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REVIEW

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ENVIRONMENT RESEARCH

Wastewater management decision-making: A literature review and synthesis

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Abstract

Wastewater management decision-making is complicated because of: (1) a complex regulatory structure, (2) the wide variety of conflicting expectations by stakeholders external and internal to the responsible utility, and (2) constrains including regulatory requirements, available technologies and practices, and customer willingness to pay. This review synthesizes the results from over 200 papers published since 2000 and presents a decision-making structure and process which is (1) science and fact-based, (2) reflects sustainability, (3) clear and transparent, (4) inclusive, (5) produces an objective-oriented decision, (6) scalable, (7) repeatable, and (8) efficient. Tools supporting the decision-making process are reviewed, including Multi-Criteria Decision Analysis (MCDA), Data Envelopment Analysis (DEA), Analytic Hierarchy Process (AHP), process modeling, economic assessments, Life Cycle Assessment (LCA), and Social Life Cycle Assessment (SLCA). Ultimately it was determined that engagement of decision-makers and relevant stakeholders to assess their values and preferences, coupled with supporting data and analyses, is necessary to reach a decision that, critically, has the support needed for it to be implemented. The results demonstrate that an understanding of the components of the decision process, coupled with an orderly process, enables good wastewater management decision-making.

Practitioner Points

- A decision-making structure and process leading to the selection of implementable solutions is presented.
- The process possesses the following attributes: (1) science and fact-based, (2) reflect sustainability, (3) clear and transparent, (4) inclusive, (5) produce an objective-oriented decision, (6) scalable, (7) repeatable, and (8) efficient
- An extensive summary and analysis of tools supporting the decision process are provided, including Multi-Criteria Decision Analysis (MCDA), Data

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Envelopment Analysis (DEA), Analytic Hierarchy Process (AHP), process modeling, economic assessments, Life Cycle Assessment (LCA), and Social Life Cycle Assessment (SLCA).
- The critical role of internal and external stakeholders and differentiating their involvement relative to decision-makers is emphasized.

KEYWORDS
decision-making, LCA, management, MCDA, SLCA, sustainable, wastewater

INTRODUCTION

Wastewater system decision-making is complicated because these systems must function within a complex regulatory structure, coupled with a wide variety of conflicting expectations by stakeholders both external and internal to the responsible utility (USEPA, 2012, 2015). Management options are constrained by a number of factors, including regulatory requirements, available technologies and practices, customer willingness to pay, and public acceptance (Harris-Lovett et al., 2019; Kiker et al., 2005; Lienert et al., 2011). To the extent possible, decisions should be based on available data and sound science but also reflect the values and preferences of a wide variety of stakeholders (Erb-Institute, 2021).

This review was completed as a component of a study evaluating and developing a municipal wastewater utility system decision-making process based on sustainability principles. As presented in the Results section below, we found that the existing literature primarily discusses the technical tools used during the wastewater management decision-making process and has not analyzed their application in the more complex decision-making environment described above. In contrast, we were seeking a comprehensive decision-making process applicable in actual applications based on the sustainability triple bottom line of environmental, economic, and social considerations (Bradley & Daigger, 2004; Daigger & Crawford, 2004; Erb-Institute, 2021). This method should also require the direct involvement of relevant parties, such as decision-makers and stakeholders, and thereby result in the selection of a solution implementable by the decision-makers and acceptable to the relevant stakeholders. Given these objectives, our review considered environmental, economic, and social assessment methodologies to more broadly address the overall sustainability of the wastewater management options identified and evaluated. This review also investigated tools to actively involve decision-makers and stakeholders.

The results of the review were synthesized into a decision-making structure that reflects the key components of effective decision-making and describes a process by which an implementable decision can be achieved. We define an implementable decision as one that meets established requirements, is consistent with constraints, and is consistent with the values and preferences of relevant stakeholders so that the implementation of the selected solution is supported. We established the following criteria for the decision-making process synthesized: (1) science and fact-based, (2) reflect sustainability considerations (triple bottom line of environment, economy, and society), (3) clear and transparent, (4) inclusive, (5) produce an objective-oriented decision, (6) scalable, (7) repeatable, and (8) efficient. The review presented here also summarizes available tools to conduct the necessary supporting analyses. The decision-making structure is built on the triple bottom line of sustainability (environment, economics, and society). While comprehensive to address broad wastewater management questions, it is also scalable to address more focused decisions by adjusting the range and intensity of stakeholder engagement and the corresponding level of supporting analysis.

METHODS

The reviewed papers were selected through a keyword search of Web of Science publications authored between 2000 and 2020. The papers were divided into five research categories: technical, environmental, economic, social, and decision-making, each aligned with the objectives of the search. The keywords related to the technical assessment included “compliance, performance, risk, and operation”. For the environmental assessment, the terms “environmental, greenhouse gasses, human health, ecotoxicity, and LCA” were used. The economic assessment used keywords such as “cost, benefit, LCCA, economic, construction, financial, and feasibility”. For the social assessment, searches were conducted using the keywords “community, stewardship, social, customer, and stakeholder”. Concerning the decision-making category, the search was performed using “decision-making and decision support” as keywords. A total of 789 papers were

identified. Out of these, selections were narrowed down to those specifically relevant to municipal wastewater management, excluding papers without connection to the research topic. For instance, papers dealing with industrial wastewater treatment-related decisions were removed, since this study focused only on the retrofitting and new installment decisions of municipal wastewater management facilities. Ultimately, 201 papers were selected for review.

An affinity analysis was conducted to classify the reviewed papers into four categories: technological, environmental, economic, and social assessment. These categories addressed the topics included in previous reviews, along with the components of sustainability. Papers were placed into multiple categories, such as environmental and economic categories, when appropriate. Decision-making tools were described by dividing them into multi-criteria decision analysis (MCDA), Analytical Hierarchy Process (AHP), composite indicators, Environmental Decision Support System (EDSS), and fuzzy logic.

RESULTS

The results of the literature review are presented in the following sections.

Multi-criteria decision analysis (MCDA)

The MCDA approach represents a broad class of decision support system (DSS) methodologies used to support rational decision-making that can satisfy multiple objectives. We found five categories, consisting of general MCDA, Analytical Hierarchy Process/Analytic Network Process (AHP/ANP), composite indicators, Environmental Decision Support System (EDSS), and Fuzzy MCDA. Table S1 in the Supporting Information provides a summary of the application of these methods.

General MCDA

The general MCDA approach (Eisenführ et al., 2010; Greco et al., 2016; Thakkar, 2021) has been used to prioritize sites, select environmental technology, perform environmental impact assessment, and build natural resources management (Kiker et al., 2005) and has played a significant role in wastewater management decision-making. General MCDA provides the ability to pursue multiple objectives and encourages the participation of various stakeholders, facilitating the evaluation of various alternatives by setting multiple criteria, often within economic, environmental, and social categories. The final ranking is provided by incorporating the values of decision-makers and stakeholders. It is a suitable wastewater management decision-making method as it can consider multiple criteria and the preferences of decision-makers and stakeholders.

While a diverse range of decision-makers, stakeholders, and experts often participate in the decision-making process, the methods described in the literature often rely on assessments by experts, with the decision-makers and stakeholders not clearly identified (Table S1 in Supporting Information). Consequently, these roles are often conflated in the literature, and most studies present rankings of alternatives that reflect the opinions of stakeholders or experts rather than decision-makers (Arroyo & Molinos-Senante, 2018; Chrispim et al., 2020; De Gisi et al., 2014; Gherghel et al., 2020; Lienert et al., 2011; Lizot et al., 2020; Strapasson & dos Santos, 2020). Kalbar et al. (2012, 2015, 2016) ranked alternatives using weights established by the researcher without the participation of decision-makers and stakeholders. In contrast, Lienert et al. (2013) investigated stakeholder analysis to determine the role that the power of stakeholders had on the decision and the impact the outcome had on them. They also used social network analysis to evaluate the role of social interactions and networks among stakeholders in decision-making. Mirabi et al. (2014) pointed out that the ranking of alternatives is sensitive to the risk attributes of decision-makers. The roles of decision-makers and stakeholders in the decision-making process are critical for the support and long-term success of the decision and should be distinctly identified with their preferences and risk attitudes gathered and documented as part of the decision-making process.

Environmental, economic, and social criteria (the sustainability triple bottom line) were generally used in the general MCDA analyses evaluated. Technical criteria related to wastewater management system operation and maintenance were also often included. Environmental criteria, mainly included pollutant removal efficiency, Global Warming Potential (GWP), and Eutrophication Potential (EP). Capital and Operation and Maintenance (O&M) costs were commonly used as economic criteria, and in some cases, Life Cycle Cost (LCC), which includes all costs and revenues, were also used (Arroyo & Molinos-Senante, 2018; Gherghel et al., 2020; Kalbar et al., 2012, 2015, 2016; Strapasson & dos Santos, 2020). Qualitative criteria, such as public acceptance, were mainly used as social criteria (Arroyo & Molinos-Senante, 2018; Chrispim et al., 2020; Kalbar et al., 2016;

Lizot et al., 2020). Arroyo and Molinos-Senante (2018) also adopted odor, noise, visual impact, public acceptance, and complexity of operation as social criteria. Lienert et al. (2011) utilized media coverage and acceptance of authorities as social criteria to achieve the objective of "good public perception". Using the opinions of diverse stakeholders to determine the incorporated social criteria tended to increase the overall acceptance of the implementation of the final outcome. Cornejo et al., 2019 provide a comprehensive list of metrics to assess the sustainability of water resource recovery facilities.

