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Review

Planning the centralization level in wastewater collection and treatment: A review of assessment methods

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ABSTRACT

Centralized wastewater treatment has been the favorite wastewater treatment strategy until a few decades ago, in order to exploit each possible scale economy. Nowadays, water stress and resource scarcity, due to population growth and climate change, call for water reuse and resource recovery, and these goals do not often find in centralization the best solution. Today, the reuse of reclaimed water can take place at different levels and represents an option of primary importance; therefore, in some cases, centralized systems may be economically and environmentally unsustainable for this additional purpose, and the search for the optimal infrastructure centralization degree must take into account these goals. This review analyzes studies that investigated the search of the best centralization level of wastewater collection and treatment, focusing on the methodologies applied to take the decision and highlighting strengths and weaknesses of the different approaches and how they have evolved over time. The final goal is to guide planners and decision-makers in choosing and handling the most suitable method to assess the centralization level of wastewater infrastructures, based on the objectives set out. The reviewed studies cover a period of twenty years. The differences found along this time span show an ongoing paradigm shift towards hybrid systems, which combine centralized and decentralized wastewater treatments that promote the storage of treated water and various forms of local water reuse and resource recovery. The protection of human health and the environment (which primarily promotes water reuse and resource recovery) has become the main challenge of wastewater treatment systems, that will presumably improve further their economic, social and environmental sustainability to achieve urban development in the context of the water-energy-food security nexus.

1. Introduction

One of the main decisions in wastewater collection and treatment planning is the level of centralization of the planned infrastructure. The choice of the most suitable wastewater management strategy is not an easy task, as it involves several factors that are often difficult to identify and evaluate (Libralato et al., 2012).

In general, two main strategies are recognized: centralized or decentralized management systems. In centralized systems, wastewater is collected and treated in a wastewater treatment plant (WWTP) located outside the served area; conversely, in decentralized systems, wastewater is treated near the source (Crites and Tchobanoglous, 1998). Decentralized wastewater management has been the most common strategy until the middle of nineteenth century, when the outbreak of diseases caused by the spread of pathogenic microorganisms contained in human excreta highlighted the need to transport and treat wastewater away from urban areas (Hophmayer-Tokich, 2006). Since then, the increasing urbanization and the search for economy of scale led to prefer the centralized wastewater management (Burian et al., 2000), even in cases where decentralized systems are generally more suitable, such as rural and mountain areas (Bakir, 2001).

Nowadays, water scarcity due to population growth and climate change calls for different wastewater management strategies, especially in metropolitan and densely populated areas (Tchobanoglous, 2019), as wastewater is considered a valuable source for water reuse (Lazarova et al., 2001). The discharge of treated wastewater according to established quality standards is no longer the only objective of WWTPs, and centralized systems may turn out to be economically and environmentally unsustainable when additional purposes are considered, thus highlighting the importance of finding the optimal centralization degree of the infrastructure (Angelakis and Snyder, 2015).

The reuse of reclaimed water has become an option of primary

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importance, and it can take place at different levels for non-potable and even potable reuse (Salgot and Folch, 2018). In general, decentralized systems are more suitable for reuse purposes that require low quality standards, since the points of use of reused water tally with the points of wastewater production, thus avoiding the double delivery to the WWTP and back. Conversely, centralized systems are preferable when high-quality treated wastewater is required, due to the complex treatments required, which cannot be easily decentralized. Therefore, the new paradigm consists of hybrid systems, which combine centralized and decentralized systems that enable the storage of treated water and various forms of local water reuse (Tchobanoglous, 2019). Hybrid configurations represent decentralized systems installed and interconnected to centralized systems that seek the right balance between off-site and on-site treatments (Arora et al., 2015), thus promoting a sustainable urban development in the context of the water-energy-food security nexus. Worldwide, water-energy-food connections have become the heart of sustainable development, as the population growth and the raising living standards have increased the demand for utilities and commodities that require a more conscious management. The term water-energy-food nexus indicates the strong interdependence of these three aspects and their importance for the benefit of human well-being and poverty reduction (Capodaglio, 2020).

Wastewater treatment also offers several opportunities to recover different resources than water itself (such as energy and nutrients), thus reducing the pressure on natural resources (Guest et al., 2009); however, this chance raises further questions concerning the choice of the centralization degree. Specifically, energy recovery from biodegradable organic matter is possible if anaerobic digestion is adopted for sludge stabilization and biogas production, but this choice requires careful considerations as its success is subjected to economies of scale and strongly depends on the characteristics of wastewater sludge (Verstraete et al., 2009).

These considerations show that an appropriate wastewater management may represent a turning point for sustainable development in different urban contexts and socio-economic realities, such as developing countries (Massoud et al., 2009), metropolitan cities (Vázquez-Rowe et al., 2017) and even regions without specific water problems (Gómez-Román et al., 2020). Many authors have discussed about centralized or decentralized wastewater management, analyzing advantages, disadvantages and characteristics of the two strategies (Maurer et al., 2005). In many cases, decentralized systems are assumed as small facilities that serve at most a few thousands of population equivalents (Ho and Anda, 2006); however, decentralization can be applied at different scales, involving WWTP sizes ranging from small to large, as stated by Gikas and Tchobanoglous (2009). Between the two extreme scenarios of full centralization and on-site treatment, several intermediate solutions are possible, and the only valid definitions about centralized or decentralized systems refer to the distance of the treatment site from the wastewater production place. The evaluation of the best centralization level is not obvious and requires the use of decision support systems (DSSs) that help planners and decision-makers in finding the best solution.

This review analyzes studies that investigated the centralization level of wastewater collection and treatment systems, focusing its attention on the methodologies applied to take the decision. The aim of this paper is to compare the different technical approaches and to highlight their strengths and weaknesses and how they have evolved over time. The main purpose is to guide planners and decision-makers in choosing and handling the most suitable methods to assess the centralization level of wastewater infrastructures, based on the objectives set out. In authors' knowledge, there are no other review papers available on this specific topic.

The main DSSs used in wastewater collection and treatment planning can be grouped in three categories: optimization models (OMs), multi-criteria decision analysis (MCDA) and life cycle assessment (LCA). These methodologies differ in characteristics, skills and scopes, returning different types of results and making it difficult to identify the most appropriate DSS to use. Mannina et al. (2019) provided a thorough description of these methods and their general use in wastewater issues. In addition, there are some applications of LCA-inspired methods that are always based on life cycle thinking, namely life cycle costing (LCC), social life cycle assessment (S-LCA) and life cycle sustainability assessment (LCSA), while other studies applied hybrid methodologies or methods based on mathematical models (MMs). Clearly, a combined use of these methodologies is almost always possible. The choice of the most suitable evaluation method strongly depends on the purposes to be achieved.

Fig. 1 provides an overview of the structure of this review and the topics that will be analyzed in the following chapters, after some remarks on the implications of the water-energy-food security nexus.

1.1. Insights into the water-energy-food security nexus

Water, energy and food are fundamental resources for human needs and sustainable development. The water-energy-food security nexus highlights the connections between these sectors, as changes in any of them can affect the others. Today, the availability of water, energy and food is threatened by increasing urbanization, demands and global warming. The main goal must then be to ensure sufficient and safe access to water, energy and food, thus encouraging an integrated approach to management strategies and resource allocation policies (Cansino-Loeza et al., 2022).

In this context, WWTPs can be seen as systems that recover water and energy. Non-potable reuse of treated wastewater, in compliance with required quality standards, is considered a way forward to address water scarcity (Yang et al., 2021), especially for irrigation (Ofori et al., 2021). Energy recovery through anaerobic digestion of sludge is well known, but other technologies are also emerging. For instance, microbial fuel cells (MFCs), which allow for simultaneous wastewater treatment and bioelectricity generation (Nawaz et al., 2022), have shown promising results (Adeniran et al., 2016) and are subjected to continue improvements and development (Ramya and Senthil Kumar, 2022). WWTPs could also include food-related aspects. Zan et al. (2022) recently proposed the nexus between food waste-wastewater-energy/resource by diverting food waste from the solid waste stream to wastewater stream to improve system sustainability.

This example highlights how WWTPs can play a central role in the current transition towards urban sustainability. Up-to-date wastewater planning must consider trade-offs between wastewater treatment and resource recovery, as shown in the next sections.

2. Overview of the methods applied in the reviewed studies

A literature search on academic engines was conducted to find the relevant studies. It focused on papers assessing the best centralization degree of wastewater systems and adopted the two-stage process proposed by Lam et al. (2020). The first stage was a massive collection of papers including at least two of the following keywords: wastewater treatment plant, centralization, decentralization, decision support system, optimization and planning; the most relevant studies were then selected, based on their contents. In the second stage, the lists of references of the papers selected were checked, to identify further studies of interest. In total, 47 papers (published between 2002 and 2022) were selected. Table 1 lists the reviewed articles, showing for each study the methods used, the decision level considered and the intended purposes.

As mentioned, OMs, LCA and MCDA were the most used DSSs. OMs have been applied mainly in the first decade of the considered period to determine the maximum or minimum value of an objective function subjected to a set of constraints (Ding et al., 2020). The LCA approach gained great attention in the last decade. It is a tool for assessing the potential environmental impacts associated with a product or a service during its entire life cycle (Finnveden et al., 2009) that can be used to

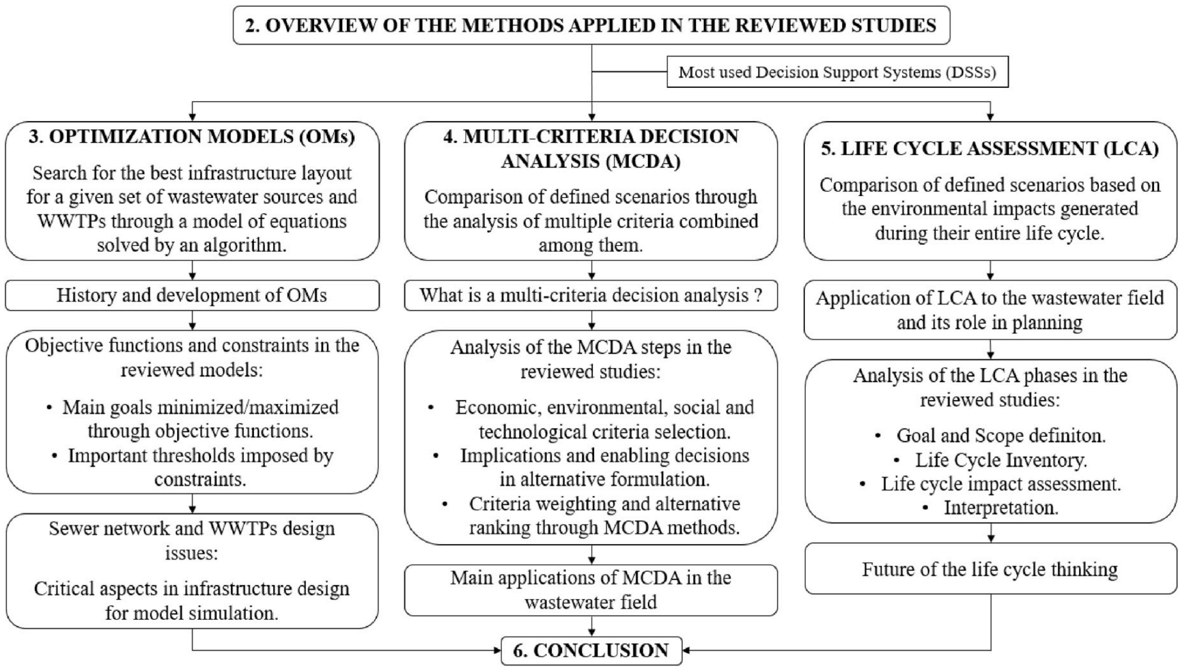

Fig. 1. Structure of the review and topics analyzed.

compare several planning scenarios. MCDA is an “umbrella term” to describe an approach dealing with multiple criteria (Baltussen et al., 2019). The MCDA methodology has been employed less frequently than OMs and LCA, and its applications are not concentrated in a specific time interval. Five studies have also used three variations of the LCA approach, named LCC (three studies), S-LCA and LCSA. LCC (life cycle costing) is an estimation method of the total cost of a product or service occurring during its entire life cycle (Ilyas et al., 2021); S-LCA (social life cycle assessment) is a tool to assess positive and negative social impacts along the life cycle (Garrido, 2017); LCSA (life cycle sustainability assessment) provides a holistic analysis of all life cycle-based approaches by combining LCA, LCC and S-LCA (Visentin et al., 2020). As LCC and S-LCA methods were derived from LCA, their applications in wastewater field are quite recent.

In five reviewed studies, some of the methods described so far were combined, trying to overcome the weaknesses of the individual methods while covering all possible aspects. Leong et al. (2019) and Arden et al. (2021) applied both LCA and LCC. Opher et al. (2018) and Opher et al. (2019) integrated MCDA into S-LCA and LCSA, respectively, obtaining tools useful to aid result interpretation in life cycle approaches (Zanghelini et al., 2018). Sun et al. (2020) used LCA to quantify environmental criteria in MCDA.

The purposes, characteristics and applications of the methods listed above will be explored in depth in the next paragraphs.

