ISSN 2664-4150 (Print) & ISSN 2664-794X (Online)
South Asian Research Journal of Engineering and Technology
Abbreviated Key Title: South Asian Res J Eng Tech

| Volume-7 | Issue-3 | May-Jun- 2025 | DOI: https://doi.org/10.36346/sarjet.2025.v07i03.001

Review Article

Artificial Intelligence for Operational Optimization in Sequencing Batch Reactors (SBRs): A Comprehensive Review

Mohammad Reza Fadaei Tehrani[1*], Mahboubeh Sayedbarzani[2], Milad Irajpoor[3]

[1]Assistant Professor and Faculty Member, Isfahan Higher Education and Research Complex, Niroo Research Institute (NRI), Iran
[2]Postgraduate in Civil Engineering-Environmental at Isfahan University of Technology (IUT), Iran
[3]Master's student in Environmental Civil Engineering at Daneshpajoohan Pishro University

***Corresponding Author:** Mohammad Reza Fadaei Tehrani
Assistant Professor and Faculty Member, Isfahan Higher Education and Research Complex, Niroo Research Institute (NRI), Iran

Article History
Received: 24.03.2025
Accepted: 29.04.2025
Published: 06.05.2025

Abstract: This review article examines the integration of Artificial Intelligence (AI) in Sequential Batch Reactors (SBRs) to enhance operational efficiency in wastewater treatment. SBRs facilitate the treatment process through distinct phases—fill, react, settle, and decant—within a single tank. The transitions between these phases are pivotal for optimizing treatment performance. Traditional control strategies often rely on manual interventions and fixed schedules, which may lead to inefficiencies and suboptimal outcomes. AI technologies, including machine learning and predictive analytics, present a transformative opportunity to improve operational management by enabling real-time monitoring, adaptive control, and predictive maintenance. This article discusses various AI applications in SBR systems, highlighting their potential to enhance treatment efficiency, reduce energy use, and improve effluent quality. Furthermore, it addresses the challenges and future directions of implementing AI within wastewater treatment frameworks, emphasizing the need for continued innovation to meet evolving environmental standards. Through a comprehensive analysis, this review underscores the role of AI in revolutionizing wastewater treatment processes, paving the way for more sustainable and efficient practices in the management of water resources.

Keywords: Artificial Intelligence, Sequential Batch Reactor, Wastewater Treatment, Operational Efficiency, Predictive Maintenance, Machine Learning.

1.0 INTRODUCTION

The SBR process traces back to 1914, when Ardern and Lockett introduced indirect aeration techniques to the activated sludge method (Luo 2018).

Sequencing Batch Reactor (SBR) process, a sewage treatment technology emerged as an improvement over the conventional activated sludge treatment process. Due to the increasing need for effective sewage treatment driven by economic growth and rising living standards, SBR has gained popularity since the 21st century, particularly with advancements in automatic control technology (Jing, Wei-Li, and Fu-Chuan 2021).

The complete operational process of a Sequencing Batch Reactor (SBR) can be segmented into five distinct stages. The first stage, the fill phase, involves adding influent wastewater to the reactor. At this point, pre-aeration or agitation may be employed to facilitate semi-aeration, which leads into the subsequent aeration phase where microorganisms actively decompose organic contaminants. Following aeration, the process enters the sedimentation phase, during which both the agitation and aeration are halted, allowing for the separation of solids from liquids as sludge settles at the bottom. This phase is characterized by a completely static environment within the reactor, akin to secondary settling. After sedimentation, the drainage phase occurs, where the treated water is removed via a designated drainage pipe or decanter.

Excess sludge is expelled through a dedicated sludge discharge pipe, while a portion can be retained for use as return sludge in the next operational cycle. The final stage is the idle phase, which serves as a transition, preparing for the next cycle. During this idle period, the discharged sludge may either be eliminated or undergo further static sedimentation. It's worth noting that the idle phase might be omitted entirely. Oxygen supply is critical as it influences the rate of organic material degradation, and enhancing aerobic conditions reduces organic matter concentration (Jing, Wei-Li, and Fu-Chuan 2021).

SBRs operate normally on a fixed switching schedule about some safety factors for probable inaccuracies, making operations highly inefficient (Marsili-Libelli 2006).

