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Review article

Digitalization of phosphorous removal process in biological wastewater treatment systems: Challenges, and way forward

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A R T I C L E I N F O

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A B S T R A C T

Phosphorus in wastewater poses a significant environmental threat, leading to water pollution and eutrophication. However, it plays a crucial role in the water-energy-resource recovery-environment (WERE) nexus. Recovering Phosphorus from wastewater can close the phosphorus loop, supporting circular economy principles by reusing it as fertilizer or in industrial applications. Despite the recognized importance of phosphorus recovery, there is a lack of analysis of the cyber-physical framework concerning the WERE nexus. Advanced methods like automatic control, optimal process technologies, artificial intelligence (AI), and life cycle assessment (LCA) have emerged to enhance wastewater treatment plants (WWTPs) operations focusing on improving effluent quality, energy efficiency, resource recovery, and reducing greenhouse gas (GHG) emissions. Providing insights into implementing modeling and simulation platforms, control, and optimization systems for Phosphorus recovery in WERE (P-WERE) in WWTPs is extremely important in WWTPs. This review highlights the valuable applications of AI algorithms, such as machine learning, deep learning, and explainable AI, for predicting phosphorus (P) dynamics in WWTPs. It emphasizes the importance of using AI to analyze microbial communities and optimize WWTPs for different various objectives. Additionally, it discusses the benefits of integrating mechanistic and data-driven models into plant-wide frameworks, which can enhance GHG simulation and enable simultaneous nitrogen (N) and Phosphorus (P) removal. The review underscores the significance of prioritizing recovery actions to redirect Phosphorus from effluent to reusable products for future considerations.

Nomenclature

A^2O	Anaerobic, anoxic and oxic	LBRF	LogitBoost random forest
AAD	Absolute average deviation	MLPNN	Multilayer perceptron neural network
ABRF	AdaBoost random forest	Mn	Manganese (mg/L)
ACO	Ant colony optimization	MF	Mean fitness
ADM	Anaerobic digestion mode	MLR	Multiple linear regression
AIG	Algorithm of Innovative Gunner	MFT	Multi-Frameworks Technique
AI	Artificial intelligence	MAPE	Mean absolute percentage error
ASM	Activated sludge model	MMA	Multi-Models Approach
ANFIS	Adaptive network-based fuzzy inference system	MLP	Multi-layer perceptron neural network
BOD	Biological oxygen demand	MSE	Mean square error

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BF	Hybrid beamforming	MgOH	Magnesium oxide
BRT	Boosted Regression Tree	MAE	Mean absolute error
BiLSTM	Bidirectional long short-term memory	MLSS	Mother liquor suspended solids
BN	Bayesian Networks	MUCT	Modified university of cape town
BRF	Bagging Random forest	RMSE	Root mean square error
BPNN	Backpropagation (BP) neural network algorithm	NN	Neural network
BWTP	Biological wastewater treatment plants	N	Nitrogen
CO_2	Carbon dioxide	N_2O	Nitrous oxide
CH_4	Methane	NH	Ammonia
COD	Chemical oxygen demand	NARXNN	Nonlinear autoregressive exogenous
DT	Decision tree	NO	Nitric oxide

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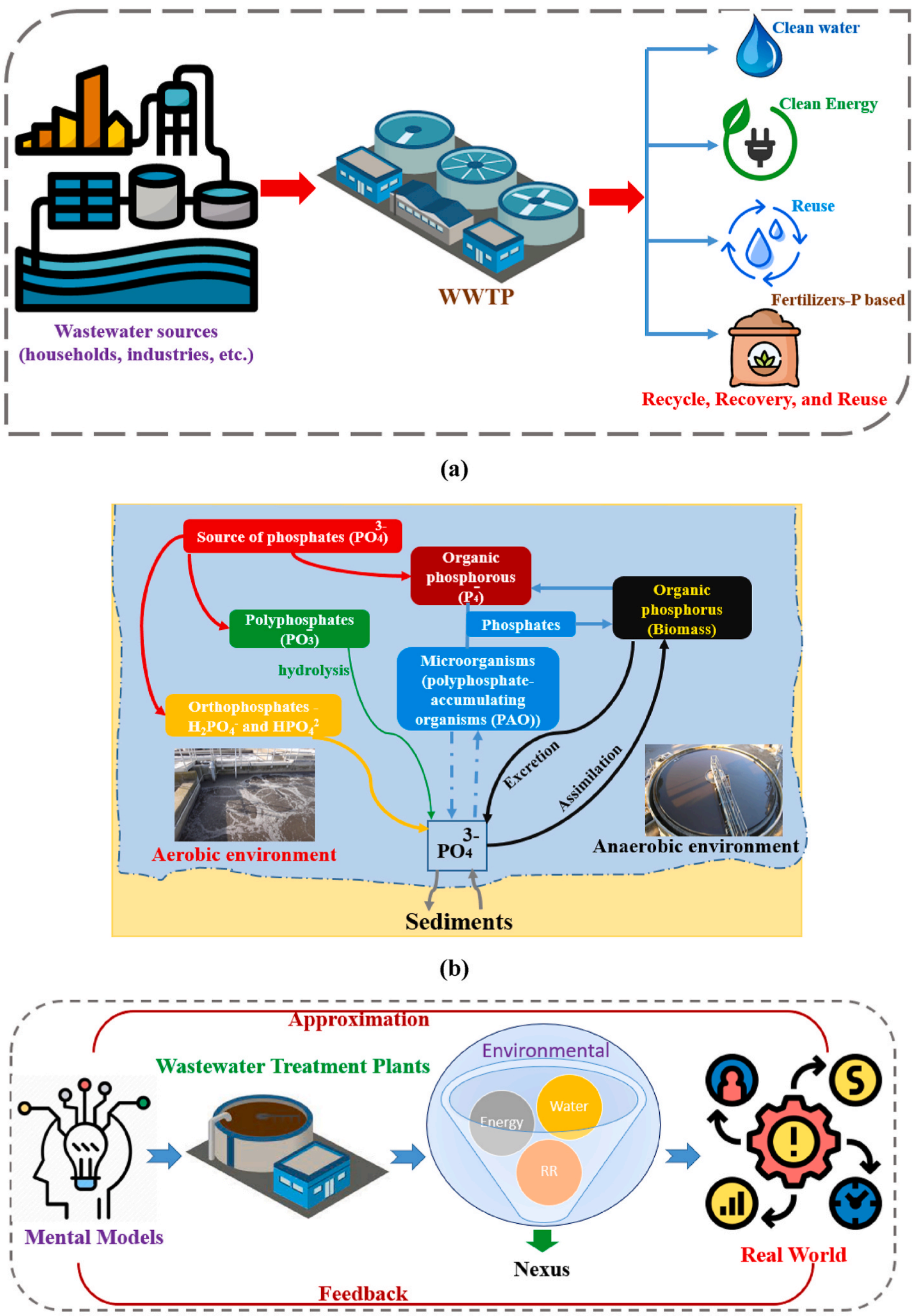
DO	Dissolved oxygen (mg/L)	NSGA-II	Multi-objective genetic algorithm
DNN	Deep neural network	PPV	Positive predictive value
DOC	Dissolved organic carbon (mg/L)	PS	Particle swam
EC	Electrical conductivity (μS/cm)	PCA	Principal component analysis
ELMNN	Extreme learning machine neural network	P	Phosphorous
EGB	Extreme gradient boosting	PI	Proportional integral
FA	Factor Analysis	Pr	Propranolol (ng/L)
FPI	Fractional order-PI	RF	Random forest
Fe	Iron	Q_{intr}	Internal recycle
$FeSO_4$	Iron sulfate	Q_w	External recycle
FLC	Fuzzy logic controller	RBFNN	Radial basis function neural network
FFNN	Feed-forward neural network	S	Sulfur
FMF	Fuzzy Membership Framework	SATS	Soil aquifer treatment systems
GEP	Gene expression programming	SSE	Sum of square-error
GHG	Greenhouse Gas	SDF	Standard DRASTIC-Fr Framework
GA	Genetic Algorithm	SS	Suspended solids
GFI	Groundwater Footprint index	SES	Single exponential smoothing
GPR	Gaussian Process Regression	SVM	supports vector machine
GRNN	Generalized regression neural network	SLA	Superposition-based learning algorithm
GMDHM	Group method of data handling model	STW	Sewage Treatment Works
HHO	Harris Hawk's optimization	SK-STW	Sai Kung
H-DO	Higher level-DO	SRT	Solid retention time
ICA	Independent Component Analysis	ST	Sha Tin
K_La	Oxygen mass transfer coefficient	SCI	Stonecutters Island
CNN	k-nearest neighbors neural network	SMT	Sham Tseng
LCA	Life cycle assessment	SWH	Shek Wu Hui
LR	Linear regression	R2	Coefficient of determination
LSSVR	Least-squares support vector regression	RF	Random forest
MPC	Model predictive control	RVM	Relevant Vector Machine
NMPC	Non-linear MPC	TKN	Total kjeldahl nitrogen
ENMPC	Economic NMPC	TP	Total Phosphorous
PI	Proportional integral	THP	Thermo hydrolysis process
PO_4	Orthophosphates	TN	Total nitrogen
PCA	Principle component analysis	TP	Tai Po
		TSS	Total suspended solids
		WO	Whale optimization
		XGB	Xtreme gradient boost
		VZIF	Vadose zone infiltration
		YL	Yuen Long