Additionally, some studies using hybrid methodologies that cannot be included in a well-specified DSS category, or methods based on MMs are summarized below:

- Woods et al. (2013) developed and compared water reclamation/reuse alternative scenarios based on costs and greenhouse gas (GHG) emissions, derived from energy consumptions. The study investigated different centralization degrees and considered both non-potable and indirect potable reuse (groundwater augmentation). In doing so, the authors used an existing DSS that was modified to include construction and operation and maintenance (O&M) costs to aid water supply planning.
- Roefs et al. (2017) and Garrido-Baserba et al. (2018) made economic comparisons of centralized wastewater systems with decentralized and hybrid source-separated systems. Specifically, Roefs et al. (2017) investigated alternatives under urban development uncertainty using a MM constituted by models simulating urban growth and wastewater discharge, infrastructure design and conversion of design parameters into discounted costs of the asset life cycle. Garrido-Baserba et al. (2018) studied alternatives in two different scenarios (new developments and existing-infrastructure retrofitting) using recognized economic assessment and modelling tools, including Maurer et al. (2013) and Roefs et al. (2017).
- Van Afferden et al. (2015), Clemens et al. (2020), Khurelbaatar et al. (2021) and Breulmann et al. (2022) used a DSS named ALLOWS (Assessment of Local Lowest-Cost Wastewater Solutions), a tool based on a geographic information system (GIS) aimed at identifying the lowest-cost wastewater management system for any geographic and demographic context. ALLOWS generates financial indicators of different scenarios and uses them to select the most cost-effective configuration. Although ALLOWS’s purpose is to find an optimal solution, it is considered a hybrid OM, since it selects the best configuration among alternative scenarios that are generated manually, while OMs generally explore mathematically all possible solutions. In these four case studies, that used the same DSS, the analyzed scenarios were developed considering sustainability factors such as urban development, groundwater vulnerability to wastewater pollution and water reuse options. Furthermore, Khurelbaatar et al. (2021) provided a detailed application of the ALLOWS method for countries with scarce data.
- Lahmouri et al. (2019) evaluated water reclamation with resource recovery strategies at different scales by using the carbon footprint method, which is a technique quantifying the amount of GHG emissions associated with the life cycle of a product or service, thus determining its contribution to climate change (Balaguera et al., 2018). The carbon footprint method has an approach similar to LCA: the features of this methodology will be discussed in chapter 5; however, as stated by the authors themselves, the carbon footprint method has the limit of focusing only on climate change, while LCA offers a more complete overview by considering different impact categories on the environment and human health.

The studies summarized above used GIS and MMs as the main analysis tools, but also several other studies used GIS, MMs, or both as

Table 1
Overview of the reviewed studies.

Reference	Method(s)	Decision scale	Main purposes and applications
Sousa et al. (2002)	OM	Regional	Search for the minimum cost configuration.
Wang and Jamieson (2002)	OM	Regional	Search for the minimum cost configuration, complying with BOD limit concentration in receiving water body.
Leitão et al. (2005)	OM	Regional	Search for the minimum cost configuration.
Cunha et al. (2009)	OM	Regional	Search for the minimum cost configuration, complying with DO, N, P and Nkj limit concentrations in receiving water body.
Zeferino et al. (2010)	OM	Regional	Multi-objective OM for minimizing total costs and maximizing DO in receiving water body.
Brand and Ostfeld (2011)	OM	Regional	Search for the minimum cost configuration.
Zeferino et al. (2012)	OM	Regional	Three robust OMs dealing with total costs and DO concentration in receiving water body, and considering river flow as source of uncertainty.
Lee et al. (2013)	MCDA	City	Rank water and resource recovery configurations, considering monetary and non-monetary criteria.
Woods et al. (2013)	Modified DSS	Metropolitan city	Comparison between scenarios for potable and non-potable water reuse, considering the total costs and GHG emissions.
Eggimann et al. (2015)	OM	Community	Search for the minimum cost configuration.
Bradford-Hartke et al. (2015)	LCA	Cluster	Assessment of environmental impacts of implementing phosphorous recovery systems in wastewater management.
Hendrickson et al. (2015)	LCA	Building	Evaluation of energy consumption and GHG emissions of a new wastewater recycling treatment in an office building.
Ishii and Boyer (2015)	LCA	Community	Evaluation of environmental and economic impacts of nitrogen and phosphorous management in urine.
Lam et al. (2015)	LCA	Community	Comparison of environmental impacts generated by source-separation systems with other domestic wastewater management systems.
Morera et al. (2015)	LCA	WWTP	Evaluation of environmental and economic impacts of the integrated operation of two neighboring WWTPs.
Van Afferden et al. (2015)	Hybrid OM	Community	GIS-based tool to evaluate the local minimum cost solution, considering demographic development, groundwater vulnerability and benefits from water reuse.
Cornejo et al. (2016)	LCA	City	Evaluation of wastewater treatment systems integrated with water reuse, energy recovery and nutrient recycling.
Kavvada et al. (2016)	LCA	Metropolitan city	Assessment of energy use and GHG emissions of urban non-potable water reuse systems.
Opher and Friedler (2016a)	LCA	City	Comparison between the environmental impacts of wastewater treatment options for non-potable urban reuse.
Zheng et al. (2016)	MCDA	Community	Comparison between different infrastructure alternatives under uncertainty in terms of their sustainability.
Hasik et al. (2017)	LCA	Building	Compare environmental impacts of water and wastewater treatment processes required by a net-zero water/net-zero energy building and two reference buildings.
Roefs et al. (2017)	MM	City	Economic evaluation of different urban development scenarios under uncertainty.
Zeferino et al. (2017)	OM	Regional	Two OMs dealing with total costs and DO concentration in receiving water body.
Garrido-Baserba et al. (2018)	MM	Community	Techno-Economic evaluation of different urban development scenarios.
Jeong et al. (2018)	LCA	City	Comparison between the environmental impacts of on-site greywater reclamation system and centralized water system in Atlanta city.
Jung et al. (2018)	OM	Community	Search for the minimum cost configuration.
Kavvada et al. (2018)	OM	Metropolitan city	Search for the optimal non-potable water reuse system scale, minimizing the total costs and energy intensity (GHG emissions).
Opher et al. (2018)	S-LCA & MCDA	City	Evaluation of social benefits and impacts of urban domestic non-potable water reuse options.
Lahmouri et al. (2019)	Carbon footprint	Community	Comparison between water reclamation integrated with resource recovery scenarios by considering GHG emissions.
Leong et al. (2019)	LCA & LCC	Building	Comparison of environmental and economic impacts of mixed urban water provision under tropical climate conditions.
Opher et al. (2019)	LCSA & MCDA	City	Evaluation of environmental, economic and social impacts of urban water reuse scenarios.
Rezaei et al. (2019b)	MCDA	City	Comparison between different urban water reuse alternatives based on three dimensions of sustainability.
Rezaei et al. (2019a)	OM	Metropolitan city	Multi-objective OM for minimizing total costs and GHG emissions and maximizing the value of water recovered for reuse (considered as social indicator).
Santana et al. (2019)	LCA	Community	Evaluation of environmental impacts of hotel water reuse systems in a tourism-dependent community.
Yerri and Piratla (2019)	LCC	District	Evaluation of life cycle costs and benefits of greywater reuse systems.
Zanni et al. (2019)	LCA	Building	Comparison of environmental impacts deriving from water recovery solutions.
Arias et al. (2020)	LCA	City	Comparison of environmental and economic impacts of wastewater treatment systems for population living in neighborhoods.
Clemens et al. (2020)	Hybrid OM	Community	GIS-based tool to evaluate the local minimum cost solution, considering demographic development, groundwater vulnerability and benefits from water reuse options.
Kobayashi et al. (2020)	LCA	Community	Evaluation of environmental impacts of greywater management systems with reuse in cold regions.
Skrydstrup et al. (2020)	LCA	Industrial process	Assessment of eco-efficiency of wastewater management systems produced in a dairy.
Sun et al. (2020)	MCDA & LCA	City	Comparison between different alternatives based on their sustainability and resilience.
Arden et al. (2021)	LCA & LCC	Building	Evaluation of environmental and economic impacts of non-potable water reuse options.
Besson et al. (2021)	LCA	City	Comparison of environmental impacts of wastewater management systems aimed at protecting the environment from the eutrophication and maximizing resource recovery.
Khurelbaatar et al. (2021)	Hybrid OM	Settlement	GIS-based tool to evaluate the local minimum cost solution, considering data-reduced scenario generation.
Risch et al. (2021)	LCA	City	Comparison of wastewater management systems from an environmental point of view.
Breulmann et al. (2022)	Hybrid OM	District	GIS-based tool to evaluate the local minimum cost solution, considering demographic development, groundwater vulnerability and water reuse opportunity.
Huang et al. (2022)	OM	Community	Search for the cost-effective pattern for rural wastewater treatment, considering the local environmental demand.

DSS = decision support system, LCA = life cycle assessment, LCC = life cycle cost, LCSA = life cycle sustainability assessment, MCDA = multi-criteria decision analysis, OM = optimization model, S-LCA = social life cycle assessment.

support tools. MMs are processes of encoding and decoding of reality, in which a phenomenon is reduced to a formal numerical expression (May Tzuc et al., 2019), and are used to understand the behavior of variables that are difficult to evaluate. GISs are computer-based tools able to analyze large volumes of data within a specific geographic setting (Kempf-Leonard, 2004), and are generally used to optimize parameters that depend on topographic or morphological characteristics of the study area. Their contribution to the general problem is significant and will be explained better in the next sections.

In short, Table 1 confirms the new wastewater concepts and the paradigm shift in progress. Along the way, the planning level has progressively narrowed from regional to city/community level, studying the development of interconnected systems that seek the right balance between centralized and decentralized systems. Similarly, the main interests of most studies moved to investigating the best trade-off between water reuse/resource recovery opportunities and environmental sustainability, thus making the LCA approach the most popular DSS for evaluating the centralization level of wastewater infrastructures. Conversely, OMs, which focus mainly on economic aspects, represented the main option up to the year 2015. Fig. 2 shows the cumulative frequency curve of the most used DSSs for the period investigated.

2.1. Geographic origin of the reviewed studies

Most of the reviewed studies (40 out of 47 papers) investigated specific geographic areas. Europe, North America and Asia dominated the publication of DSS applications in wastewater planning, with 30%, 32.5% and 32.5%, respectively. One paper each was assigned to Australia-Oceania and South America, while no publications were referred to Africa.

Fig. 3 shows the geographical distribution of DSS applications by continent, providing interesting insights. The prevalence of a method probably depends on specific attitudes of each country. For instance, Europe and North America, having more tradition in wastewater treatment, exhibit interest in issues such as reducing environmental impacts and improving social acceptance, while trade-offs in resource recovery have aroused recent interest in life cycle approaches. Conversely, in Asia, OMs and MMs are more frequently adopted, probably because several Asian developing countries still lack adequate sanitation (Massoud et al., 2009), and OMs/MMs are better suited to design and economic aspects.

3. Optimization models

3.1. History and development of optimization models

OMs consist of MMs aimed at finding the best solution of the problem, in which an objective function is maximized or minimized by adjusting variables subjected to constraints (Ding et al., 2020). In wastewater planning, OMs are usually employed to find an optimal solution for the infrastructure layout, including sewers, pumping stations and WWTPs, according to the purposes expressed by model equations. OMs are solved using algorithms that explore possible solutions in different iteration steps. The process stops when no better solutions are found.

The use of OMs is well established in the literature and claims a long tradition in wastewater collection and treatment planning. The first applications date back to the beginning of the second half of the 20th century (de Melo and Câmara, 1994), and proposed approaches such as dynamic programming (Converse, 1972), integer programming (Downey Brill and Nakamura, 1978), mixed integer programming (Wanielista and Bauer, 1972) and heuristic methods (McConagha and Converse, 1973). Nevertheless, these early models required a wide range of simplifying assumptions, often far from reality, which negatively affected the results. An important development occurred with the birth of modern heuristics, which employs search strategies inspired by natural processes able to find configurations closer to global optimal solutions (Michalewicz and Fogel, 2004).

3.1.1. Algorithms used to solve the reviewed models

The algorithms used to solve the OMs in the reviewed articles are listed in Table 2. Simulated annealing algorithm (SAA) and genetic algorithm (GA), respectively inspired by the thermodynamic process of metal annealing (Pacheco-Torgal et al., 2016) and the Darwinian theory of species evolution (Leardi, 2009), are popular modern heuristic methods which represent the most used algorithm types in the reviewed studies. Leitão et al. (2005), Eggimann et al. (2015), Kavvada et al. (2018) and Huang et al. (2022) applied heuristic modelling approaches using the so called *greedy* algorithms, which search the global optimal solution by choosing the best local solution at each iteration step (Cormen et al., 2009). The assumption that local optimal solutions would lead to a global optimal solution is not always true and this results in the great success of modern heuristics, which is generally able to avoid local optimal solutions (Cunha et al., 2009). The models developed by Zeferino et al. (2012) and Zeferino et al. (2017) tried to overcome such issues by combining SAA with a local improvement (LI) procedure aimed at searching improvements among the solutions in the neighborhood of the best solution found through SAA. In addition to the greedy algorithms, Eggimann et al. (2015) and Jung et al. (2018) used the classic Dijkstra algorithm to find the shortest path between nodes in a graph (Dijkstra, 1959).

