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The Operation of Urban Water Treatment Plants: A Review of Smart Dashboard Frameworks

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Abstract

By locating useful characteristics and determining the perfect circumstances to meet ideal water quality criteria, this study seeks to improve the operation of a water treatment facility. The research comprises gathering data from personnel and exposure to system events, as well as from explicit and tacit knowledge sources. The problem at hand is a multi-objective, multi-criteria problem with many variables in spatial and temporal dimensions, requiring the use of powerful tools for analysis. All engineering problems have an objective function consisting of smaller sub-functions, typically in the form of cost or error minimization. To solve such problems, optimization methods based on natural patterns have been introduced, including genetic algorithms, evolutionary algorithms, and particle mass optimization. By optimizing the operation process of the water treatment plant, the quality of the water provided can be improved to meet standards set by organizations such as Iran 1053, WHO, and EPA. The study's findings could be used to implement changes to the plant's management and operation processes to achieve more ideal water quality conditions. Ultimately, the optimization of water treatment plant processes could have significant positive impacts on public health and well-being, as well as the environment.

Keywords: *Water treatment plan; Optimization; Multi-objective; Multi-criteria; Natural pattern*

INTRODUCTION

The progress and development of welfare and health standards in countries have led to improvements in the structural and functional aspects of water and sewage treatment systems. The complexity and extent of exploitation processes involved in updating water and wastewater treatment systems require the ability to provide "momentary decisions" during normal operation and in the face of predicted or unexpected challenges. The large volume of information output from refinery units cannot be analysed by human resources alone in a limited time, making it necessary to use machines to read and analyse the presented data. The time-consuming nature of gathering expert forces and using their experiences during operation has practically destroyed the short period of action, causing damage to treatment plant units, and putting the security of water supply to citizens at risk.

To address these challenges, data logging of events and challenges that occurred during refinery unit operation, along with experiences gained from solutions presented to deal with them, and results of activities carried out using techniques such as machine learning can be used. Creating a smart dashboard consisting of the experience and expertise of experienced forces can lead to an increase in the speed and accuracy of information analysis, and bring acceleration, capability, and action to specialized forces in exploitation units. The way operators of refinery units react to challenges has economic, environmental, social, managerial, and political-security consequences, so the operator must measure conditions in the least possible time and implement the best solution by weighing and prioritizing options. A smart dashboard can help the operator find the most optimal solution to deal with the crisis by using available data, previously recorded experiences, and scientific prioritization. The use of a smart dashboard in operating units improves daily performance of the system, and the solutions available in the dashboard database are developed and become more accurate over time, leading to quantitative and qualitative exploitation of refineries over time.

RESEARCH BACKGROUND

In recent years, there has been a significant focus on the design and operation of water systems, particularly water and wastewater treatment systems. The objective is to increase the ability to collect data and quickly make informed decisions. Decision support systems (DSS) are an integral part of the smart dashboard system for treatment plant management. DSS utilizes collected data, scientific foundations, standards, refinery conditions, and previous experiences in the system to present operators with reliable solutions in specific conditions. Arab et al. in [1] proposed a smart soft sensor using various Machine Learning (ML) algorithms to predict and control the Coagulation and Flocculation Process (CFP) in water treatment. The ML algorithms used include Random Tree, Random Forest, Artificial Neural Networks, Linear Regression, Gaussian Method, Decision Stump Method, SMOreg, and ANFIS. Central Composite Design with Response Surface Methodology was used for optimization. Nakhaei et al. in [2] presented a framework for evaluating Water Distribution Networks (WDN) for energy recovery using Micro-Hydropowers (MHPs) with the application of statistical optimization, simulation, and artificial intelligence techniques. After modelling a WDN in Mashhad, Iran, the potential of energy recovery using MHP technology was optimized with the application of Design of Experiment (DOE) methods and the model prediction ability was improved by Artificial Neural Network (ANN) technique. Results show that the combination of Taguchi and Response Surface Methodology (RSM) methods could successfully optimize energy recovery potential and detect high potential positions for MHP placement based on a high-performance operational decision-making methodology. Gheibi et al. in [3] proposed a sustainable decision support system for the removal of cyanide contamination from drinking water by chlorination. The study defines three contamination scenarios with different levels of cyanide and suggests optimal chlorine dosages for each scenario. A hybrid approach based on a Gaussian model and genetic algorithm is developed to model residual cyanide, and a multilayer perceptron algorithm is used to forecast residual cyanide as a soft sensor, demonstrating a strong positive relationship with injected chlorine. Manina et al. in [4] investigated the use of DSS systems in wastewater treatment systems to address management and operational challenges. DSS systems are a reliable tool for integrated plant management and can provide solutions based on the operator's needs. The design of DSS systems should consider the adaptability of innovative solutions for wastewater treatment systems, such as sustainability, treatment of new pollutants, reduction of waste, and operating costs. Improving the user relationship of DSS systems can help to improve the culture of using this system in wastewater treatment plants. In [5] Simion et al. conducted research on a DSS system based on fuzzy control for an anaerobic wastewater treatment plant. The controlled parameters are divided into four input areas, including Acidogenic activity, Methanogenic activity, and gas management. The variables and constants within each area are essential to the process and are reflected in the DSS system. Four separate operating modes have been designed for the system, which are described in Table 1.

Table 1. Types of process exploitation modes

Types of process operation modes	Description
Basic modes	Each operating component of the process is controlled separately.
Higher modes	Each component of the process operation can be activated or deactivated.
Original modes	The operator should act in all 4 defined areas and take the necessary measures.
Fuzzy Logic	Algorithms for decision-making maintain the stability and optimal conditions of the process and take the necessary measures based on possible changes that may occur in the system.