Certain advancements in the SBR development process concentrate specifically on the procedural aspects. Over the years, various deformation methods have emerged, enhancing the fundamental SBR process. These include techniques like the ICEAS process, CASS process, and casting process, among others. In their research, Gu Wei and Yuan Yajing applied the DAT-IAT Process for the treatment of pharmaceutical wastewater. Their findings indicate that, in comparison to conventional SBR technology, the DA-TIAT method offers a greater aeration volume ratio and requires fewer blowers, thereby lowering overall equipment costs (Jing, Wei-Li, and Fu-Chuan 2021).

Yang and colleagues investigate various SBR process variants, including ICEAS, CASS, DAT-IAT, and SBBR, each tailored for specific wastewater characteristics. They found that despite advances in SBR technology, it still faces challenges such as long treatment cycles and the need for improved automation. The authors suggest that further development and investment in SBR technology are essential for effectively addressing sewage treatment issues, especially in China, where the technology has already seen significant application. Overall, the article emphasizes the importance of continuous innovation in SBR technology to meet modern environmental standards and improve the efficiency of sewage treatment processes (Jing, Wei-Li, and Fu-Chuan 2021).

SBR is an evolving sewage treatment technology that requires ongoing updates and enhancements to its associated management systems and approaches. Traditional SBR methods face several challenges, including lengthy treatment durations, frequent changes in inflow and outflow, stringent automation requirements, and significant fluctuations in water levels. There remains considerable potential for optimizing operational adjustments in this area.

The most common drawbacks in operating SBR systems that require operators' attention are listed below.

DO Control: Operating DO at a set point for ON/OFF aeration is most common practice in SBR Plants. These set points are based on plant operation experience and judgments. However, proper attention needs to be taken to evaluate these set points from time to time based on process operation performance and effluent quality. Failing to do so may lead to higher operational and maintenance costs or exceed effluent target limits. Although the sequencing of an SBR occurs quite slowly and is not difficult to carry out manually, it requires an operator to be at the plant 24 hours/day and to be constantly aware of process status.

Scum Management: Removing scum in SBRs can be challenging; effective decanting mechanisms are crucial to prevent scum from entering downstream processes (de Silva 2003).

Wastewater Discharge Level: The level of wastewater discharge is usually maintained above the settleable solids to avoid disturbing the sludge and causing it to float to the surface. An increase in the Sludge Volume Index (SVI) corresponds with a rise in the settleable solids, which in turn reduces the volume of wastewater that can be released. Therefore, effective management of the decanter is crucial, requiring careful observation of the sludge settling behavior to optimize both the settling and discharge processes. However, there have been no documented cases of monitoring the settling properties of activated sludge and automatically adjusting the decanter according to the suspended solids concentration in the wastewater. (Kwon *et al*. 2023).

Recently, the incorporation of artificial intelligence (AI) in wastewater management has become a prominent area that has the potential to transform our approach to addressing environmental issues. With the rise in global population and the rapid pace of industrial and urban development, there is a pressing demand for efficient and sustainable solutions in wastewater treatment. (Ahmad *et al*. 2022).

Specifically, artificial intelligence techniques are utilized for overseeing and designing intricate non-linear real-world issues like wastewater treatment systems (WWTS). Nonetheless, given the intricate nature of biological processes, there is still a significant lack of evidence-based research regarding WWTS. Artificial Intelligence, which includes machine learning, neural networks, and various computational techniques, enables us to examine large datasets, enhance process parameters, and forecast results in real-time (Y. Wang *et al*. 2023).

The findings suggest that currently, AI is mostly employed to assess the elimination of pollutants—both conventional and emerging—as well as to enhance models and process parameters. This research offers significant perspectives on the potential opportunities and challenges faced by scientists utilizing AI in wastewater treatment (Zhang *et al*. 2023).

Incorporating AI technologies presents a novel approach to tackling these challenges by enhancing the efficiency, precision, and automation of wastewater treatment procedures. Through the application of machine learning algorithms, predictive modeling techniques, and advanced data analysis, AI has the potential to greatly enhance multiple facets of wastewater management (Obaideen *et al*. 2022).

Summary of Artificial Intelligent in Sequencing Batch Reactor

Statistical Models:

These models use statistical methods to analyze historical data and predict future outcomes. Common statistical techniques include regression analysis, where relationships between different variables (such as contaminant concentration and microbial activity) are explored. Statistical models can provide insights into the expected performance of bioremediation efforts under various conditions.

Machine Learning Models:

Rodríguez-Rángel and colleagues found that machine learning techniques, including decision trees, random forests, and neural networks, are being increasingly applied in the field of bioremediation. These algorithms can identify intricate relationships within data without the need for direct coding. For example, a neural network can be trained using past data to identify patterns linked to effective bioremediation efforts, facilitating immediate predictions and recommendations.