1. Introduction

The scarcity of natural resources has become a pressing issue, driven by rapid population growth and economic development. As a result, humans face many challenges, such as providing water, energy, and food, and protecting the environment. A key policy objective in protecting future generations is the development of sustainable and integrated strategies between the water, energy, food, and environment (WEFE) sectors (Longo et al., 2019). Nexus assessment emphasizes not just the connection between water and energy but also the network with other fields such as water-energy-food, water-energy-food-climate (WEFC), water-energy-pollution (WEP), and water-energy-resource recovery-environment (WERE) (Landa- Cansigno et al., 2020). The knowledge of the marine P cycle is only one aspect of humanity's interaction with this significant natural resource, and there are still many unknowns surrounding the future of marine P under anthropogenic change (Duhamel et al., 2021). Among possible denitrifying phosphorus-accumulating bacteria, *Enterobacter cloacae* show changes in the composition of the microbial community when it acclimated to various phosphorus-rich environments according to Wan et al. (2017). Climate change, shortage of fresh water, and environmental pollution have steadily risen to the forefront of public consciousness over the past few decades, elevating the importance of ecological issues and sustainable development (Yang et al., 2023). The use of the activated sludge process has been prevalent since the 1970s in WWTPs throughout the world. However, inadequate solids-liquid separation, sludge bulking, a large footprint, and recirculation flow requirements have rendered the widely used activated sludge process unsustainable (Bengtsson et al., 2019; Sarvajith and Nancharaiah, 2023). Nowadays, it is essential to operate WWTPs with lower operating costs, fewer greenhouse gas emissions, and discharges with higher effluent quality. Several factors, such as severe deterioration of groundwater quality in urban areas, make recycling of treated water and resource recovery a top priority. All reactors and settlers within WWTPs are affected by the significant settling of microorganisms during the operation and sedimentation process (Sheik et al., 2022b). Furthermore, the significant variations in flow rates and influent composition can cause disturbances, increasing the complexity of controlling WWTPs. Several forms of P are present in wastewater such as in particles, dissolved forms, and organic or inorganic forms (Liang et al., 2022). Water loss and P accumulation produce a huge one-way flow of geological P reserves into aquatic habitats (Amann et al., 2018; Pinelli et al., 2022). Designing microbial communities containing various polyphosphate-accumulating organisms (PAOs), aiming to potentially enhance efficiency and stability in processes, poses a considerable challenge, as indicated by recent findings by Roy et al. (2021). Phosphorus recovery would be limited by increased sludge production and decreased accessibility to P during intense chemical precipitation (Lei et al., 2021). A lot of attention has been paid to biological P removal in WWTPs, particularly the EBPR process (Flores-Alsina et al., 2016; Solon et al., 2017; Santos et al., 2020; Ikumi et al., 2020; Flores-Alsina et al., 2021). Chemical treatment is regarded as more expensive and environmentally harmful (Mbamba et al., 2019). In contrast, EBPR is entirely dependent on polyphosphate-accumulating organisms and a growing knowledge of these biochemical phenomena is gaining momentum. The growth and proliferation of PAOs are influenced by carbon, glycogen, and electron acceptors (Bunce et al., 2018). It is widely acknowledged that the EBPR process is prominent in WWTPs, but there is still a trade-off problem between N and P when trying to follow the legal upper limits. The reason for that is that P uptake is affected by nitrate interactions. The chemical oxygen demand (COD) ratio and the carbon source have a significant role in these P-removal process failures (Guerrero et al., 2014).

In some cases, such as under limited COD content in wastewater, the complete concurrent removal of N and P may not be possible (Guerrero et al., 2011). Since EBPR was not sufficient enough to remove large amounts of P in the WWTP processes, simultaneous biological and chemical (addition of carbon) precipitation removal was used (Garikiparthy et al., 2016). A bio-based P removal process can be improved by potential sludge generation and chemical dosages according to Srivastava and Kazmi (2023); Yuan et al. (2023). As part of the effluent treatment process, WWTPs are used to reduce the concentrations of organic matter, ammonia, nitrogen, chemical oxygen demand, biological oxygen demand, and P. A global focus has been placed on the recovery of P from sewage sludge, leading to extensive research and investigations in this area (Yu et al., 2022; Sarvajith Nancharaiah 2023). P-WERE nexus should be used to analyze holistically with potential techniques and biological cycles and reveal their interactions and feedback loops. The modeling of socio-economic (e.g. food) and non-economic (e.g. environment, climate) sectors requires a multi-sectoral system analysis framework that symbiotically manages different resources (e.g. water, energy). By examining the complex interactions and relationships between these sectors, synergies can be promoted, and antagonistic tensions reduced (Hülsmann et al., 2019). For this, the potential of digitalization in water and wastewater treatment is substantial. Systems analysis and assessment must be based on innovative approaches to achieve integrated management of WWTPs. Because of its ability to improve the efficiency, sustainability, and dependability of treatment operations, digitalization is becoming increasingly important for its sustainable operations (Sheik et al., 2023). The use of digital technologies allows for real-time control and surveillance, allowing operators to optimize the operation, trim energy consumption, and alleviate chemical use. Wastewater treatment plants may make more informed decisions about process enhancement, equipment maintenance, and resource allocation by using the potential of data-driven decision-making. Predictive maintenance, made feasible by digitalization, can minimize expensive malfunctions and downtime by regularly tracking equipment status (Liu et al., 2023). Furthermore, digital solutions assist compliance with severe environmental rules, ensuring that treatment operations continuously meet criteria and avoid legal liabilities. Digitalization, through the integration of the process models and control, life cycle assessment (LCA), and artificial intelligence (AI), may enable wastewater treatment plants to improve efficiency, adaptability, and projections for the future, eventually protecting public well-being and the surroundings (Solon et al., 2017; Li et al., 2022; Singh et al., 2022).

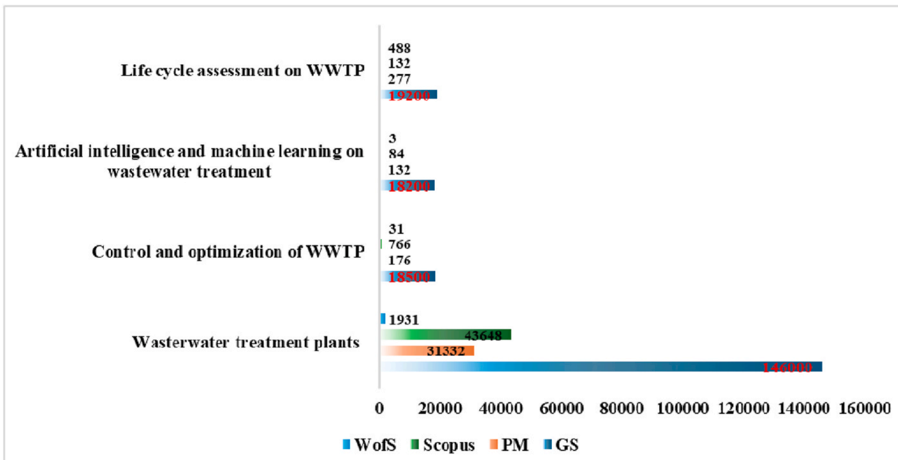
The smart water systems are an emerging technology for controlling physical systems using digital tools (e.g., use of sensors) (Wang et al.,



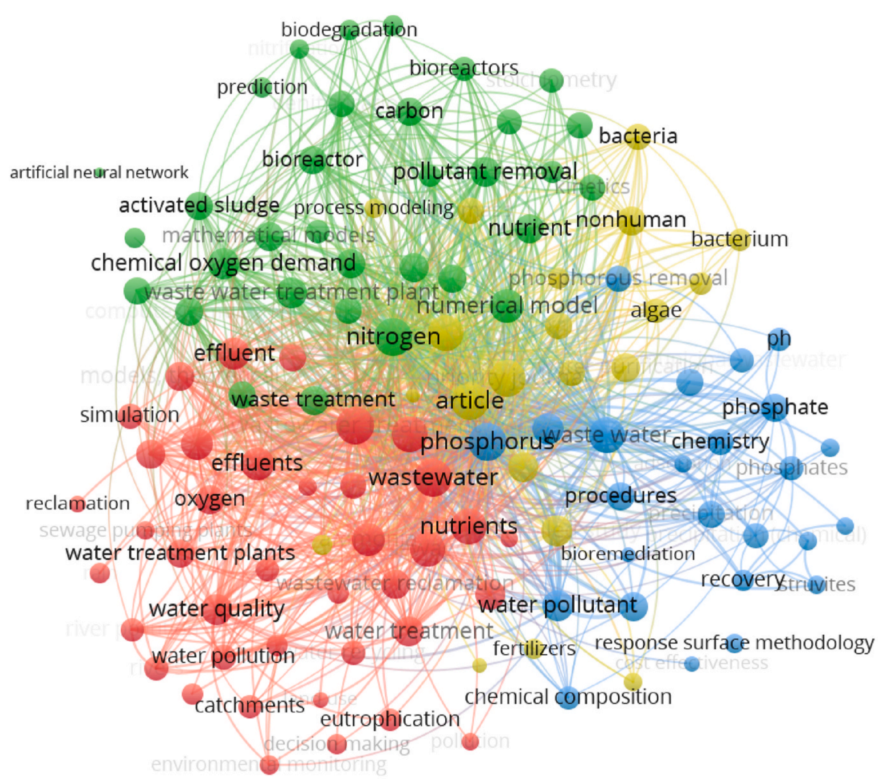
(c)

Fig. 1. **(a)** Wastewater resource via value-added products, **(b)** Summarizing P cycling in a P-containing wastewater treatment system, and **(c)** WWTP towards the WERE.

2008, 2015). Digital solutions, such as cutting-edge sensors and knowledge-driven evaluation, could provide multi-source information systems to support the decision-making process in wastewater treatment by providing real-time data. However, the smart water systems in WWTPs usually consist of various utilities operating subsystems that are designed as complex networks. Consequently, interoperability is a major issue for these integrated systems. Fig. 1 depicts the (a) wastewater resource via value-added products, (b) summarizing P cycling in a P-containing wastewater treatment system and (c) WWTPs towards the WERE. This review examines the tools and models employed to study the interdependencies and linkage among the P-based water, energy, resource recovery, and environment sectors, with a particular focus on WWTPs. The unique contribution of this review lies in its exploration of the integration of the P-WERE nexus with smart water and digitalized solutions, offering fresh and upgraded perspectives. The review is structured as follows: The initial section addresses the concept of the WERE nexus in the context of WWTPs, highlighting its significance, followed by an exploration of foot printing tools and models commonly used to quantify the interlinkages within urban-scale WWTPs. The subsequent section delves into the P-WERE nexus in precision smart water modeling with a specific emphasis on the reuse of treated water and resource recovery in simulation-based models with advanced applications such as BSM models, control strategies, LCA, and AI.



(a)



(b)

Fig. 2. Comparative bar graph literature survey of WWTP, AI and ML, control and optimization, LCA on P (b) Co-occurrence network map of author keywords.

2. Analysis of article keywords and current literature

After searching Google Scholar (GS), PUBMED (PM), Scopus, and Web of Science (WoS) databases, the number of publications for the keywords "WWTPs, Control and Optimization of WWTPs, AI and machine learning (ML) on WWTPs, and Life cycle assessment on WWTPs" are shown in Fig. 2(a): wastewater treatment plants: GS (146000), PM (31332), Scopus (43648), and WoS (1931). Control and optimization of WWTPs: GS (18500), PM (176), Scopus (766), and WoS (31). Artificial intelligence and machine learning on wastewater treatment: GS (18200), Scopus (132), PM (84), and WoS (3). Life cycle assessment on WWTP: GS (19200), PM (277), Scopus (132), and WoS (488). In summary, the number of publications for the provided keywords varied across the three databases. However, there are several articles from the provided references that are relevant to the keywords and provide insights into the optimization of WWTPs, P removal, the use of AI and ML for this purpose, and LCA. Information was gathered between 2013 and 2024, and each keyword has been checked individually.