Anzaldi et al. in [6] conducted research on the use of management tools to better prepare for challenges in water systems. DSS systems enhance operational processes by applying decision-making knowledge. Modifying and adjusting the practical features of knowledge and experience can create a systematic structure to improve inter-system communication and uncover hidden behavioral patterns. Hamouda et al. in [7] analyzed variable factors in water and wastewater treatment systems to create a system that includes environmental criteria and public health in the face of emerging pollutants. Statistical-mathematical programming processes, simulation, and artificial intelligence were used to create a DSS system that analyzes purification problems, gathers and presents knowledge, identifies and evaluates control indicators, and makes optimal decisions. Stathaki and King in [8] investigated the application of an IDSS system in a wastewater treatment plant's data collection and control unit. The IDSS system manages a wide range of decisions to keep the refinery in normal conditions, providing continuity in human resource management and decision-making in complex processes and severe environmental conditions. Additional research on the smartening of water and wastewater treatment plants is presented in Table 2.

Table 2. DSS systems used in water systems

No.	Water system	Design feature	Applied techniques and tools	Ref
1	Refinery	Obtaining refinery data from the STOAT simulator to simulate operating conditions	LCA/MM[1] with the optimization approach	[9]
2	Refinery	Located in the province of Alicante in Spain	MM with an optimization approach	[10]
3	Refinery	Located in Whyalla in South Australia	MCDM[2] with the optimization approach	[11]

[1] Life Cycle Assessment/ Mathematical Modeling
[2] Multi-Criteria Decision Making

4	Refinery	Municipal sewage treatment plant in China	MM with the approach of optimizing exploitation and improving the quality of the outgoing effluent	[12]
5	Refinery	Active sludge treatment system in Germany and Holland	IDSS/MCDM with energy consumption optimization approach	[13]
6	Sewage facilities	Sewage infrastructure in Delhi, India	LCA/MM with the approach of optimizing energy consumption and environmental sustainability	[14]
7	Refinery	Used in Betanzos and Calafell refinery in Spain	LCA with the approach of optimizing exploitation and environmental sustainability	[15]
8	Refinery	Modeling based on the plan of the existing treatment plant	MCDM with an environmental sustainability approach	[16]
9	Refinery	Sewage treatment plant or capacity to serve 1 million people	LCA/MM with the approach of improving the quality of the effluent	[17]
10	Refinery	The sewage treatment plant in Copenhagen, Denmark	LCA with an environmental sustainability approach	[18]
11	Water treatment plant	Considering the uncertainty of functional variables and their impact on public health	Systematic analysis based on Bayesian probability networks	[19]
12	Water treatment plant	Risk assessment and cost reduction	Systematic analysis based on modeling and simulation, analysis, and multi-criteria decision making	[20]

Based on the topics presented in Table 2, it can be concluded that smartening water and wastewater treatment plants is a fixed problem, but different methods and techniques are utilized to organize purification processes. However, creating a decision-making process support system (DSS) to develop a smart dashboard and make water treatment plants more intelligent has received less attention, indicating a research gap.

DEFINING AND IDENTIFYING THE PROBLEM

Tehran metropolis

Tehran metropolis has an urban area of 720 square kilometers and, according to the Iran Statistics Center's general population and housing census in 2015, has a population of 8,693,706 people [21]. Being the political and economic center of Iran, it is crucial to improve the quality of urban services such as security, energy supply, water supply and treatment, sewage collection and treatment, public health, public transportation, and education to serve everyone. Water supply and purification are one of the key areas of urban service provision, and water treatment plants are the key symbols of this domain, as they provide safe drinking water for health purposes. The city of Tehran currently operates 5 water treatment plants, with one under construction [22]. Managing them is difficult and dangerous due to the assigned volume of water supply and the quality standards that must be met.

Water treatment plant

Currently, there are various types of water treatment plants available, but most of them follow the same structure, as illustrated in Figure 1. Water treatment plants typically comprise of several components, including garbage collection, aeration basin, coagulation and flocculation, clarifier, filtration, disinfection, storage tanks, and final delivery to the relevant department. As noted by [23], the distribution of urban water is a critical issue that needs to be addressed. The operation of these sections is affected by various parameters, some of which are highlighted in Table 3.

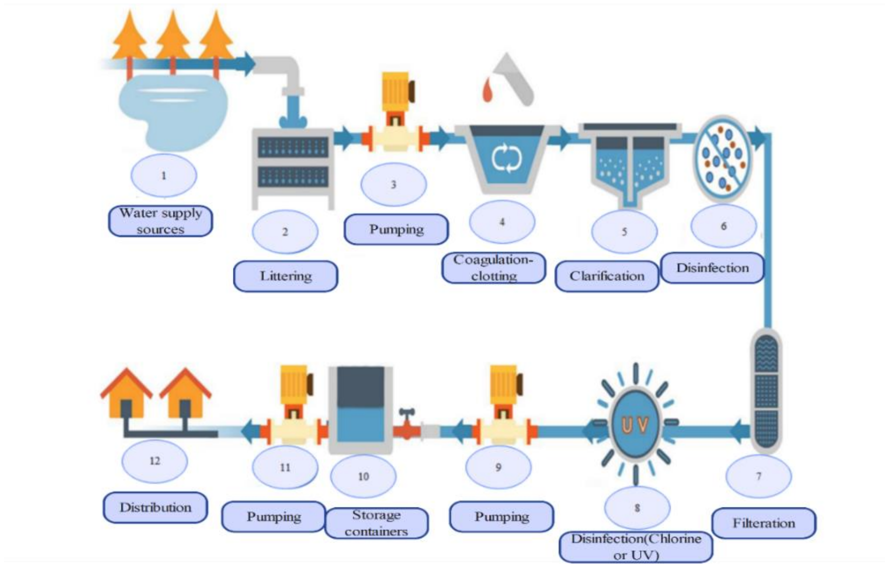

Figure 1. Process diagram of a conventional water treatment plant

Table 3. Some effective variables in the operation process of the water treatment plant

Refinery department	Some effective variables in the exploitation process
Garbage collection unit	Inlet flow rate, hydraulic and organic load, and backwash
Aeration pond unit	Unit type and functional system
Coagulation and clotting unit	Type and concentration of coagulant, pH
Clarifier unit	Unit type, parameters related to backwash and bed regeneration
Filtration unit	Type and arrangement of filters, inlet flow rate
Disinfection unit	The type and concentration of the disinfectant and its by-products

Area of the use of the water treatment plant

The operation process of a water treatment plant has a significant impact on various stakeholders, including the society, operational employees, local government, investors, health and environmental regulators, and others. Each of these beneficiaries has a different role to play in ensuring that the plant operates smoothly and efficiently. Figure 2 illustrates the different use cases of a water treatment plant and how each stakeholder interacts with the system.