AI can further refine this by continuously analyzing real-time data to adjust cycle times dynamically based on varying influent characteristics and operational conditions. Machine learning algorithms could predict the most efficient operational parameters based on historical data and current conditions, potentially identifying even shorter or longer cycles that might yield better results under different scenarios.

Artificial intelligence encompasses a field dedicated to utilizing data and algorithms to replicate human learning processes, enhancing accuracy over time; this area is referred to as machine learning. These algorithms are employed in various applications, including fault detection, object classification, control systems, diagnostics, and predictive analytics (Rodríguez-Rángel *et al*. 2022).

As the process shifts from the fill phase to aeration, the timing and intensity of aeration play a crucial role. Artificial Intelligence can analyze real-time data to identify the best time to start aeration, ensuring that conditions are ideal for microbial activity. For instance, if the influent is rich in organic matter, the AI system can extend the aeration period to enhance treatment. Furthermore, after aeration, the sedimentation phase is crucial for separating solids from the treated effluent. AI can optimize this phase by controlling the duration and conditions under which sedimentation occurs. By analyzing data on solid concentration and settling rates, the AI system can predict the best time to commence decanting, thereby improving effluent quality and reducing the need for additional treatment processes.

Dynamic Simulation Models:

The control strategy employs real-time monitoring of parameters such as pH, temperature, dissolved oxygen (Do), oxidation-reduction potential (ORP), and oxygen uptake rate (OUR) to identify the completion of key biological processes, including ni-trification and denitrification (Kwon *et al*. 2023).

In the field of wastewater treatment, there has been significant research into the application of artificial intelligence (AI) and machine learning (ML) techniques. By combining AI models with traditional methods and Internet of Things (IoT) frameworks, the design of intelligent wastewater treatment systems can be significantly improved, facilitating effective reuse. AI models are recognized as robust tools for predicting, modeling, and optimizing various processes involved in wastewater treatment. Their applications span a wide range of areas, including the removal of color, heavy metals, organic compounds, solids, microbial contaminants, pharmaceuticals, nutrients, and pesticides from water (Mazloom *et al*. 2020).

Internet of Technology

The introduction of IoT technology provided real-time monitoring of nutrient concentrations, enabling automatic adjustments to the SBR operation based on fluctuating inflow conditions. This approach not only improved treatment efficiency but also facilitated better control of the biological processes involved in nitrogen removal.

This article provides an in-depth exploration of the latest uses of various AI models in wastewater treatment, focusing on areas such as pollutant removal, real-time monitoring of parameters that reflect effluent quality, and fault detection in sequencing batch reactor (SBR) operations. (Kwon *et al*. 2023).

Publication of AI in wastewater treatment

The yearly trends in A1-related publications within the wastewater treatment sector, as depicted in Figure 1, provide valuable insights into the evolution and trends of research in this area over the last ten years. The data shows a consistent upward trajectory, indicating an interest in the use of A1 in wastewater treatment studies (Baarimah *et al*. 2024).

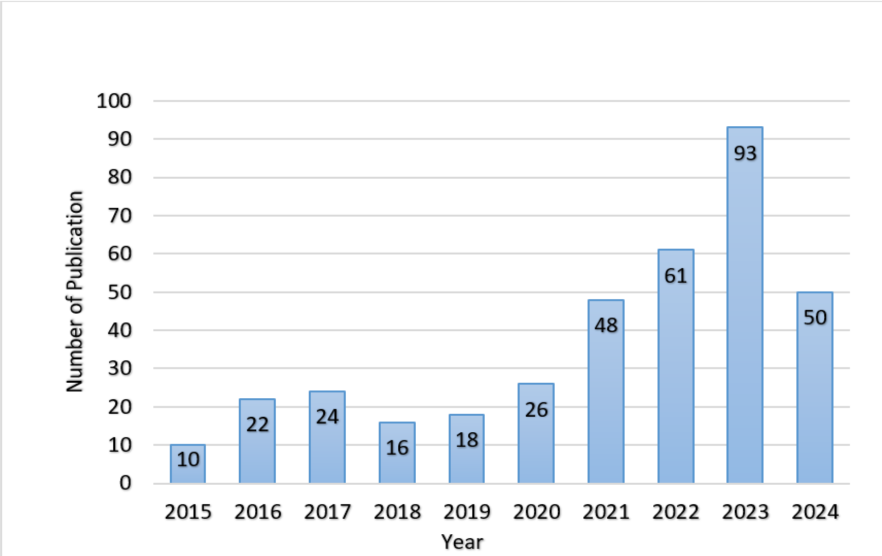


Figure 1: Yearly publications concerning artificial intelligence in wastewater treatment, according to Scopus data (up to April 2024)