The study begins with a list of keywords linked to direct wastewater, and other related topics (keywords). The following keywords were used in this study:' wastewater OR treatment, and phosphorous". Furthermore, the Scopus database, which is one of the most trustworthy scientific databases, has been chosen as this study's primary data source. A maximum of less than 2000 'new' OR 'highly cited' articles were retrieved and translated to CSV files for each round of search. VOSviewer, a freely available and freely accessible bibliometric tool, is used to evaluate information. Over 1835 publications in the fields of wastewater, phosphorus, and related topics were employed in this study for data collection and study. For specific topics like digitalization and wastewater treatment less than 100 publications in the period of 2013–2024. Following the loading of data into VOSviewer, data filtration was initiated to remove unrelated repetitive keywords (such as paper, study, etc.), and various combinations of the terms (wastewater and waste management) were merged and accounted for as one unique term. The initial data mapping result is shown in Fig. 2(b). The research on wastewater and phosphorus can be divided into three groups (colors). Large circles indicate the significance and repetition of keywords like wastewater, pollutant removals, and nutrients. Furthermore, the closer the distance between two items and the more prominent interactions between two items imply that there is an overlap among two keywords. Fig. 2(b) shows that the author keywords (Scopus database) allocated for modeling and wastewater treatment articles formed different clusters (by color), which depicted the global hotspots in the P-related field.

3. Process models for removal of phosphorus from wastewater

The strict effluent quality regulations have enabled significant advancements in wastewater treatment plant design. The activated sludge models are integrated with nitrification-denitrification with the enhanced biological phosphorus removal (EBPR) process in anaerobic, anoxic, and aerobic reactors in series i.e., A^2/O. These features, along with the modification of influent concentrations through pre-fermentation and/or primary sedimentation, produce a highly varied mixed culture of microbes (Ekama, 2011). These improvements have culminated in the development of sophisticated mathematical models that are frequently employed to explain the fundamental processes in WWTPs, both in the sludge line (ADM1-Batstone et al., 2002) and water line (ASM2d-Henze et al., 2000). A significant number of elements and procedures in the model have increased notably as ascribed to recent advances, involving an adequate description of the physicochemical processes associated with multi-phase P transformations in conjunction with plant-wide modeling (Flores-Alsina et al., 2016, 2022; Hauduc et al., 2015; Solon et al., 2015). There are numerous configurations which have been proposed in the literature (Metcalf et al., 2014; Ramin et al., 2022; Sheik et al., 2022a) to improve the uptake of volatile fatty acids (VFAs) by PAOs in anaerobic zones by altering the internal and external recycling sludge in WWTPs. The effectiveness of EBPR systems is primarily determined by the optimal enrichment of PAOs under both anaerobic and anoxic/aerobic environments (Ekama, 2011). According to the provided literature, for a system with low biodegradable COD and high levels of variability in influent concentrations, the University of Cape town (UCT), and Modified University of Cape town (MUCT) are determined to be resilient configurations for P removal (i.e., greater performance and lower degree of uncertainty) (Metcalf et al., 2014; Ramin et al., 2022; Al et al., 2019). Due to the fact both configurations allow for extremely minimal nitrate entry into the anaerobic reactor, the uncertainty in the influential TKN/COD ratio tends to not affect anaerobic capacity. Nevertheless, the plant's denitrification capability is harmed when fewer substrates become accessible for denitrification (Ramin et al., 2022). However, to reduce the amount of nitrate in returned activated sludge that enters the anaerobic zone, it was proposed that the A^2O and Johannesburg (JHB) process must control the internal nitrate recycle flow under uncertain or fluctuating influent TKN/COD ratios. This may also apply to UCT because in this case, internal mother liquor suspended solids recycle flow is removed from the same anoxic zone as underflow recycle flow. However, a sufficiently large anaerobic volume fraction is employed to mitigate the effect (Metcalf et al., 2014; Ramin et al., 2022). The robust reaction of UCT and MUCT to influent profile variation, which ensures both N and P removal within a lower solid retention time (SRT) change, is another operational benefit over A^2O and JHB. However, depending on the influent load, A^2O and JHB require modifications of SRT within a greater range, making the plant's operation more susceptible to the uncertainty of the influent profile (Zeng et al., 2014; Ramin et al., 2022; Metcalf et al., 2014).

Several biological wastewater treatment configurations (Ramin et al., 2022; Metcalf et al., 201) have been designed for improved P removal, often with the addition of chemicals. However, the capacity for sludge generation can also be reduced by reducing chemical dosages in an improved bio-removal process. Reversed-A^2O (R-A^2O) could undergo more thorough denitrification of nitrogen, which would improve bacteria's capacity to absorb P in aerobic conditions. Total phosphorus is more efficiently removed with the R-A^2O process than the A^2O process (Fang et al., 2016a; Sheik et al., 2022a). In practice, the plant-wide configuration is required to achieve P removal, but most model-based research concentrates on the secondary treatment in the WWTPs for the configuration adjustments. This modeling enables the assessment of different scenarios, such as variations in influent characteristics, process configurations, and operational conditions, to optimize the design of the WWTPs as a decision-making tool. Fig. S1 in the supplementary data depicts the P removal process in WWTP such as (a) A^2O (b) UCT (c) MUCT, (d) BSM2 at plant-wide level (e) JHB, and (f) R-A^2O. While the secondary, as well as plant-level treatment procedures used in WWTPs, are good at lowering organic matter, ammonia, and total suspended solids and they are not always successful at dissolved P removal. A few plant-wide therapies are as follows.

- In WWTPs, particulate phosphorus, often linked with organic matter and suspended solids, is typically eliminated through secondary settling processes. However, dissolved phosphorus poses a challenge as it may not be efficiently removed during this process, potentially leading to elevated levels of phosphorus in the effluent. The effectiveness of phosphorus removal in secondary treatment can fluctuate due to factors like seasonal changes and operational conditions. Variables such as temperature, pH, and the initial concentration of dissolved phosphorus in the influent can greatly influence the efficiency of secondary treatment operations. Understanding and managing these factors can significantly enhance phosphorus removal from secondary settling tanks, thus improving overall WWTP performance.
- The phosphorus removal process can behave dynamically depending on several variables, including influent composition, chemical

dosing methods, and microbial activity. It can be difficult to capture and reliably simulate these dynamics in plant-wide modeling models. Modeling WWTPs requires accounting for non-linearity, microbial interactions, input parameters, disturbances in operating conditions, and measurement errors, all of which can be challenging to capture comprehensively. Dynamics in plant-wide processes often evolve over time, with variables changing continuously. Capturing these time-dependent dynamics accurately requires sophisticated modeling techniques, such as differential equations or discrete event simulation. Inaccurate estimations of the effectiveness of P removal may result from oversimplification or inadequate depiction of dynamics. For the removal of P, chemical precipitation is frequently utilized, such as the addition of metal salts (such as alum or ferric chloride). The price of these chemicals can be high, particularly for big treatment facilities. Additionally, several variables, including temperature, alkalinity, and pH, affect the success of the chemical precipitation process.
- Due to the various interrelated processes involved, calibration and validation of plant-wide wastewater treatment models for P removal can be challenging. Validation against independent data is essential to determining the model's performance after calibration, which often calls for correct data. The findings of the simulation may be subject to uncertainty due to the difficulty of acquiring suitable data for calibration and validation purposes.

When running simulations of the whole wastewater treatment processes for P removal, it is crucial to be attentive to these limitations. To overcome these constraints, data collecting efforts and process validations must be improved, models must be calibrated using reliable data, and simulation results must be verified using further data (Flores-Alsina et al., 2016; Ramin et al., 2022). The resilience and dependability of the simulation results can also be gleaned from taking uncertainties into account and doing sensitivity assessments.

3.1. Modeling of biological phosphorus removal

Wastewater treatment models can improve performance, reduce costs, and improve understanding of how wastewater treatment processes work (Mbamba et al., 2016; Solon et al., 2017, 2019). Modeling WWTPs is often a complex undertaking that involves multiple layers of analysis. At a fundamental level, mathematical models are employed to capture the dynamic nature of activated sludge activities in WWTPs. However, constructing models for WWTPs is challenging due to the complex interplay of various kinetic, stoichiometric, and state characteristics that regulate process reactions. Significant progress has been made in developing metabolic models for polyphosphate-accumulating organisms (PAOs) by incorporating diverse carbon sources, including amino acids, glucose, lactate, and succinate. The latest developments in PAO metabolic modeling include advancements in incorporating diverse carbon sources and refining kinetic and stoichiometric parameters to better simulate the behavior of these organisms in biological wastewater treatment plants. Additionally, there have been efforts to integrate omics data (such as genomics, transcriptomics, and proteomics) to improve model accuracy and predict metabolic pathways more effectively. Furthermore, there is ongoing research into developing dynamic models that can account for variations in environmental conditions and substrate availability, allowing for more robust predictions and optimization of phosphorus removal processes in WWTPs. Unfortunately, existing models have not fully accounted for concurrent phenomena, prompting the International Water Association (IWA) to establish a task group to develop a comprehensive mathematical model for WWTPs (Henze et al., 2000). This model aims to realistically predict the efficiency of single sludge systems, encompassing carbon oxidation, hydrolysis, nitrification, denitrification, and the growth of PAOs, according to Henze et al. (2000); Rieger et al. (2001); Solon et al. (2017); Solon et al. (2019); Flores-Alsina et al. (2016); Monje et al. (2022). It is crucial to implement control strategies to ensure WWTPs operate efficiently. Even though many control approaches have been proposed throughout history, their comparison and analysis cannot be understood based on simulation alone. A benchmark model developed by the IWA is introduced to address these intricate issues and provide a comparison and evaluation of different control applications (Flores-Alsina et al., 2016; Gernaey and Jeppsson, 2014; Nopens et al., 2010). To describe the main reactions in the water line, modified ASM models are used such as ASM2d, and ASM3bioP (Henze et al., 2000; Sheik et al., 2022b). During microbial decay, electron acceptor dependency caused by magnesium and potassium are accounted for, as well as oxidation and reduction reactions involving sulfur (S) and iron (Fe). The anaerobic digestion model No.1 (ADM1) is also integrated with P, S, and Fe reactions that are reported in Batstone et al. (2002); Flores-Alsina et al. (2016); Ikumi and Harding (2020). The total suspended solids differentiation between organic and inorganic compounds in the ASM and ADM as discussed by Ekama and Wentzel (2004) is explicitly outlined. Detailed descriptions of the extended ASM and ADM models, along with their parameter values, are provided by Flores-Alsina et al. (2021) and Solon et al. (2017). In the ADM, the decay of PAO lead to the release of accumulated phosphorus in the activated sludge section. Additionally, other organic particulates like biomass, lipids, and inert are also reported (Ikumi and Harding, 2020). Inorganic precipitates, such as struvite and calcium phosphate, are formed in a separate fraction. Notably, calcium and magnesium cations in the anaerobic digester play a crucial role in this process, as discussed by Mbamba et al. (2015, 2016), and Solon et al. (2019). The most soluble portion, obtained by using centrate, is returned to the water line. During the thermal hydrolysis process, phosphorus is generated by combining non-biodegradable organic compounds with soluble and particulate phosphorus compounds. Importantly, the formation of phosphorus compounds with non-biodegradable organic compounds does not impact the overall efficiency of phosphorus removal, as highlighted by Flores-Alsina et al. (2021). According to Flores-Alsina et al. (2022), a physicochemical model yields comparable results when applied to chemistry models of high complexity at the plan-wide level.