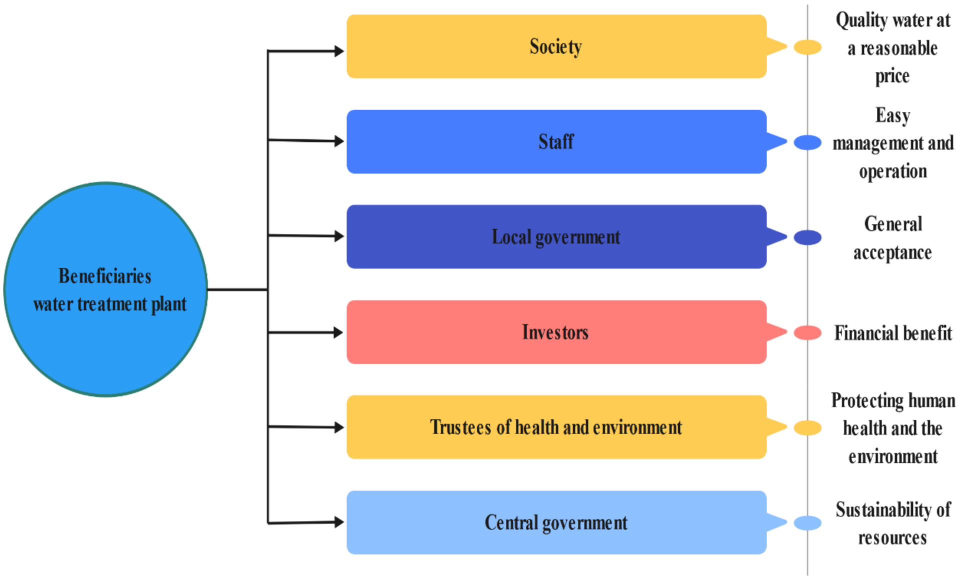

Figure 2. Area of the use of the water treatment plant

Knowledge management

Operating a water treatment plant involves a complex process with numerous parameters, leading to a vast amount of information presented to the operating force. The operating force must quickly receive, read, analyze, and make the optimal decision with accuracy, which may be impossible, leading to disruption and senior management's high-handed orders. Moreover, the absence of expert forces during the management of the treatment system results in the underutilization of the expert operating forces' full capacity. The knowledge of senior managers gained from years of management experience and facing various challenges in the processing system goes unused during the cycle of changing managers that occurs due to various reasons. Converting the tacit knowledge of expert and experienced managers into explicit knowledge can enhance decision-making and tackle refinery challenges within the knowledge management framework. The knowledge management structure, as shown in Figure 3, converts raw numerical data into information and knowledge, which improves the operating force's decision-making power or wisdom.

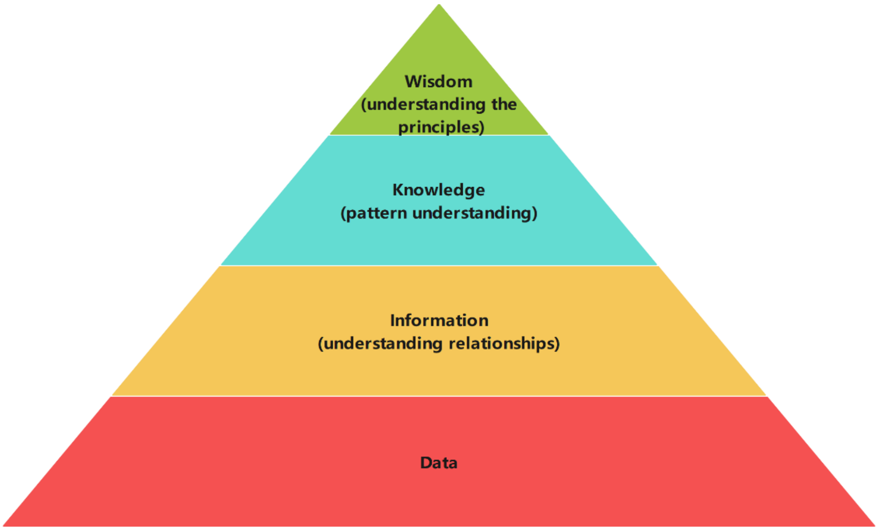

Figure 3. Hierarchy of data, information, and knowledge [24]

Hence, it is crucial to identify the existing situation and assess the strengths and weaknesses of the management and operational organization to formulate a knowledge management strategy. These strategies are classified into three categories, namely human-centered, system-centered, and hybrid and dynamic strategies, as shown in Table 4, which considers both tacit and explicit knowledge.

Table 4. Correlation of strategy type with tacit and explicit knowledge [25]

Type of strategy	Implicit/hidden knowledge	Explicit knowledge
System oriented	• Creating networks through information and communication technology • Facilitating remote face-to-face meetings Example: problem-solving through video conference	• Codification of knowledge in knowledge-sharing systems and its maintenance and recovery Example: expert systems
Humanistic	• Work teams, discussion groups, emphasis on person-to-person communication Example: teacher-student relationships	• Expansion and development of existing obvious concepts using face-to-face meetings Example: training course

Many models have been presented in the direction of knowledge management according to the content parameter, which can be models such as Nanoka Takachi, Beckman, Hissing, Lawson, six-stage, etc. Figure 4 presents the flow chart for developing a six-step dynamic knowledge management strategy.