In a study by Nagpal *et al*. a range of individual models, such as support vector machines (SVMs), artificial neural networks (ANNs), genetic algorithms (GAs), fuzzy logic (FL), and decision trees (DTs), have been utilized for processes modeling in wastewater treatment plants. Additionally, hybrid approaches are used, which involve integrating two distinct models, either in a sequential or parallel manner, to achieve greater accuracy than the separate models, as well as more complex structures like models (Nagpal *et al*. 2024).

Real-life WWCE using AI for operation

Several wastewater treatment plants around the world have begun incorporating artificial intelligence (AI) technologies to enhance their operations. Some notable examples include:

Chicago, Illinois, USA: The Water Reclamation District has been utilizing AI to optimize operations and reduce energy consumption at its wastewater treatment facilities.

Singapore: The Changi Water Reclamation Plant has implemented AI and machine learning to enhance process control and predictive maintenance, improving overall efficiency in treating wastewater.

Barcelona, Spain: The city's wastewater treatment facilities have integrated AI systems to monitor and manage processes more effectively, leading to enhancements in energy savings and operational efficiency.

Amsterdam, Netherlands: The city's wastewater treatment plants have adopted AI for various applications, including optimizing treatment processes and predictive maintenance.

Los Angeles, California, USA: The Hyperion Water Reclamation Plant has started using AI technologies to improve its operational efficiency and reduce energy consumption.

Melbourne, Australia: The Western Treatment Plant is utilizing AI for process optimization and predictive maintenance to enhance the reliability of its operations.

2.0 LITERATURE REVIEW

To regulate dissolved oxygen levels within the SBR, three control strategies have been identified: proportional integral (PI), fractional proportional integral (FPI), and fuzzy logic controllers. Control algorithms were created utilizing plant data, coupled with SBR and SSBR models based on the ASM2d framework. In a comparative analysis, the FPI controller exhibited a significant decrease in nutrient levels and improved effluent quality, achieving a 0.86% enhancement over the PI controller. The SSBR is designed to optimize nutrient delivery and aeration, striking a careful balance that reduces oxygen demand while maintaining vital biological processes. Notably, in assessing the FPI controller's efficiency concerning total air volume consumption, the step-feed SBR method achieved an impressive reduction of 11.04%. A pilotscale SBR was operated with 6-hour cycles encompassing anoxic, anaerobic, and oxic phases. Figure 2 illustrates the conventional and modified operational cycle of the SBR (Dey *et al*. 2024).

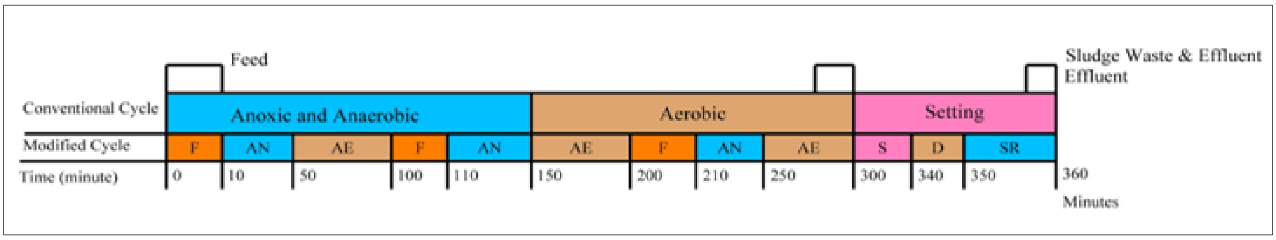
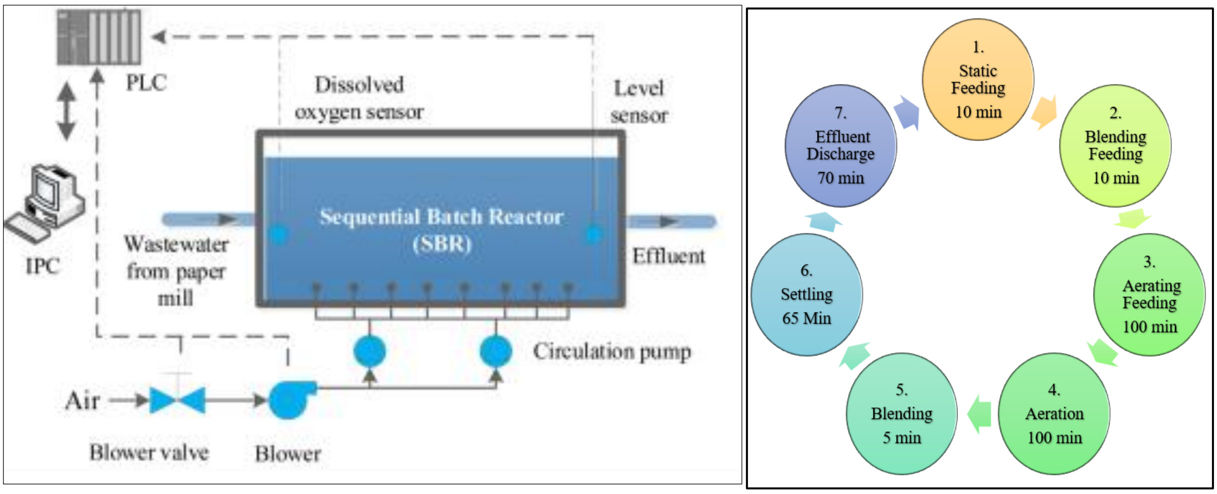