Criteria weighting reflects the preferences of decision-makers and stakeholders., and Diverse methodologies can be applied to determine criteria weights. The most widely identified method was paired comparison, such as with the AHP and Paired Comparison Technique (PCT) (De Gisi et al., 2014; Gherghel et al., 2020; Lizot et al., 2020). AHP is commonly used because the consistency of paired comparison results can be evaluated. In contrast, Lienert et al. (2011) and Schuwirth et al. (2012) developed a reverse swing method and used it to determine the weight of stakeholder criteria. They found the reverse swing method easy to apply as it determines weights based on the differences in the values of various stakeholders when changing from the best state to the worst state.

Various general MCDA ranking tools are used, such as Simple Additive Weighting (SAW), Technique for Order of Preference Similar to Ideal Solution (TOPSIS), and ELimination Et Choix Traduisant la REalit'e (ELELTRE) (Lizot et al., 2020). SAW and TOPSIS were identified most often. SAW ranks alternatives by calculating the total weighted score of each alternative, while TOPSIS compares the geometric distance of each alternative from an ideal solution and an anti-ideal solution. Other methodologies such as Choosing-by-Advantages (CBA) and ValueCharts were also utilized. Kalbar et al. (2015) compared five ranking tools: SAW, TOPSIS, Compromise Programming (COMPRO), EVAluation of MIXed Data (EVAMIX), and ELECTRE-1 and concluded that the ranking tool selected was less important than framing the decision issues and structuring the weighting step. They did find that TOPSIS was the most applicable tool for wastewater management alternatives because it considers the ideal and anti-ideal states simultaneously and provides clear and distinct scores for each alternative.

AHP and ANP

AHP and ANP are functionally also MCDA tools. AHP, a theory of measurement developed by T.L. Saaty in the 1970s, creates the decision process as a hierarchic structure with focus-criteria-sub-criteria-alternatives with decision-makers and stakeholders implementing pairwise comparisons for criteria and alternatives according to Saaty's scale. The process reveals the relative importance of each criterion and alternative, and the outcome of the analysis is used for multi-criteria decision-making. AHP allows the facilitators to check the consistency of the pairwise comparison results (Saaty, 1987), but the decision is often subjective as AHP inherently relies on the opinions of decision-makers and stakeholders. AHP also assumes independence among alternatives and criteria within the hierarchy, while this assumption must be carefully addressed to ensure independent alternatives and orthogonal evaluation criteria. ANP overcomes this limitation by considering the interdependencies of alternatives and criteria (Molinos-Senante, Gomez, et al., 2015).

Both AHP and ANP have been used to select the best wastewater treatment technologies. Bottero et al. (2011) applied AHP and ANP to determine the most sustainable treatment technology for small cheese factory wastewater and concluded that ANP gave better results than AHP because the former provided a more advanced analysis. Molinos-Senante, Gomez, et al. (2015) evaluated seven wastewater treatment technologies for small communities using ANP and determined that constructed wetland and pond systems were the most feasible. Both groups of researchers inferred that ANP is a suitable method for complex wastewater management decision-making due to a better explanation of the interdependence between criteria and alternatives. AHP/ANP facilitates reasonable wastewater management decision-making by trading off multiple objectives, a crucial stage in which the relevant parties make subjective judgments on each criterion and alternative. Some studies reported that ANP shows more sophisticated results due to consideration of the interdependence between decision components. Since these methodologies are inherently influenced by subjective judgments derived from decision-makers and stakeholder values, these individuals should be clearly identified and diverse participants included in the decision process.

Composite indicators

The composite indicator methodology converts individual indicators (criteria in MCDA) into a single indicator to evaluate performance and determine the ranking for decision-making. OECD (2008) presented the following steps to construct the composite indicator: (1) theoretical framework, (2) data selection, (3) imputation of missing data, (4) multivariate analysis, (5) normalization,

(6) weighting and aggregation, (7) uncertainty and sensitivity. This procedure is intrinsically similar to MCDA in the way that ranking is determined by normalizing and weighting multiple criteria.

Sun et al. (2020) used four indicators (cost, carbon emission intensity, eutrophication potential, and resilience) to compare four wastewater treatment alternatives (activated sludge, membrane bioreactor, decentralized system, and hybrid system). Thirty-two stakeholders were interviewed to determine weights using AHP to compile these 4 individual indicators into a single composite indicator. Molinos-Senante et al. (2014) combined 17 individual indicators in environmental, economic, and social categories to construct a single composite indicator through AHP to evaluate wastewater treatment technologies. The paired comparison was conducted with 45 experts, and the individual opinions were averaged as the geometric mean. Sabia et al. (2016) prioritized 44 WWTPs using a single composite indicator composed of eight individual environmental/land/socio-economic indicators using factor analysis and paired comparison. Cossio et al. (2020) used 21 technical, environmental, social, economic, and institutional indicators to evaluate the sustainability of existing WWTPs. In their study, a local assessor and a researcher evaluated alternatives according to the scoring scale. The final ranking was then determined by combining the alternative scores and the indicator weights. The composite indicator approach primarily utilized AHP/PCT to determine the weights to construct the single indicator.

EDSS

The knowledge-based Environmental Decision Support System (EDSS) decision-making methodology utilizes a database compiled from published documents in the literature and the experience of subject matter experts in relevant fields (Dias & Ferreira, 2009; Sorour et al., 2002). EDSS is generally divided into three steps: (1) problem analysis, (2) collecting data and knowledge acquisition, and (3) knowledge implementation. The decision problem is identified, followed by structuring Knowledge Bases (KBs): Specification KB (S-KB) for regional characteristics through a local community survey, Compatibility KB (C-KB) for wastewater treatment alternatives from literature and experts' opinions, and Environmental and Legal KB (E-KB) for the receiving environment based on aquatic data and regulation information (Garrido-Baserba et al., 2016; Garrido-Baserba, Reif, Hernandez, & Poch, 2012; Garrido-Baserba, Reif, Rodriguez-Roda, & Poch, 2012). These KBs are then anthologized into an EDSS which is used for decision-making (Comas et al., 2003). EDSS is primarily used to combine potential treatment technologies and configure the Process Flow Diagrams (PFDs) to be evaluated. These knowledge-based systems can be advantageous during the generation of alternatives but have limitations in most decision-making steps, such as selection of relevant criteria, weighting of decision-makers and stakeholders' preferences, and diversity of ranking tools. Castillo, Cheali, et al. (2016) developed a decision-making methodology addressing these limitations. After generating alternatives using a KB system, the alternatives are optimized using a mathematical model, and ranking is determined using a general MCDA. They applied their framework to two retrofitting and three new installations WWTP case studies to validate the developed methodology. The most appropriate technology was selected using 12 criteria in environmental, operational, and economic categories, and the final ranking was determined using the SAW tool.

Notable shortcomings of studies using EDSS include that decision-makers and stakeholders were not clearly indicated, and case studies in actual WWTPs were limited. The system seems to be advantageous when applied as a preliminary step in decision-making, as multiple alternatives can be generated using the knowledge base. Localized tools are needed, however, that address regional characteristics and accurately represent the decision-maker and stakeholder subjective values.

Fuzzy MCDA

Fuzzy MCDA combines fuzzy set theory and MCDA tools. Fuzzy set theory was developed by Lotfi A. Zadeh and defines a fuzzy set as "a class of objects with a continuum of grades of membership" and is characterized by a membership function ranging between 0 and 1 (Zadeh, 1965). In contrast to other MCDAs, the fuzzy method uses a range of values and possibilities, rather than a single crisp number. Introducing fuzzy set theory into MCDA studies addresses wastewater management decision uncertainties, including inconsistent and unstable attributes such as variable operation and simulation data and disparate preferences of decision-makers and stakeholders. Crisp values are converted into fuzzy values through fuzzification, the final fuzzy values are calculated using MCDA, and the results are de-fuzzified into final crisp values. Zhang et al. (2020) evaluated wastewater treatment options through expert opinions using picture fuzzy numbers, which is a variation of the fuzzy set, and selected Sequencing Batch Reactor (SBR) as a suitable technology for rural areas. The weight of each criterion was determined using fuzzy AHP. The

intuitionistic fuzzy set (IFS), another variation, was used by Zhou et al. (2018) to evaluate three wastewater management plans and determine the ranking through Fuzzy TOPSIS. Ren and Liang (2017) evaluated alternatives through IFS with the participation of three stakeholder groups and determined criteria weights to finalize the ranking through the group MCDA method. Fuzzy AHP was primarily used for criteria weighting (Asgarian et al., 2018; Kamble et al., 2017; Mahjouri et al., 2017; Ouyang et al., 2015). Fuzzy versions of SAW, TOPSIS, and weighted average were also used as ranking methods (Asgarian et al., 2018; Chhipi-Shrestha et al., 2017a, 2017b; Dursun, 2016; Kamble et al., 2017).