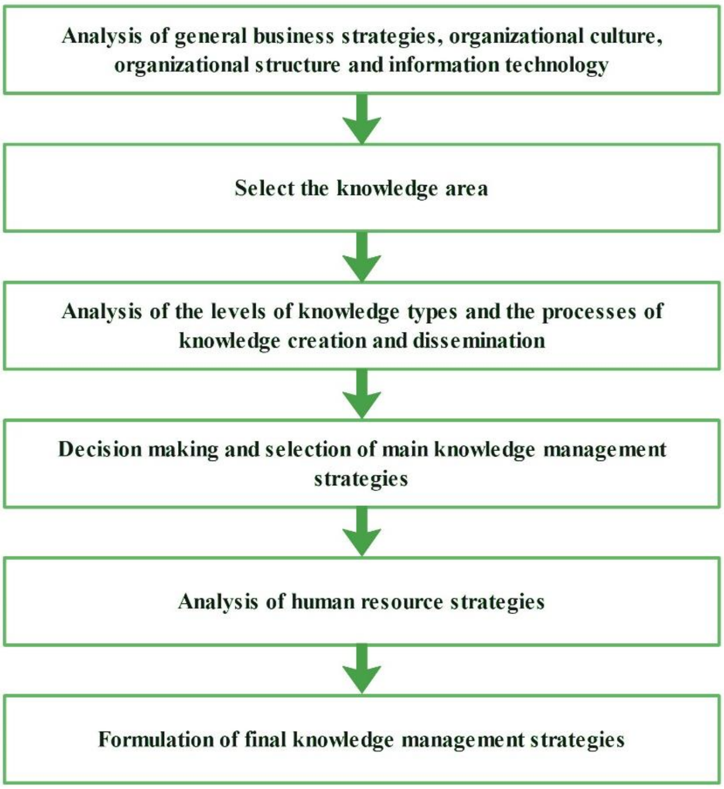

Figure 4. The flow chart of developing a six-step dynamic knowledge management strategy [26]

Smart water management dashboard

By using the knowledge management structures, and the system of suggestions of the experienced and operating experts, a dynamic system can be created in the form of a smart water management dashboard, which leads to better preparation of the experts in managing the process of operating the system and facing He presented possible challenges in the system. This system, by reading a large volume of information and analyzing data based on standards, instructions, and previous experiences of the operating forces, according to the existing conditions of the system operation and the desired parameters of the operating forces, in a short period. and helps the user in making the best decision. Converting the experiences of experts and the history of water treatment system operation into a mathematical model is one of the requirements for creating a smart water management dashboard (SWMD) structure. Figure 5 shows the functional process of the smart water management dashboard structure.

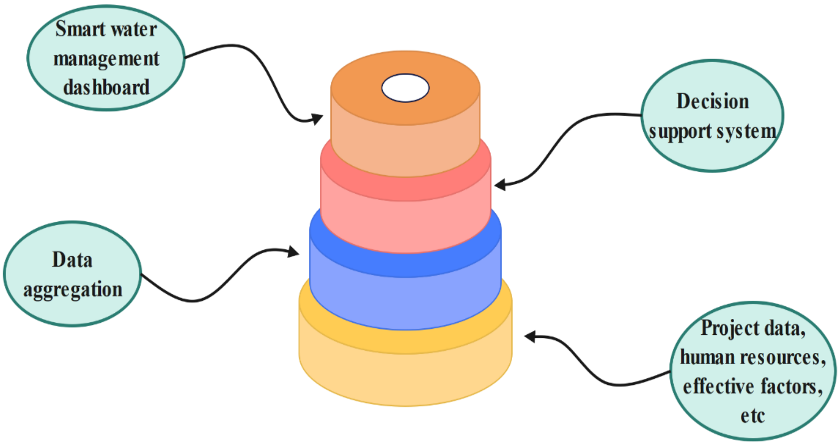

Figure 5. The functional process of the intelligent water management dashboard structure

Decision Support System

A Decision Support System (DSS) is a computer-based program that aims to collect, organize, and analyze available data to aid in quality decision-making for management, operation, and planning units [27]. An appropriately designed DSS system can greatly assist system management in providing data such as raw data, documents, and the tacit knowledge of employees, mid-level and senior managers. DSS systems can play an invaluable role in identifying and solving problems within complex systems, and help relevant managers throughout the process. These systems are comprised of three main components: a database, software system, and user interface. The components of a DSS system are shown in Figure 6.

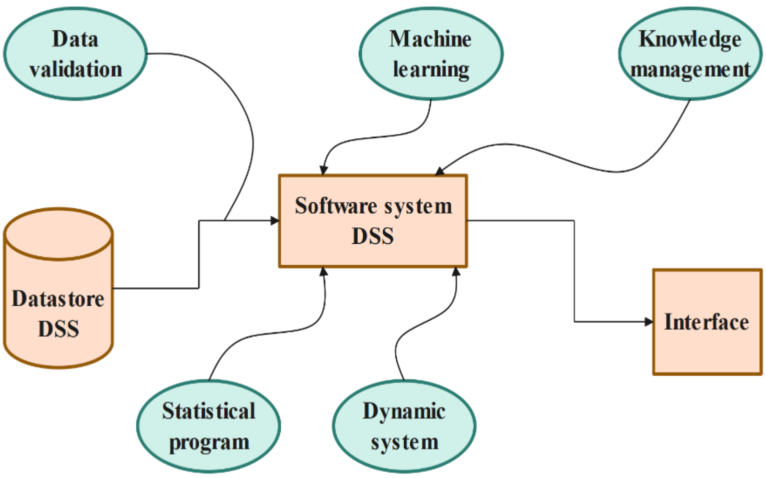

Figure 6. Components of DSS systems

DSS systems in the process of decision-making and management on features such as facilitation, interaction, frequency of use (repeated use), identification capability (expansion and correlation to other systems) and finally influencing the features It affects the quality and productivity of the system [28]. The features of DSS systems are presented in Table 5.