3.2. Objective functions and constraints in the reviewed models

Table 2 summarizes the parameters adopted as objective functions and constraints in the reviewed models. While the objective functions identify the targets to be maximized or minimized, the constraints are not less important, as they express important thresholds to respect, especially with regard to environmental impacts (Cunha et al., 2009). Additionally, OMs include constraints required for mathematical/numerical integrity, such as continuity or non-negativity, which are not shown in Table 2 as they are common to all the reviewed studies.

3.2.1. Economic aspects

As highlighted in Table 2, most of the OMs are single-objective models consisting in the minimization of the overall cost, based on the estimation of investment and O&M costs. The model developed by Jung et al. (2018) represents a singular case, as it aims at minimizing the sewer network distance between wastewater sources and WWTPs. The goal of minimizing the overall costs is implicit, since costs are mostly influenced by pipeline length. However, this assumption may be not true when, for instance, the topography affects the number of planned pumping stations; therefore, site-specific conditions must be accurately evaluated before implementing any simplifications.

3.2.2. Environmental impacts and social aspects

Few studies included environmental impacts, generally implemented as constraints. Zeferino et al. (2010), Zeferino et al. (2012) and Zeferino et al. (2017) proposed models aimed at maximizing the dissolved oxygen (DO) concentration in the receiving water body, while costs were considered either as objective functions or as constraints (as spending limits to be respected). The life of aquatic species is strongly affected by the level of DO, which is interconnected with other crucial environmental parameters. The discharge of organics-polluted effluents causes oxygen depletion in the receiving water bodies, putting fish under threat, but the consumption of oxygen is subsequently compensated by reaeration; therefore, it is important to evaluate the critical DO level reached during this process (Cunha et al., 2009). DO concentration is related to the oxidation reduction potential (ORP) and is surely a primary water quality standard, but also other parameters must be considered. Chemical oxygen demand (COD), biological oxygen demand (BOD), total suspended solids (TSS), nitrogen (N) and phosphorous (P)

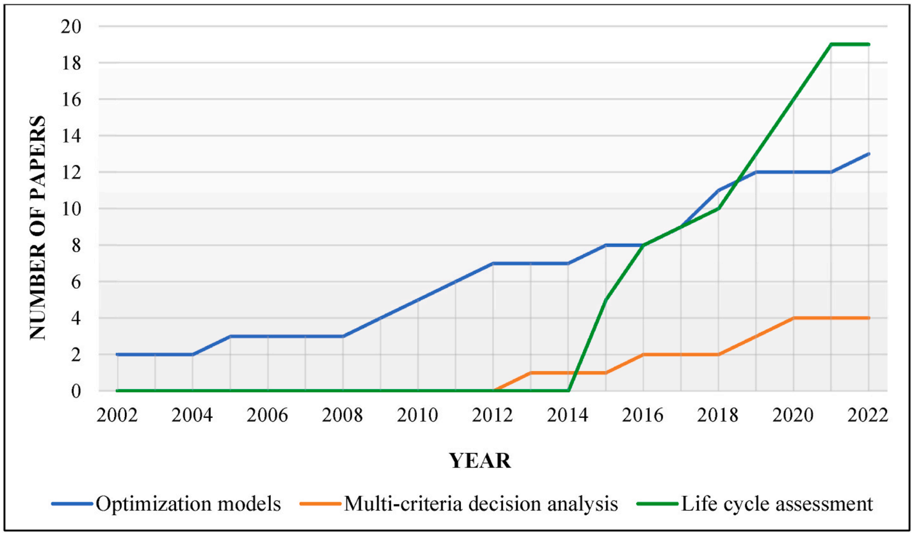

Fig. 2. Cumulative frequency usage curve of the most common DSSs.

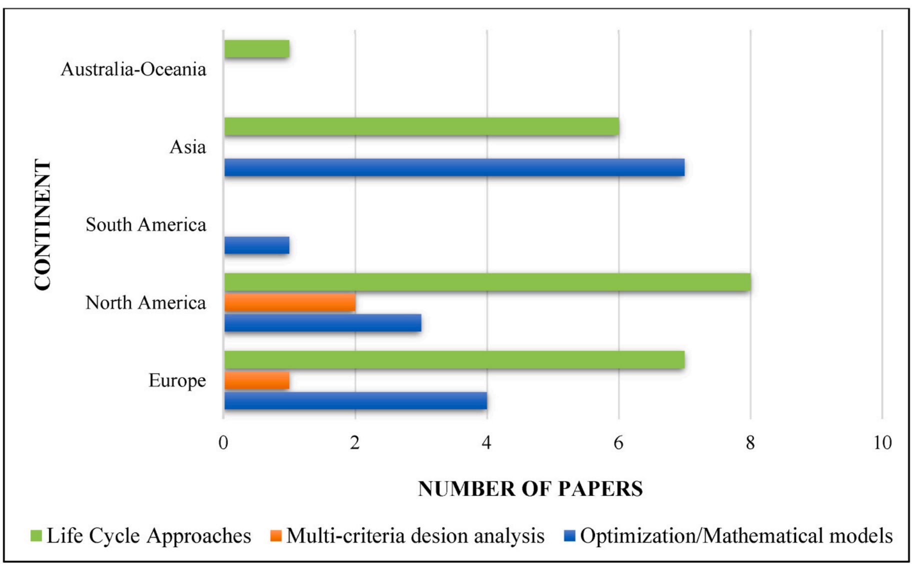

Fig. 3. Geographical distribution of DSSs by continent.

Table 2
Objective functions (O) and constraints (C) adopted in the reviewed OM studies.

Reference	Algorithms used	Total costs	DO concentration in RWB	BOD concentration in RWB	N, P concentration in RWB	Water reuse	GHG emission
Sousa et al. (2002)	SAA	O	–	–	–	–	–
Wang and Jamieson (2002)	GA	O	–	C	–	–	–
Leitão et al. (2005)	Greedy algorithm	O	–	–	–	–	–
Cunha et al. (2009)	SAA	O	C	C	C	–	–
Zeferino et al. (2010)	SAA	O	O	–	–	–	–
Brand and Ostfeld (2011)	GA	O	–	–	–	–	–
Zeferino et al. (2012)	SAA, LI	O	O	–	–	–	–
Eggimann et al. (2015)	Greedy algorithm, Dijkstra algorithm	O	–	–	–	–	–
Zeferino et al. (2017)	SAA, LI	O, C	O, C	–	–	–	–
Jung et al. (2018)	Dijkstra algorithm	O	–	–	–	–	–
Kavvada et al. (2018)	Greedy algorithm	O	–	–	–	O	O
Rezaei et al. (2019a)	Triangle Splitting method	O	–	–	–	–	O
Huang et al. (2022)	Greedy algorithm	O	C	C	C	–	–

BOD = biological oxygen demand, DO = dissolved oxygen, GHG = greenhouse gases, N = nitrogen, P = phosphorous, RWB = receiving water body.

should be considered, especially in regional-level planning, where the discharge of large amounts of nutrient-rich effluents may cause eutrophication, which is another cause of oxygen depletion. Furthermore, some correlations among these parameters, such as the BOD/COD ratio, can be included in the models as indexes of biodegradability (Saeed and Khan, 2019). For instance, Cunha et al. (2009) included river water quality in their OM using most of the above-mentioned parameters as constraints. Indeed, the introduction of water quality standards involves the implementation of water quality simulation models (WQSMs) to predict the effect of several combinations of pollution indicators on the receiving water body. For this reason, many studies implicitly considered water quality issues in constraints by setting limits on the maximum amount of wastewater to be treated in WWTPs or assuming fixed discharge standard of pollutants, based on treatment technology and local environmental demand (Huang et al., 2022). In this regard, Wang and Jamieson (2002) studied the differences between fixed emission standards and water quality objectives, using a WQSM replicated through an artificial neural network (ANN).

On the other hand, Kavvada et al. (2018) and Rezaei et al. (2019a) considered water reuse and environmental sustainability as issues of current interest. In particular, the model of Rezaei et al. (2019a) aims at minimizing greenhouse gas (GHG) emissions associated with energy consumption and maximizing the value of resource recovery to capture their social benefits. Conversely, the model developed by Kavvada et al. (2018) identifies the optimal non-potable water reuse system scale, defined as the population served by the recycled water, while minimizing energy intensity (or GHG emissions).

3.2.3. Management of multi-objective models and uncertainty parameters

Four studies are multi-objective optimization models. Tradeoffs between goals are handled by means of weighted terms in Zeferino et al. (2010) and Zeferino et al. (2012), while the models developed by Kavvada et al. (2018) and Rezaei et al. (2019a) generate different configurations for each optimal solution. In addition, Zeferino et al. (2012) proposed a robust optimization (RO) approach to deal with OM under uncertainty (Sahinidis, 2004), as an improvement on classic OMs, which generally neglected uncertain parameters. For instance, all of the reviewed OMs considered sanitary sewers in stationary conditions (Sousa et al., 2002), while combined or sanitary sewers receiving the first flush from stormwater sewers (Barco et al., 2008) to treat the initial part of the run-off (Perera et al., 2021), should more appropriately be considered in the most up-to-date modeling. In this view, Zeferino et al. (2012) handled the river flow as the only uncertainty source.

3.3. Main skills of optimization models

Objective functions and constraints may cover the most interesting fields in wastewater system planning, even though the complexity of the models increases with the number of targets. Therefore, a selection of the objectives to be achieved is required and results strongly depend on the model's ability to simulate a wastewater infrastructure design process as close to real design practices as possible. OMs outline wastewater treatment systems by means of nodes and arcs, with nodes representing wastewater sources and locations for possible WWTPs, and arcs representing sewer-pipelines linking nodes. As ever, infrastructure characteristics are defined through model constraints.

3.3.1. Sewer network design issues

3.3.1.1. Pipeline modeling. For gravity-driven pipelines, the models must respect structural and hydraulic criteria such as minimum and maximum slopes, flow velocity, trench depth and pipe diameter. In some studies, design and verification of sewer pipelines were managed by hydraulic simulation models (HSMs), as shown in Table 2. However, this provision alone can be insufficient for reliable results, and the excessive simplification of some models can get them out of touch with reality.

Many studies considered gravity-driven pipelines as straight lines. According to Leitão et al. (2005), a straight line may not define the optimal distance between two nodes, for the possible presence of natural and artificial obstacles. Hence, they used a digital terrain model (DTM) to represent land topography, thus highlighting GIS potentiality. Based on the model of Leitão et al. (2005), Eggimann et al. (2015) underlined the strong correspondence between sewer and street network, and developed a model able to design sewer pipelines following both the shortest-path along street network and the land topography; however, the decision was based on local design practice, while a choice based on economic convenience would have been more appropriate (Huang et al., 2022). The difficulties associated with the design of sewer networks are accentuated in rural areas: Huang et al. (2022) recently developed an OM to determine the cost-effective pattern for rural wastewater treatment. The variable social and geographical characteristics of the rural areas may result in different optimal configurations, especially when considering large-scale areas (Huang et al., 2021); therefore, the model incorporated economic aspects, treatment scales and technologies, topographical conditions and local environmental demands. Conversely, the provision of pipes strictly following the street network may be reasonable when planning at city level, where the streets represent the only possible paths for sewers, as in the case of Jung et al. (2018). When possible, such assumptions can be very useful simplifications of the models.

3.3.1.2. Pumping station modeling. When land topography hinders gravity flow, specific provisions are required. All the reviewed models considered only pumping stations, but other technologies could also be considered, such as inverted siphons or microtunneling. The installation of a pumping station depends on land characteristic and requires an accurate representation of the study area. Most of the reviewed models introduced intermediate nodes to define the topography but, given the great development of GISs, the use of a DTM appears more appropriate, as shown by Leitão et al. (2005), Eggimann et al. (2015) and Huang et al. (2022). Pumping stations require supplementary pipelines and devices, thus involving higher costs and different hydraulic criteria. This aspect was considered explicitly only by Brand and Ostfeld (2011).

Pumping stations may be convenient also in flat land, where gravity-driven pipelines require trenches so deep to cause excessive costs. Few studies explicitly dealt with this topic. Jung et al. (2018) excluded solutions where the maximum established depth was reached. Alternatively, according to Eggimann et al. (2015), introducing a pumping station when the minimum slope cannot be maintained within the maximum allowed trench depth can be a more convenient criterion. They defined the minimum acceptable slope as the lowest slope ensuring gravity-driven flow with acceptable speed, and adopted it in flat land, while in steep land they assumed for the sewer the same slope of the land itself. The framework proposed by Eggimann et al. (2015) does not optimize the number of pumping stations along a pipeline, but it is probably the best approach to minimize overall costs associated with sewer network design. As a general approach, Van Afferden et al. (2015) and Clemens et al. (2020) generated different scenarios identifying micro-catchments that favored wastewater gravity flow, in order to avoid or minimize the presence of pumping stations. However, a gravity-flow sewer pipeline is not always the most economical solution, especially when it involves longer distances.

3.3.2. WWTP design issues

OMs determine the best WWTP configuration, returning locations, sizes and, in some studies, treatment technologies.