Technical assessments

Technical assessments support alternative identification and the environmental and economic evaluation of wastewater management alternatives by addressing a variety of quantitative factors such as effluent quality, energy requirements, and cost. Topics addressed here include technical efficiency and performance assessments, risk assessment and flood resilience, and optimization and mathematical modeling. Table S2 in the Supporting Information summarizes our assessment of the literature reviewed.

Data Envelopment Analysis (DEA) has been widely used for performance evaluation across numerous industries, including banking, health care, agriculture and farm, transportation, education, and recently energy and environment (Liu et al., 2013; Norton & Weber, 2009). Many wastewater management performance assessment studies use DEA (Fuentes et al., 2020). Most compare the relative performance of WWTPs within a region. One study also evaluated the efficiency of municipal wastewater treatment (Ayyildiz et al., 2021). Wastewater management performance was primarily evaluated using the amount of pollutants removed (output) against the invested cost (input). Molinos-Senante (2018) evaluated the energy efficiency of wastewater treatment technologies using energy consumption as the input variable. Studies since then substituted various factors as input variables, such as O&M costs, energy consumption, and labor (Fuentes et al., 2020; Jiang et al., 2020). The amount of pollutants removed (organics, solids, nitrogen, and phosphorus), a fundamental wastewater management function, has most frequently been used as the output variable. Fuentes et al. (2020) determined sludge production as an undesirable output, along with conventional output variables (pollutant removal), in their DEA model. The undesirable outcome was minimized using the Weighted Russell Directional Distance Model (WRDDM), which can optimize the directional distance function. Jiang et al. (2020) incorporated the wastewater management water reuse function by adding the amount of reclaimed water as a desirable output.

The use of the traditional DEA model has been extended in the last 10 years. The DEA with tolerance model, which considers the uncertainty of input and output data, was used to provide more reliable efficiency results (Sala-Garrido et al., 2012). Molinos-Senante et al. (2016) applied a weighted slacks-based DEA model that factors in the differing importance of parameters, as each pollutant (e. g. suspended solids, COD, N, and P) has a distinct environmental impact. Wastewater management systems can perform at varying levels of efficiency depending on the applied wastewater treatment technology. For example, conventional activated sludge (CAS) and trickling filter (TF) have distinctive biological treatment system functional mechanisms, so energy consumption and pollutant removal may differ. To consider this difference in performance, the efficiency of each technology was compared using the metafrontier DEA and the Metafrontier Malmquist Productivity Index (MMPI) (Molinos-Senante, 2018; Molinos-Senante, Hernandez-Sancho, & Sala-Garrido, 2015). The Hicks-Moorsteen Productivity Index (HMPI) was also used to compare the performance of WWTPs during two separate years to evaluate possible improvements (Molinos-Senante et al., 2016). Ayyildiz et al. (2021) utilized the Extended Stepwise Weight Assessment Ratio Analysis (SWARA) method to select important parameters among various inputs and outputs in DEA implementation.

Technical performance evaluations using DEA are sometimes referred to as eco-efficiency for environmental outcome versus cost or energy efficiency for environmental efficiency versus energy. DEA is a useful method for measuring efficiency, but currently, it is primarily used for comparing the operational efficiencies of existing wastewater management systems, not new ones. DEA offers advantages for evaluating alternatives for new options during the design or decision stage. More diverse parameters should also be applied to inputs and outputs. For example, input parameters may include workforce, energy consumption, and required space, as well as cost. Desirable outputs may include reclaimed water, produced biogas, and recovered nutrients, in addition to pollutant removal. Undesirable outputs may encompass not only sludge production but also greenhouse gas emissions, human health impact, ecosystem impact, etc.

Another evaluation criterion important to wastewater decision-making is the resiliency of operations under stress conditions. Wastewater systems experience numerous stressors, such as flooding due to severe rain events,

shock load to the biological reactors, inflow of toxic pollutants, facility mechanical failure, and electricity and natural gas shutdown. When these various stressors and risk factors occur, system performance will enter a stage of degradation after reaching the resistance threshold, as shown in Figure 3. Performance deteriorates rapidly if the stressor persists, but the system begins to recover if the stressor disappears and finally reaches normal performance (P_0). The time from the start of the recovery to the normal state is called the recovery time. The system will struggle to comply with regulations while the stress is imposed. Reliability is typically defined as the ability to comply with regulations under stress and can be quantitatively calculated from stress load and resistance. Resilience represents the ability to return to normal system performance (P_0) after performance degradation occurs due to stress, as shown in Figure 1 (Karamouz et al., 2018; Olyaei et al., 2018). The reader is referred to Juan-Garćia et al. (2017) who provide a review of resilience theory as applied to urban wastewater systems. Karamouz et al. (2018) assessed resilience according to four criteria (redundancy, resourcefulness, robustness, and rapidity). Reliability and resilience are crucial for wastewater management system operation and are primarily determined qualitatively, but two studies quantitatively assess flood risk (Karamouz & Farzaneh, 2020; Olyaei et al., 2018).

Multiple methods, such as risk management tools, vulnerability assessment index, reliability, and resilience assessment, have been developed and applied for the evaluation of various risks. Wastewater management system risks can be classified into individual process risks and overall plant risks, such as floods and power outages, as summarized in Table S3 in the Supporting Information. The major identified risks include influent flow rate changes from climate change and flooding, stricter regulations, and various operational threats. Loj-Pilch and Zakrzewska (2020) used a risk management system to evaluate two types of operational risks, overall plant risk (power outage) and individual process risks (clogging and bulking in the unit process). A risk map was created based on the frequency and amount of loss. The risk of flooding and an increase in influent flowrate due to climate change was evaluated using the vulnerability assessment index (Kim et al., 2017). The effect of climate change on system operation was investigated by identifying the relationship between temperature-flowrate-nitrogen concentration through statistical data analysis (Plosz et al., 2009).

Qualitative and quantitative evaluations of the effect of flooding on system operation have been conducted. They assessed the reliability and resilience of the system against floods and compared the effects of best management practice (BMP) applications. Flood reliability was assessed by selecting criteria in load and resistance categories, assigning a weight to each, and combining them through MCDA (PROMETHEE) (Karamouz et al., 2020; Karamouz & Farzaneh, 2020). Flood resilience was evaluated using four criteria: rapidity, robustness, resourcefulness, and redundancy. The weight for each criterion was calculated using expert opinion through AHP, and the final resilience score was determined using the PROMETHEE tool (Karamouz et al., 2016; Karamouz et al., 2018).

Linear programming has been used to optimize wastewater management system operations. For example, Zhou et al. (2017) applied linear programming (Interval Two-Stage Programming, ITSP model) to optimize the

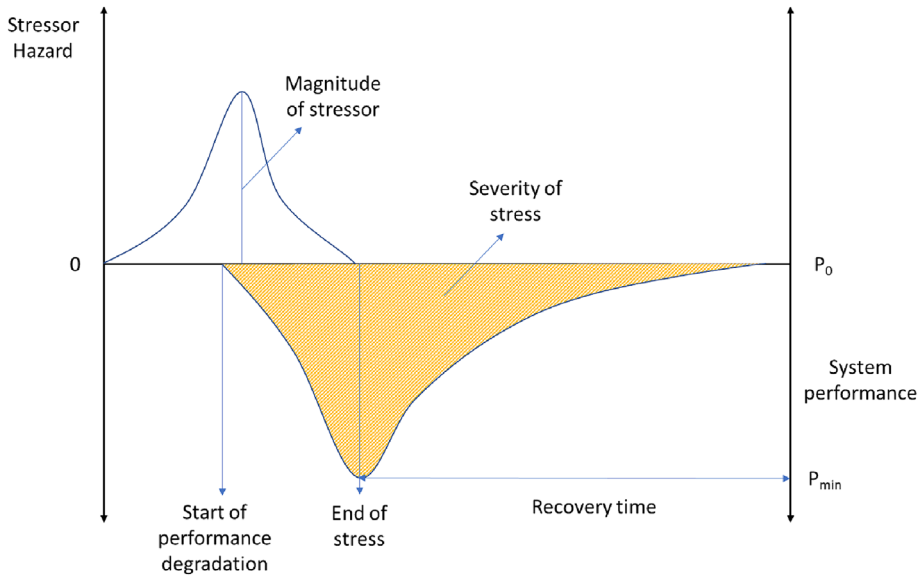


FIGURE 1 Response of system to stress and following recovery when stressor is removed. Note that recovery could begin earlier than end of stress. Modified from (Holloway et al., 2019; Olyaei et al., 2018).

activated sludge process using minimal cost as a single objective. While single-objective studies have been conducted frequently, multi-objective optimization studies have increased to address the multiple objectives required of these systems. Multi-objective optimization is a method to find Pareto efficient solutions by establishing a multi-objective function under system constraints. Multiple optimal solutions on the Pareto front can be discovered through optimization, but the most preferred alternative cannot be determined given that it often emerges from the trade-off between criteria. To overcome this problem, Padron-Paez et al. (2020) optimized three objectives (cost, energy consumption, and reclaimed wastewater) using mixed-integer nonlinear programming and determined the best sustainable treatment technology by trading off criteria through TOPSIS. Similarly, Hakanen et al. (2011) utilized process modeling (GPS-X) and an optimization tool (IND-NIMBUS) to address three objectives: ammonium concentration in effluent, alkalinity dosage, and energy consumption. Decision-maker preferences are reflected in the optimization process, and the best alternatives are then presented. Hakanen et al. (2020) further improved the communication process between decision-makers and multi-objective optimization by introducing visual analytics.