Table 5. Characteristics of DSS systems

Property	Description
Facilitate	DSS facilitates activities and processes related to decision-making
Reaction	A DSS is a computer-based system designed for use by considering the operator's interactions (the person who manages the process sequence).
Frequent use	DSS systems are designed for repeated use; These systems can be used for everyday use
Identifiable	DSS systems can take data from other related or connected systems and operate in an integrated information management system.
Influence on the decision	DSS systems lead to improving the accuracy, timeline, quality, and overall productivity of a particular decision and a set of decisions.

Multi-criteria decision-making process (MCDM)

Multi-criteria decision-making systems can be categorized into two types: multi-objective decision-making systems and multi-indicator decision-making systems [29]. The selection of either system depends on the environmental conditions. Water treatment plant systems use both methods, depending on their technical situation in terms of operation and design parameters. The general functional structure of multi-criteria decision-making systems is illustrated in Figure 7. To understand the significance of this tool, one must familiarize themselves with the general model of multi-criteria decision-making systems, as well as their structure and operation process. Therefore, Figure 8 presents the general model of the system, which is briefly explained.

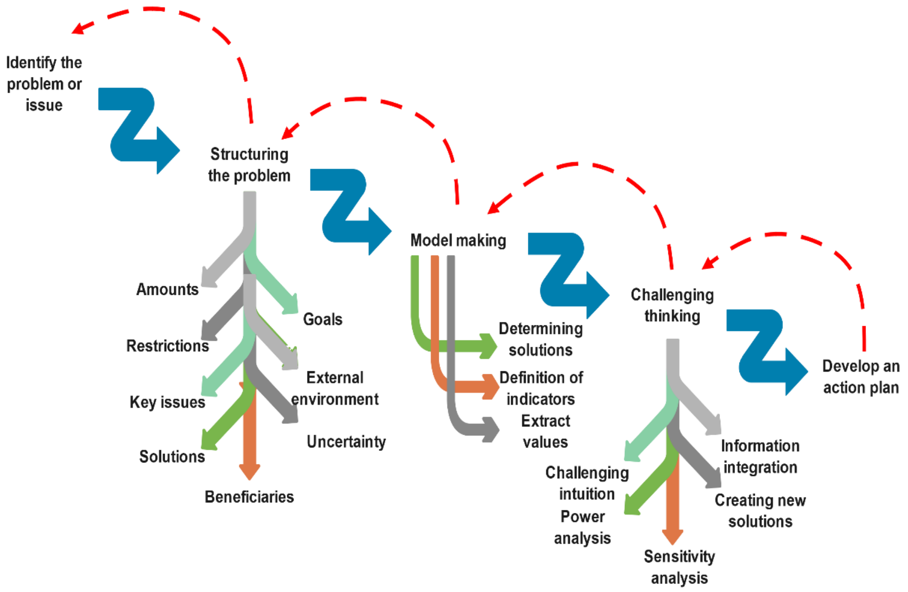

Figure 7. Functional structure of MCDM

Flowchart explanation steps:

First step: defining the problem and its scope

In this step, the characteristics of the problem and its scope are defined under considerations such as determining the number of solutions, features, limitations, and other issues. The available information about the problem and its scope forms the basis for choosing the most appropriate MCDM solutions and is used to solve the problem.

The second step: extraction of criteria and indicators

Determining the desired evaluation criteria is essential because these criteria have a great impact on the output of the MCDM method selection process. Of course, the use of every index in the selection process does not easily lead to the determination of the best method because the more indices are used, the more information will be needed and as a result, the computational costs will increase. The evaluation index defined as MCDM features and input data in the decision matrix will be used to select the method.

The third step: analysis of solutions

A solution is proposed among the alternatives when it is superior to other solutions in at least one or more characteristics. The selected MCDM methods are discarded in competition with the superior MCDM method that does not require assumptions and information transformation. Screening of the best decision according to the steps: comparing the first two solutions (if one solution is better than the other solution, the weaker solution is discarded), comparing the best solution from the previous step with the third solution, and continuing these steps until comparing the last available solution. Accepting the conjunctive method is used to discard the solutions that the decision-making group approves according to its desired characteristics.

The fourth step: prioritizing evaluation indicators

Usually, after completing the initial screening stage, several MCDM methods are left, otherwise, the only remaining method is directly selected to solve the decision-making problem. This step strengthens the prioritization of indicators. Another feature of this step is to help identify indicators that are preferable to other priorities and have the greatest effect on the final choice.

The fifth step: choosing the MCDM method

This step includes choosing one of the MCDM methods among the common and used methods. MAUT[3], AHP[4], SMART[5], ELECTRE[6], GP[7], SAW[8], etc. are among the conventional methods. Other methods, to determine the final MCDM method, the advantages and disadvantages of each method, the scope of application, library studies, and background should be considered. The use of each method should be considered. The method is presented in Table 6, a comparison

[3] Multi-Attribute Utility Theory

[4] Analytic Hierarchy Process

[5] Simple Multi-Attribute Rating Technique

[6] Elimination and Choice Expressing Reality

[7] Goal Programming

[8] Simple Additive Weighting

between different types of MCDM methods according to each method's advantages, disadvantages, and scope of application.

The sixth step: evaluating the MCDM method

To evaluate the existing MCDM methods and classify them, different methods can be used to provide a comparison between the methods, and the most common method of evaluating and classifying them is to use a mathematical program.