3.3.2.1. Selection of WWTP locations. The possible positions of WWTP nodes are in most cases predetermined. This approach seems to be the most reasonable, as it enables an earlier definition of the most suitable area for building a WWTP. Huang et al. (2022) selected the node with the lowest elevation as the WWTP location, in order to implement the use of gravity-driven pipelines. In Eggimann et al. (2015) and Jung et al. (2018), possible WWTP nodes were not established a priori and final locations resulted from model elaborations, based on economical convenience. Admittedly, this different approach gives greater freedom in the choice of systems. For instance, in Jung et al. (2018), the centralization degree is an input parameter entered by users and WWTP locations are chosen randomly each time the model is run: it results in the need to run the model multiple times to find the best solution but, on the other hand, it allows to investigate more configurations. Conversely, the model used by Eggimann et al. (2015) investigated only two source nodes at each step, evaluating the best configuration based on the two investigated nodes. Moreover, at the end of the iteration process, it allowed to explore possible WWTP merging due to economy of scale. However, these models may give rise to unfeasible solutions because of technical reasons or social acceptance; therefore, a preliminary study on possible WWTP locations is recommended.

3.3.2.2. Selection of treatment technologies. The costs associated with WWTPs include both capital expenditures (Capex) and operating expenses (Opex) (Eggimann et al., 2015). Capex refer to the construction costs of WWTPs, including treatment area purchase cost (Brand and Ostfeld, 2011). Opex refer to the O&M costs of WWTPs, such as energy, labor and chemicals (Rezaei et al., 2019a). WWTP cost functions may depend on both plant size and treatment technology. While WWTP capacities are model outputs, resulting from incoming wastewater flow, treatment technologies must be explicated in advance, if the WWTP cost functions depend on treatment type. Only Wang and Jamieson (2002), Rezaei et al. (2019a) and Huang et al. (2022) developed models able to return treatment technologies based on required treatment level, while most studies established a priori the WWTP types to be used. In all studies, WWTPs were assumed to achieve the required effluent quality standards.

4. MULTI-CRITERIA decision analysis

Multi-criteria decision analysis (MCDA) (also known as multicriteria decision-making, MCDM) is a DSS in which multiple criteria are combined. The use of MCDA may be appropriate to pursue a global improvement of the facilities, considering several targets (Mannina et al., 2019).

MCDA involves the ranking of a finite set of alternatives under evaluation, based on several criteria. The criteria are selected to identify the objectives to be optimized and may be in conflict with each other, as they often refer to different aspects, such as reduction of costs or gas emissions or resource recovery (Triantaphyllou and Baig, 2005). Compared to studies where different objective are analyzed separately, MCDA is a consolidated methodology that aggregates data by a decision-making method, in order to balance criteria and provide an integrated response.

Wang et al. (2009) indicated four main stages in MCDA. (1) Alternatives are formulated from a set of selected criteria based on normalized data. This phase is crucial to set up the study correctly and obtain reliable results; the alternatives must cover all relevant options and the criteria selected with quantitative metrics must be consistent with the objectives of the study (Mutikanga et al., 2011). (2) The weights of the criteria, representing their relative importance, are determined, often by means of weighting methods. (3) The alternatives are ranked by MCDA methods, which are based on criteria weights and aimed at balancing the criteria. (4) Alternatives are ranked: if the orders of preference obtained by different MCDA methods converge the analysis is completed, otherwise the results are aggregated again and the best scheme is selected.

The last two phases refer to studies that explore several MCDA methods. Studies employing more MCDA methods are more solid, but if a single method is used the best alternative is selected based on a single preference order. Table 3 summarizes the reviewed studies that implemented a MCDA, showing criteria, alternatives and methods applied. Table 3 does not include Opher et al. (2018) and Opher et al. (2019), since they used MCDA only as a tool to support the life cycle approach.

4.1. Multi criteria systems in wastewater planning

Since wastewater planning involves a wide range of aspects and considerations, MCDA has the advantage of considering multiple criteria that can be weighted and combined providing a rational ranking of the alternatives explored. The following sections present the choices made in the reviewed papers. To the best of our knowledge, only few papers used MCDA to plan wastewater treatment in the last years. However, they provide a broad view of the topic, and it will be our task to examine the reasons why this methodology is less popular than OMs and LCA when it comes to wastewater planning.

4.2. Criteria selection

Criteria selection is one of the first steps in MCDA and represents a crucial point for the next stages. Criteria are selected based on the set targets and should be comprehensive, non-redundant and able to discriminate among alternatives (Georgopoulou et al., 1998). The number of criteria required for proper management should be just right, meaning they must be highly meaningful and relevant for the case studied and must cover the main aspects involved. Considering the ability of MCDA to combine data of different nature, criteria should be able to measure the overall sustainability dimensions of the alternatives and are usually categorized as economic, environmental and social criteria (Mutikanga et al., 2011). Based on a literature review, Bernal et al. (2021) listed, classified and prioritized the key parameters to be considered in wastewater planning.

4.2.1. Economic criteria

Economic indicators, namely the capital and O&M costs of the alternatives, are common criteria for all the reviewed studies. In addition, Lee et al. (2013) included the revenue resulting from the sale of reclaimed water for non-potable reuse, assuming a reclaimed water cost of 0.95 $\$/m^3$, and avoided the costs of energy import, thanks to several adopted energy recovery options. Avoided costs indicate economic advantages deriving from the production or recycling of a good and should always be considered when studying systems with resource recovery. However, avoided costs, as well as avoided impacts, which account for environmental advantages deriving from the production or recycling of a good, are important and very common concepts in life cycle approaches, as shown later.

Economic criteria are surely fundamental indicators since they determine the actual feasibility of the projects (Balkema et al., 2001). However, in a world moving towards the environmental and social sustainability, capital and O&M costs can no longer be the only parameters to evaluate. The greatest merit of MCDA lies precisely in the possibility to consider multiple criteria and, not surprisingly, all the reviewed studies identified different sets of criteria to group the main issues involved in wastewater planning and take a holistic view of the problem.

4.2.2. Environmental criteria

Environmental criteria refer to a wide range of issues (such as effluent quality, resource consumptions, pollutant emissions …) that can be evaluated in several ways. Zheng et al. (2016) tried to enclose the most relevant issues in a generic top-level objective (*Protection*) that aims at surface and ground water conservation (for instance, from chemical pollution) and efficient use of energy and nutrients. According to this study, the transport and treatment of wastewater amounts to 45–60 kWh/person/year. In addition to discharge quality and resource saving, authors included the possible damages deriving from structural failure of sewers, which may cause pollutant release into the soil and groundwater contamination (Reynolds and Barrett, 2003). Conversely, Lee et al. (2013) mainly focused on recovery systems and considered directly the fraction of energy demand met by biogas recovered and the fraction of water use met by recycled water in a baseline year, assuming that increased water recovery enhances resilience to water stress. According to them, the values of renewable energy and water ranged between 11-56% and 0–35%, respectively, based on the alternatives analyzed.

The explicit computation of the energy and water fractions recovered is an immediate proof of effectiveness of the recovery systems, but it does not necessarily imply the best convenience from an environmental point of view. Indeed, the recovery of resources saves them, but sometimes at the cost of a higher overall impact on the environment (Diaz-Elsayed et al., 2020). In this regard, Rezaei et al. (2019b) considered carbon footprint (CF) and eutrophication potential (EP) as significant environmental impact indicators of the analyzed systems. CF was computed by electricity consumption, having proven its strong dependency on this parameter in the water (Loubet et al., 2014) and wastewater industries (Pintilie et al., 2016). EP was computed based on nitrogen and phosphorous concentrations in the reclaimed water, as it largely depends on the loads of these two nutrients (Smith et al., 1999).

Environmental impacts may refer to a specific time frame or to the overall life cycle of a product or service. When only a part of the processes is considered, phases that are particularly harmful to the environment risk to be ignored, leading to an underestimation of the potential effects. Accordingly, Sun et al. (2020) used LCA to estimate the potential environmental impacts throughout the life cycle of the analyzed systems, including direct and indirect emissions to the environment for both the construction and operation phases (Foley et al., 2010). They used the CML[2] Baseline 2001 v2.5 method to quantify EP and global warming potential (GWP) generated by the alternatives. Similarly to previous studies (Corominas et al., 2013), Rezaei et al. (2019b) and Sun et al. (2020) chose EP and GWP as environmental indicators for their relevance in the current environmental policies (United Nation, 2015) and for the high energy intensity and direct discharge of organics that characterize the wastewater field.

4.2.3. Social criteria

In a sense, environmental criteria act in part as social indicators, since respect of the environment is in the interest of the community. However, targeted social criteria should not be neglected. Rezaei et al. (2019b) considered the value of the recovered resource as the only social criterion, assuming that the users' willingness to pay increases with the value of the reclaimed water. Sustainability assessment of water reuse applications is the main goal in the study of Rezaei et al. (2019b); however, concentrating social implications in a single factor may be reductive, especially in planning problems that involve several aspects. Indeed, Zheng et al. (2016) used indicators to evaluate managerial and infrastructural issues that can influence social acceptance by local community. To this end, they estimated parameters such as: (a) the management and operation quality of the wastewater systems; (b) how much and in which way the citizens can take part in the planning process; (c) the time to be invested by end users to operate and maintain the systems (especially in case of decentralized treatment units, which may be installed at the end users location); (d) the shares of private property to be provided by end users to place treatment units (in case of decentralized systems); (e) the incidence of construction sites and road works in the planning phase, based on the collaboration level between the main infrastructure and the service suppliers (transportation, gas supply, energy supply with district heating, telecommunication, water supply and wastewater disposal). According to the authors, in the worst case, end users have to invest 10 h/person/day and treatment units require up to 10 m^2 of area on private property. In general, it appears to be the best solution to cover a number of aspects that are difficult to grasp.

4.2.4. Technological criteria

In terms of sustainability, the potential impact of climate change is significant. Although its potential effects are not yet fully understood, climate warming has altered the natural hydrological cycle, leading to an increase in the magnitude of storms and a decrease in flooding return periods around the world (Kundzewicz et al., 2014). Therefore,

Table 3
Criteria, alternatives, weighting methods and MCDA methods adopted in the reviewed MCDA studies.

Reference	Criteria	Alternatives	Weighting method(s)	MCDA method(s)
Lee et al. (2013)	Initial investment cost; O&M cost; Revenue and avoided cost; Net life cycle cost; Renewable energy (%); Resilience to water stress (%).	1 centralized configuration and 2 hybrid configurations with satellite treatment.	Based on author experience	PROMETHEE I; PROMETHEE II • Outranking relations; pairwise comparison of alternatives; acceptance of incomparable metrics.
Zheng et al. (2016)	Equity; Protection; Safe WW disposal; Social acceptance; Low costs.	13 decision alternatives differing on five aspects: management, O&M, drainage system, stormwater handling and wastewater and stormwater treatment.	Variant of SMART/SWING, based on stakeholder preferences	MAUT • Possibility of independence between weight elicitation and alternatives; suitable for uncertain data; non-acceptance of incomparable metrics.
Rezaei et al. (2019)	Capital costs; O&M costs; Carbon footprint; Eutrophication; Value of resource recovered.	1 centralized and 1 decentralized treatment system for distributed unrestricted urban water reuse.	Based on stakeholder preferences	Regret-based model • Applicable to a limited number of alternatives; less knowledge required; easier application.
Sun et al. (2020)	Construction costs; Operation costs; Eutrophication potential; Global warming potential; Robustness; Rapidity.	2 centralized configurations, 1 decentralized configuration and 1 centralized-decentralized hybrid differing on treatment technologies and source separation.	AHP	Composite indicator approach • Acceptance of incommensurable metrics; suitable for sustainability assessment; easier ranking.

especially in case of WWTPs receiving wastewater from combined sewers, indicators referring to reliability and resilience of wastewater systems should be included (Juan-García et al., 2017). These criteria can be considered a sort of hybrid, since both environmental and social problems could arise from them. In this regard, Sun et al. (2020) considered WWTPs' ability to maintain their own functions following an unexpected perturbation (*Robustness*) and the time required to restore an ordinary operating state after a disturbance (*Rapidity*), highlighting how climate change scenario modified design parameters. To this end, the authors investigated a 100-year flood natural disaster stressor. Contextually, Zheng et al. (2016) considered system reliability to prevent flooding and hygienic wastewater disposal (*Safe WW disposal*), in order to reduce risks associated with overflow of the wastewater treatment systems. Indeed, if drainage systems have insufficient hydraulic capacity, untreated wastewater containing pollutants and pathogens may overflow into streets or houses, posing serious dangers for human health and the entire ecosystems (Weyrauch et al., 2010). Furthermore, the authors included the flexibility of the infrastructures to future adaptations (*Equity*) by evaluating the shift of the rehabilitation burden to the next generations. However, these criteria can be considered to address both climate change and uncertainty related to urban developments, as mainly done by the authors.

4.3. Alternative formulation

In studies that used MCDA to assess the best centralization level of wastewater infrastructures, the alternatives are represented by different wastewater management scenarios. Compared to OMs, all possible configuration systems cannot be explored by means of an MCDA; hence, the scenarios to be evaluated must be modeled in advance, including infrastructure layout and user allocation.

4.3.1. General implications in alternative formulation

As in the case of the criteria, the number of alternatives could be high, and a selection of the most relevant scenarios is required. Alternatives must be formulated based on the objectives and depend on the study context.

4.3.1.1. Stakeholder involvement. In wastewater planning problems, several actors from different decision levels and sectors interact with each other and it is therefore advisable to involve stakeholders in this stage so as to create options that satisfy the interests of all of them, thus promoting social acceptance.