Indicators have also been used to optimize the operation of WWTPs. Gordon and McCann (2015) developed the Sustainable Optimization Indicator (SOI) to assess system operational performance. Parameters were selected by collecting the opinions of stakeholders (plant managers/operators) through a questionnaire. Kaddoura et al. (2020) subsequently evaluated the physical, environmental, and operational condition of WWTPs through the Condition Rating Index (CRI) and assessed the performance of the primary treatment and biological process using the Treatment Performance Index (TRI). The intervention model for maintenance was optimized using these two indicators. Advanced analytics were applied to optimize WWTP operation and reduce cost (Zadorojniy et al., 2019).

Wastewater management system decision-making requires a variety of information to enhance the understanding of decision-makers and stakeholders. Process modeling provides valuable information by estimating the future performance of alternatives. Olsson et al. (2003) proposed a decision support system based on three stages, detection, diagnosis, and advice, and demonstrated that the application of quantitative and qualitative models in the diagnosis stage provided key information for the decision process. Similarly, Daigger (2011) reported that a process model systematically represents system functions in a decision support system and noted that the project phase will determine its required modeling approach. In earlier phases, such as determining management options, a simpler model is required, while in later phases such as the design and operation stages a detailed model is needed to accurately estimate performance. Using mathematical models to assess alternatives has the advantage of facilitating the evaluation of not only existing facilities but also new technologies (Salem et al., 2002). Further approaches combine the WWTP and river water quality model (Benedetti et al., 2010) and predict performance using a Bayesian network model (Li et al., 2013). Modeling not only provides technical performance information but also supplies essential data for environmental and economic analysis, discussed below.

Economic assessments

Economic assessments generally consist of capital (CAPEX), operation and maintenance (OPEX), and life cycle cost (LCC), which can also include revenue such as from biogas, recovered resources (fertilizers), and reclaimed water. The economic feasibility of wastewater management is primarily evaluated through (1) cost-effectiveness analysis and (2) cost–benefit analysis. Cost-effectiveness analysis compares the cost of projects (alternatives in MCDA) and the effects obtained from them, such as pollutant removal, while cost–benefit analysis compares the cost and the monetary value of the resulting benefit. Cost–benefit analysis requires the conversion of the benefits from wastewater management into monetary value. Cost–benefit analysis for wastewater management can be challenging as environmental benefits are often externalities that are not traded in the market, making their price undetermined. Thus, benefits must be monetized separately.

Costs are generally assessed using cost models or actual data (Table S4 in the Supporting Information). Huang et al. (2020) compared the cost-effectiveness of a conventional WWTP and a constructed wetland using the annual cost of the two systems and estimated the removal efficiency of nitrogen and phosphorus using process modeling. Goffi et al. (2018) calculated the cost of treatment trains using a Monte Carlo simulation based on cost data (investment cost, O&M cost, electricity cost, and area required) collected from the literature. Cost-effectiveness was assessed and compared by categorizing each treatment train into three classes (primary. Secondary, and advanced treatment) according to pollutant removal efficiencies (organic matter, solids, nitrogen, phosphorus). Benedetti et al. (2013) evaluated the effectiveness of water quality improvement measures by applying an integrated model with three components: the

WWTP, the receiving water body (river), and the sewer. CAPEX and OPEX were calculated using cost functions and then combining the results to assess the cost-effectiveness of multiple scenarios.

In contrast, cost–benefit evaluations evaluate wastewater management benefits relative to cost. Sena et al. (2020) presented three monetary valuation methods to quantify the environmental benefits of phosphorus removal: (1) economic consequences, (2) mitigation and restoration, and (3) willingness to pay. The economic consequence method estimates the cost of phosphorus-induced pollution in five economic categories (property value, health effects, fisheries, tourism, and drinking water treatment). The mitigation and restoration method calculates the cost of removing phosphorus and restoring the impacted ecosystems. The willingness-to-pay method often relies on survey data to determine the maximum payment individuals are willing to pay for a service or good. Bellver-Domingo et al. (2017) estimated the environmental benefit of the elimination of Pharmaceutical and Personal Care Products (PPCPs) through the shadow price method, which is applicable to goods or services that have no market value (Hernandez-Sancho et al., 2010). Faere et al. (1989) developed the distance function theory to calculate the shadow price of undesirable outcomes from externalities. The shadow price for PPCPs could be different depending on the receiving water body, so an analysis was conducted to consider specific aquatic systems such as wetlands, rivers, and seas. Hernandez-Sancho et al. (2010) used the shadow price method to estimate the environmental benefit of conventional pollutant removal (nitrogen, phosphorus, solids, BOD, and COD). Ultimately, the environmental benefit can be converted into a monetary value by multiplying the amount of pollutant removed (kg) and the unit price ($/kg) of the pollutant, which is estimated through economic valuation. These calculated outcomes provide the basis for cost–benefit analysis. In a review of wastewater management cost- benefit analyses, Molinos-Senante et al. (2012) pointed out the difficulty of properly estimating external benefits and proposed the shadow price method based on ease of use and fewer limitations and biases than other conventional methods. Molinos-Senante et al. (2010) calculated the cost required for energy, staff, reagent, waste management, and maintenance along with environmental benefits using the shadow price method for 22 WWTPs. They found shadow prices of 0.1312 €/kg (COD), 0.0051 €/kg (SS), 8.0604 €/kg (N), and 30.9442 €/kg (P).

Wastewater management cost estimation involves conventional cost analysis using cost models and LCC Analysis (LCCA). Pereira and Moura (2018) used cost analysis to determine which technology is more economical in different Population Equivalent (PE) ranges. They reported that the combination of Conventional Activated Sludge (CAS) and Standard Rate Anaerobic Digestion (SRAD) was advantageous at 10,000–35,000 PE, while the CAS + High Rate Anaerobic Digestion (HRAD) combination was beneficial at 35,000 PE or higher. Gratziou and Chrisochoidou (2013) used the CAPDET (Computer Assisted Procedure for Design and Evaluation of wastewater treatment systems) model to estimate the total and annual cost of various nitrogen removal technologies. Engin and Demir (2006) used cost analysis to compare the economic expenditure of wastewater management systems within small communities. To provide a more accurate prediction of energy cost, Castellet-Viciano et al. (2018) suggested an energy cost model by analyzing 322 WWTPs in Spain. They presented a specific energy cost function, where variables were wastewater volume, COD removal, and aging. Ruiz-Rosa et al. (2016) utilized the activity-based costing technique to analyze the cost of an individual process in a WWTP. They divided WWTP processes into five main activities and eight auxiliary activities and categorized them according to eight cost groups. The cost of secondary treatment (37.82%) was the highest in the main activities, and maintenance (35.88%) occupied the largest proportion in the auxiliary activities. McNamara et al. (2017) assessed the net present value (NPV) for 24 scenarios established depending on PE, effluent limit, and sludge disposal and determined that constructed wetlands were the most economical alternative if sufficient land is available. Rawal and Duggal (2016) analyzed the LCC of different options (trickling filter, waste stabilization pond, and CAS) for a semi-urban area and concluded that waste stabilization ponds are the most economical option for the lifetime of the WWTP.

Environmental assessments

Life cycle assessment (LCA) is a principal tool used to assess the environmental impacts of wastewater management options. LCA is often supplemented with specific greenhouse gas (GHG) and energy/resource recovery assessments.

LCA is a comprehensive tool to "address[es] the environmental aspects and potential environmental impacts throughout a product's life cycle from raw material acquisition through production, use, end-of-life treatment, recycling, and final disposal" (ISO, 2020). LCA consists of four phases: (1) goals and scope definition, (2) inventory analysis, (3) impact assessment, and (4) interpretation (Figure 2). The functional unit and the system boundary are determined in the goal/scope phase. The functional

units often used for wastewater management LCA's include the volume of wastewater, the volume with a treatment objective, the mass of sludge, and PE (Corominas et al., 2020). The system boundary defines the process scope suitable for analysis and often entails wastewater and sludge treatment, but in some instances may include wastewater collection, sludge transport, sludge disposal, and energy and resource recovery. The functional unit and system boundary are varied depending on the purpose of the analysis and the anticipated outcome.

Input and output data are collected in the inventory analysis phase to create the Life Cycle Inventory (LCI). The inventory should be prepared for the entire wastewater management life cycle, including construction, operation, and end-of-life stages. Given the long life of WWTP structures (e.g. 50–100 years), the environmental impacts during construction and end-of-life stages are often considered relatively insignificant. Thus, wastewater management LCAs (other than constructed wetlands) often focus on the operation stage (Corominas et al., 2020). Rebello et al. (2021) reported that 57% of the reviewed papers only investigated the operation phase, and only 9% included the entire life cycle (construction, operation, and end-of-life). The inventory analysis phase collects and evaluates data from wastewater characteristics, chemicals and energy consumption, and sludge disposal. Pollutant emissions to water, air, and soil are calculated based on input and output data and compiled in an inventory.