3.2. Challenges in the mathematical modeling of P removal in WWTP

- Microorganisms are involved in the biological phosphorus removal process, and depending on variables such as temperature, pH, and influent characteristics, they may behave differently. It can be difficult to precisely model these biological processes.
- The mathematical model must frequently be calibrated to match real-world facts to be accurate. It might be difficult and time-consuming to select the appropriate parameters and coefficients for the model.
- Interactions with other pollutants in the wastewater, such as nitrogen compounds, may affect the removal of phosphorus. The complexity of the modeling process can increase by taking these relationships into account.
- Time-dependent variables notably influent fluctuations and sludge age frequently have an impact on the removal of phosphorus. It can be challenging to model these dynamic processes.

3.3. Benchmark simulation models (BSMs)

A benchmark model developed by the IWA is introduced to address these intricate issues and provide a comparison and evaluation of different control applications (Flores-Alsina et al., 2016; Gernaey and Jeppsson, 2014; Nopens et al., 2010). Numerous studies (Flores-Alsina et al., 2016; Henze et al., 2000; Nopens et al., 2010; Solon et al., 2017; Takács et al., 1991) have demonstrated the success of BSMs such as BSM1, BSM2, BSM2P, etc. These models have been specifically designed to assess the effectiveness of modeling and control techniques for WWTPs (Gernaey and Jeppsson, 2014). BSMs and their expansions have become pivotal in evaluating and implementing management strategies for WWTPs. Over time, the BSM has emerged as a standardized framework for comparing various control strategies (Copp, 2002). The BSM serves as a comprehensive platform encompassing a predefined plant configuration, bioprocess models, influent loads, sensors, actuators, and a set of evaluation criteria. Within this framework, various standardized BSM models exist, built upon activated sludge process models. For instance, BSM1-P represents an anaerobic, anoxic, aerobic process followed by sedimentation (Sheik et al., 2022b; Solon, 2015). Additionally, there are plant-wide extended models such as BSM2-P, BSM2PSFe which include an activated sludge process, primary and secondary sedimentation units, a thickener, anaerobic digestion unit, storage unit, and a dewatering unit with both internal and external recycle (Flores-Alsina et al., 2016; Sheik et al., 2022c; Solon et al., 2017, 2019). Additionally, incorporation of the struvite unit as a resource recovery unit in the BSM2P platform. The basic component of fertilizers, as well as slow-release fertilizers, can be made from struvite. Sludge from the dewatering unit is treated with sodium hydroxide, and magnesium dosages to form P-based fertilizers (Sheik et al., 2022c; Solon et al., 2017, 2019). Using the ASM2d-N_2O model based on Massara et al. (2018), and Solís et al. (2022) improved the simulation of N_2O emissions in the BSM-PSFe-GHG (Flores-Alsina et al., 2011) with a stripping model. An analysis of the literature revealed three pathways for N_2O production, especially those that are produced by PAOs during denitrification, and that the ADM1 model relates P, S, and Fe, and detailed how they interact biologically and chemically. An updated model of the N and P removal system has been developed to improve the performance and nutrient recovery of WWTPs using new control strategies and process options. Through multivariate and multi-objective approaches, it is possible to correlate energy consumption or operational costs with WWTPs performance for the optimization of the performance (Qiao and Zhang, 2018; Zhang et al., 2014). Different operating strategies were evaluated using LCAs combined with BSM2 (Arnell et al., 2017; Flores-Alsina et al., 2010). The key features of developing integrated wastewater models, the steps in developing them, calibration, validation, optimization, and uncertainty have already been discussed elsewhere (Arashiro et al., 2022; Copp, 2002; Flores-Alsina et al., 2022; Gernaey and Jeppsson, 2014; Henze et al., 2000; Kar et al., 2023). The various models of benchmark mark simulation models are reported in Table 1.

Table 1
Selection of BSMs for the operation of P removal in WWTP.

Models (BSM)	State variables	Substrates and ASM	Process	References
BSM1-P	19	CNP, and ASM2d	21	Henze et al. (2000)
BSM1-BioP	17	CNP, and ASM3+BioP	23	(Meijer, 2004; Solon, 2015)
BSM1-Technical University Denmark	18	CNP, and ASM2d + TUD	22	(Meijer, 2004)
BSM1-MUCT	16	CNP + ASM2d	35	(Hu et al., 2007)
BSM2P	36	CNP, and ASM2d	–	(Flores-Alsina et al., 2016; Solon et al., 2017)
BSM-Meta-ASM		CNP, metals and ASM2d	110	Santos et al. (2020)
BSMPSFe	52	CNPSFe, and ASM2d	55	(Sheik et al., 2022c; Solon et al., 2017)
BSM2PSFe-GHG	52	CNPSFe, and ASM2d	55	Solís, et al. (2022)
BSM2PSFe-Thermohydro pyrolysis	52	CNPSFe, and ASM2d	55	Flores-Alsina et al. (2021)
Industrial-WWTP	5	CNPSFe, and ASM2d	–	Monje et al. (2022)

3.4. Process control and simulations as energy tapping option

The use of process control in WWTPs facilities enables them to operate at peak efficiency, extending their long run and lowering their unit product as well as operating costs (Agarwal et al., 2016; Åmand et al., 2013). Several feed-forward controllers have been applied to WWTPs to enhance effluent quality and performance, particularly in biological N and organic matter removal (Nopens et al., 2010; Tejaswini et al., 2020). To meet the necessary P discharge levels, improved organic P removal is considered the most reasonable approach (Solon et al., 2017). It is still uncommon for researchers to implement optimal control systems for P-removal in complete WWTPs. There is potential for enhancing the chances of explicitly controlling discharge P composition through advanced control frameworks (Sheik et al., 2022c; Solís et al., 2022; Solon et al., 2019). In BSM1, 2P, 2PSFe, and 2PSFe-THP, four different control schemes (C1: dissolved oxygen (DO)-controller, C2: DO- controller and nitrous oxide (NO) controller, and C3: ammonia (NH)-DO cascade controller, and C4: total suspended solid controller; C5: phosphorus-based controller) were used with different control combinations as well as the advanced and intelligent controller (Dey et al., 2023; Sheik et al., 2021; Solís et al., 2022; Solon et al., 2017). A DO set-point of 2 gO_2/m^3 under appropriate SRT and carbon source addition could provide the optimal sustainable operation of wastewater treatment without compromising effluent quality index (EQI), operational cost index (OCI), or GHG emissions. Four scenarios were simulated to assess the effects of operational conditions on the EQI, OCI, and GHG emissions based on two proportional-integral (PI) control loops (DO-PI controller and NO-PI controller) applied in BSM2P (Sheik et al., 2021; Solís et al., 2022). According to the authors' findings, plant wide WWTPs may experience higher GHG emissions because of local energy optimization methods (such as aeration energy savings). Changes in main clarifier efficiency have a minimal impact on total GHG emissions, but they have a significant impact on EQI and OCI. The appropriate configuration of control/operational parameters (such as DO, SRT) and the regulation of DO, NO, and NH concentrations play a crucial role in tandem, as is clear. Huang et al. (2020) deployed three DO-PI controllers in three aerobic tanks, respectively, in the integrated model of BSM1 and GHG emission model, to further examine the impact of DO control on various GHG emission sources. The simulation findings demonstrate how DO management helps to reduce GHG emissions. The carbon dioxide consumption during the nitrification process and the energy savings from the aerator are the key drivers of the GHG reduction achieved by using the DO control technique. Traditional PI controllers were used in the research mentioned above. More creative control methods have been created in recent years to reduce GHG emissions, maintain high-quality effluent, and lower operational expenses. Combination or integration is one form of enhanced control approach. Table 2 reports the state of the art on applying control strategies of P in secondary and plant-level treatments. The availability of readily degradable carbon substrates may limit the rate of denitrification in activated sludge systems using external carbon sources (methanol or acetic acid). The method helps to reduce nitrate and nitrite accumulation during peak loading by increasing denitrification rates on demand. However, this process does require the addition of a carbon source in the anaerobic tank, leading to increased operating costs on high dosages (Guerrero et al., 2014; Nair et al., 2021; Sheik et al., 2022a). Insoluble metal phosphates and hydroxides are added to wastewater. Wastewater alkalinity and orthophosphate concentration are determined by precipitates formed with metals. Typically, a metal dosage is added to the aerobic reactor, and excessive doses will increase operational costs (Guerrero et al., 2014; Mbamba et al., 2016; Sheik et al., 2022a). In conjunction with GHG emissions indicators, WWTPs operation/control may become more challenging, especially as performance indicators increase. The application of conventional control methods or optimization strategies alone is not adequate for achieving satisfactory performance. In previous studies, both optimization and control have been emphasized.

Table 2
Control strategies of P in secondary and plant level WWTP.