Typically, a stakeholder analysis is performed to understand those involved; however, stakeholder analysis alone may lack quality and consistency and, especially in view of climate change and future developments, a more participatory and long-term planning approach should be adopted (Lienert et al., 2013). In this regard, Zheng et al. (2016) conducted an accurate stakeholder identification by combining stakeholder analysis and social network analysis, which is an approach that has already proven to give satisfactory results and detailed information on water infrastructure planning processes (Lienert et al., 2013).

4.3.1.2. Comparison of different wastewater management systems. Scenario building enables the comparison of different wastewater management systems with each other, including elements that are usually avoided in OMs, such as dynamic loads, stormwater management, hybrid systems and various uncertainty sources. Sun et al. (2020) evaluated the sustainability of centralized, hybrid and decentralized alternatives (Fig. 4) that separate grey water (wastewater produced in households or office buildings without fecal contamination) from black water (wastewater collected from toilet) (Roefs et al., 2017). In source-separated systems, grey water and black water are conveyed in separate pipelines. Hence, source-separated systems require more pipes and may involve additional costs. However, they may also increase the sustainability of systems, with greater water savings (Zeeman et al., 2008), improved energy and nutrient recovery (Kujawa-Roeleveld and Zeeman, 2006), and improved properties for sludge reuse in agriculture (Tervahauta et al., 2014). Zheng et al. (2016) explored several configurations including wastewater source separation, stormwater treatment, drainage systems and considering four future scenarios to capture external socio-economic uncertainties (Lienert et al., 2015). Lee et al. (2013) studied centralized wastewater treatment systems that implement local treatments at satellite facilities. Satellite wastewater treatment facilities (SWWTFs) are connected to the centralized connection system: wastewater is removed from the centralized collection system, resources are recovered locally, and residual wastewater and waste solids are returned to the centralized collection system for treatment (Gikas and Tchobanoglous, 2009). According to Tchobanoglous (2019), SWWTFs may represent a valid strategy to address water shortages in metropolitan areas: in centralized systems, water reuse is often inhibited by infrastructure costs for transporting reclaimed water, as centralized WWTPs are generally located away from the point of use; conversely, SWWTFs require fewer pipeline lengths and energy for delivery, and this may lead to lower management costs, thus maximizing the potential benefits of water recovery.

4.3.2. Enabling decisions in scenario building

Generally, scenario building involves three enabling decisions: identification of boundaries, selection of WWTP locations and treatment technologies, and definition of pipeline routes (Lee et al., 2013).

4.3.2.1. Identification of boundaries. The clusters served are selected taking into account the scale of interest, and may be established on the basis of existing political boundaries (Lee et al., 2013) or land characteristics (Rezaei et al., 2019b). The adoption of the existing political boundaries is a fairly simplifying choice in catchment-scale planning that should not generate acceptability problems as each district treats its own wastewater but does not ensure technical-economic feasibility of the project. Some areas enclosed within the established boundaries may be difficult to reach by pipelines both for wastewater collection and water reuse; therefore, distances and obstacles between WWTPs and served areas should be taken into consideration.

4.3.2.2. Selection of WWTP locations and treatment technologies. The selection of WWTP location is a topic already discussed in the previous chapter, since OMs may request the identification of the WWTP nodes for algorithm implementation. Even in this case, the most suitable areas for WWTP location must be selected in advance, in order to combine economic advantages with environmental benefits and limit NIMBY conflicts (Vasiloglou et al., 2009). Although MCDA itself is a widely used methodology in this type of analysis, WWTP placement may follow various logics. For instance, Sun et al. (2020) applied two different scale-dependent criteria, locating decentralized WWTPs based on population density and centralized WWTP for the purpose of a shorter outfall distance in the 100-year flood zone. This choice is quite unusual when compared to the other reviewed studies that explicitly addressed the question, but it appears to be an acceptable method to include the uncertainties due to hydrological changes in scenario planning and to create wastewater systems that progress towards sustainability considering future prospects. Obviously, the selection of the most suitable WWTP location cannot depend on these parameters alone.

At the same time, similarly to OMs, technologies investigated may also represent a limiting factor in MCDA studies. Lee et al. (2013) simplified their study by choosing treatment technologies a priori, but a larger suite of technologies should be considered, especially for resource recovery system analysis. Indeed, the performances of resource recovery systems depend on the type of technologies used (Lee et al., 2013), and the achievement of precise water quality standards for water reuse or biogas production for energy recovery may affect the outcome of the

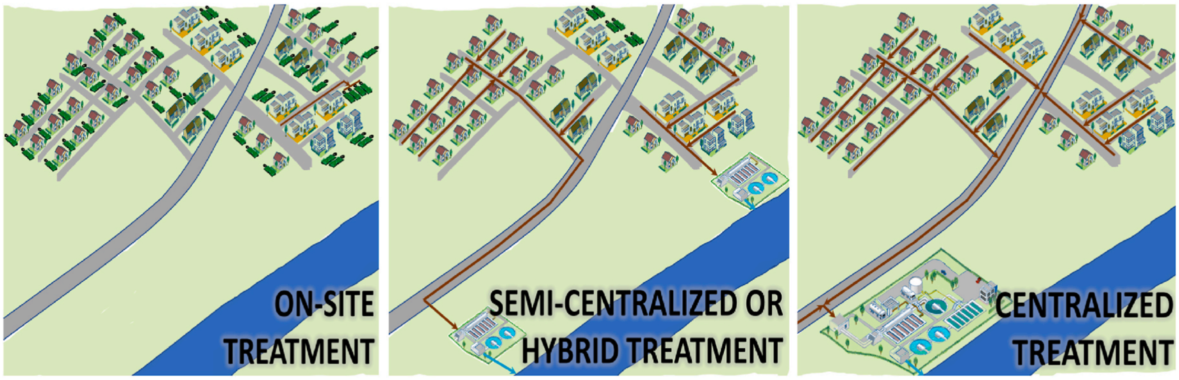

Fig. 4. Examples of on-site, hybrid and centralized wastewater treatment.

analysis both in economic and environmental terms.

4.3.2.3. Definition of pipeline routes. Finally, the pipeline design can concern both wastewater collection and distribution of reclaimed water, based on the scenarios to be analyzed. Pipelines and pumps must comply with regulatory aspects and hydraulic criteria and their characteristics depend on water balances and geographic factors of the served areas. The choice of pipeline routes is not clearly addressed by the reviewed studies, but pipeline layout should follow the goal to optimize transport networks in order to reduce costs.

4.4. Criteria weighting and alternative ranking

Criteria weighting and alternative ranking represent the last two stages in MCDA, which almost always involve rational methods for their resolution. The selection of the most appropriate methods often depends on the characteristic of the study conducted.

4.4.1. Criteria weighting

Criteria weighting is necessary to define the relative importance of criteria and establish the priority degree of the objectives. Criteria weights have a direct impact on final results and must be chosen in order to obtain their rationality and veracity by accounting for the variance degree and independency of criteria and the subjective preferences of the decision-makers (Wang et al., 2009).

In general, there are two methods for criteria weighting: the equal weights method and the rank-order weights method (Wang et al., 2009). The equal weights method assigns to each criterion the same weight, that is defined as:

$$W_i = \frac{1}{n};\; i = 1, 2, \ldots, n \tag{1}$$

The equal weights method is surely easy to be applied and does not require special skills. Nevertheless, it ignores relative importance among criteria, while priorities should be expressed in planning problems, especially if some objectives predominate over others. The rank-order weighting methods allow to diversify criteria weights. Wang et al. (2009) provided detailed descriptions and summarized the most applied rank-order weighting methods, which can be classified into three different groups: subjective weighting method (criteria weights depend only on decision-makers' preferences), objective weighting method (criteria weights are obtained by mathematical methods) and combination weighting method. In addition to this categorization, each method has its own internal characteristics that make it more or less suitable and appropriate; for this reason, the choice of the method to be used is controversial (Diaz-Balteiro et al., 2017).

4.4.1.1. Criteria weighting applied in the reviewed studies. Lee et al. (2013) calculated criteria weights by means of preference scores assigned based on their experience with the community of the case study. Finding optimal solutions in wastewater planning requires communication, coordination and sharing among the different stakeholders (Harris-Lovett et al., 2019). In this regard, Zheng et al. (2016) followed the procedure proposed by Lienert et al. (2015) for the preliminary steps of a structured decision making for sustainable water infrastructure planning and involved the identified stakeholders throughout, comprising weight assignment. Specifically, the identified stakeholders were asked to quantitatively elicit the weights of the objectives first by means of an online questionnaire and then in face-to-face interviews. Although the total stakeholder involvement requires considerable efforts, especially in terms of time, this is a comprehensive approach to facilitate urban transition towards sustainable infrastructures, taking into account social dynamics that are not always specified by criteria.

Subjective methods clearly express evaluations but, while recognizing a deep knowledge of the study area, weights obtained by a subjective method could be affected by preferences and knowledge of decision-makers. At the same time, objective methods are relatively weak (Wang et al., 2009); therefore, in accordance with Wang et al. (2009), an integrated approach would be preferable. In view of that, Zheng et al. (2016) used a variant of the SMART/SWIMG method to elicit the weights expressed by stakeholders (Mustajoki et al., 2005). This method was developed to facilitate online implementation of weight elicitation. Even Sun et al. (2020) used a questionnaire to determine the preferences of stakeholders and applied the Analytical Hierarchy Process (AHP) method to allocate weights (Saaty, 1988). The AHP was preferred since it is recommended for studies with less than seven alternatives (Kalbar et al., 2012). Generally, AHP is one the most applied and popular methods to allocate criteria weights due to its flexibility, faculty to consider the stakeholder perspective and ability to control inconsistencies (Zeng et al., 2007).

4.4.2. Alternative ranking: characteristics and applications of MCDA methods

After computing the criteria weights, the preference orders of the alternatives are determined by MCDA methods. Wang et al. (2009) provided an overview of the most used MCDA methods and divided them into three main categories: elementary methods, unique synthesizing criteria methods and outranking methods.

Each MCDA method has its own properties showing pros and cons (Cinelli et al., 2014), so that the choice of the most adequate method depends on conditions and parameters of the case study. Zheng et al. (2016) used the Multi-attribute Utility Theory (MAUT) (Keeney and Raiffa, 1979) as is particularly recommended to manage data and values affected by uncertainties; they considered four future scenarios and applied several models to predict alternative performances. Moreover, they elicited criteria weights independent of the decision alternatives for simplicity and MAUT is advisable in this case, as rank reversals or removal of a lower ranked alternative may occur using other methods (Zheng et al., 2016). Rezaei et al. (2019b) admitted that the most appropriate method for their case study was not investigated previously and used a regret-based model, which requires less knowledge and skills. This model can be applied when the number of alternatives is limited and, despite its simplicity, it provides a wide range of applicability options and returns results similar to those of more complex methods. In addition, the authors used a regret-based model based on the minimax regret criterion, which allows for the inclusion of decision-making uncertainties (Kolios et al., 2016). Sun et al. (2020) developed a composite indicator to assess the sustainability of alternatives (Molinos-Senante et al., 2019), while only Lee et al. (2013) used more than one MCDA method, namely PROMETHEE I and II (preference ranking organization method for enrichment evaluations I and II) (Behzadian et al., 2010), which are two outranking methods that perform a pair-wise comparison of the alternatives. The authors chose these two methods because outranking methods allow the comparison of criteria that have incomparable metrics, since they distinguished between monetary and non-monetary criteria.

4.5. The use of MCDA in wastewater field

As shown in Table 1, only few papers used MCDA among the reviewed studies, indicating that this methodology is not usually applied in wastewater planning. Probably, this is because the choice of the centralization degree involves all the economic, environmental, social and technological issues concerning the wastewater collection and treatment processes. Collecting and managing all the necessary criteria to address wastewater planning problems is rarely feasible and perhaps discourages the use of MCDA for this purpose.

In addition to the complexity of MCDA itself, additional software and tools for computing certain parameters are often required, thus increasing project times and costs. For instance, Zheng et al. (2016) used sound models to estimate hydraulic performance and decay of sewer networks and prediction models to estimate the pollution levels and the chemical state of water body; finally, as already mentioned, Sun et al. (2020) applied LCA as the tool to evaluate GWP and EP.

Although MCDA offers an overall view of the systems analyzed, researchers and practitioners seem to prefer methods that allow them to investigate in depth specific issues such as costs or environmental impacts, and to make assumptions on the remaining aspects involved. In view of that, MCDA can be used as support tool for other methods in wastewater planning. Opher et al. (2018) and Opher et al. (2019) applied AHP in S-LCA and LCSA, respectively. Both studies used AHP to attribute weights to social criteria starting from expert judgment elicitation and to evaluate impact intensities for quantitative and qualitative social indicators. In particular, for qualitative indicators, the use of a MCDA method is fundamental to convert verbal judgment and evaluations on sustainable criteria into numerical data.