The Seventh step: apply the selected method to the data

This step includes all mathematical calculations (each method has its unique calculations) of the selected method.

The eighth step: the results and their evaluation

The final step includes a row of outputs from all the mentioned steps. Sensitivity analysis to choose the MCDM method should be done to analyze the power according to the changes of parameters such as the instability of decision-making prioritization information and input data.

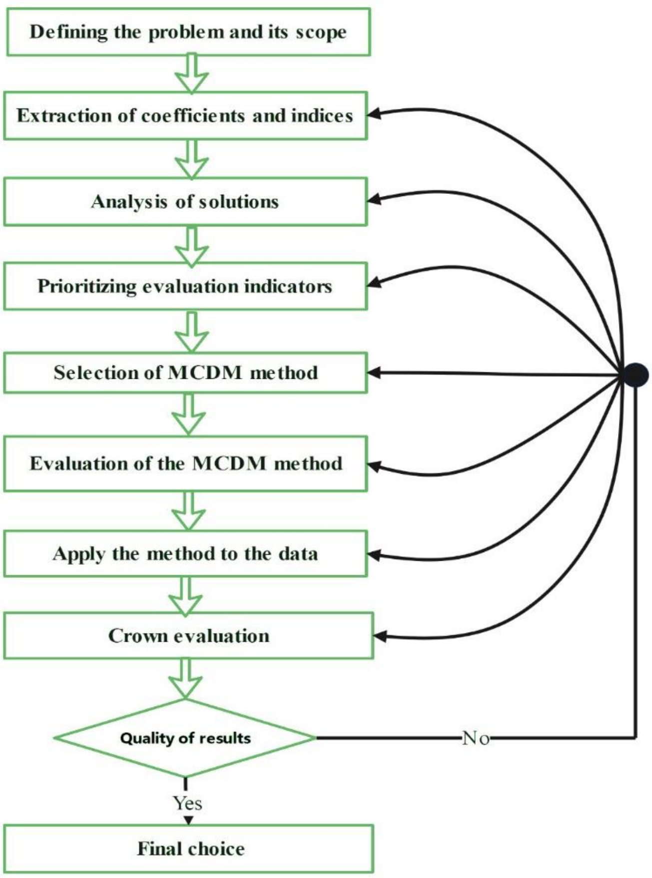

Figure 8. General MCDM model [30]

Table 6. Comparison between MCDM systems [31]

Method	Advantages	Disadvantages	Scope of application
MATU	Considering uncertainty, the ability to combine priorities	Need a large number of inputs, the accuracy of priorities	Economy, finance, water management, energy management, and agriculture
AHP	Easy to use, adaptability of the hierarchical structure to the size of the problem	The mutual dependence between indicators and solutions leads to a lack of continuity between the judgment and classification of indicators.	Issues of exploitation, resource management, collection policy, and planning
Fuzzy Set Theory	Ability to receive incomplete input, including inappropriate information	The difficulty of its development, the need for numerical simulation before use	Engineering, economics, environmental, social, and management
SMART	Simple, usable for all kinds of weighting techniques, and less effort for decision-makers	The method may not be suitable and the format of the work should be taken into account	Environmental, construction, transportation, military affairs, production, and assembly problems
GP	Ability to manage large-scale issues and create solutions without limitation in the number	Weakness in weighting coefficients; It is usually necessary to use this method in combination with other MCDM methods	Production planning, portfolio selection, distribution systems, water reservoir management, and energy planning
ELECTRE	Considering uncertainty and ambiguities	The process and output of those LAYMAN terms are not well interpreted and it leads to not identifying the strengths and weaknesses of the solutions.	Energy, economy, environment, and water management
PROMETHEE	Easy to use, no assumptions required for relative indices	Lack of a precise tool for weighing	Ecology, hydrology, water management, chemistry, and energy
SAW	Understandable for decision-makers, simple calculations without the need for complex computer programs	It usually does not show the real conditions well, the results are not always logical	Water management, business, and financial management
TOPICS	An easy process, easy to use and program, the constant number of steps regardless of the number of properties	The use of Euclidean distance does not consider the correlation of properties; The difficulty of weighting and maintaining the continuity of judgment	Supply chain management, environment, human resources, water resources management

Machine learning

Modelling interactions in water systems is essential to strengthening the security and stability of the system. The advancement of technology has made it possible to produce a large amount of data corresponding to the performance of different departments. By using the techniques of statistical sciences and machine learning, it is possible to extract the characteristic patterns of different parts of the system transparently and clearly [32]. Table 7 shows the types of machine learning techniques and their subgroups.

Table 7. Machine learning techniques and their subgroups [33]

No.	Category	Types	Characteristics
1	Supervised learning	Regression analysis	Estimation between a dependent variable and one or more independent variables
		ANN	Ability to learn functional relationships between dependent and independent variables
		SVM	Classification and regression
		Decision trees	Classification and regression
		Time history analysis models	Using the Box-Jenkins model for forecasting
		Comparative analysis of supervised techniques	Evaluation of applied techniques to increase forecasting accuracy
2	Unsupervised learning	Hierarchical clustering	Finding the hidden structure of patterns, relationships, and similarities from unlabeled data
		Principal component analysis	
3	Integrative learning	Bayesian learning models	Considering model uncertainty in statistical analysis
		Random forests	Classification and regression with high accuracy and flexible statistical technique
		Hybrid models	Considering model uncertainty in statistical analysis
4	Reinforcement learning		Learning the behavior of agents by getting feedback from the environment

The use of machine learning has led to the creation of conditions to facilitate the reading and analysis of data, which can be used for capabilities such as 1) exploring patterns and relationships in the data, 2) showing the heterogeneity of the data, 3) prediction of water variables, 4) modelling of unobservable variables and 5) integration of models [34]. Table 8 shows the application of machine learning in water systems.