S. No	ASM	BSM	Control Algorithm	Control variables	Manipulating variables	Effluent quality (EQ)	Energy cost (EC)	Comment	Reference
Control combinations employed in secondary treatment (BSM1P)									
1	A^2/O (ASM2d)	BSM1P	PI, metal, carbon dosages	DO	K_La	Improved EQ	EC increases	Improved P removal	(Gernaey et al., 2004)
2	A^2/O (ASM2d)	BSM1P	PI	Different DO, NO, NH, TSS, PO_4	K_La, H-DO, Q_w, Q_{intr}	Improved EQ	EC increases	Improved P removal	(Ingildsen et al., 2006)
3	A^2/O (ASM2d)	BSM1P	PID	DO	K_La	Improved EQ	EC reduction achieved	Improved P removal	(Shen et al., 2010)
4	A^2/O (ASM2d)	BSM1P	Cascade MPC, PI	DO, NH, NO	K_La, H-DO, Q_{intr}	Improved EQ	EC increases	Improved P removal	(Liu et al., 2012)
5	A^2/O (ASM2d)	BSM1P	PI	Different DO, TSS, NH	K_La, $Q_{w,}Q_{intr}$	Improved EQ	EC increases	Improved P removal	(Xu and Vilanova, 2013)
6	A^2/O (ASM2d)	BSM1P	PI, override control	NO, PO_4	Qintr, NO	Improved EQ	EC increases	Improved P removal	Guerrero et al. (2014)
7	A^2/O (ASM2d	BSM1P	PI, Fuzzy	DO, NO	K_La, Q_{intr}	Improved EQ	EC increases	Improved P removal	(Xu and Vilanova, 2015)
8	A^2/O (ASM2d)	BSM1P	PI, MPC	DO, NO	K_La, Q_{intr}	Improved EQ	EC increases	Improved EQ	(Hongyang et al., 2018)
9	A^2/O (ASM2d)	BSM1P	PI	DO, TSS, $PO_{4,}$ NH, NO	K_La, H-DO, $Q_{r,}$ QW	Improved EQ	EC increases	Improved EQ	(Luca et al., 2019)
10	A2/O (ASM2d)	BSM1P	Robust optimal control, FNN	DO, NH, NO	K_La, H-DO, Q_{intr}	Improved EQ	EC decreases	Improved P removal	(Han et al., 2022)
11	A^2/O (ASM3bioP)	BSM1P	PI, Oveide, Fuzzy	DO, NH, PO_4, NO	K_La, H-DO, NO and Q_{intr}	Improved EQ	EC increases	Improved P removal	(Sheik et al., 2022b)
12	A^2/O, R-A^2O, I-A^2O (ASM2d)	BSM1P	PI	DO-carbon and metal dosages	K_La	Improved EQ	EC increases	Improved P removal	(Sheik et al., 2022a)
13	A^2O (ASM3bioP)	BSM1P	FPI, Fuzzy	DO, NO, and NH	K_La, H-DO, and Qintr	Improved EQ	EC increases	Improved P removal	Dey et al. (2023)
Control combinations employed in plant-wide treatment (BSM2P)									
1	A^2O (ASM2d)	BSM2P & BSM2PSFe	PI, Mg dosages	DO, TSS, and NH	K_La, H-DO, Q_W	Improved EQ	EC and OC decreases	Improved P removal	Solon et al. (2017)
2	MBR (ASM2d)	BSM2P-MBR	PI, Iron dosages	DO, NO, $FeSO_4$ dosages	K_La, and Q_{intr}	Improved EQ	EC and OC decreases	Improved P removal	Mbamba et al. (2019)
3	A^2O (ASM2d)	BSM2P	PI, MPC, Fuzzy	DO, NO, NH	K_La, H-DO Q_{intr}	Improved EQ	EC increases	Improved P removal	Sheik et al. (2021)
4	A^2O (ASM2d)	BSM2Pd	EMPC	MgOH dosages	P, flow	Improved resource recovery	EC and OC decreases	Improved P removal	Nair et al. (2021)
5	A^2O (ASM2d)	BSM2PSFe	PI	DO, NO, TSS, MgOH, N_2O, NH	K_La, H-DO, Q_W	Improved EQ	EC and OC decreases	Improved P removal	Solís et al. (2022)
6	A^2O (ASM2d)	BSM2PSFe	PI, Fuzzy	DO, NH	K_La, H-DO	Improved EQ	EC increases	Improved P removal	(Sheik et al., 2022c)

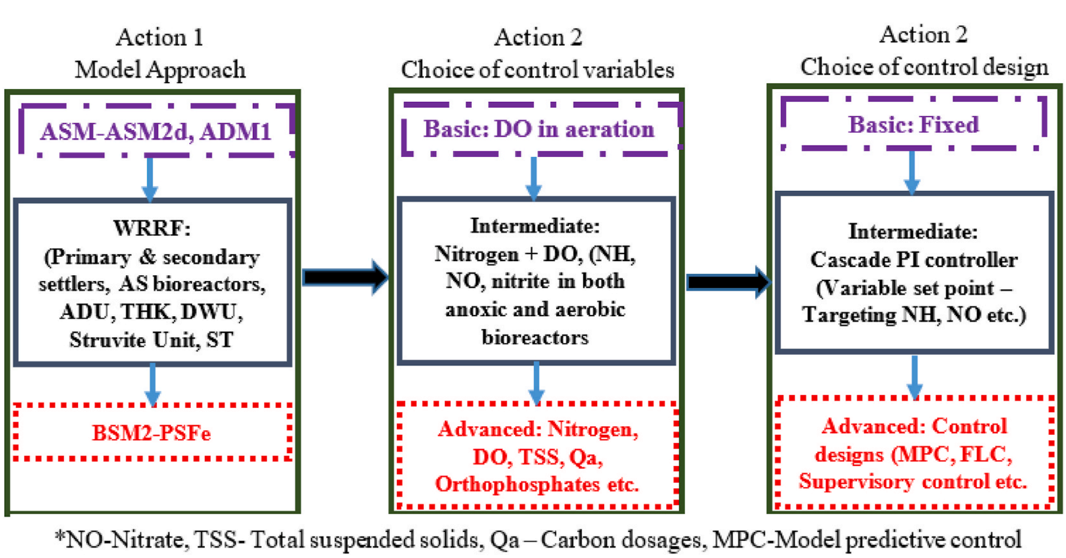


Fig. 3. Systematic approach of control strategies.

Moreover, nitrous oxide (N_2O) emissions have generally received more attention because N_2O accounts for a significant proportion of the total carbon footprint, and since mainstream processes have difficulty recovering energy from N_2O emissions (Wu et al., 2020). The heuristic fuzzy controller was designed at the sequential batch reactor, which noticed all pollutant concentrations were within regulatory limits. The cost savings were greater than 9%. The outflow pollutant regulations were also met at the same time. The DO control was of a high grade with hog P removal (Piotrowski, 2020). It is optional to appropriately simplify or approximate models, which saves on the enormous computational expenses associated with sophisticated mechanistic models. The optimization of control/operation parameters can be seen as a multi-objective optimization issue given the increasing performance demands of WWTPs. The optimal operating parameters obtained through the optimization solution can directly influence how wastewater treatment should operate, and the optimal control parameters can be added to the control strategy design unit to produce an optimal control strategy that takes the trade-off of multiple objectives into account. Fig. 3 depicts (a) a systematic approach of control strategies, and (b) feedback control schemes. Research on improving the operational management of WWTPs is typically still primarily concentrated on control or optimization approaches considering water quality, operational expenses, or energy usage. The wastewater treatment process must operate at a low carbon intensity if global GHG emissions and nutrients are to be reduced, and longer-term consideration will also be given to more detrimental environmental effects. The autonomous control and optimal operation of sustainable WWTPs present certain challenges and opportunities from the perspective of control strategies. Most of the manipulating variables deal with P removal such as SRT, TSS, chemical dosages, and sludge control strategies are used mostly in classical PI control. It needed an advanced novel and intelligent control application to deal with more productive plant performance.

- To formulate mitigation control strategies for specific WWTPs, the plant-wide model must be further developed by integrating mechanistic and data-driven models for effluent quality, operational cost, and GHG simulation.
- Indeed, from the literature and practical observations, it is evident that EBPR processes can be relatively slow compared to other wastewater treatment methods. Several reasons contribute to this characteristic: a) Biological nature: Biological processes inherently take time to reach optimal performance levels due to microbial growth rates, and the time required for acclimation to specific conditions (Diaz et al., 2022). (b) Sensitivity to operating conditions: Any fluctuations in temperature, pH, and nutrient availability parameters can affect the performance of the process and may require adjustments to optimize phosphorus removal efficiency (Zhang et al., 2011). c) Competing microbial processes: Other microbial processes occurring within the treatment system, such as denitrification or sulfate reduction, may compete with EBPR for resources and influence the overall treatment efficiency (Wu et al., 2023). d) Inhibitory Substances: The presence of inhibitory substances, such as heavy metals or certain organic compounds, can adversely affect the growth and activity of microorganisms involved in EBPR, leading to slower phosphorus removal rates (Klein et al., 2020). e) Carbon source limitation: In some cases, the limited availability of organic carbon in wastewater influent can restrict the rate of phosphorus removal, resulting in slower overall treatment kinetics (Meng et al., 2023). This leads to a process being altered or disturbed, it may take the microbial community hours or even days to adjust and effectively remove P. This sluggish response reduces the ability of control systems to swiftly adapt to shifting conditions.
- In the process of treating wastewater, P and N removal are frequently combined. Control measures intended to maximize P removal may unintentionally impact nitrogen removal procedures or lead to nutrient imbalances. It can be difficult to strike a compromise between accomplishing effective P removal and preserving the stability and performance of the entire process.

To overcome these constraints, a complete strategy combining cutting-edge monitoring technology, precise modeling, adaptive and intelligent control (model predictive controller (MPC), nonlinear MPC (NMPC), economic NMPC (ENMPC), fuzzy logic controllers, etc.) algorithms, and process optimization techniques is needed (Sheik et al., 2023). There are continuous attempts to improve real-time measuring capabilities, increase understanding of P removal mechanisms, and create more effective and long-lasting control techniques for P removal in wastewater treatment facilities.

3.5. Life cycle assessment

Different wastewater-based P recovery and reuse options have been assessed using LCA according to Diaz-Elsayed et al. (2020) and Lam et al. (2020). LCA serves as a valuable tool for comparing various technological options, identifying areas of concern in terms of environmental impact, and gaining insights into environmental trade-offs. These technologies encompassed the recovery of P from the liquid phase, sewage sludge, and sludge ashes. The findings revealed that the recovery from the liquid phase, such as the precipitation of struvite and calcium phosphorous (CaP) from sludge digester liquors, generally resulted in lower GHG emissions and reduced energy demand (Bradford-Hartke et al., 2015). For the design and operation of WWTPs and P recovery process, the process perspective is useful for assessing environmental impacts (also called the waste management perspective). However, the end users of recovered P products are unaware of the lifecycle environmental impacts of using these recovered products (Lam et al., 2020). Although LCA has many advantages, it does have some limitations. For instance, there are differences between papers in terms of results and influence indicators. Several reasons may be responsible for this, such as differences in assessment methods used, simulated inventory data, and the integration of different models to quantify the environmental impacts (Zang et al., 2015). The economic variables are excluded from LCA because they could affect the control strategies. The environmental impacts of WWTPs are assessed in detail using LCA, but their economic effects are not considered. A third limitation of the life cycle inventory is the availability and quantity of data. Researchers used secondary data in some cases to model effluent emissions (Niero et al., 2014). Another report (Corominas et al., 2020) determined impact categories based on site characteristics. It also reveals disparities in the effects of manufacturing phosphate fertilizer from diffuse contrast to concentrated P resources. Part of the environmental costs of WWTPs are allocated to sludge production. Here the computation is done on three average ratios of the gross effects of various combinations of the processes used to produce phosphate fertilizer based on sludge compared to the methods used to produce Trisodium phosphate (TSP) to analyze these variations (Tomei et al., 2016).

- Influence of P recovery process/impact of TSP production
- TSP production/effect of sludge generation process + impact of P recovery procedure).
- Effect of TSP production throughout the whole life cycle of sludge-based fertilizer.

Sena and Hicks (2018) conducted a review, and they found that several authors describe a functional unit that focuses on exploiting struvite precipitation to recover or remove P from the waste stream. They conducted their analyses from a "waste" LCA perspective as a result, failing to account for upstream costs of wastewater treatment when estimating the environmental effects of struvite production. The fact that some of them rely on their P recovery methods on waste feedstock makes it evident that they adopt the "zero burden assumption" (Hörtenhuber et al., 2019). Other researchers, such as Linderholm et al.

(2012), contrast the application of mineral fertilizers using TSP with fertilizing using P recovered from WWTPs. The sludge treatment and wastewater treatment lines are not considered to be part of their system. The literature found that P recovery had a climate change impact that was 3–557 times greater than the sum of the TSP manufacturing process, their analysis estimated that struvite precipitation had slightly less of an impact on climate change than mineral fertilizers (Sena and Hicks, 2018). The authors conclude that struvite precipitation offers more advantages than disadvantages as compared to conventional fertilizer production. In general, studies like those of Johansson et al. (2008) and

Table 3
Literature summary of studies used LCA approach based on the P.

