modelled using ASM1, with configuration facilitating nitrification-denitrification for biological nitrogen removal. The model utilises PI controllers to control the dissolved oxygen (DO) level by manipulating the oxygen transfer coefficient, and nitrate level setpoints, by changing the internal recycle rate in the fifth and second compartments respectively (IWA, 2018). The performance assessment of the plant is based on two main KPIs; the effluent quality index (EQI) and overall cost index (OCI). The EQI is the weighted sum (weightings from literature) of effluent contaminant TSS, COD, BOD, Kjeldahl nitrogen (TKN), and nitrate (NO). The OCI combines cost factors of sludge production, aeration energy, pumping energy, mixing energy, and external

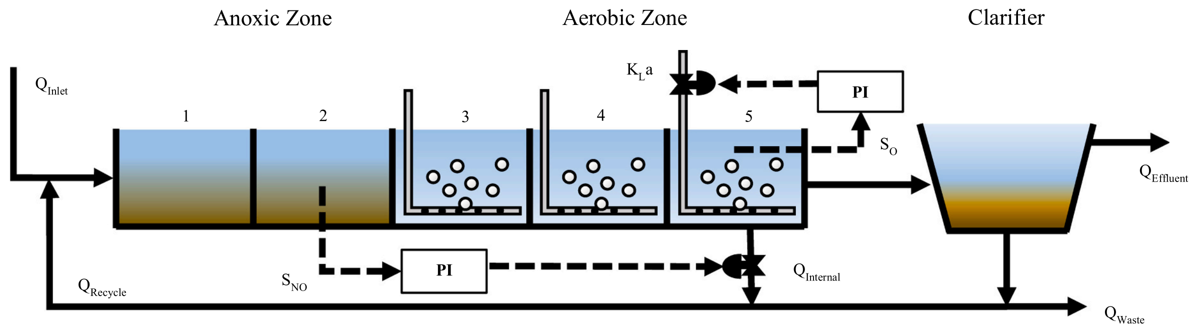

Fig. 5. BSM1 process flow diagram and control systems based on a figure from the IWA (2018) where Q is the flowrate, S is the set point, PI is the controller, and K_La is the transfer coefficient.

carbon consumption (Alex et al., 2018). BSM2 utilises the same wastewater treatment process, with the addition of sludge anaerobic digestion to the balance heat energy required and energy generated from methane production. The number of effluent limit violations and duration must be reported, meaning operation is constrained by discharge limits of NH_4 ≤4 mg/l; TN ≤18 mg/l; TSS ≤30 mg/l; BOD ≤10 mg/l; COD ≤100 mg/l (Alex et al., 2018).

4.1. DSS goals

In Section 3 it was revealed that MCDM technology selection DSS aims are too generic, meaning it is difficult to relate indicator selection to desired outcomes. Many of the multi-objective process optimisation DSSs reviewed in Table 3 take the opposite approach, as twelve stated the KPIs targeted for optimisation in their aims. This definition enables users to clearly understand the outcomes that can be expected when implementing this optimisation technique, however, many of these DSSs relied on BSMs meaning there is little flexibility in the indicators utilised. Another helpful method of defining DSS aims for the user is to identify its specific function. For example, Borzooei et al. (2019) and Revollar et al. (2021) aimed to *optimise the production of renewable energy* and improve the eco-efficiency of WWTPs respectively, making it clear to users the reasons for implementing this DSS and selecting indicators for optimisation. Still, a significant number of multi-objective optimisation DSS developers use vague language when stating their aims. Eight DSSs aim to either *optimise* or *improve performance* of WWTPs, whilst three DSSs aim for *sustainable* operation or control of WWTPs, without explicitly stating which areas are targeted. Therefore, DSSs clearly define their aims, but few explicitly relate this to sustainability or circularity objectives, aiming to generally 'optimise WWTP performance' or improve conventional operation KPIs.

4.2. Static vs dynamic control

Of the twenty-six DSSs reviewed in Table 3, six provided users with static control strategies for improving the operation of WWTPs, meaning the results are used by operators to make decisions rather than the DSS dynamically altering operation. Borzooei et al. (2019) created a simulation of a large-scale WWTP and altered the SRT between 10 and 40 days, then plots the EQI and EC results to establish the optimal SRT for process operation. Mannina et al. (2020) goes a step further by using TOPSIS to optimise five operational parameters using ten KPIs and combining this with E-FAST sensitivity analysis to understand the influence of operating parameters on performance. These static DSSs allow users to observe and understand what an optimised system may look like, enabling them to derive and implement the WWTP control strategy. The remaining twenty DSSs are able to dynamically alter operation parameters without user interference. For example, Heo et al. (2021) uses the fuzzy c-mean algorithm to process and cluster influent data to predict initial BSM2 setpoints, a deep neural network then completes the multi-objective optimisation calculation for EQI, OCI, and biogas generation performance indicators, and finally the NSGA-II algorithm searches for the optimal setpoint of each controller. Therefore, the WWTP can maintain optimal performance and respond to fluctuations in influent composition. The use of DSSs for dynamic optimisation means that indicator selection must focus on KPIs that are calculated from data that is easily and reliably monitored over a given period.