Figure 2: Conventional SBR operation phases versus modified SBR operation phases (SSBR)

A model was developed by Heo and his colleagues to simulate the Partial Nitritation (PN) process in a full-scale Sequencing Batch Reactor (SBR), acting as a predictive tool to assess various influencing factors. The model was calibrated using AI techniques to optimize levels of ammonium (NH_4), nitrite (NO_2), and nitrate (NO_3) by fine-tuning parameters with real-time data. Sensitivity analysis identified key biological parameters affecting the PN process, allowing for targeted control. Additionally, an AI-based strategy called AI-OpAS was created to optimize aeration, balancing oxygen needs with energy efficiency, achieving a NO_2/NH_4 ratio of 1.1 while saving up to 31.38% in energy (Heo *et al*. 2023).

The integration of Internet of Things (IoT) technology into the sequencing batch reactor (SBR) system was aimed at improving nitrogen removal and tackling challenges associated with fluctuating inflow rates. To manage these variations, an automatic mechanical decanter was created, which optimizes the settling and discharge time (TRSD) by observing both the sludge-blanket height and the suspended solids concentration. This advancement allowed for a significant reduction in average TRSD to just 1 hour, achieving a decrease of 27-59% in comparison with conventional SBR techniques used for domestic wastewater treatment. The system enhanced performance by increasing the bio-reaction time while maintaining the total cycle time. The nitrogen removal efficiency was further improved through a two-step influent introduction process, utilizing an 8:2 ratio, which yielded a total nitrogen removal rate of 92-93% for the step-feed approach, in contrast to 82-88% for the single-feed method. Despite a 51-minute increase in bio-reaction time during the step-feed mode at temperatures ranging from 13-16 °C, the overall cycle time was kept below 6 hours thanks to the shorter TRSD. The adoption of IoT technology facilitated more dependable SBR operations and significantly boosted total nitrogen removal efficiency (Kwon *et al*. 2023).

Zhou and his team introduced an enhanced version of multi-way principal component analysis (MPCA) to tackle the challenge of diagnosing faults in actuators over multiple periods within a sequencing batch reactor (SBR). Their study focused on identifying faults in the SBR process used for treating wastewater in a papermaking facility. Data was gathered from the paper mill, including metrics such as blower current, SBR reactor levels, dissolved oxygen (DO) in the wastewater, and the opening of the blower valve. For analysis, the data from three complete batches of the SBR process were divided into seven segments, reflecting the cyclical nature of the operation illustrated in Figure 3. This segmentation helps reduce the effects of interference and interactions between faults occurring at different times. The findings affirm the effectiveness and reliability of the proposed MPCA method. Figure 3 shows the SBR process and SBR cycle in the Guangzhou paper mill (Zhou *et al*. 2021).



(a) (b)

Figure 3: (a) SBR process and (b) SBR cycle in Guangzhou paper mill

To enhance wastewater treatment efficiency, pattern recognition technology was employed to determine the process switching points using pH and DO measurements. DO and oxidation-reduction potential (ORP) were suggested as control parameters in the process, demonstrating consistent trends that could stabilize the process. The effluent concentration of ammonium was maintained below 2 mg/L, achieving a removal efficiency of 97% and a nitrite accumulation rate of 98% (S. Li *et al*. 2021).