S. No	Purpose	Software	Parameters employed	Remarks	Reference
1	LCA study is being conducted in Denmark with the goal of comparing the environmental performance of several cutting-edge WW treatment methods.	Simapro software	pH, COD, TN, TP, metals, and TSS	The findings indicated that recycling P to agricultural soils appears to be a more sustainable alternative to incinerating sludge for the impact categories related to climate change and fossil fuel depletion. However, the uncertainty and sensitivity analyses indicated that no firm findings could be made for the impact categories relating to eutrophication and toxicity.	Niero et al. (2014)
2	The goal of this study is to compare three prospective approaches in order to better understand how treating agricultural wastes (such as maize stover, dairy manure, and tomato residues) may affect the ecosystem.	OpenLCA software (version 1.5.0)	TSS, TN, TP, K, VSS,	If anaerobic digestion is employed before composting, the potential for eutrophication, global warming, acidification, and ecotoxicity are all significantly reduced. The transportation distance scenario study revealed that the LCA results were significantly impacted by the location decision.	(Li et al. 2018)
3	Comparing emerging and traditional WWTP processes, as well as the LCA and economic evaluation of developing WWTP processes	GPS-X software	Flow, TSS, COD, BOD, TN, TP	An ecologically friendly and economically feasible method was proposed for the implementation of WWTPs.	(Rashidi et al., 2018)
4	This study sought to determine whether recovering dissipated P by creating phosphate fertilizer based on sludge can be a viable substitute for creating mineral fertilizers from phosphate rocks.	GaBi® v6	Geneal data, with water quality parameters (COD, TKN, TSS, TP, TOC)	The findings showed that the manufacturing of phosphate fertilizers based on sewage depletes resources that might be more important than P. Although the main goal of P recovery was to decrease mineral P depletion, resource criticality has since grown to be a major problem and has to be properly integrated into LCIA.	(Pradel and Aissani, 2019)
5	LCA is used to compare the environmental effects of using natural gas or biogas to supply the necessary energy for the WWTP's methods for treating WW.	SimaPro 7.0	TSS, TKN, TP, CO_2, NO_2, SO_2, CO, metals	Form LCA study, it was noticed that surface water resources suffer significant quality losses when the treated wastewater from the WWTP is released into them. By using biogas instead of natural gas, Tehran's WWTP significantly reduces its negative environmental effects.	(Tabesh et al., 2019)
6	To systematically investigate the environmental effects of choosing a WWTP technology with various influent concentrations and effluent standards, as well as the integration of resource recovery schemes.	BioWin software (v. 5.2)	COD, BOD, TSS, TN, TP, NH	The outcomes demonstrated the trade-off between good effluent quality and associated costs and environmental and economic harm. For a high concentration WWTP, implementing the resource recovery procedure proved more profitable.	(Zhang et al., 2020)
7	This study evaluates the costs and environmental effects of three recommended retrofits of WWTFs that consider the thermochemical conversion technologies of hydrothermal liquefaction, slow pyrolysis, and fast pyrolysis, in addition to sophisticated bioreactors.	GPS-X software	TP, Resource recovery	The retrofitting design with hydrothermal liquefaction and an up-flow anaerobic sludge blanket have the highest net present value (NPV) of \$177.36 MM over a 20-year plant lifetime despite 15% higher annual production costs than the reference design, according to the results when compared to the reference design.	(Tian et al., 2020)
8	Using multi-agent deep reinforcement learning (MADRL) for simultaneous optimization of dissolved oxygen (DO) and chemical dosage, optimized dissolved oxygen levels and chemical dose.	GPS-X 8.0		LCA based optimization is found to have low environmental impacts such as cost, energy use, and greenhouse gas emissions when compared to a baseline scenario.	(Chen et al., 2021)
9	This study investigated a new electrochemical method for precipitating struvite using a sacrificial magnesium anode and then producing hydrogen gas. This study sought to evaluate the method's projected life cycle and cost.	SimaPro (v.9.1)	Mg, NH, PO_4, Resource recovery	Both the effects of terrestrial acidification and aquatic eutrophication were diminished by struvite recovery. For numerous impact categories, trade-offs between the advantages of struvite and the costs of electrode manufacture have been identified.	(Morrissey et al., 2022)
10	This study's objective was to do an environmental assessment on a BNR system treating municipal WW using mathematical modeling and LCA approach.	Simapro 8.4	NH, TP, TSS, COD, SRT, TN	The study highlights the value of environmental credits generated by recovering energy from biogas and shows that variances in operating conditions had a minimal impact on environmental performance in WWTPs with equivalent power consumption.	(Daskiran et al., 2022)
11	By air-stripping ammonia from WWTP side streams at various nitrogen concentrations, LCA will be used to examine the environmental effects of producing AS fertilizer.	SimaPro software	NH, TN, TP, GHG	Even though recovering ammonia at high concentrations is environmentally beneficial, it can also support minimal AS production while having a smaller environmental impact.	Kar et al. (2023)
12	The current study was designed to address the knowledge gaps and upcoming issues in the highly advanced WW treatment technologies in an effort to give a combined environmental economic and energy-based evaluation of WWTPs.	GPS-X 8.0	BOD, COD, NH, TSS, VSS, TN, TP, electricity, heat, costs	His study assessed the possibilities for use in real-world applications of SBR, OAO, and OA systems. According to the optimization methodology, the SBR configuration had the highest nitrogen removal effectiveness (98.74%).	(Nowrouzi et al., 2023)

Bradford-Hartke et al. (2015) highlight the net environmental advantages of struvite precipitation relative to a reference scenario. In the latter, P recovery in centralized and decentralized WWTPs is compared, and the system boundaries are only focused on P recovery and spreading. They emphasized the fact that struvite precipitation from dewatering fluids at centralized WWTPs produces net environmental advantages in many categories, but they did not consider the upstream loads of the WWTPs. Processing, computation, and analysis of a variety of data are necessary for LCA. These several stages are made easier using LCA software, which also ensures transparency and traceability. High volumes of data are needed for LCA investigations, and the quality of the data directly affects the quality of the life cycle inventory (LCI). To illustrate this, a study conducted by Amann et al. (2018) examined the life cycle energy, global warming potential, and acidification potential associated with different P recovery technologies for WWTPs.

Several studies have explored the use of integrated LCA and plant-wide models. According to Flores-Alsina et al. (2010), economic, technical, and legal criteria should be included in the environmental assessment performed by LCA. Data collected from the dynamic simulation BSM2 were used primarily to create the inventory. The study did not assess greenhouse gas emissions from treatment processes but instead examined whether methane and nitrous oxide emissions from sludge could be used in agriculture. Plant-wide, P transformations can be modeled with BSM2-PSFe (Flores-Alsina et al., 2021). The findings of simulations that were run for a thousand days at a steady state were used in this investigation. The simulation outputs employed in LCA consist of electricity usage, heating energy usage, material usage, biogas yield, struvite/CaP yield, sludge yield, and effluent P, N, and COD contents under various scenarios (Flores-Alsina et al., 2021; Nair et al., 2021) i.e., influent pollutant concentration and pathways (i.e., baseline, recovery paths such as struvite precipitation, CaP precipitation, and with CEPT). The model of BSM2-PSFe does not simulate the downstream sludge disposal process, because the sludge ash-based was separately modeled using inventory from the literature it was not clearly mentioned (Solon et al., 2019). Among the 151 articles analyzed, the software used for conducting LCA varied. Approximately 42.45% of the articles did not mention the specific software utilized. However, out of the articles that did mention the software, the distribution was as follows: SimaPro® was used in 33.33% of the studies, Gabi® in 16.32%, OpenLCA® in 4.10%, and Umberto® in 2.80%. In addition to this commonly used software a few other tools were employed in specific studies. These included JEMAI-Pro 2.1.2 (Limphitakphong et al., 2016), Daycent (Miller-Robbie et al., 2017), Easetech (Fang et al., 2016b), WaLA implemented in Simulink/Matlab (Loubet et al., 2016), and the wastewater-energy sustainability tool (Holloway et al., 2016). It is worth noting that only 48.05% of the studies provided information about the software version used. Various software tools of LCA in WWTPs are reported in supplementary data in Table T1. This detail is significant as different software versions can have an impact on the results, particularly when the software incorporates its own database and assessment methodologies, as is the case with SimaPro®. GPS-X, BioWin, and SIMBA are a few commercial software that have emerged in recent times. Table 3 Literature summary of studies used in the LCA approach based on the P. Fig. 4(a) represents the step-by-step procedure of the flow chart to evaluate LCA in WWTPs. There are various restrictions to consider when using LCA to examine the environmental effects of P in WWTPs. The preciseness and thoroughness of the assessment may be impacted by specific challenges. Key restrictions include the following.

- When considering the full life cycle of P in WWTPs, it can be difficult to define the system limits for LCA. According to the study's unique objectives and parameters, the borders might change. Important factors to consider include the production and extraction of P sources, as well as the transportation of those sources, their processing, and any potential downstream effects of P discharge. Accurate and reliable data are crucial to LCA. However, it might be challenging to find thorough and accurate data regarding P-related processes throughout the life cycle. It may be difficult to find information on the effectiveness of P extraction, production, transportation, and treatment. This may result in ambiguities and possible bias in the outcomes of the assessment.
- It could be difficult to capture this variability in LCA and how it affects the assessment outcomes, particularly when there is little data available or when the variability is not effectively modeled. Typically, during the operation of WWTPs, LCA often concentrates on the immediate environmental effects related to the stages of the P life cycle. It can be difficult to fully account for indirect consequences, such as those connected to the production and extraction of P sources or possible environmental effects of P discharge in the future.

For a thorough analysis of the life cycle costs and inventories for various recovery scenarios and plant configuration design, steady-state simulations are often sufficient (Kar et al., 2023). In realistic-based scenarios, dynamic simulations are needed, though, for optimization studies and for learning more about the behavior of systems. As discharge limits and GHG emissions are both significantly impacted by daily or weekly peak loads, dynamics should also be considered while evaluating these parameters. Additionally, it was demonstrated how crucial it is to consider both water and sludge lines when analyzing GHG emissions and highlighted how strongly N_2O or CH_4 emissions can affect the environment. Despite these drawbacks, LCA is still a useful method for assessing how WWTPs of P affect the ecosystem. It indicates areas for improvement and offers insights into the overall viability of P management techniques. To overcome these constraints, it is necessary to increase data accessibility, improve modeling strategies, harmonize methodology, and incorporate more thorough and reliable effect assessment techniques that are particular to P-related processes.