Table 8. Application of machine learning in water systems

Row	Water system	Machin learning system	Function	Reference
1	Water treatment plant	SVM/KNN	Prediction of coagulant concentration in the water treatment plant	[35]
2	Water treatment plant	Time history analysis/SVM	Anomaly detection in the water treatment plant	[36]
3	Sewage treatment plant	ANN/SVM	Forecasting the effluent concentration of the wastewater treatment plant	[37]
4	Sewage treatment plant	SVM	Predicting the quality of the effluent from the wastewater treatment plant	[38]
5	Multi-operator water system	Reinforcement learning	Multi-objective optimization of water systems	[39]

Optimization

In this research, an attempt has been made to study the structure of the water treatment plant and identify the effective parameters in the operation process, to find the most optimal possible conditions to achieve the ideal conditions for the management and operation of the treatment plant. Water should be provided. For this purpose, it is necessary to prepare the used standards such as Iran 1053, WHO, and EPA, and in line with that, collect information from the tacit and explicit knowledge of the collection and operating staff and the knowledge from exposure to the events included in the system. To optimize the operation process of the water treatment plant, an understanding of the problem must be obtained. The present problem is a multi-objective and multi-criteria problem that has many variables in spatial and temporal dimensions. Therefore, according to the complex conditions in the water treatment plant operation management process, the creation and use of powerful tools to analyse the answers should be considered.

All problems in engineering fields have a general objective function, which includes smaller sub-functions. The objective function of these problems can be maximization, fitness, and profit function, or minimization, cost function, and error function. In any case, all these problems are defined in the form of minimization or cost function, because the default tool (used software) of all these algorithms is in the form of minimization. Each of the maximization problems is also transformed into a cost function by analogy or inverting the shape of the functions. Gradually, optimization techniques based on natural patterns have been created to address the issues produced by previously described methodologies. These techniques include genetic algorithms, simulations of steel hydration, evolutionary algorithms, colony optimization, and particle mass optimization.

CONCLUSION

This research focused on the optimization of water treatment plants by identifying effective parameters and finding the most optimal conditions for operation. To achieve this, various standards such as Iran 1053, WHO, and EPA were used, and information was collected from the staff and from exposure to events in the system. The problem of optimizing the operation process of water treatment plants is complex due to the large number of variables in spatial and temporal dimensions, making it a multi-objective and multi-criteria problem. Thus, powerful tools for analysing the answers are required. Optimization problems in engineering fields typically have an objective function that includes smaller sub-functions, such as maximization or minimization functions. While many optimization methods have been introduced in the past, those based on natural patterns have been gaining popularity, such as genetic algorithms, evolutionary algorithms, and particle swarm optimization. These methods have been shown to be effective in solving complex problems with multiple objectives and criteria. Overall, optimizing the operation process of water treatment plants can lead to improved water quality and better management practices. The methods and findings of this research can be used as a basis for future studies on water treatment plant optimization, and can ultimately contribute to the sustainability of our water resources.

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CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interests associated with this publication.

REFERENCES

[1]. Arab, M., Akbarian, H., Gheibi, M., Akrami, M., Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., & Tian, G. A soft-sensor for sustainable operation of coagulation and flocculation units. Engineering Applications of Artificial Intelligence. 2022; 115, 105315.

[2]. Nakhaei, M., Akrami, M., Gheibi, M., Coronado, P. D. U., Hajiaghaei-Keshteli, M., & Mahlknecht, J. A novel framework for technical performance evaluation of water distribution networks based on the water-energy nexus concept. Energy Conversion and Management. 2022; 273, 116422.

[3]. Gheibi, M., Eftekhari, M., Akrami, M., Emrani, N., Hajiaghaei-Keshteli, M., Fathollahi-Fard, A. M., & Yazdani, M. A sustainable decision support system for drinking water systems: Resiliency improvement against cyanide contamination. Infrastructures. 2022; 7(7), 88.

[4]. Mannina G, Rebouças TF, Cosenza A, Sànchez-Marrè M, Gibert K. Decision support systems (DSS) for wastewater treatment plants–A review of the state of the art. Bioresource technology. 2019 Jul 16:121814.

[5]. Simion CA, Chenaru OA, Florea GH, Lozano JI, Nabulsi SA, Reis MA, Cassidy JO. Decision support system based on fuzzy control for a wastewater treatment plant. Int J Environ Sci. 2016;1:344-9.

[6]. Anzaldi G, Rubion E, Corchero A, Sanfeliu R, Domingo X, Pijuan J, Tersa F. Towards an enhanced knowledge-based decision support system (DSS) for integrated water resource management (IWRM). Procedia Engineering. 2014 Jan 1;89:1097-104.

[7]. Hamouda MA, Anderson WB, Huck PM. Decision support systems in water and wastewater treatment process selection and design: a review. Water Science and Technology. 2009 Oct 1;60(7):1757-70.

[8]. STATHAKI A, Robert E. An intelligent decision support system for wastewater treatment plant management. Int. Journal of Engineering Simulation (IJES). 2007;8(1).

[9]. Torregrossa D, Marvuglia A, Leopold U. A novel methodology based on LCA+ DEA to detect eco-efficiency shifts in wastewater treatment plants. Ecological indicators. 2018 Nov 1;94:7-15.

[10]. Díaz-Madroñero M, Pérez-Sánchez M, Satorre-Aznar JR, Mula J, López-Jiménez PA. Analysis of a wastewater treatment plant using fuzzy goal programming as a management tool: A case study. Journal of cleaner production. 2018 Apr 10;180:20-33.

[11]. Chow CW, Liu J, Li J, Swain N, Reid K, Saint CP. Development of smart data analytics tools to support wastewater treatment plant operation. Chemometrics and Intelligent Laboratory Systems. 2018 Jun 15;177:140-50.

[12]. Zeng S, Chen X, Dong X, Liu Y. Efficiency assessment of urban wastewater treatment plants in China: Considering greenhouse gas emissions. Resources, Conservation and Recycling. 2017 May 1;120:157-65.