4.3. Modelling platform

Of the nineteen DSSs that dynamically control WWTP operation, fourteen are implemented in BSM1 without being tested on real processes. In most cases these DSSs are made up of two algorithms, one responsible for the multi-objective optimisation of KPIs (commonly a neural network) and another for determining the set point of controllers (such as a NSGA-II or AMODE algorithm (Heo et al., 2021; Ortiz-Martínez et al., 2021; Qiao et al., 2019, 2018; Tejaswini et al., 2021)). The repeated investigation of different algorithm combinations is necessary to which results in the best EQI and OCI outcomes, and lowest controller error (Du and Peng, 2023). Two DSSs are used to control the operation of BSM2, enabling users to optimise operation considering biogas production as part of the OCI. Two DSSs are utilised for the dynamic control of actual processes including the work of Han et al. (2021) which runs initial tests on BSM1 then uses data extracted from the SCADA system of a 10,000 m^3/d plant in Beijing, China to run experimental tests. Lastly, Dai et al. (2019) developed their own optimisation models, using ASM-2D to optimise a WWTP for inducing crystallisation. Therefore, few DSSs have been tested on real systems so may not perform as expected when applied at different scales or locations, especially under unexpected influent loadings. It is recommended that users test DSSs in real systems or on models that represent the specific process it will be applied to, ensuring optimisation reflects the operational expectations of decision makers.

In the cases of static control, the DSSs developed usually rely on simulation software or the development of process models. Four DSSs used their own models which facilitated the selection and utilisation of less conventional KPIs, including regenerated water usage (Díaz-Madroñero et al., 2018), energetic self-sufficiency (Campana et al., 2021), and environmental impact (kg CO_2eq) (Caligan et al., 2022). Two DSSs simulated WWTPs in Hydromantis's GPS-X software, with configurations based on real-world processes (Chen et al., 2021) and fed with historic data taken from plant SCADA systems (Borzooei et al., 2019). Lastly, Revollar et al. (2021) specify four scenarios (fluctuating DO, NH_4, and internal recycle setpoints) in BSM2, which enables the calculation of eco-efficiency indicators for comparing control strategies. Therefore, static control systems are able to optimise a greater variety of KPIs, like the EQI and OCI, and operational parameters, including solids retention time (Borzooei et al., 2019; Mannina et al., 2020) or process flowrates (Caligan et al., 2022; Revollar et al., 2021).

4.4. Indicators selected

The reliance of DSS developers on BSM platforms results in little variability of selected indicators. In fact, Table 3 shows eighteen reviewed DSSs used only the inbuilt indicators of BSMs, including EQI, OCI, or its sub indicators (pumping, aeration, and total energy consumption). Although indicators are fixed in the platform, little justification or reasoning for selecting these indicators is given by DSS or BSM sources, except that they cover both economic and environmental impacts (Li et al., 2021), reflect the operational state of the WWTP, and can evaluate process performance (Han et al., 2022a). EQI and OCI indicators reflect the traditional goals of water related literature and regulations, such as for human health protection and cost functions, that will always be important to maintain WWTP performance. However, modern water sector targets relate to areas such as GHG emissions and resource recovery, therefore, expansion to include KPIs that reflect these goals is recommended for further development of BSMs. This is needed as inclusion of sustainability and circularity dimensions would enable users to optimise WWTP operation considering the wider impacts to stakeholders and achieve targets defined in Section 2.1, such as those defined in the CEAP.

Subsequently, the eight remaining DSSs developed integrated other indicators to optimise process operation considering impacts other than cost and effluent quality. Three DSSs calculate process GHGs, including Mannina et al. (2020) that consider a combination of CO_2 and N_2O emissions, direct and indirect GHGs, and air-EQI to understand how MBR operational parameters impact emissions. Caligan et al. (2022) also considered GHGs emissions and compared this with cost functions, whilst Chen et al. (2021) conducted full LCC and LCA to investigate the impact of indicator prioritisation on a 10,000 PE WWTP. Other DSSs selected indicators to investigate a specific function of a WWTP, namely freshwater and regenerated water use (Díaz-Madroñero et al., 2018), eco-efficiency (Revollar et al., 2021), treatment time reduction (Fox et al., 2022), and energetic self-sufficiency (Campana et al., 2021). These indicators align better with modern water sector sustainability goals compared with EQI and OCI indicators. However, they all employed self-selection methods and generally circularity indicators were mitigated from optimisation DSSs, showing this is yet to become a priority of WWTP operators.