MCDA tools have found wide use in optimization problems related to energy and environmental issues (Kumar et al., 2017). It could be argued that the use of MCDA in wastewater planning is discouraged by the wide range of aspects involved, which results in a strong criteria selection and in the use of further analysis tools and software that increase project time and costs. Indeed, in wastewater field, MCDA found broad applications in more specific studies, such as wastewater sludge management (Garrido-Baserba et al., 2015), wastewater treatment technology selection (Kalbar et al., 2016), sustainability assessment of existing wastewater treatment systems (Molinos-Senante et al., 2014). Regarding the choice of the best centralization degree, MCDA has been widely used for the selection of the most suitable areas for WWTP locations, an already mentioned topic that is a fundamental preliminary step for a correct scenario building. Hama et al. (2019), Ansari et al. (2017) and Deepa and Krishnaveni (2012) used AHP to select the most suitable locations. Criteria related to land and area characteristics are indicators in common to the three studies; in addition, based on their purposes, authors included costs (Deepa and Krishnaveni, 2012), treatment technologies (Deepa and Krishnaveni, 2012), potential water reuse (Ansari et al., 2017) and the depth of the sewer pipes in case of existing sewer networks (Hama et al., 2019). Finally, Hama et al. (2019) and Deepa and Krishnaveni (2012) combined MCDA with GIS, which is proven to be a powerful tool in land evaluation.

Since these are narrower decision-making fields, the number of variables should be lower and it should be easier to focus and manage the fundamental aspects of the problem, thus obtaining a more detailed overview with fewer uncertainties. Probably, this justifies the great success of MCDA in other wastewater issues.

5. Life cycle assessment

5.1. Definition of life cycle assessment and application to the wastewater field

LCA is a method to assess potential environmental impacts associated with all the stages of a product life cycle, starting from raw material extraction to material processing, manufacture, distribution, use, and disposal/recycling. ISO standards 14040 (International Standard Organisation, 2006, 2006a) and 14044 (International Standard Organisation, 2006, 2006b) provide general guidelines for conducting a correct LCA, which is constituted by four steps: goal and scope definition, life cycle inventory analysis (LCI), life cycle impact assessment (LCIA) and interpretation of the results. Compared to other existing methodologies to assess the environmental impacts, such as Environmental Impact Assessment (EIA), LCA does not evaluate local environmental impacts: the consideration of both direct and indirect impacts associated with the entire supply chain offers a more global perspective and allows to discover environmental impacts that were not immediately evident before the analysis. Hence, LCA is the preferred framework for making decisions based on potential environmental impacts caused by a product, process or service analyzed by a “cradle-to-grave” or a “cradle-to-cradle” approach (Corominas et al., 2020).

Compared to OMs and MCDA, the first applications of the LCA approach in the wastewater field are more recent (EMMERSON et al., 1995), since LCA was initially referred to product processes (Corominas et al., 2013). However, the paradigm shift described in the introduction has led to a new perspective on the wastewater concept: wastewater and wastewater sludge should no longer be considered a “waste”: they must now be seen as a “product” from which resources can be recovered (Pradel et al., 2016); therefore, over the past two decades, LCA approach has gained great popularity and has been widely used in several wastewater sectors (Parra-Saldivar et al., 2020), such as nutrient recycling (Lam et al., 2020), domestic wastewater treatment (Sabeen et al., 2018) and struvite precipitation (Sena and Hicks, 2018), offering evaluations and insights from an environmental point of view. The next sections will focus on the application of LCA in wastewater planning.

5.2. The role of LCA in wastewater planning

Almost all the reviewed LCA studies evaluated the opportunity to recover resources through wastewater treatment: this practice represents a strong option for alleviating the pressure on natural resources (Lahlou et al., 2022), but it generally comes at a cost (Diaz-Elsayed et al., 2020). Indeed, following the basic principles of the circular economy, sustainable development should combine resource protection with economic and environmental conveniences (Lehmann, 2018); this is not always taken for granted, as recycling processes can be very expensive and can also cause an increase of polluting emissions.

In view of that, in wastewater planning, LCA is a decision-making tool usually used to compare the existing wastewater management scenario, generally referred to the classic centralized wastewater management, with other hypothetical future scenarios at different scales of aggregation. By exploring different treatment scales, LCA allows to investigate how the WWTP sustainability varies according to the scale of implementation, in order to maximize benefits and reduce harms to the environment and human health (Cornejo et al., 2016). Nowadays, these topics are of prior importance and therein lies the great success gained by the LCA method in the study of wastewater and water strategic planning over the last years (Lundie et al., 2004).

5.2.1. General orientation of the reviewed studies

Table 4 summarizes the reviewed studies that implemented an LCA, showing the reference unit used for the study (functional unit), the processes included in the LCA analysis (system boundaries), the characteristics of the investigated recovery systems, the methods and categories considered for the impact assessment. These aspects represent the crucial points of the four LCA phases, which will be discussed in detail in the following sections. Here the discussion is limited to an overview of the reviewed studies.

5.2.1.1. LCA of source-separated wastewater systems. In accordance with the current transition from wastewater treatment to resource recovery both locally and globally, most of the reviewed studies using LCA investigated hybrid or decentralized systems implementing source separations (Table 4 shows the source separations explored by the LCA studies reviewed). These systems tend to be decentralized due to the high costs required (Besson et al., 2021). The potential benefits of source separation have been partly mentioned in the previous chapter; however, it should be emphasized that alternatives including source-separated systems are often present in LCA studies because source separations can further increase both recovery performance and environmental advantages, which are precisely two of the main goals of the LCA approach when applied to wastewater planning focused on resource recovery.

Two main source-separated strategies were tested: urine source separation and blackwater/greywater source separation (Skambraks et al., 2017). Urine separation promotes the production of nutrient-rich fertilizers as urine has been shown to account for 80% of total nitrogen and more than 50% of phosphorous present in wastewater, although urine represents a small part (around 1%) of the total wastewater volume (Ishii and Boyer, 2015). Blackwater separation allows to extract around 50% of the organic matter fraction contained in total wastewater volume and promotes both energy recovery (by means of biogas produced from sludge anaerobic digestion) and nutrient recovery by means of next treatment stages (Besson et al., 2021). Furthermore, blackwater separation involves greywater collection, which is considered in many studies as a mean to implement water reuse. The low pollution load of greywater makes it easily treatable to reach quality levels suitable for non-potable reuse (Eriksson et al., 2002), thus representing an opportunity for sustainable development in metropolitan cities (Jeong et al., 2018). This is particularly true in tourist centers showing a large floating population (Santana et al., 2019) and in urban centers with tropical (Leong et al., 2019) or cold (Kobayashi et al., 2020) climates. Furthermore, rainwater collection and treatment may be an option to reduce drinking water consumption for non-potable purposes, thus alleviating urban water scarcity, as studied by Leong et al. (2019), Zanni et al. (2019) and Arden et al. (2021).

5.2.1.2. Further applications and hybrid LCA models. In addition to the aspects mentioned above, the need to continuously improve the sustainability of the systems has led to the investigation of new strategies, such as the reuse of air conditioner condensate (Arden et al., 2021) or the development of innovative technologies at building scale, as done by Hasik et al. (2017) and Hendrickson et al. (2015).

On the other hand, LCA methods can be applied in centralization studies not involving any resource recovery strategy, or in the resolution of decision-making problems at local scale from an environmental and life cycle perspective. For instance, Skrydstrup et al. (2020) evaluated the decentralized treatment of wastewater produced in a dairy factory, while Morera et al. (2015) investigated the potential environmental impacts due to the connection of two adjacent medium-sized WWTPs, taking into account the minimum ecological flow in the receiving water body.

Finally, Hendrickson et al. (2015) and Kavvada et al. (2016) used a hybrid LCA combining process-based LCA and economic input-output (EIO) LCA (Corominas et al., 2020). By means of models referring to the US economy, EIO-LCA associates economic values of industrial sectors with the corresponding input/output environmental impacts (Tam and Le, 2019). Although EIO-LCA is more comprehensive as it considers larger system boundaries, its results are geographic and sector specific; this is probably the reason why EIO-LCA is less applied than process-based LCA. Hybrid LCA is implemented to overcome the limitations related to EIO-LCA; however, the selection of the LCA type to be used requires care and depends on the objectives of the study (Corominas et al., 2020).

Table 4 summarizes the most relevant aspects considered by the LCA studies. The two studies that used EIO-LCA were not included as some LCA steps are different than the process-based approach. The study conducted by Sun et al. (2020) was also excluded, as LCA is used more as a support tool for MCDA, and the approach taken is not as detailed as it is in proper LCA analyses.

Despite LCA is regulated by ISO standards, different choices can be made, based on the objectives. The following sections will show how the reviewed papers addressed LCA phases in wastewater planning studies.

5.3. Interpretation of LCA phases in wastewater planning

The following sections analyze how the selected papers dealt with the 4 typical phases of LCA studies. The discussion is strictly related to wastewater planning. The driving reasons to use LCA analysis in the wastewater field based on the investigated level (e.g., planning, design, optimization, retrofitting) were examined by Corominas et al. (2020).

5.3.1. Goal and scope definition

In the goal and scope definition, all the decisions and assumptions required to carry out the LCA are explained. The topics covered by the LCA approach are today of great interest to various stakeholders and decision-makers. LCA studies follow a standardized methodology and maximum transparency is required for a correct reception of the results (Corominas et al., 2013). Here we focus on the crucial aspects of this phase: definition of the objective of the study, choice of the functional unit (FU) and choice of the system boundaries.

5.3.1.1. Definition of the objective of the study. First of all, the purposes of the study must be clearly defined (the goals of the LCA studies reviewed were already displayed in Table 1), as well as the target audience to whom the work is dedicated, in order to guide the interpretation of assumptions and results (Byrne et al., 2017). Scenarios and treatments to be compared are also described in this phase. It should be emphasized that when scenarios are preliminarily created, the use of GIS software (Kavvada et al., 2016) and simulation models to predict the performance of wastewater systems is frequent, as shown by Arden et al. (2021), Arias et al. (2020), Leong et al. (2019) and Zanni et al. (2019), and extensively described for MCDA alternatives.

5.3.1.2. Choice of the functional unit. Scenarios are compared based on the adopted functional unit (FU). The FU defines the qualitative and quantitative aspects of the reference object of the study to which all the input and output data must be scaled in the inventory phase (Rebitzer et al., 2004). Corominas et al. (2020) noted that the most commonly applied FUs in wastewater LCA are volume based. Zanni et al. (2019) used 1 m^3 of treated water, following the major literature, while Arias et al. (2020) considered the wastewater volume generated in one day by

Table 4
The main aspects considered in the reviewed LCA studies.

Reference	Functional unit (FU) and system boundaries (SB)	Source separations (SS) and resources recovered (RR)	Life cycle impact assessment methods used	Impact categories analyzed
Bradford-Hartke et al. (2015)	FU: the recovery of 1 kg of plant available phosphorus; SB: CP, OP, DRR.	SS: urine; RR: fertilizer.	ReCiPe(H) midpoint (v1.08), CML	Mineral depletion, eutrophication, global warming, ozone depletion potential, human toxicity, terrestrial ecotoxicity, particulate matter formation, photochemical oxidant formation, fossil fuel depletion, salinization.
Ishii and Boyer (2015)	FU: the conveyance, storage, and nutrient management of the expected production of urine during 1 year; SB: PWTS, CP, OP.	SS: urine; RR: fertilizer.	TRACI	Ozone depletion, global warming, smog, acidification, eutrophication, carcinogenics, non-carcinogenics, respiratory effects, ecotoxicity, fossil fuel depletion.
Lam et al. (2015)	FU: the wastewater discharged annually by one person. SB: CP, OP, DRR.	SS: blackwater/greywater; RR: fertilizer, water for irrigation.	LIME-2	Global warming, acidification, eutrophication.
Morera et al. (2015)	FU: the volume of wastewater treated during 20 years; SB: CP, OP, DRR.	SS: -; RR: fertilizer, electricity.	CML 2 baseline 2000	Abiotic depletion, acidification, eutrophication, global warming potential, ozone layer depletion, human toxicity, freshwater aquatic ecotoxicity, marine aquatic ecotoxicity, terrestrial ecotoxicity, photochemical oxidation.
Cornejo et al. (2016)	FU: 1 mc of treated water; SB: CP, OP, DRR.	SS: -; RR: water for irrigation, energy, fertilizer.	Cumulative energy demand (CED), IPCC 2007 GWP 100a, Eco-indicator 95.	Embodied energy, carbon footprint, eutrophication potential.
Opher and Friedler (2016a)	FU: the supply, reclamation and reuse of water consumed during one year; SB: PWTS, CP, OP, DRR.	SS: blackwater/greywater; RR: water for irrigation and toilet flushing.	ReCiPe(H) midpoint (v1.07)	Marine ecotoxicity, freshwater eutrophication, freshwater ecotoxicity, human toxicity, marine eutrophication, fossil depletion, climate change, terrestrial acidification, particulate matter formation, metal depletion, photochemical oxidation formation, water depletion.
Hasik et al. (2017)	FU: one year of a building's water service; SB: PWTS, CP, OP, DRR.	SS: rainwater; RR: flush water.	TRACI 2.1, cumulative energy demand (CED).	Ozone depletion, global warming, smog, acidification, eutrophication, carcinogenics, non-carcinogenics, respiratory effects, ecotoxicity, fossil fuel depletion, embodied energy.
Jeong et al. (2018)	FU: 1 mc water used for outdoor irrigation and/or toilet flushing; SB: PWTS, CP, OP, DRR.	SS: blackwater/greywater; RR: water for irrigation and toilet flushing.	TRACI 2.1 (v1.02)	Ozone depletion, global warming, smog, acidification, eutrophication, carcinogenics, non-carcinogenics, respiratory effects, ecotoxicity, fossil fuel depletion.
Leong et al. (2019)	FU: the collection, storage, and distribution of 1mc of non-potable water for both toilet flushing and irrigation; SB: PWTS, CP, OP, DRR.	SS: blackwater/greywater, rainwater; RR: water for irrigation and toilet flushing.	CML 2001, TRACI 2.1	Abiotic depletion potential, acidification potential, eutrophication potential, freshwater aquatic ecotoxicity potential, global warming potential, human toxicity potential, ozone layer depletion potential, photochemical ozone creation potential, water stress index.
Santana et al. (2019)	FU: 1 year of operation of the entire water management system; SB: PWTS, CP, OP, DRR.	SS: blackwater/greywater; RR: water for irrigation and toilet flushing.	ReCiPe, AWARE.	Carbon footprint, metals depletion, marine eutrophication, water footprint.
Zanni et al. (2019)	FU: 1 mc of reclaimed water; SB: CP, OP, ELP, DRR.	SS: blackwater/greywater, rainwater; RR: water for irrigation and toilet flushing.	ReCiPe2008(H) midpoint	Climate change, ozone depletion, terrestrial acidification, freshwater eutrophication, marine eutrophication, human toxicity, photochemical oxidant formation, particulate matter formation, terrestrial ecotoxicity, freshwater ecotoxicity, marine ecotoxicity, ionizing radiation, agricultural land occupation, urban land occupation, natural land transformation, water depletion, mineral resource depletion, fossil fuel depletion.
Arias et al. (2020)	FU: 1 resident served; SB: OP, DRR.	SS: blackwater/greywater; RR: water for irrigation, electricity and heat.	ReCiPe(H) midpoint	Climate change, water consumption.
Kobayashi et al. (2020)	FU: the annual treatment of greywater generated per person; SB: PWTS, CP, OP, ELP, DRR.	SS: blackwater/greywater; RR: water for non-potable reuse.	TRACI 2.1	Global warming potential, eutrophication potential, human health-carcinogenic potential.
Skrydstrup et al. (2020)	FU: the treatment of 1,000 mc of wastewater; SB: PWTS, CP, OP, DRR.	SS: -; RR: potable water, electricity, heat, fertilizer.	Several methods modeled in EASETECH (v2)	Climate change, terrestrial acidification, terrestrial eutrophication, photochemical oxidant formation, stratospheric ozone depletion, human toxicity carcinogenic, human toxicity non-carcinogenic, ionizing radiation, freshwater eutrophication, marine eutrophication, ecotoxicity, abiotic depletion, abiotic depletion fossil, particulate matter, freshwater withdrawal.
Arden et al. (2021)	FU: 1 gallon of non-potable reuse water provided to the building; SB: CP, OP, DRR.	SS: blackwater/greywater, rainwater, air-conditioning condensate; RR: water for non-potable reuse, thermal energy.	Several methods and adapted approaches.	Global warming potential, total energy demand, fossil fuel depletion potential, water consumption, water scarcity.