3.6. *Resource recovery*

In general, water utilities are less focused on recovering struvite (magnesium ammonium phosphate ($MgNH_4PO_4$) than reducing the operational issues caused by the formation of struvite scale (Urdalen, 2013). Typical struvite recovery rarely exceeds 25% of the influent phosphate load. To maximize phosphate recovery, alternative methods to struvite recovery should be considered. For instance, P-laden biochar and P-rich sludge are two of the wastewater-recovered P products that can be directly used as fertilizer or soil amendment. Furthermore, the concentrated liquid can be crystallized into struvite and Mg/Ca-enhanced minerals to be used as slow-release fertilizers. The treatment of wastewater containing phosphate and its recovery requires more complex chemistry and microbiology than that found in ASMs (Hauduc et al., 2015; Santos et al., 2018; Sheik et al., 2022c). The phosphate phase chemistry can be easily integrated with the geochemical modeling software such as PHREEQC33-35 or with the aqueous phase chemistry modules by coupling ASM with geochemical modeling software such as PHREEQC33-35. No matter how biochemical models are coupled to a geochemical modeling software or how well they are coded, expert knowledge is of paramount importance in ensuring that all relevant chemical components and species are considered, regardless of whether an external geochemical modeling software is used, or self-coded aqueous phase chemistry and precipitation models are used. Fig. 4(b) depicts the applications of emerging cyber-tools towards resource recovery. Alternatively, P can be recovered by incineration of sludge followed by acid extraction and adsorption. Ashes contain phosphate that can be recovered (Franz, 2008). Due to the inclusion of P in the sludge fraction, recovery models are not needed in this case. The recovery of P from the ashes has several drivers, such as the cost-benefit of selling recovered phosphate and an attempt to avoid high disposal costs (Egle et al., 2016). It is crucial to emphasize the value of plant-wide modeling and simulation for assessing how well recovery techniques are integrated into WWTPs (Parsons and Doyle, 2004; Solís et al., 2022; Nair

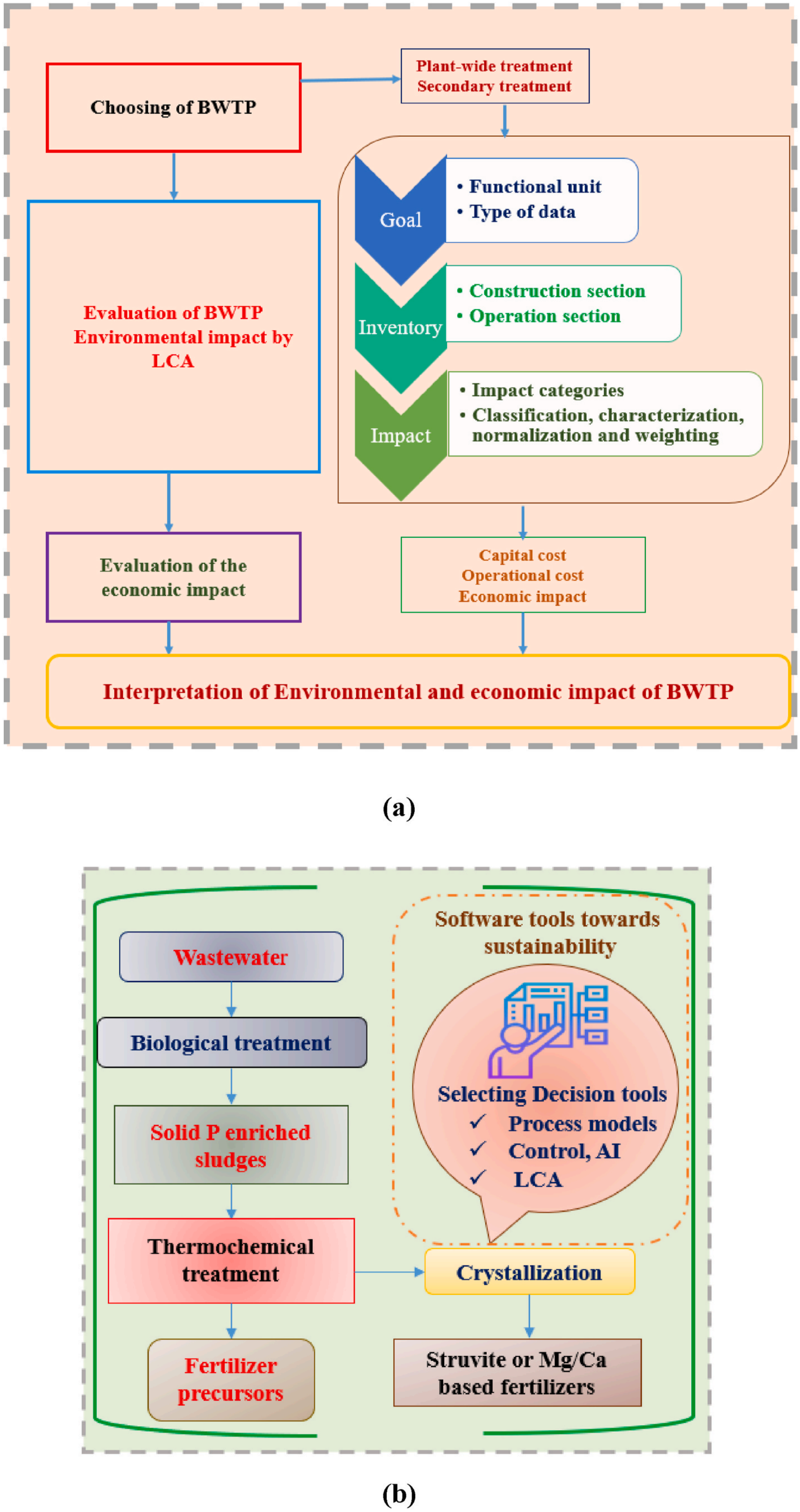


Fig. 4. **(a)** Step by step procedure to evaluate LCA in WWTPs, and **(b)** Application of emerging cyber-tools towards resource recovery.

et al., 2021; Sheik et al., 2022c). The performance of the entire plant may be analyzed using plant-wide models, which also could help to understand the interdependencies between the various unit processes and establish the groundwork for new plant layouts for WERE design. The need for integrated modeling will undoubtedly increase if extraction facilities for resource recovery are installed on-site. Artificial intelligence and machine learning could make it possible to evaluate and compare the viability of P recovery and the costs, life cycle analysis, and environmental footprint of both existing and newly created wastewater treatment technology more efficiently.

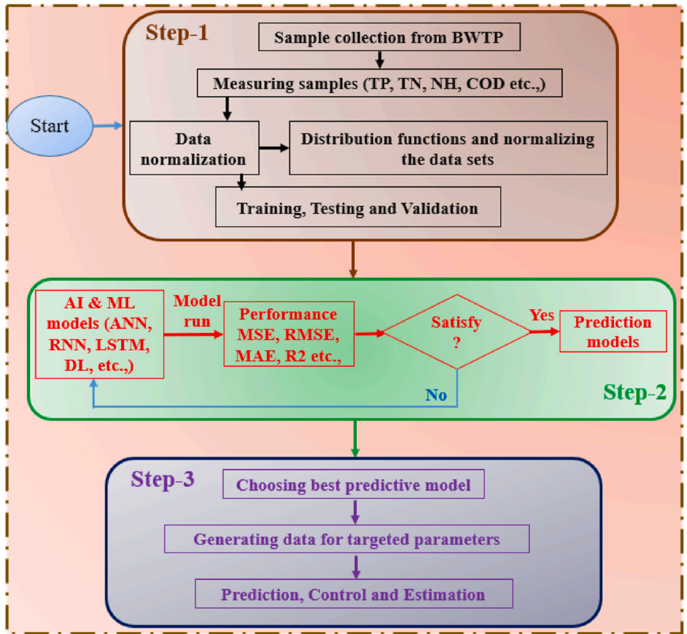
3.7. Prediction of phosphorus using artificial intelligence (AI)

In the past century, AI has been suggested as a brand-new approach to solving complicated environmental issues (Li et al., 2022). After being taught with enough raw data, AI may forecast outcomes of situations using modeling of how human neurons function. AI may be able to ignore the basic principle of a problem and focus only on its conditions and outcomes, which means that it may be able to deal with complicated problems that conventional mechanistic models are unable to resolve. Accurate prediction of P concentration can aid in controlling chemical conditions and subsequent purification, thus assisting the feed-forward controller of the WWTPs. However, simulating multivariable time-series forecasting of total P using current deep-learning methods is a critical issue due to the lack of physical mechanics, nonlinearity, and dynamic complexity of WWTPs. The support vector machine, fuzzy logic, random forest, extreme learning machine, and artificial neural network models are some of the popular AI models used (Liu et al., 2023). Recent advances in computer technology have made it possible to predict the behavior and fate of wastewater concentrations to a certain degree using ML techniques (Lyu and Yin, 2023; Zaghloul and Achari, 2022). For dynamic modeling and system identification, FFNNs have been outperformed by recurrent neural networks (RNNs) in deep learning (DL) and ML literature (Goodfellow et al., 2016; LeCun et al., 2015). LSTMs have been implemented in BSM2 for applying to WWTP benchmark scenarios to predict ammonium and total nitrogen concentrations (Pisa et al., 2019a, 2019b). Based on user input and output datasets, models are generated using machine learning and deep learning methods, creating a predictability model that is then applied to physical processes (De Clercq et al., 2020; Deng et al., 2021). Despite this, these studies were found to have two main shortcomings. One of the limitations of these methods is that they are heavily dependent on the manual extraction of features based on expert experience. Another problem is that neural networks have a shallow architecture that is insufficient to find the nonlinear relationships within each model. Deep learning focuses on optimizing the analysis and learning of unsupervised and supervised data using different learning procedures when compared with ML (Liu et al., 2023). In this regard, RNN has been used for forecasting multiple steps of total nitrogen in more than one step (Geng et al., 2023). Long short-term memory (LSTM) models have been used in recent research to enhance the applicability of RNN, which allows basic input features to be distinguished from lesser ones while letting time series data extract features. Table 4 summarizes the estimated and predicted outcomes of P by utilizing AI and ML. Despite its potential to estimate and predict various parameters in WWTPs, including P levels, artificial intelligence also has several limitations. Fig. 5(a) systematic procedure for the application of AI, and 5(b) validation and decision-making concept of AI. A few key limitations and challenges need to be considered.

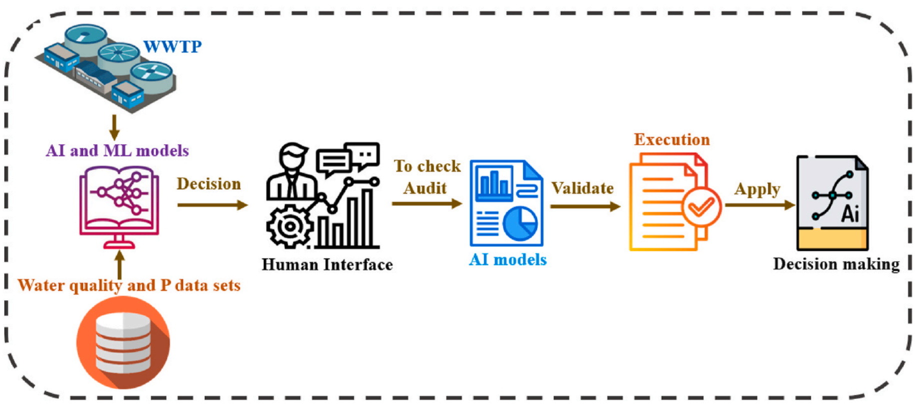
- Reliable predictions require accurate and representative data from AI models. Data on P levels in WWTPs are challenging to obtain in a

Table 4
Summarized the estimated and predicted outcomes of P by utilizing the AI and ML.