4.5. Indicator prioritisation

Again, there is a difference between static and dynamic DSS indicators in how they are analysed to produce the optimal solution. The majority of dynamic calculations aim to minimise the performance indicators selected, including BSMs trying to minimise both EQI and OCI (or energy consumption). This results in an optimisation problem (Heo et al., 2021) since decreasing one of these KPIs increases the other, for example greater removal efficiency requires additional energy consumption from aeration and recirculation pumping. Therefore, DSS algorithms must cope with KPI trade-offs, known Pareto sets, which derives a sub-optimal solution for the chosen KPIs but establishes that both results are better than the rest of the potential outcomes in the search space (Qiao et al., 2018). Fox et al. (2022) developed one of the only dynamic optimisation DSSs to employ a weighting method, with the hope of considering site-specific requirements. Local plant operators assigned weights, which were combined with KPI result rankings to decide on the soft sensors that produces the best control strategy. In previous years it was common to weight KPIs to create a single objective optimisation (Niu et al., 2022), however, this necessitates real-time supervision by plant operators to achieve optimal control (Han et al., 2014).

Of the static DSSs, three utilise KPI weighting to achieve the optimal solution. Díaz-Madroñero et al. (2018) used fuzzy goal programming to incorporate decision maker preferences and trade-offs between objective functions. Alternatively, Chen et al. (2021) normalises LCA impact indicator results and uses weights defined in literature, whilst Mannina et al. (2020) weights all ten objective functions selected equally. The use of decision maker weighting strategies is recommended, as it enables the goals of local stakeholders to be integrated within optimisation outcomes. Lastly, some DSS developers did not provide a method for selecting the optimal strategy, leaving it to the interpretation of the user to compare KPI results (Revollar et al., 2021), such as Borzooei et al. (2019) which relies on optimisation curves showing EQI vs OCI to select the best operational SRT parameter. Although weighting strategies are useful, the dynamic optimisation of KPIs is now accepted as best practice to enable automatic, supervisory control of plants, placing greater emphasis on proper selection of KPIs to reflect decision maker needs during WWTP operation.

4.6. Error and uncertainty

These DSSs aim to provide an optimised control strategy for the operation of WWTPs, however, alternative controllers, KPIs, or conditions may result in differing performance. Therefore, it is critical to test the sensitivity of DSS performance on results. One of the main strategies employed was to compare the optimised KPI results with alternative controller algorithms, to ensure the adopted method achieves the best performance. Controller performance metrics including the Integral of Absolute Error (IAE) (no error weighting), Integral of Squared Error (ISE) (penalises larger errors), and Root Mean Square Error (RMSE) were utilised. In fact, six DSSs compare the controller algorithm deployed using the IAE with other algorithms (Han et al., 2022a, 2021; Li et al., 2022; Qiao et al., 2019, 2018; Xie et al., 2022), one utilised both ISE and IAE for comparison (Han et al., 2018), and another implemented RSME (Qiao and Zhou, 2018) to investigate whether the method used results in the lowest error. Additionally, six DSSs compared controller algorithms using KPI results only (Han et al., 2022b; Li et al., 2021; Mannina et al., 2020; Niu et al., 2022; Pisa et al., 2019; Zhou and Qiao, 2019), which is a useful exercise to reassure the user their DSS will produce the best outcomes. However, investigating errors is important as it indicates the size and longevity of potential disruptions to system performance.

Multi-objective optimisation DSSs utilise similar approaches to those discussed in Section 3.7 for MCDM for uncertainty analysis. For example, the DSS developed by Caligan et al. (2022) formulated scenarios to investigate the impacts of events that WWTP operators may face, including how the fluctuation of biofuel prices, inlet wastewater quality, and requirements for wastewater and sludge disposal, impact on cost and GHG emission KPIs. Ortiz-Martínez et al. (2021) created scenarios simulating lack of aeration due to process error and mitigation of flow recirculation due to maintenance, to investigate the effect on process optimisation. Alternatively, some authors investigated optimisation strategies through prioritisation of certain indicators to see how the system responds. DSSs were tested by optimising either the environmental (i.e. EQI) or economic (i.e. OCI) KPI, and comparing this with when both are optimised (Chen et al., 2021; Tejaswini et al., 2021).