(*continued on next page*)

Table 4 (*continued*)

Reference	Functional unit (FU) and system boundaries (SB)	Source separations (SS) and resources recovered (RR)	Life cycle impact assessment methods used	Impact categories analyzed
Besson et al. (2021)	FU: 1 Population equivalent (PE); SB: CP, OP, DRR.	SS: blackwater/greywater, urine; RR: water for non-potable reuse, electricity, fertilizer.	ReCiPe(H, A) endpoint, ReCiPe(H) midpoint.	All the midpoint categories of ReCiPe and endpoint indicators (ecosystem, human health, resources).
Risch et al. (2021)	FU: the collection and treatment of the domestic wastewater loading per inhabitant during a day in a rural setting; SB: CP, OP.	SS: -; RR: -.	ReCiPe 2016 (v1.03) midpoint and endpoint.	All the midpoint categories of ReCiPe and endpoint indicators (ecosystem, human health, resources).

System boundaries (SB): potable water treatment and supply (PWTS), WWTP construction phase (CP), WWTP operation phase (OP), WWTP end-of-life phase (ELP), distribution of resource recovered (DRR).

1 resident living in the served area, as shown in Table 4.

The choice of the FU depends on the objectives of the study and often includes a defined operating time to easily account for the construction burden, which is equally allocated by assuming a lifespan of the infrastructures (Corominas et al., 2020). Kobayashi et al. (2020) evaluated the annual treatment of greywater produced per person, as their study focused on greywater reuse systems. Ishii and Boyer (2015) specifically investigated separate urine management and considered the annual urine production in the studied system to highlight the role of equipment lifespan (several years) and storage times (a period of the year) relating to the FU. Hasik et al. (2017) and Santana et al. (2019) considered one year of service of the whole water management systems explored, in order to comprehensively compare the analyzed systems and evaluate changes due to water reuse, respectively.

As emphasized by Corominas et al. (2020), the adoption of an appropriate FU is essential for a fair scenario comparison. FU can affect final results, especially when comparing wastewater systems with different influent pollution loads and effluent targets (e.g., combined wastewater versus source-separated systems) (Byrne et al., 2017) and the adoption of a solely volume-based FU may ignore important aspects relating to system performance. It is therefore recommended to define the FU in an exhaustive way by adopting a FU that reflects the effluent quality objectives, as done by Arden et al. (2021), Jeong et al. (2018) and Leong et al. (2019), and the influent loads of the wastewater to be treated by means of parameters such as COD, N or P. A FU reflecting the influent loads can be expressed by means of the population equivalent (PE), which represents the per capita loadings of BOD, according to the European directive 91/271 (Besson et al., 2021); nevertheless, Risch et al. (2021) pointed out that PE is more suitable for a generic European centralized context and proposed to use a FU based on the study of the site-specific pollution loads. Anyway, the characteristics of the wastewater, the quality targets of the effluent and the design parameters of the WWTPs should be sufficiently described within the study both for greater clarity towards stakeholders and to allow others to replicate the study (Corominas et al., 2020).

5.3.1.3. Choice of the system boundaries. Processes selected to conduct an LCA, based on the objectives of the study, constitute the system boundaries, and must be clearly defined (Table 4). Ideally, all the input and output flows of matter and energy generated by the investigated systems should be quantified and considered. In wastewater planning, the processes to be considered should concern all the input/output flows involved in the construction, operation and end-of-life phases of a wastewater collection and treatment system (e.g., transports, materials, energy consumptions, chemicals, emissions to air, water and soil, waste disposal, distribution of resource recovered, etc.). Moreover, the studies often adopt a temporal dimension in the FU and assume the lifespan of the equipment as mentioned; this allows to consider the environmental impacts due to the scheduled maintenance interventions that fall within the period of operation considered.

The study conditions enable the authors to exclude some parts from the life cycle analysis and to consider the relevant factors for the intended objectives (Tillman et al., 1994), with obvious time savings. First, when comparing different alternatives, the parts that are assumed to be equal in each scenario can be excluded from LCA, as they produce no difference in results (Opher and Friedler, 2016b). The exclusion of common parts may also concern a specific aspect of the life cycle; for instance, Santana et al. (2019) excluded only the construction stage for some infrastructures that were assumed to be the same in each scenario as they did not operate at full capacity, and flow variations did not imply the expansion or modification of these systems, while changes in wastewater characteristics still influence the operation stage. Anyway, in addition to time savings, the exclusion of the subsystems that remain unchanged allows to keep data uncertainty to a minimum since less parameters are introduced in the analysis (Opher and Friedler, 2016b).

Aspects that do not fall within the study objectives are also ignored. Ishii and Boyer (2015) focused on urine nutrient management and disregarded wastewater treatment requirements not directly affecting nutrients in urine. Hendrickson et al. (2015) ignored the energy required to pump the recovered water back, as it was out of their purposes. Lam et al. (2015), Opher and Friedler (2016a) and Kobayashi et al. (2020) evinced that the expansion of the system boundaries downstream and upstream is a good strategy to solve multi-functionality of the systems and to ensure a fair comparison of the scenarios. The main resources recovered in WWTPs are water, energy and fertilizers, and are often referred as “avoided products” or “avoided impacts”, as they are able to supply equivalent products (Cornejo et al., 2016) (Fig. 5). For this reason, in addition to production processes, the distribution systems of the resources recovered (e.g., pipes and pumping stations to transport reclaimed water to consumers, on-site transport of synthetic fertilizers) and the possible implications that their use may entail (e.g., emissions to soil due to land application of synthetic fertilizers) should also be included in the system boundaries (Corominas et al., 2020), in order to assess the overall effects of the recovery processes and to make the scenarios fully comparable.

The exclusion of the parts of life cycle that are outside the scope of the study or in common among the scenarios are intuitive solutions that do not require justifications. Conversely, further cuts to the system are allowed in comparative studies. These assumptions are based on literature data to be carefully evaluated and should not subvert the final response. Kavvada et al. (2016), Jeong et al. (2018) and Santana et al. (2019) excluded the end-of life phase because previous research had shown its low impact compared to the construction and operation phases. For the same reason, Hasik et al. (2017) and Leong et al. (2019) excluded both end-of-life and on-site construction activities, while Arias et al. (2020) considered both decommissioning and the entire construction phase to be negligible in comparison to the system management phase (Lundin et al., 2000) and applied a gate-to-gate approach comparing scenarios only on the basis of the operational stage.

Sewer networks are sometimes excluded, as in the case of Kavvada et al. (2016), who assumed that the sewer networks already existed. Conversely, Risch et al. (2015) showed that the construction of sewer infrastructure can generate environmental impacts larger than WWTP construction and operation. Therefore, according to them, construction, together with energy consumptions in pumping stations and emissions due to sewers leaks, should be especially included in the environmental assessments investigating the best centralization level of wastewater systems because the length and number of the pipes may be very different (Roefs et al., 2017).

Finally, some parts of the life cycle can be excluded because of lack of data. As mentioned, a transparent and limited approach in the study helps to better communicate the results of the work done.

5.3.2. Life cycle inventory

The life cycle inventory (LCI) is the most time-consuming LCA step (Arias et al., 2020), in which all the input and output data characterizing the processes defined in the system boundaries are collected and normalized according to the adopted FU (Corominas et al., 2020). Corominas et al. (2020) provided a brief overview on the procedure to follow for data analysis in the inventory phase.

Two types of processes are usually distinguished in the LCA inventory: foreground and background. Data for foreground processes are normally retrieved from direct measurements and design documents, although the use of literature data for foreground processes is an acceptable option in wastewater planning, where hypothetical scenarios are compared (Corominas et al., 2020). Data for Background processes (e.g., production processes of chemicals and materials, electricity generation systems) are generally provided by LCI databases, such as Ecoinvent (Wernet et al., 2016). In these cases, the use of robust databases is encouraged, as well as the selection of production processes that reflect the geographical and process conditions of interest as much as possible (Corominas et al., 2020).

In the preparation of life cycle inventory, researchers and practitioners must pay attention to the multi-functionality of processes, which is very frequent in LCA studies. Pelletier et al. (2015) observed that multi-functionality issues may be critical for the LCA results if not adequately addressed, and are generally solved using three main approaches chosen considering the scope and specifics of the study, namely the system expansion and the physical and economic allocation. However, allocation should be avoided whenever possible by dividing the considered unit process into sub-processes or system expansions.

5.3.3. Life cycle impact assessment

In the life cycle impact assessment (LCIA) phase, the potential environmental impacts generated by the elementary flows collected in the LCI phase are quantified by complex environmental and technological models (Kayo et al., 2013). For a better understanding of the results, inventory data are converted into a defined number of impact categories that summarize the effects of the studied system on the environmental and human health (Corominas et al., 2020).

LCIA consists of three main steps: *selection*, where the most relevant impact categories are selected; *classification*, where elementary flows are assigned to the affected impact categories, and *characterization*, where inventory data are converted to impacts. It also includes three accessory steps: *normalization* (potential impacts are normalized to a reference value), *grouping* (impacts categories are sorted or ranked) and *weighting* (attribution of relative weights and aggregation of impact categories) (Nieuwlaar, 2004). The accessory steps are optional and rarely applied, as in the case of Jeong et al. (2018).

Several impact assessment methods are available, with a wide range of impact categories to represent the effects produced by a system. However, in order to simplify the decision-making process, a limited number of indicators must be selected to be analyzed in depth (Steinmann et al., 2016).

5.3.3.1. Selection of impact categories. For a correct choice, impact categories are generally parted in midpoint and endpoint level indicators. Midpoint indicators examine the impacts occurring along the cause-effect chain, such as global warming potential, acidification potential, ozone layer depletion potential. Endpoint indicators refer to the damage at the end of this chain, usually in three areas of protection: human health, ecosystem and resources (Bare et al., 2000). It should be noted that wastewater management traditionally focuses on local protection of human and environmental ecosystems (e.g., eutrophication, land use), while LCA is more oriented towards global impacts (e.g., global warming) distributed over longer spatial and temporal scales (Corominas et al., 2020). The selected categories should represent a mix of global and local impacts.