S. No	Approach	Specific method	Data Source	Input variables	Performance	Comment	Reference
1	SVM, ANN	–	Ulsan National Institute of Science and Technology	COD, TP, TSS, Temperature (T), pH, and TN	0.4–1.0- R2, 0.4–1.0 - NSE, and 0.76–0.99 – REC	For integrated food waste and WWTP, ANN models may be more reasonable and reliable than SVM models.	(Guo et al., 2015)
2	ANN, DNN	LSLR, RNN, RF, GBM, RNN-LSTM	Melbourne Water (open) database	N, BOD, NH, T, TP, humidity, and influent flow	MAE - 23.8 RMSE -29.9 R2 - 0.53	Based on its ability to predict nonlinear irregular patterns, GBM showed the best performance among other algorithms.	(Bagherzadeh et al., 2021)
2	LR, kNN, RF, ANN,	M-SVM, F-SVM, RT-BO, ensemble-BO, and GPR-BO	Cuyahoga, Maumee, Raisin, and Sandusky watershed units	NO, TSS, TP, flow	ANN-R2 - 0.479 to 0.745	It was found that ensemble-BO and M-SVM were more accurate than other ML models at predicting TP in agricultural and forest watersheds.	(Bhattarai et al., 2021)
3	ML	DWT, GRA, PLS, RF, and AdaBoost	Lake Baiyangdian	COD, TP, TSS, T, pH, and TN	R2, RMSE are 0.821 and 0.028 mg/L	According to the findings, bands responsive to chlorophyl are reliable indicators of the presence of TP.	(Zhang et al., 2022)
4	ANN, ANFIS, SV, GA and PSO	PSO-ANN	62 experimental data point removal of phosphate	Current Intensity (A) Initial phosphate, pH, time Electrode type Removal efficiency	MSE, R2, MAPE, PSO-ANN -7.201, 0.981, and 2.022	Lower pH values and higher initial phosphate concentrations, as well as a higher current intensity and a longer treatment time, enhanced phosphate removal.	(Shirkoohi et al., 2022)
5	ANN PCA	BPANN	Zipeng WWTP, Hefei, China	inlet flow rate, pH, NH, COD, and TP	BPANN accuracy of 0.7675% (APR)	These models may be useful for choosing the best treatment process in the design of new WWTPs, or for anticipating sudden shocks.	(S.-Z. Zhang et al. 2022)
6	LSTM	LSTM-Bayesian optimization	Kolding WWTP	Phosphate	MSE-0.44 GoF-0.12 R2-0.22	Based on the training data set, both models predict well up to 24 h into the future, with a prediction accuracy of 0.7–0.8.	(Hansen et al., 2022)
7	SVM, DT, RF, ANN, LSTM	SHAP analysis	nine-year data from a small-scale WWTP	42 variables which involves in the WWTP	R2 - 0.637 maximum accuracy −79.7%	With incomplete data sets, this study demonstrates how artificial intelligence can improve processes and reduce costs.	(Xu et al., 2023)
8	GEP, ANN, GB, RF, and RT	MLPNN, MLR, kNN	ST-STW, SK-STW, SmT-STW, YL-STW, TP-STW, SWH-STW, SCI	BOD_5, COD, TSS, NH, OrgN, InorgP and OrgP	GEP provides with R2 values of 0.784 and 0.861	Both BOD and COD values were largely affected by TSS.	(Aghdam et al., 2023)



(a)



(b)

Fig. 5. **(a)** Systematic procedure for the application of AI **(b)** Validation and decision-making concept of AI and ML.

comprehensive and high-quality manner. Predictions made by AI are often inaccurate because of incomplete, inconsistent, and low-quality data.

- Several factors can influence P behavior in these systems, such as composition, hydraulic loading, and operational conditions. The nonlinear and dynamic nature of the processes involved can make it difficult to capture the intricate relationships between these variables and P removal using AI models.
- Different conditions, such as temperature and pH, can affect P removal efficiency. The variability and uncertainty of P concentrations and removal rates may make AI models ineffective at predicting them.
- It may be necessary to adapt learning techniques, DL, interpretable artificial intelligence (XAI) or customize models to each plant, in which case extra effort and expertise are required.
- It can be challenging to understand and interpret the reasoning behind AI models, particularly deep learning models. Achieving interpretability is important for wastewater treatment operators and engineers, as it allows them to gain an understanding of how P is removed from wastewater, identify anomalies, and make informed decisions.
- Over time, the characteristics and operating conditions of WWTPs can change. AI models can be adversely affected by these changes, especially if the models were trained on historical data that may not reflect the conditions of the present or the future.

In WWTPs, AI remains valuable despite these limitations. The development of reliable and robust systems for P prediction and estimation requires careful consideration of these factors and collaboration between domain experts and data scientists. The findings of the AI in WWTPs provide policymakers and environmental decision-makers with solutions, which result in improved public health and the realization of a smart and sustainable built environment. Aside from adjusting chemical dosages and estimating aeration needs, the obtained results can also be used to minimize energy consumption and GHG emissions as the WWTPs advance.

4. Perspectives and outlook

Future modeling work for P should focus on addressing the inherent ambiguities and variabilities connected with P removal procedures. To evaluate the models' robustness and quantify the uncertainties in the projected P removal efficiency and environmental implications, Monte Carlo simulations and sensitivity analysis can be used. It would be prudent to carry out more realistic studies with model simulations to assess the suitability of the processes for WWTPs. Processes for recovering resources and removing P can be better controlled with the inclusion of real-time monitoring and sensor technologies. High-resolution data on critical parameters, including P concentrations, DO levels, and biomass activity, can be provided by advanced sensors, enabling more precise process monitoring and control. Different types of control strategies such as nonlinear model predictive control, economic nonlinear model predictive control, fuzzy logic controller, and adaptive control techniques can be carried out using this real-time data.

A multi-objective optimization approach will also be used to identify the best trade-offs for a sustainable and cost-effective operation. It would be beneficial to develop a method of AI such as machine learning and deep learning (long short-term memory (LSTM), Bidirectional LSTM) models to provide human-understandable insight into XAI. A rapid development in computer technology has facilitated the development of ML and DL techniques which now can predict the behavior and fate of P and resource recovery in WWTPs with a high degree of accuracy. To get insights, partial dependence plots, shapley additive explanations, feature importance factors, and variance inflation factors are some of the methods that have been employed to date and are useful to predict, optimize, and control P as well as resource recovery in WWTPs. As part of its future efforts towards LCA, it will be necessary to analyze the "upstream" resource recovery facility as well as the baseline system to calculate the environmental impact of wastewater-derived products, particularly P. The appropriate weighting factor for sensitivity analysis with GHG mitigation should be determined when combining models from LCA and plant-wide analysis of WWTPs. Data availability and quality will improve in future LCA studies. Fig. 6 depicts the WERE-based concept towards advanced technologies. Standardization of P data collection protocols and databases through collaboration among researchers, practitioners, and data providers is essential to develop a universal model.

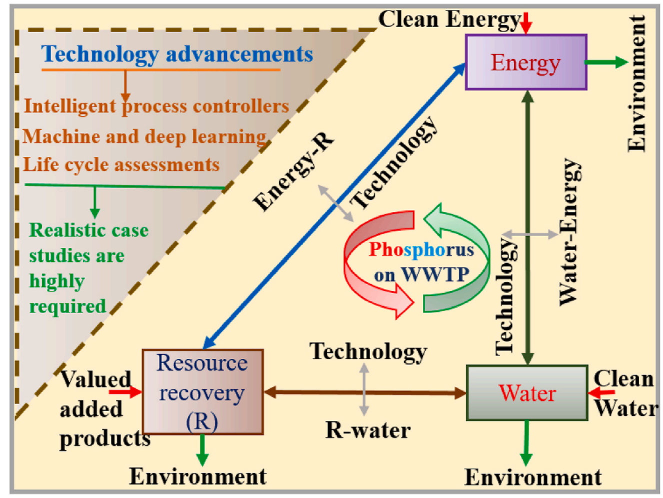


Fig. 6. P-WERE based concept towards advanced technologies.

5. Conclusion

In WWTPs, P removal and recovery are vital processes involving resource transportation, treatment, and consumption. To optimize WWTP performance, four essential simulation tools must be balanced.

1. Modeling and simulation platforms: Crucial for addressing parameters like environmental quality indicators, greenhouse gas mitigation, and resource recovery, ensuring operational efficiency.
2. Advanced and intelligent controllers: Ensuring efficient EQI discharge, energy consumption, and systematic P recovery while minimizing GHG emissions, thereby enhancing operational performance and environmental sustainability.
3. Artificial Intelligence: Revolutionizing wastewater treatment by enabling process optimization, predictive maintenance, energy efficiency, water quality control, and data analysis, significantly improving WWTPs performance and sustainability.
4. Life Cycle Assessment: A powerful tool for evaluating and comparing wastewater treatment options, guiding decision-making towards sustainable practices.

Despite complexities in evaluating modeling and simulation due to various influencing factors, integrating models with advanced controllers, AI, and LCA could offer a comprehensive evaluation framework. In conclusion, the digitalization of phosphorus removal processes in biological wastewater treatment systems represents a critical step forward in enhancing efficiency, sustainability, and environmental protection. Throughout this review, we have explored the challenges and opportunities associated with integrating digital technologies into phosphorus removal processes. From the utilization of advanced modeling and simulation platforms to the implementation of artificial intelligence and intelligent controllers, it is evident that digitalization offers immense potential for optimizing phosphorus removal while minimizing resource consumption and environmental impact. However, challenges such as data acquisition, integration, model validation, and operational implementation remain significant hurdles to overcome. Moving forward, collaborative efforts between researchers, engineers, and wastewater treatment practitioners are essential to address these challenges and pave the way for a more digitalized, efficient, and sustainable future in biological wastewater treatment systems. By embracing digitalization and leveraging innovative technologies, we can strive towards achieving cleaner water, healthier ecosystems, and a more sustainable future for generations to come.

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CRediT authorship contribution statement

Abdul Gaffar Sheik: Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Conceptualization. **Suresh Babu Naidu Krishna:** Writing – review & editing. **Reeza Patnaik:** Writing – review & editing. **Seshagiri Rao Ambati:** Writing – review & editing. **Faizal Bux:** Writing – review & editing, Supervision. **Sheena Kumari:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2024.119133.

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