The environmental exposure of pollutants is calculated during the impact assessment phase based on the emissions estimated in the previous phase. The effects of these pollutants on various receptors are assessed, such as ecotoxicity, climate change, cancer, etc. This effect stage is sometimes referred to as the midpoint impact. Finally, the damage to resources, ecosystems, and human health caused by these effects is evaluated. This damage stage is referred to as the endpoint impact. Ultimately, the impact assessment phase calculates environmental consequences using data collected from the previous LCI stage and the characterization factors from the associated impact models. Diverse models such as ReCiPe (Huijbregts et al., 2016), CML (CML, 2016), and Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) (Bare et al., 2012) can be utilized. Appropriate models should be selected according to regional characteristics and analysis objectives (Rebello et al., 2021).

Conclusions and recommendations are made in the interpretation phase based on the purpose of the analysis. The limitations of the analysis are also specified. Hotspot analysis is frequently conducted during wastewater management LCAs to identify which processes significantly influence the environment and the environmental impacts of different treatment scenarios. Uncertainty analysis is also used to assess how data uncertainties propagate and affect the final results (Rebello et al., 2021).

Numerous wastewater management LCAs have been conducted over the past three decades, but with many disparate methods, causing confusion for users. Consequently, guidelines for a more unified methodology have been proposed. Rebello et al. (2021) proposed guidelines based on an analysis of 111 wastewater management LCA studies. The biggest issue they found is that essential

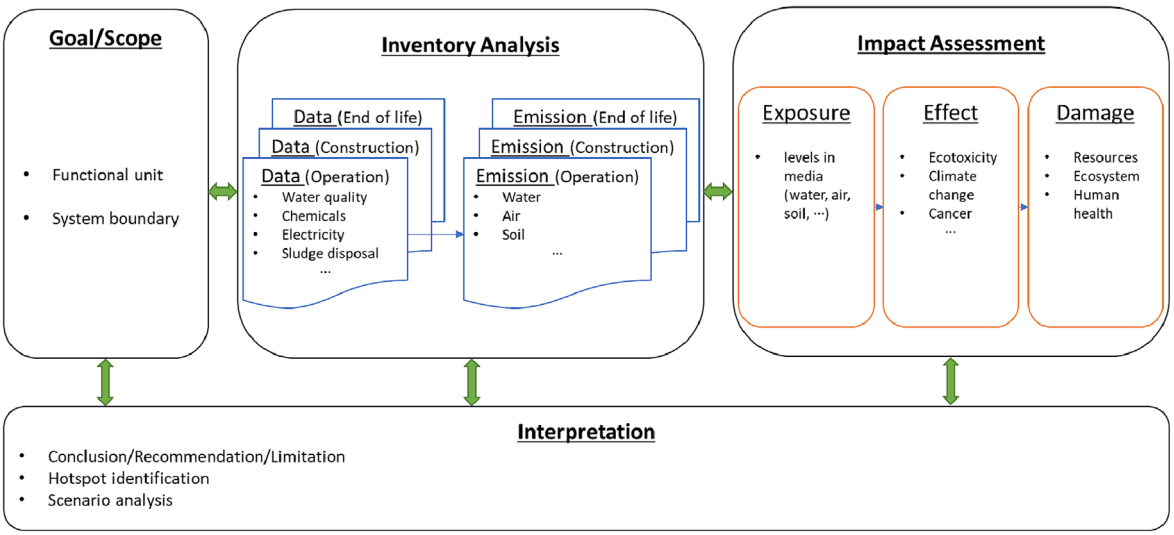


FIGURE 2 Four phases of an LCA showing principal elements of each and their interrelationship. Modified from (Huijbregts et al., 2016; ISO, 2020).

information is often missing. Corominas et al. (2020) analyzed 121 papers, summarized the issues in each phase of LCA, and presented recent research trends. Corominas et al. (2013) reviewed 45 articles and discussed the application and challenges of wastewater management LCAs. Lam et al. (2020) reviewed 65 LCA studies on wastewater nutrient recycling, discussing methodological issues, and presented a future outlook proposing integrating product and process perspectives in nutrient recycling. Zang et al. (2015) reviewed LCA studies on biological WWTPs and emphasized the importance of considering site-specific characteristics for eutrophication potential and toxicity impacts.

Numerous studies use the results of LCAs to compare the environmental impacts of various wastewater management alternatives and determine the most environmentally sustainable one (see Table S6 in the Supporting Information). LCIs were primarily created from wastewater management operating data (foreground data) and ecoinvent databases/literature (background data). Actual electricity/chemical usage and water emission data were often used for LCI development, reducing inherent uncertainty. The CML model was primarily used for impact assessment in LCIA, but TRACI, ReCiPe, and Eco-indicators were also used. Renou et al. (2008) compared the results of five different impact assessment models (CML 2000, Eco Indicator 99, EDIP 96, EPS, and Ecopoints 97) and found consistency in the greenhouse effect, resource depletion, and acidification components but noted significant differences in human toxicity depending on the selected LCIA model. While the eutrophication impact was similar for the different LCIA models, different outcomes were demonstrated in distinct eutrophication states for the receiving water body. These results indicate that the choice of the LCIA model is not material for most environmental impacts but may be important when human toxicity and eutrophication are the main foci of the study. Midpoint categories were primarily used to analyze environmental impacts because normalization based on the local characteristics of the receiving environment is needed to calculate endpoints and obtaining data on such normalization factors is often challenging. Midpoint impact categories in most studies included greenhouse gases, eutrophication, toxicity, resource depletion, and acidification. These environmental impacts are mainly caused by energy/chemical usage and pollutant emissions. Most wastewater management LCAs did not cover the impact of pathogenic pollutants. Papa et al. (2016) addressed the microbiological issue by comparing the impact on human health using a biological assay approach and showed that the human health impact is significantly influenced by the treatment processes applied. SimaPro and GaBi were the LCA software often used, but Microsoft Excel was also used for calculations.

Multiple tools, such as LCA, process modeling, and DEA, have been combined to predict the environmental impact and efficiency of alternatives more accurately. Process modeling has been used to develop data for LCAs as it provides more accurate estimates of input and output data for various scenarios. Meneses et al. (2015) used the Benchmark Simulation Model No 2 (BSM2) model to calculate the effluent quality and operation cost of various WWTP control strategies. They applied LCA to assess environmental impacts based on model outputs and determined the best control strategy by evaluating effluent quality, cost, and environmental impact using multiple evaluation criteria. Corominas et al. (2013) used a combination of the commercial process modeling software WEST and LCA to determine the best operation strategy for the Anaerobic-Anoxic-Oxic (A2O) process. Using the process model and empirical factors they estimated energy consumption and water/air emissions and, with these data, the LCA evaluated the environmental impacts of 17 control strategies. Wang et al. (2012) developed a method to generate simulation data through process modeling (BioWin) and apply it to LCA to evaluate A2O control strategies and compared the environmental impacts at three different effluent limits. LCA has also been used as an input variable for DEA to evaluate wastewater management performance (Torregrossa et al., 2018).

LCA has been combined with decision support tools in wastewater management decision-making processes. Garrido-Baserba et al. (2014) combined the results of LCA as environmental criteria with knowledge-based DSS to assess the environmental impact of 22 WWTPs using eutrophication potential and global warming potential as the essential impact categories. Bai, Zhao, et al. (2018) converted LCA outcomes into a single index using different weighting methods to compare the environmental impact of multiple alternatives. They also use Conjoint Analysis (CA) to incorporate stakeholder preferences into LCA results. By trading off stakeholder preferences for midpoint categories, they compared the total utility of each alternative. Zhao et al. (2019) and Bai et al. (2019) combined LCA with a water quality model to calculate environmental impact and then used CA to reflect stakeholder preferences on individual impact categories and compared the total utility of alternatives.

GHG emissions are often an environmental indicator used to assess wastewater management options. Wastewater GHG emissions include CO_2, CH_4, and N_2O, but CO_2 emissions are generally not included in GHG calculations as they originate from the biogenic decomposition of organic matter in influent wastewater. CO_2 emissions

are included when industrial wastewater is treated or municipal wastewater contains a significant amount of fossil fuel-based compounds (Corominas et al., 2020). Wastewater management GHG emissions can be classified into direct, indirect internal, and indirect external emissions. Direct emissions (scope 1) refer to CO_2, CH_4, and N_2O gases emitted from biological mechanisms such as nitrification/denitrification and anaerobic digestion in WWTPs. Indirect internal emissions (scope 2) are GHG emissions generated using electricity and thermal energy in WWTPs. Indirect external emissions (scope 3) refer to emissions that cannot be directly controlled within WWTPs, for example, the production of chemicals used in the process and the transportation of biosolids (Mannina et al., 2016). Chetty and Pillay (2015) used a carbon footprint calculator to estimate wastewater management GHG scope 1, 2, and 3 emissions.

Wastewater management GHG direct emissions are generally calculated using the IPCC Guideline (IPCC, 2019), while recent studies have used plant-wide modeling. Plant-wide modeling simulates GHG emissions from both liquid and solid streams, providing more accurate estimations and enabling the identification of the most reasonable comprehensive GHG reduction strategy rather than sub-optimizing individual processes (Mannina et al., 2016). Flores-Alsina et al. (2011) used the plant-wide model, BSM2G (a modified version of the IWA Benchmark Simulation Model No 2), to evaluate GHG emissions from (1) secondary treatment, (2) sludge treatment, (3) electricity, (4) chemical consumption, and (5) sludge disposal and reuse. They reported that different GHG formation mechanisms functioned according to the applied operation scenario. In particular, high uncertainty exists about N_2O generation in WWTPs, so research on formation mechanisms is ongoing. Caniani, Caivano, et al. (2019) and Caniani, Esposito, et al. (2019) reported that N_2O formation in industrial wastewater often occurs during the denitrification step in MBR, while low C/N ratio in municipal wastewater increases N_2O formation in nitrification processes. As a result, various factors, such as influent characteristics, operation conditions, nitrification and denitrification requirements, and sludge treatment processes, can influence wastewater GHG emissions.