[13]. Torregrossa D, Hernández-Sancho F, Hansen J, Cornelissen A, Popov T, Schutz G. Energy saving in wastewater treatment plants: A plant-generic cooperative decision support system. Journal of cleaner production. 2017 Nov 20;167:601-9.

[14]. Singh P, Kansal A. Energy and GHG accounting for wastewater infrastructure. Resources, Conservation and Recycling. 2018 Jan 1;128:499-507.

[15]. Lorenzo-Toja, Y., Alfonsín, C., Amores, M.J., Aldea, X., Marin, D., Moreira, M.T., Feijoo, G., 2016. Beyond the conventional life cycle inventory in wastewater treatment plants. Sci. Total Environ. 553, 71–82.

[16]. Garrido-Baserba, M., Molinos-Senante, M., Abelleira-Pereira, J.M., Fdez-Güelfo, L.A., Poch, M., Hernández-Sancho, F., 2015. Selecting sewage sludge treatment alternatives in modern wastewater treatment plants using environmental decision support systems. J. Clean. Product. 107, 410–419.

[17]. de Faria AB, Spérandio M, Ahmadi A, Tiruta-Barna L. Evaluation of new alternatives in wastewater treatment plants based on dynamic modelling and life cycle assessment (DM-LCA). Water research. 2015 Nov 1;84:99-111.

[18]. Yoshida H, Clavreul J, Scheutz C, Christensen TH. Influence of data collection schemes on the Life Cycle Assessment of a municipal wastewater treatment plant. Water research. 2014 Jun 1;56:292-303.

[19]. Zhu ZJ, McBean EA. Selection of water treatment processes using Bayesian decision network analyses. Journal of Environmental Engineering and Science. 2007 Jan 1;6(1):95-102.

[20]. Finney BA, Gerheart RA. A User's Manual for WAWTTAR. Environmental Resources Engineering, Humboldt State University, Arcata, CA. 2004.

[21]. Iran Statistics Center, detailed results of the general population and housing census of Tehran, 1956_2016

[22]. Tehran Water and Wastewater Supply and Treatment Company, Access date 5 December 2019

[23]. http://eteachingplus.de/diagram/diagram-of-water-treatment ،Access data 5 December 2019

[24]. Easterby-Smith M, Lyles MA. The evolving field of organizational learning and knowledge management. Handbook of organizational learning and knowledge management. 2011;2:1-20.

[25]. Maier R, Hadrich T. Knowledge management systems. InEncyclopedia of Knowledge Management, Second Edition 2011 (pp. 779-790). IGI Global.

[26]. Liebowitz J, editor. Knowledge management handbook. CRC press; 1999 Feb 25.

[27]. Akbarian, H., Jalali, F. M., Gheibi, M., Hajiaghaei-Keshteli, M., Akrami, M., & Sarmah, A. K. A sustainable Decision Support System for soil bioremediation of toluene incorporating UN sustainable development goals. Environmental Pollution, 2022; 307, 119587.

[28]. Shahsavar, M. M., Akrami, M., Gheibi, M., Kavianpour, B., Fathollahi-Fard, A. M., & Behzadian, K. Constructing a smart framework for supplying the biogas energy in green buildings using an integration of response surface methodology, artificial intelligence and petri net modelling. Energy Conversion and Management, 2021; 248, 114794.

[29]. Zavadskas EK, Turskis Z, Kildienė S. State of art surveys of overviews on MCDM/MADM methods. Technological and economic development of economy. 2014 Jan 2;20(1):165-79.

[30]. Singh A, Malik SK. Major MCDM Techniques and their application-A Review. IOSR Journal of Engineering. 2014 May;4(5):15-25.

[31]. Velasquez M, Hester PT. An analysis of multi-criteria decision making methods. International Journal of Operations Research. 2013 May;10(2):56-66.

[32]. Das K, Behera RN. A survey on machine learning: concept, algorithms and applications. International Journal of Innovative Research in Computer and Communication Engineering. 2017 Feb;5(2):1301-9.

[33]. Zaidi SM, Chandola V, Allen MR, Sanyal J, Stewart RN, Bhaduri BL, McManamay RA. Machine learning for energy-water nexus: challenges and opportunities. Big Earth Data. 2018 Jul 3;2(3):228-67.

[34]. Kim YH, Im J, Ha HK, Choi JK, Ha S. Machine learning approaches to coastal water quality monitoring using GOCI satellite data. GIScience & Remote Sensing. 2014 Mar 4;51(2):158-74.

[35]. Zhang K, Achari G, Li H, Zargar A, Sadiq R. Machine learning approaches to predict coagulant dosage in water treatment plants. International Journal of System Assurance Engineering and Management. 2013 Jun 1;4(2):205-14.

[36]. Inoue J, Yamagata Y, Chen Y, Poskitt CM, Sun J. Anomaly detection for a water treatment system using unsupervised machine learning. In2017 IEEE International Conference on Data Mining Workshops (ICDMW) 2017 Nov 18 (pp. 1058-1065). IEEE.

[37]. Guo H, Jeong K, Lim J, Jo J, Kim YM, Park JP, Kim JH, Cho KH. Prediction of effluent concentration in a wastewater treatment plant using machine learning models. Journal of Environmental Sciences. 2015 Jun 1;32:90-101.

[38]. Li-juan W, Chao-bo C. Support vector machine applying in the prediction of effluent quality of sewage treatment plant with cyclic activated sludge system process. In2008 IEEE International Symposium on Knowledge Acquisition and Modeling Workshop 2008 Dec 21 (pp. 647-650). IEEE.

[39]. Mariano-Romero CE, Alcocer-Yamanaka VH, Morales EF. Multi-objective optimization of water-using systems. European Journal of Operational Research. 2007 Sep 16;181(3):1691-707.