Mult-objective optimisation DSSs have other inherent uncertainties to deal with when modelling WWTP systems, such as climatic changes and fluctuating wastewater concentration (Chen et al., 2018). DSS developers tackled this uncertainty by investigating the effects of the wastewater influent on performance using fluctuation of the TKN/COD inlet ratio (Heo et al., 2021) and fuzzification of inlet composition (Díaz-Madroñero et al., 2018). However, further uncertainty analysis is recommended to test how WWTP optimisation models respond to external factors. MC simulations are commonly used for modelling input uncertainty as different probability distributions (normal, parametric etc.) can be selected depending on error attributes and case study characteristics (Haag et al., 2019). Testing the uncertainty of DSS performance is critical and for a complete study it is recommended to make comparisons in KPI performance and controller error with other systems, and investigate fluctuations to influent load and process operation to ensure the DSS will meet all user expectations when deployed at a real WWTP.

4.7. Recommendations

Following the review of twenty-six multi-objective DSSs for optimisation of WWTP process operation, some final recommendations and comments are provided in Table 4. However, it can again be concluded that although these DSSs aim to optimise WWTP performance there is little attention given to how this results in the indicators selected for optimisation, nor an explanation of how subsequent operation aligns with sustainability aims, and mitigate circularity dimensions entirely.

5. Future work

5.1. Indicator selection

Unfortunately, it has been shown that the indicators utilised by most wastewater DSSs do not align with water sector sustainability and circularity targets. Currently, there is a lack of standardised assessment methodologies that combine circularity and sustainability dimensions, and confusion due to the excess of indicators developed (Valls-Val et al., 2022). Most methods rely on the user cherry picking indicators from a predetermined list, therefore, when an organisation adopts an innovative activity it can result in redundant indicator selection and efforts or resources being allocated incorrectly (Peral et al., 2017). There are additional difficulties to consider in the water sector, particularly for circularity assessments, as the main focus until now has been enhancing the performance of technical systems. For example, processes that safely return biotic and water resources to the environment can be seen as effective waste management (Chojnacka et al., 2020), whereas this can occur during landfilling or incineration for abiotic resources which are non-circular actions, meaning many indicators are not appropriate. This means it is currently very difficult to assess wastewater systems for the selection and optimisation of technology that facilitates decision maker goals. It has been shown in the literature, and this review, that CE indicators have been aligned with sustainability dimensions to validate decision making (Harris et al., 2021), whilst the opposite can be said when using LCA impacts to evidence enhanced circularity (Corona et al., 2019). Therefore, there is a large knowledge gap regarding how circularity and sustainability indicators can be combined. Overcoming this issue requires the development of methods that assess the circularity of resource flows and is supported using wider sustainability analysis to quantify economic, environmental, and social benefits. Only then can wastewater decision making facilitate governmental circularity and sustainability targets, whilst maintaining WWTP performance, and meeting the customer expectations.

Table 4
Summary of issues, recommendations, and beneficial outcomes related to the reviewed wastewater treatment multi-objective process optimisation DSSs.

Issue	Recommendation	Outcome
Few DSSs are applied to real WWTP systems, mitigating the impacts of local climate and influent composition	Test DSSs in realistic process models or trial them in real-world systems	User achieves the expected performance when DSS is applied to their system
Although KPI selection is fixed for many of the DSSs reviewed, rigorous indicator selection is often overlooked	Develop process models that utilise KPIs considering local stakeholder and business objectives for WWTP optimisation, rather than depending on those integrated within BSMs	DSS will optimise WWTP in a way that generates desired benefits for stakeholders
Focussing on EQI and OCI (or energy consumption) KPIs provides a narrow view of 'optimal' or 'sustainable' WWTP performance	Expansion of indicators to include environmental, social, circularity, and technical aspects	Align WWTP operation with modern sustainability and circularity aims of the water sector
Dynamic control and optimisation of WWTPs aligns better with the water sector's digitisation goals, mitigating plant operator decision making capabilities	Implement robust indicator selection to ensure optimal performance facilitates decision maker goals at a plant level	Responsive systems that optimise performance in terms of selected KPIs, rather than relying on intuitive decision making of operators
Many DSSs did not investigate the performance of controller algorithms using appropriate metrics	IAE and ISE are recommended for understanding the response of the selected algorithm to process alterations, especially as dynamic operation of WWTPs evolves	Better understanding of how the investigated WWTP will respond to external stressors