Energy use and resource recovery are other environmental impacts often used to differentiate wastewater management options. Thurlimann et al. (2015) used energy and effluent water quality as Key Performance Indicators (KPIs) and presented them using visualization tools. Mucha and Mikosz (2016) evaluated WWTP upgrade options from an energy balance and effluent quality perspective using a process model (GPS-X). Li et al. (2018) proposed a gray fixed-weight clustering method to assess WWTP energy efficiency. Ultimately, energy efficiency in WWTPs is determined by comparing energy input with pollutant removal output. Indicators and simulation by process models can be used for this evaluation.

Energy and resource flows in wastewater management systems have been analyzed to provide a basis for decision-making. Energy and resource analysis includes both consumption and recovery of energy and chemicals. The flow of energy and resources can vary greatly depending on wastewater management system scale, treatment technology, local regulation, and influent characteristics. He et al. (2019) statistically evaluated the energy usage of 1184 WWTPs in China, presenting the unit energy consumption based on their scale, effluent standards, and applied technologies and found that unit energy consumption tended to decrease as the scale increased and tended to increase as effluent standards became stricter. Process models are used to predict complex energy and mass flows more accurately. Fernandez-Arevalo et al. (2017) evaluated energy and mass fluxes for multiple wastewater management options using plant-wide modeling (BSM2). They visualized the fluxes of energy, COD, TN, and TP using energy and mass Sankey diagrams and reported that 29% of influent COD was converted to biogas in a conventional WWTP while retrofitting (thermal hydrolysis and nutrient recovery/control) could allow for 34–36% of COD to be used as biogas. Sadhukhan (2014) evaluated the avoided environmental impact using Combined Heat and Power (CHP) energy recovery with biogas production from sewage sludge and reported that 1 m^3 of biogas can replace 0.92 m^3 of natural gas through CHP energy recovery and that 1 MJ of biogas can reduce GWP by 0.0793 kg CO2 equivalent. Torregrossa et al. (2017) proposed the use of WWTP real-time data to evaluate energy consumption based on a knowledge base and fuzzy logic.

The emergy methodology has been used to evaluate the total energy and resource flow of WWTPs. Emergy is defined as "All the available energy that was used in the work of making a product and expressed in unit of one type of energy" (Odum, 1996). Emergy analysis uses a common unit (solar emjoules, sej) to quantify the input of energy, resources, and labor. It includes natural capital (such as water, energy, minerals, etc.), which is an aspect different from economic accounting. While LCA focuses on minimizing environmental impact, emergy analysis aims to optimize energy and resource use, suggesting a complementary relationship between the two methods. Arden et al. (2019) applied emergy analysis and reported that aeration and incineration were the highest emergy processes. They also compared the results of emergy analysis to those of LCA and LCCA and found that energy

recovery processes such as anaerobic digestion could improve the resource (emergy), environmental impact (LCA), and cost (LCCA) of WWTPs. Shao et al. (2014) compared the GHG emissions and emergy of sequencing batch reactors and constructed wetlands using environmental (sunlight, rain, wind, etc.) and economic (civil work, equipment, energy, material, labor, etc.) inputs to calculate the emergy inventory. Clauson-Kaas et al. (2001) analyzed the energy and resource flow for each unit process in a WWTP to evaluate environmental impacts (global warming, acidification, nutrient enrichment, toxicity, slag/ashes).

Social assessments

Social assessment of wastewater management options involves evaluating the social impacts of each alternative on multiple stakeholders, such as communities and employees. Social assessment includes the stakeholders to be identified, establishment of criteria suitable for their social needs, and evaluation of the impacts of alternatives. The Social Life Cycle Assessment (SLCA) method has recently begun to be applied, as described below.

The wastewater management decision-making process begins with identifying and analyzing stakeholders, as follows: (1) identify stakeholders, (2) differentiate and categorize stakeholders, and (3) investigate the relationships between stakeholders. Stakeholder identification can be conducted through focus group brainstorming, semi-structured interviews, snowball sampling, etc. Once stakeholders are identified, they are categorized according to their characteristics using top-down methods such as the power-interest matrix or bottom-up approaches such as stakeholder-led categorization. Methods such as social network analysis can be used to investigate the relationships between stakeholders (Reed et al., 2009). Erb-Institute (2021) proposes the following four steps for stakeholder engagement: (1) define the scope, (2) identify the economic, environmental, and social impacts on the business and the stakeholders, (3) map issues and stakeholders, (4) plan and implement engagement. The organizational, operational, and geographical boundaries for the decision are first outlined to establish the scope. The impacts and issues related to the decision are then identified, and stakeholders for these issues are identified. Stakeholders are placed in a power and interest 2 × 2 matrix which classifies stakeholders concerning their impact on the implementation of the decision and their interest in it. As illustrated in Figure 3, the location of a stakeholder on the diagram indicates how the subject stakeholder should be engaged in the decision process. The power dynamics between stakeholders can be understood by representing the relationships between stakeholders on a diagram. While stakeholder analysis has traditionally been used in the business sector, it has recently been expanded to include natural resource and environmental management (Grimble & Wellard, 1997; Reed et al., 2009). Lienert et al. (2013) pioneered the application of stakeholder analysis in the



FIGURE 3 Power and interest matrix for stakeholder analysis (Erb-Institute, 2021).

water sector. They divided 41 stakeholders related to water infrastructure planning into local, cantonal, and national levels according to the decision level and analyzed the impacts and interests of stakeholders in planning by creating a stakeholder matrix based on their influence on and how they are affected by planning. They further investigated the relationships between each stakeholder through social network analysis and concluded that combining stakeholder analysis and social network analysis can provide more insightful and complementary outcomes in water infrastructure planning.

Stakeholder opinions play various roles in decision-making, particularly in selecting decision objectives, criteria, and criteria weighting. Lienert et al. (2011) established four decision objectives and eight criteria for treating pharmaceuticals in hospital wastewater by reflecting stakeholder opinions. They then used the reverse swing method to determine the relative importance of each criterion, taking into account stakeholder preferences. Harris-Lovett et al. (2019) selected five goals, thirteen objectives, and thirteen criteria for nutrient management decision-making in the San Francisco Bay Area by reflecting on stakeholder opinions and used the swing method to determine the weight of each criterion for individual stakeholders. They concluded that such stakeholder involvement stimulates discussion and collaboration, leading to more beneficial and more supported solutions. Bao et al. (2013) actively reflected stakeholder preferences in the wastewater treatment system for a small town in Vietnam. They used the AHP method to determine the weight of each criterion based on the opinions of three stakeholder groups (academics, policymakers, and local residents) and ranked sanitation scenarios accordingly. Some studies also use stakeholder opinions to interpret LCA results and rank alternatives. Bai, Zhu, et al. (2018) surveyed stakeholders' preferences for LCA midpoint impacts and determined their relative importance and reported that the relative importance of the four LCA midpoint impact categories was as follows: eutrophication was 77.95%, global warming was 9.77%, ecotoxicity was 7.81%, and resource depletion was 4.47%. They then combined stakeholder relative importance and LCA midpoint outcomes to determine the total utility of each alternative.

The stakeholder involvement process is very complex, involving interactions among stakeholders and changes in stakeholders' opinions during decision-making. Olsson et al. (2011) explained these stakeholder interactions as social learning, a theory that suggests that knowledge transfer occurs among stakeholders during the decision-making process, leading to the development of new and collective solutions beyond individual perceptions of the decision problem and solution. Yoon et al. (2019) assessed stakeholder interactions quantitatively, applying the equilibria of social power which uses game theory to quantify the interactions. They quantified the equilibria of interaction between municipalities and project developers when selecting an urban wastewater system. Consumer awareness is also an essential social factor in WWTP decision-making. Petrescu et al. (2019) surveyed 125 Romanian consumers to determine their awareness of wastewater treatment services and found that consumers had a high awareness of the harmful impacts of untreated wastewater and a strong understanding of the need for wastewater treatment.

A limited number of studies have applied SLCA to wastewater management decision-making. SLCA is "a methodology for assessing the social impacts of products and services across their life cycle, from the extraction of raw materials to the end-of-life phase" (UNEP, 2020), evaluating the impacts on stakeholders' social interests and well-being throughout the entire production, use, and disposal process. Similar to the LCA assessment process, SLCA has the following four phases: (1) goal and scope, (2) social life cycle inventory, (3) social life cycle impact assessment, and (4) interpretation (Figure 4). Since SLCA evaluates the social impacts on stakeholders, the stakeholder categories affected by the decision (e.g., workers, local communities, society, consumers, and value chain actors) are selected first. The social impact categories affecting these stakeholders (e.g., human rights, working conditions, health and safety, cultural heritage, governance) are then determined, and their impacts are evaluated.