For such reasons, the selection of impact categories plays an important role in communicating the results obtained; it depends on the objectives of the study and requires careful evaluations. As shown in Table 4, Santana et al. (2019) assessed marine EP of wastewater treated by the systems under study and discharged into the sea. Kobayashi et al. (2020) considered GWP, EP and human health carcinogenic potential (HHCP). Not surprisingly, climate change, eutrophication and ecotoxicity were recognized by Corominas et al. (2020) as recommended key indicators in wastewater LCA; in particular, EP and GWP are the most commonly assessed impact categories in wastewater LCA studies (Gallego-Schmid and Tarpani, 2019): EP is the most relevant indicator in wastewater studies, while GWP represents the indicator with the highest political and social influence today (Kobayashi et al., 2020). In this regard, Opher and Friedler (2016a) evaluated the magnitude of the impact categories proposed by the LCIA method used, according to the global normalization factors available, and found that climate change is two orders of magnitude lower than the three topmost impactful categories, namely freshwater eutrophication, freshwater ecotoxicity and marine ecotoxicity. Nevertheless, Opher and Friedler (2016a) evinced that the global normalization factors available are not entirely suitable to local or regional conditions; as a consequence, they analyzed all the indicators up to two orders of magnitude lower than the most impactful categories. Therefore, the normalization step is rarely applied in the LCIA phase, as mentioned above.

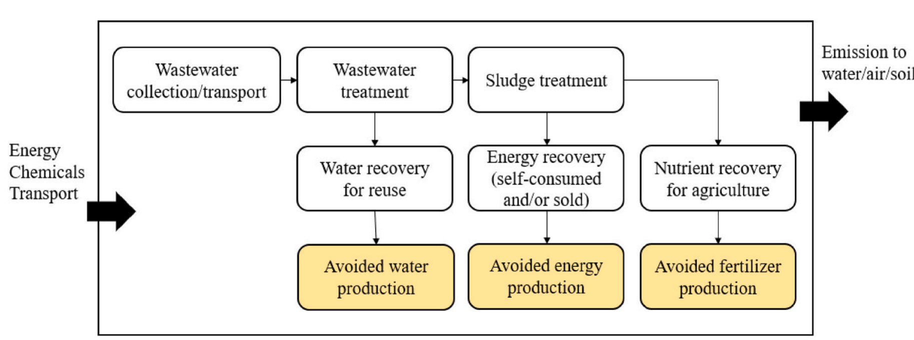

Fig. 5. Example of system boundaries for WWTP, including avoided products (inspired by Corominas et al., 2020).

The environmental benefits deriving from the possible recovery of resources must be considered at this stage. The recovered resources can be included directly as offsets (e.g., avoided production of fertilizers in agriculture through nutrient recovery, avoided production of potable water for irrigation through water reuse) and the market in which they would be recovered should be considered (Corominas et al., 2020). Furthermore, since the importance of water reuse is increasing, it would be advisable to use LCIA methods considering an indicator explicitly referring to water depletion, especially in studies that implement water recycling, as done by Opher and Friedler (2016a), Zanni et al. (2019) and Arias et al. (2020). In this regard, despite the interest of water recovery systems as shown in Table 4, LCIA methods including impact categories about water quantity are still few (Corominas et al., 2020). For instance, Jeong et al. (2018) studied greywater reclamation systems and evaluated the freshwater withdrawal reduction by estimating the potential water savings, since the method they used does not assess the impact of freshwater depletion.

5.3.3.2. Selection of the Life Cycle Impact Assessment (LCIA) method. The choice of the most suitable LCIA method requires careful evaluations. Many LCIA methods are available in the existing LCA software, such as Simapro, Gabi, Open LCA, and most of them consider both the midpoint and endpoint levels. As mentioned, LCIA may include different impact categories, in turn including embedded features that are less or more appropriate based on the purposes of the study (Corominas et al., 2020). As shown in Table 4, Morera et al. (2015) and Leong et al. (2019) used the CML midpoint method for its wide literature application in wastewater LCA studies (Loubet et al., 2014). Ishii and Boyer (2015) and Hasik et al. (2017) conducted LCA studies on the management of wastewater produced in U.S. locations and applied the TRACI midpoint method developed by the U.S. Environmental Protection Agency (Bare et al., 2003). Bradford-Hartke et al. (2015), after assuming that all recovered phosphorous products were applied to land, used the Recipe midpoint method as it includes the terrestrial ecotoxicity impact category and takes into account all key aspects concerning the human toxicity. Besson et al. (2021) and Risch et al. (2021) used Recipe method at both the midpoint and endpoint levels. Corominas et al. (2020) highlighted that the endpoint indicators are at the end of the cause-effect chain and result from normalization and aggregation of impacts from midpoint categories for an easier understanding of decision-makers, thus increasing the level of uncertainty. For similar reasons, midpoint indicators are generally preferred. However, Corominas et al. (2020) identified TRACI and Recipe midpoint and endpoint levels as the most appropriate LCIA methods in wastewater studies.

The use of different LCIA methods to assess specific impact categories is possible. For instance, Bradford-Hartke et al. (2015) analyzed wastewater systems aimed at phosphorus recovery, and used the CML method to evaluate the impact category of mineral resource depletion because CML was the only model that included phosphorous in this category. Hasik et al. (2017) used the cumulative energy demand (CED) method to focus on the embodied energy. Leong et al. (2019) used the water stress index to measure water scarcity, while Santana et al. (2019), Skrydstrup et al. (2020) and Arden et al. (2021) used AWARE (Boulay et al., 2018), which is the recommended method for assessing the water footprint metric (Corominas et al., 2020): as said, most of the available LCIA methods do not include impact categories related to water depletion, despite its growing importance.

5.3.4. Interpretation

The last phase in an LCA study is the interpretation of the results and consists in a systematic control of the choices made in the previous phases and a synthesis of the results obtained. Three main steps are provided in the interpretation phase (Lluís Corominas et al., 2020).

In the first step, the significant issues are identified, based on the results obtained in LCI and LCIA. In wastewater planning, this section generally reports the contribution analysis of the life cycle processes considered (construction, operation, maintenance, end-of-life, recovery and distribution of the resource recovered) on the analyzed impact categories and highlights the most relevant factors.

The second step represents an overall evaluation of the performed study, considering completeness, sensitivity and consistency checks. The completeness check has the purpose of verifying that the information and data necessary for the interpretation are available and complete; any missing information must be declared and justified and, in cases of particularly important gaps that cannot be filled, could lead to a modification of the goal and scope (Corominas et al., 2020). The sensitivity analysis is a systematic procedure to evaluate the reliability of the results. A sensitivity check should be performed on parameters considered as uncertain in the performed study (Besson et al., 2021) or as such in the literature, in order to quantify the influence of the assumptions made. Sensitivity analysis can be performed on transport distance (Bradford-Hartke et al., 2015), energy intensities (Leong et al., 2019) or several input parameters of interest (Ishii and Boyer, 2015). Regardless of the specificity of each LCA study, Kobayashi et al. (2020) showed a general approach conducting a sensitivity analysis by considering a different electricity mix and different lifespans of water transport systems and greywater treatment systems. Indeed, the electricity consumption is often one of the main impact factors in water systems and electricity generation systems are continuously developing (Jeong et al., 2018), while the difficulty in estimating the lifetime of wastewater infrastructure may affect the results (Risch et al., 2015). Sensitivity analysis can also concern the methodologies adopted; for instance, Leong et al. (2019) also applied the LCIA method TRACI to validate the results obtained by using the CML method (Table 4). In addition to sensitivity check, an uncertainty analysis should also be performed, in order to assess the degree of uncertainty of input data and the robustness of the final conclusions. Uncertainty analysis was generally carried out in the reviewed studies and can be conducted by both qualitative and quantitative methods such as the Monte Carlo simulation approach (Laurent et al., 2020). The consistency check verifies that assumptions, while methods and data are applied consistently with goals and scope.

Finally, in the third phase the conclusions, limitations of the study and recommendations for future research are explained.

5.4. Future of the life cycle thinking

As mentioned, the impact assessment from a life cycle perspective has made it possible to avoid problem-shifting in the product system (for example, from one life cycle stage to another), and LCA became in recent years one of the most used DSSs to translate the science of sustainability to aid decision-making. However, sustainability intends to encompass the balance of three different dimensions, namely environmental, economic and social aspects (Visentin et al., 2020), while LCA only covers environmental issues, thus favoring the development of life cycle thinking tools (Finnveden et al., 2009).

5.4.1. Life cycle costing

Economic factors are often decisive and may guide the decision-making process. Some of the reviewed studies carried out economic evaluations by means of preliminary investigations including costs and revenue (Ishii and Boyer, 2015). On the other hand, connected to life cycle thinking, life cycle costing (LCC) is a method to quantify the economic costs of the entire life cycle of a product or service. Three types of LCC are classified by The Society of Environmental Toxicologic and Chemistry (SETAC): conventional LCC, environmental LCC and societal LCC. Conventional LCC only considers internal costs incurred by one of the actors involved in the product chain (e.g., user or manufacturer). In addition to internal costs, environmental LCC also includes some external costs and considers costs incurred by all the actors involved. Environmental LCC represents an extension of the conventional LCC; it is closely related to LCA and is often conducted in parallel with LCA, using the same system boundaries and LCI to internalize externalities. Societal LCC is of latest development and considers social issues, thus representing a link with cost-benefit analysis. However, there are studies in the literature that have proposed models to combine societal LCC with conventional and environmental LCC in the same case study; a detailed discussion concerning LCC techniques and their integration with LCA was provided by Ilyas et al. (2021).

Despite the growing popularity of the life cycle approach, environmental LCC does not have a well-defined framework, while societal LCC is still in a primordial stage of development; in any case, the goals and scope, system boundaries, application of discount rate and functionality are identified as the basis of the LCC analysis (Ilyas et al., 2021). When focusing on wastewater planning, LCC analysis should take into account the expected benefits deriving from wastewater systems aimed at resource recovery, as in the LCC analysis conducted by Yerri and Piratla (2019) that considered the direct benefits of greywater reuse in the form of reduced utility bills and reduced freshwater withdrawal from groundwater.

5.4.2. Social life cycle assessment (S-LCA)

Social dynamics are often neglected in decision-making processes, although it has been demonstrated that social acceptance facilitates the success of projects (Ross et al., 2014). In this regard, social analysis gained interest in recent years, and social life cycle assessment (S-LCA) represents an emerging tool to assess the potential social impacts generated by a product or service along its life cycle. Like LCA, S-LCA includes four main steps: goal and scope definition, inventory analysis (data collection by means of indicators through databases, literature review, questionnaires), impact assessment (the social data retrieved in the previous stage is translated into potential social impacts). In most cases, it is carried out by comparing the social data with performance reference points and interpretating the results (Santos et al., 2020). In the only reviewed study that applied S-LCA to compare urban water reuse alternatives, Opher et al. (2018) considered the same scenarios, functional unit and system boundaries already used in a previous LCA study (Opher and Friedler, 2016a), and used the AHP method to weight the social criteria based on interviews with experts, and to evaluate impact intensities for both qualitative and quantitative social indicators, as mentioned in section 4.2.

5.4.3. Life cycle sustainability assessment (LCSA)

Life cycle sustainability assessment (LCSA) represents a comprehensive approach to sustainability from a life cycle perspective, as it results in the integration of LCA, LCC and S-LCA in a single formulation (Visentin et al., 2020). Nevertheless, the three life cycle methodologies are performed separately, thus requiring notable efforts in terms of time and skills. In this regard, Opher et al. (2019) conducted a LCSA analysis using proven considerations in previously published studies already discussed in this review, namely (Opher et al., 2018) and (Opher and Friedler, 2016a), and evinced the difficulties in showing the LCSA results: The United Nations Environment Programme (UNEP) recommends to avoid the use of aggregation forms between the results of LCA, LCC and S-LCA analysis, in order to reveal any existing trade-offs; on the other hand, data aggregation could be useful for providing holistic sustainability information to stakeholder.

6. Conclusions

This paper presented a review of the methodologies applied to assess the best centralization level in wastewater collection and treatment planning. The aim of this paper was to provide guidance for planners and decision-makers in choosing the most suitable approach according to their needs, highlighting strengths and weaknesses of the different reviewed methods and the main purposes that should be considered for a complete analysis. The paper also highlighted the main trends in current wastewater planning, consisting in the search for hybrid systems aimed at resource recovery and various forms of local water reuse.

To the best of our knowledge, three main methodologies have been applied to evaluate the best centralization degree, and the following conclusions can be drawn:

- OMs can find the optimal layout of the wastewater infrastructure, providing size and location for the sewer networks, WWTPs and pumping stations. However, difficulties seem to appear in some cases of actual interest, such as hybrid systems, resource recovery and environmental sustainability: this is probably due to the tendency to avoid too complex and ineffective models.
- MCDA could incorporate all the economic, environmental, social and sustainability-related aspects concerning a wastewater planning process but, perhaps, the combined management of many criteria discourages the use of this methodology for planning purposes.
- LCA provides information on the sustainability of the systems by assessing the potential environmental impacts generated by wastewater treatment from a life cycle perspective and has been the most used methodology in wastewater planning in recent years, although its analysis is limited to environmental issues.
- LCSA can be a useful approach for comprehensive analysis of the investigated systems considering the entire life cycle of the involved processes, but it needs to be further developed and standardized. Future research efforts should focus on developing methodologies using a holistic view of the problem and representing a systematic framework accessible and suitable for as many purposes as possible.

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

No data was used for the research described in the article.

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