5.2. Data

Inefficient use of data is one of the main problems in plant management which many WWTPs struggle to solve. The WWT process is complicated and decentralised, so data is scattered, and managers can struggle to supervise the whole plant leading to poor management. The water industry is still developing data collection, management, analytics, and controls to more effectively use this data to inform decision making across all management and operational functions (Corominas et al., 2018). As a result, much of this data is relatively untapped to support decisions that would enable higher levels of performance and control. Subsequently, online optimisation of WWTP control has not been widely applied to real-world systems, due to the complex, nonlinear behaviour of biological WWT systems (increasing the computational requirements), lack of visualisation techniques, and low-quality sensor measurements (Matheri et al., 2022). Types of advanced control known as model predictive controllers, use data-driven techniques for early correction of process operation to reduce process faults and therefore costly downtime, effluent violations, and resource consumption (Ntalaperas et al., 2022). The combination of this with effectively constructed multi-objective optimisation DSSs results in powerful and desirable tools for the water sector to achieve its goals. Finally, the use of data-driven techniques can also be extended to improve the selection of indicators, including the use of techniques combined with expert knowledge, to find precise KPIs for monitoring specific strategic goals. This would enable the differentiation between performance (lead) and result (lag) indicators, and create numeric thresholds and benchmarks (del Mar Roldán-García et al., 2021), providing more knowledge for decision making purposes.

5.3. Uncertainty

There are many levels of uncertainty associated with WWTP DSSs, namely model structure (misrepresented boundaries, inaccuracy of construction, subjective judgement, and mitigation of important mechanisms), data (quality, processing, measurement error, and reliability), and relationship with the natural environment (knowledge gaps, dynamic system, and uncertain future) (Uusitalo et al., 2015; Walling and Vaneeckhaute, 2020). It is important to map the source and magnitude of uncertainty in DSSs, for which many techniques have been discussed in Sections 3 and 4, however, uncertainty is still recognised and treated differently by decision makers in the water sector. Even though the water sector has additional complexities that result from its strong relationship and dependency with the natural environment, a standardised methodology to identify, quantify, reduce, and report uncertainty to support decision making is still missing (Walling and Vaneeckhaute, 2020). A large number of techniques have been implemented to reduce uncertainty, depending on the MCDM method or model utilised, including the use of expert assessments, sensitivity analysis (scenario, GSA, or MC based), model emulators (Gaussian processes), deterministic models (temporal and spatial variability), and heterogeneous data assimilation (meteorological and hydrological) (Pelissari et al., 2021; Uusitalo et al., 2015). Consideration of future climate impacts is particularly challenging for water decision makers, when making operational decisions in the face of uncertain conditions. In this case, stochastic modelling frameworks and decision tree approaches are recommended to assign future conditions a probability of occurrence (Horne et al., 2016). Furthermore, to achieve more standardised protocols these methods must be aligned with the type and magnitude of uncertainties, ensuring that resultant decisions are with acceptable ranges, thereby permitting dissemination. Identifying uncertainties that have the greatest impact on results will help water sector decision makers create knowledge bases with which to refine future studies and models (Horne et al., 2016).

6. Conclusions

WWTP decision makers face stricter regulations regarding human health, environmental protection, and emissions reduction, meaning they must optimise performance and replace infrastructure, whilst maintaining positive economic performance. This creates complex multi-objective problems when operating and selecting technologies for improving WWTPs, meaning many DSSs have been developed for the water sector. Currently, there is a mismatch in terms of the decision maker goals and KPIs selected for DSSs, so water sector objectives at a European level were summarised. The regulation and action plans from the European Commission highlight their recent ambition for greater levels or sustainability, circularity, and environmental and human health protection. Following this, DSS literature was reviewed and showed the main function of MCDM tools was for WWT technology selection, whereas multi-objective optimisation DSSs focused on optimal set-point control to improve effluent and cost indicators. A large contrast was found regarding the aims of DSS typologies, as optimisation strategies tend to clearly define their goals in terms of the KPIs used, however, MCDM tools often use vague language making it difficult for users to make a connection between indicators selected and resultant outcomes. Considering these issues several recommendations were made to improve DSS deployment, such as more rigorous indicator selection protocols including participatory approaches and expansion of indicators sets (specifically for multi-objective optimisation), or greater analysis of results whether it is the use of sensitivity/uncertainty analysis or ISE/IAE indicators. Lastly, to facilitate the success of DSSs implementation, development should focus on standardised methods of indicator selection that directly links outcomes with decision maker goals, and the water sector's circularity and sustainability targets.

CRediT authorship contribution statement

D. Renfrew: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **V. Vasilaki:** Conceptualization, Methodology, Validation, Writing – review & editing. **E. Katsou:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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