Examples of the application of SCLA to wastewater management decision-making are summarized in Table S7 in the Supporting Information, along with a summary of the criteria used in Figure S4. These studies assessed stakeholder categories such as workers, value chain actors, society, local community, and consumers for their wastewater management-related social impacts. Foglia et al. (2021) added water utilities as a stakeholder and evaluated impacts using indicators such as resilience, scalability, and integration. Padilla-Rivera et al. (2016) used 25 indicators for stakeholders to assess the social impacts of two WWTPs in Mexico. They reported that SLCA facilitates the comparison of different wastewater management options and identifies their social strengths and weaknesses. Serreli et al. (2021) selected 19 impact categories for stakeholders to evaluate social impacts in an industrial wastewater treatment plant using the Product Social Impact Life Cycle Assessment (PSILCA) database. While SLCA appears to be a valuable tool to assess wastewater management option social impact issues and their impacts on different stakeholders, further research is needed, along with application guidelines.

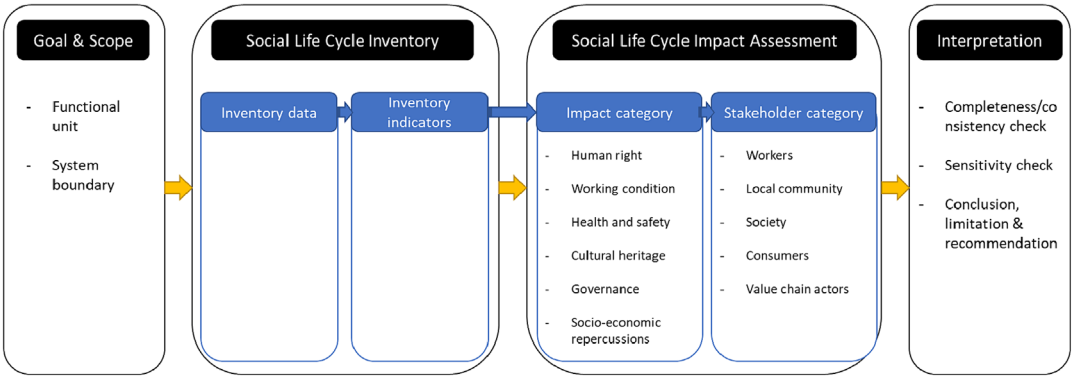


FIGURE 4 Four phases and assessment system for SLCA.

DISCUSSION

Development of an integrated decision-making structure and process

Our review of the literature on wastewater management system decision-making indicated that decision-makers and stakeholders are often not clearly identified nor included in the decision process. Instead, most wastewater decision-making studies are limited to the use of technical methodologies. This is a significant deficiency since, as discussed in the Introduction, wastewater decision-making occurs within a much broader structure. Successful implementation of a wastewater management strategy depends on the support of a diverse range of internal and external stakeholders who often have widely varying, and often conflicting, expectations. To a significant, this narrower focus occurs because the technical analyses are more established and well-developed. As also noted in the Introduction, decisions should be based on available data and sound science, to the extent possible, but also reflect the values and preferences of a wide variety of stakeholders. Stakeholder support is not only essential to identify and reach consensus regarding implementable solutions but also consistent with the objective of achieving sustainable solutions that meet environmental, economic, and social goals.

The review also revealed that well-developed procedures exist to conduct many of the technical analyses needed to support effective decision-making. Procedures to assess economic performance are also well established, and LCA is now accepted as an appropriate method to assess environmental performance.

The review also indicated that MCDA and similar tools are well established and accepted to facilitate the assessment of preferences and values as an important component of a wastewater management system decision-making process. Decision-maker and stakeholder interests, concerns, and preferences can form the basis for factors that affect the wastewater management system question(s) being evaluated and the relative importance of each relevant factor. Processes such as stakeholder identification and analysis are also available. Moreover, while research and practical experience with social assessment to support wastewater management decision-making is substantially limited, pioneering studies have begun to apply approaches such as SLCA. What is needed is an integrated wastewater management system decision-making structure and process that assesses the environmental, economic, and social performance of relevant alternatives and engages decision-makers and stakeholders in the process in a meaningful way. We offer such a structure and process based on our assessment of the literature presented above.

Figure 5 summarizes the wastewater management decision-making structure synthesized from the literature review. It can be viewed from both bottom-up and top-down perspectives. From a bottom-up perspective, it is based initially on relevant data of different types and from different domains, ranging from technical to social. These data are synthesized into knowledge and information that informs the environmental, economic, and social dimensions of sustainability relevant to the decision to be made. From a top-down perspective, the decision is based on the values, interests, and perspectives of the organization responsible for the implementation of the decision (for example, a wastewater utility) and the relevant external and internal stakeholders. It is the combination of these values, interests, and perspectives that determines the nature and diversity of solutions to be considered and, consequently, the relevant information, knowledge, and data needed to discriminate between the relevant solutions and support the decision-making process. As noted on the right-hand side of the diagram, the structure is based on objective data, knowledge, and information which informs what is ultimately

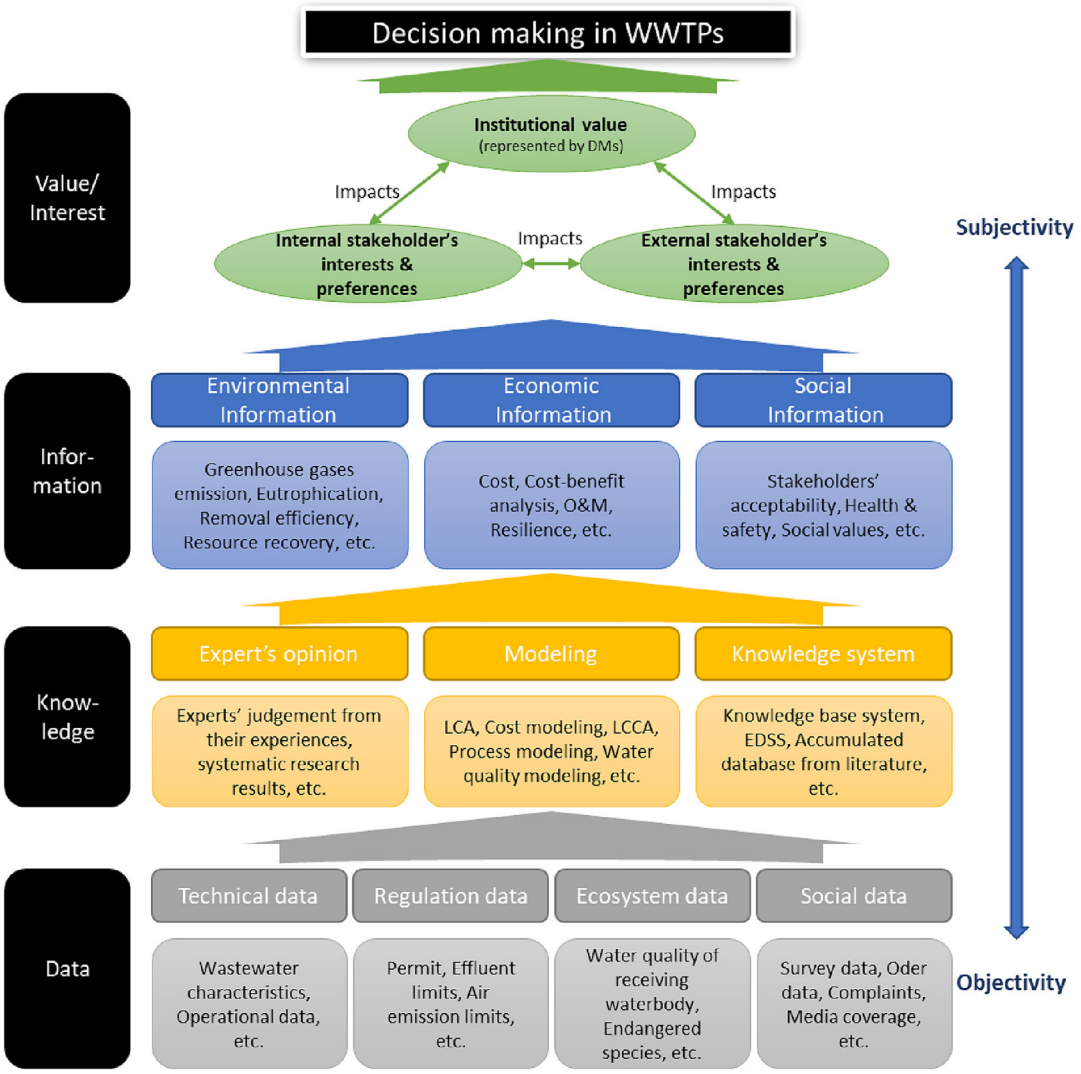


FIGURE 5 Wastewater management decision-making structure (WWTPs: wastewater treatment plants, DMs: decision-makers, O&M: operation and maintenance, LCA: life cycle assessment, LCCA: life cycle cost analysis, EDSS: environmental decision support system).

a subjective assessment and ultimate decision. The resulting decision is based on the sustainability triple bottom line and is fact- and science-based but reflective of the objectives and preferences of the affected parties (decision-makers and stakeholders).

This structure must be supported by a process to sequence the necessary steps in a logical and efficient manner. Figure 6 summarizes the proposed process. While presented generally as a linear process, it incorporates feedback loops and can be iterative in nature, depending on application and need. The first steps are to identify the parties relevant to the decision to be made and enlist them to frame the issues to be addressed. Relevant parties include (1) decision makers (DMs), who are understood to be the combination of individuals who have the organizational authority to direct the actions necessary to implement the decision, and (2) stakeholders, who are individuals or representatives of formal and informal groups affected by the outcome of the subject decision and who often can influence its subsequent implementation. Framing the issue includes background, identification of objectives to be met (and supporting metrics to the extent they can be identified at this stage), and constraints. This leads to the problem/solutions definition stage in which an initial set of options for addressing the problem to be solved are identified and screened, and an initial MCDA, described below can be conducted.

The outcome of the Problem/Solution Definition Stage is the knowledge and understanding to allow a clear statement of the needed decision to be articulated and a better definition of the alternatives that can inform the decision. This sets the Trade-Off Stage where detailed analysis of the identified alternatives is

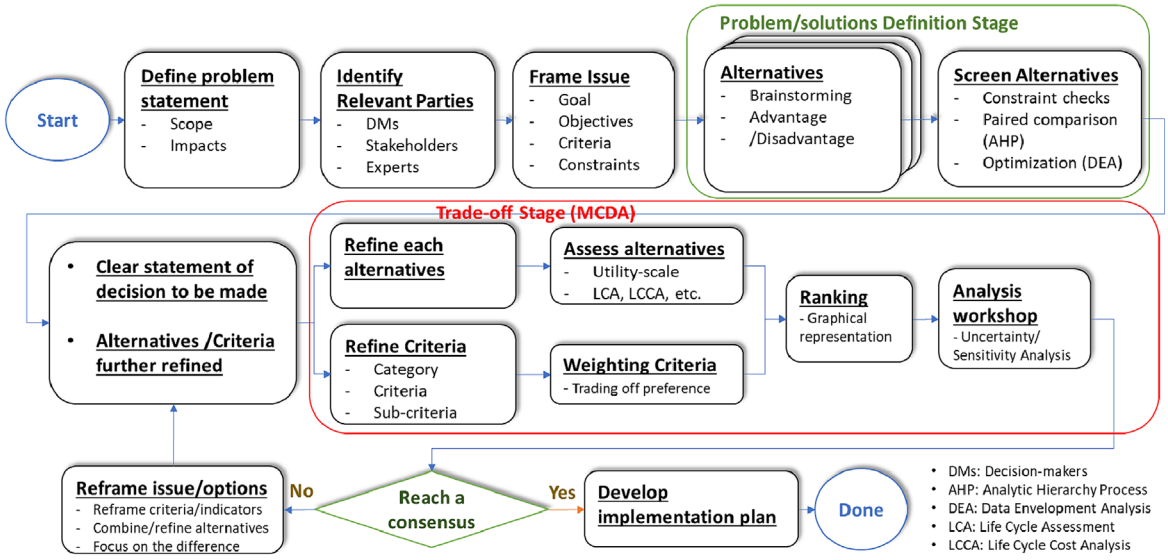


FIGURE 6 Wastewater management decision-making process.

conducted, often using a more formalized MCDA analysis supported by the appropriate assessment methodologies, for example as discussed in the Results section above. This often leads to a workshop where the DM's and select stakeholders and technical experts are engaged to review the results of the analysis to date. If consensus is reached concerning the decision to be made, the team conducting the evaluations proceeds to develop an implementation plan and implementation can proceed. If a consensus is not reached, further alternatives and/or the additional analyses needed are identified, and the Trade-Off Stage is repeated. In short, the process continues until an alternative is selected and the plan to implement it is developed.

The combined decision-making structure and process leads to science- and fact-based solutions that reflect broader sustainability and organizational objectives along with the value and objectives of the decision-makers and stakeholders. The process is clear and transparent, inclusive of the relevant parties, produces an objective-oriented decision, and is repeatable. It is also scalable. For many decisions the nature of the decision is well-understood, the options are already well defined, and the relevant stakeholders and their concerns and preferences are well-known. In such cases, it may only be necessary to conduct a modest analysis and convene a relevant group of decision-makers, stakeholders, and technical experts to efficiently work through the process and produce a documented decision and implementation plan. In other cases, the nature of the decision may not be clear, the available alternatives not defined, and the range of concerns and preferences of the relevant stakeholders not defined. In such cases, more extensive use of the tools identified in the Results section may be needed. Importantly, the extent and duration of engagement of the relevant stakeholders with the decision-makers and supporting technical experts must be sufficient to not only conduct the needed work but also accomplish the social learning needed to arrive at an implementable solution that is supported by all parties.

Future research needs

A review of the relevant literature also allowed the identification of research needs to advance the understanding of and effectiveness of wastewater management system decision-making.

1. Future research is needed to evaluate integrated decision-making processes such as presented in Figure 6. Effective decision-making integrates factual information relevant to the decision to be made, with system constraints, and uses the objectives and preferences of a diverse range of parties, including decision-makers and stakeholders. Further development of methods to functionally integrate this diverse range of factors into the decision process is needed, along with metrics to assess the effectiveness and efficiency of the process. Interdisciplinary research may be particularly effective in addressing these topics.
2. Guidelines for evaluating alternatives and preparing and selecting environmental, economic, and social criteria to enhance the sustainability of wastewater

management decisions are needed. Comprehensive lists of criteria that can be used for sustainability evaluations during wastewater management decision-making can form the basis for standards used for individual decisions. Figures S1 through S4 in the Supporting Information provide summaries of criteria from the literature review as a starting point for the assembly of such lists. Assessment tools for each criterion are also needed to facilitate their use.

3. The area currently requiring the most research to assist with the evaluation of alternatives is the social assessment. While existing social assessments have centered on qualitative evaluations, more quantitative assessments are anticipated through the introduction of new methodologies, including SLCA. Research in this area should be prioritized. Further work on the development of stakeholder analysis methodologies suitable for wastewater decision-making will contribute to clearer stakeholder identification. While pioneering studies have begun to apply SLCA, more studies are needed to assess the social impacts on various wastewater management stakeholders. It is anticipated that substantial research on the evaluation of the social impact of wastewater management and the development of guidelines to standardize these methodologies can be conducted. This research is likely to be highly interdisciplinary.
4. While there has been extensive research on technical performance, including DEA and mathematical modeling, studies on risk assessment for operations and flooding are limited. More quantitative research is needed on operational risk assessment, a crucial component in wastewater management decision-making.
5. While there has been considerable research on wastewater management cost estimation through the application of CAPEX, OPEX, and LCCA, research to quantify the environmental benefits of wastewater management is limited. While there are a few studies quantifying environmental benefits for certain pollutants like phosphorus, they are confined to specific regions, indicating a need for more extensive research.
6. LCA is primarily used for environmental impact assessment in WWTPs. Extensive research is ongoing in this area, including the development of guidelines for LCA methodologies for wastewater management decision-making. Research is also being conducted to combine process models with LCA for more accurate inventory compilation. This combination facilitates more precise and detailed information for decision-makers and stakeholders during the decision process and will likely continue to be advanced.

SUMMARY AND CONCLUSIONS

This review analyzed over 200 papers published in 2000 to examine various tools to support wastewater management decision-making. We also investigated technical, environmental, economic, and social assessment methodologies to prepare the information needed to inform these decisions. Through this review, the following points were found:

- MCDA is widely used as a wastewater management decision support system. Wastewater management systems must satisfy multiple objectives, and that MCDA can trade off the values of decision-makers and stakeholders relative to multiple criteria makes it a relevant tool.
- Many wastewater management studies use DEA to evaluate technical performance. Research is being conducted to assess reliability and resilience as components of operational risk.
- Conventional cost analysis and cost–benefit analysis are consistently used for economic assessments. Methods to measure the economic value of the benefits of wastewater management options continue to be developed.
- LCA has been actively applied to assess the environmental impacts of wastewater management options. A guideline for conducting LCAs for wastewater management options has recently been proposed, and further efforts to standardize LCAs are expected in the future.
- Stakeholder analysis is applied to the water sector to systematically identify the stakeholders and their preferences. SLCA is just beginning to be applied to explore the diverse social impact of wastewater management.

While numerous tools are available to support comprehensive wastewater management system decision-making, an integrated structure and process that combines technical analysis with the values and objectives of the relevant decision-makers and stakeholders is needed. An integrated structure and process are developed and presented based on the results of this literature review.

Wastewater management decision-making is ultimately a process of reconciling the interests of various actors to achieve decision goals/objectives. This process involves evaluating the environmental, economic, and social aspects of alternatives and balancing the values of decision-makers and stakeholders to increase the sustainability of the wastewater management system. Discussions and interactions among decision-makers and

stakeholders during the decision process referred to as social learning, can lead to an agreeable and reasonable solution.

AUTHOR CONTRIBUTIONS

Daehyun Ko: Conceptualization; investigation; writing—original draft; methodology; validation; visualization; formal analysis; data curation. **John W. Norton Jr:** Conceptualization; funding acquisition; writing—review and editing; methodology. **Glen T. Daigger:** Conceptualization; investigation; funding acquisition; methodology; validation; visualization; writing—review and editing; formal analysis; project administration; data curation; supervision; resources.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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