Salari and *et al*. conducted an assessment of a Sequencing Batch Reactor in petrochemical wastewater treatment, with the goal of determining the optimal cycle duration for effective processing. The SBR operated in an aerobic suspended biomass configuration, monitoring essential parameters such as pH, temperature, and dissolved oxygen throughout the treatment. The study concluded that a 7-hour cycle, comprising a 15-minute filling phase, a 6-hour reaction period, 30 minutes for settling, and a 15-minute withdrawal, delivered the best results. Testing under various organic loading rates (12.88, 18.02, and 31.39 g COD/L.d) revealed maximum removal efficiencies of 84% for Chemical Oxygen Demand (COD), 67% for Total Solids (TS), and 92% for Total Suspended Solids (TSS). The optimal aeration duration was identified as 6 hours, beyond which efficiency improvements were minimal but energy costs escalated significantly (Salari, Ataei, and Bakhtiyari 2017).

The performance of SBR wastewater treatment systems in cheese manufacturing facilities was also evaluated, as the waste generated is typically high-strength and exhibits an intermittent nature due to cheese production, making it well-suited for SBR treatment. The SBRs were tested with two filling strategies: React Fill (RF), which included mixing and aeration, and Static Fill (SF), which lacked these features. Results indicated that the SF method outperformed RF, leading to a 50% increase in polyhydroxybutyrate (PHB) production and a 15% increase in glycogen production (Ranieri, Goffredo, and Schroeder 2011).

Aguado and *et al*. analyzed data from a P-removal SBR. They discussed the use of Kohonen Self-Organizing Maps (SOM) and Principal Component Analysis (PCA) to analyze and interpret multidimensional data from a biological wastewater treatment process aimed at enhanced biological phosphorus removal (EBPR). They describe the operation of a sequencing batch reactor, designed to facilitate EBPR, detailing the reactor's cycles and the types of data collected. It was concluded that both methodologies provide powerful tools for extracting relevant information from high-dimensional data sets, facilitating diagnosis and process optimization in wastewater treatment operations (Aguado *et al*. 2008).

Improving the performance of a continuous-inflow sequencing batch reactor (SBR) using a real-time control system that monitors-oxidation reduction potential (ORP) and pH levels. The study found that the real-time controlled SBR surpassed conventional systems in substrate removal efficiency and cost-effectiveness, achieving a total nitrogen removal efficiency of 91%, compared to 81% for sequential control. It also demonstrated higher removal rates for chemical oxygen demand (COD), total Kjeldahl nitrogen (TKN), and ammonia (NH4) at 93%, 89%, and 91%, respectively. Additionally, the real-time control system led to a 14-32% reduction in aeration energy and an 11-29% decrease in reactor capacity needs, resulting in lower operational costs (Marsili-Libelli 2006).

Marsili-Libelli *et al*. suggested approaching managing timing through an inference process that utilizes indirect indicators such as pH, ORP, and DO. These indicators provide insights into the process's condition, using a fuzzy clustering algorithm to determine when each phase is nearing completion. Experimental findings indicate that this method can significantly reduce the duration of treatment cycles, allowing for the processing of larger volumes of wastewater. Although no settling issues were observed during the experiments, the duration was too brief to dismiss potential sludge-related effects, and it remains uncertain whether prolonged operation could influence settling characteristics. While the results for phase-length management were promising, further exploration is needed in several areas. The established hard time limit may prove insufficient in cases of overload, and additional fuzzy rules might be necessary to adjust to varying operational conditions. Moreover, effective initial cluster training and the incorporation of problematic data are vital, as they enhance the controller's understanding and ability to identify unusual scenarios, enabling it to implement a robust defensive strategy (Marsili-Libelli 2006).

Casellas presents a control strategy for improving nitrogen and phosphorus removal in a Sequencing Batch Reactor (SBR) by utilizing real-time monitoring of pH, oxidation-reduction potential (ORP), and oxygen uptake rate (OUR). This allows for dynamic adjustments to reaction phases, enhancing efficiency and reducing energy consumption. Experiments showed that the optimized strategy outperformed a fixed 24-hour cycle, achieving pollutant removal efficiencies of 94% for carbon, 96% for nitrogen, and 88% for phosphorus. The new approach reduced treatment time by 45% and aeration time by 50%, resulting in significant energy savings and adaptability to varying wastewater loads. The study concludes that this strategy effectively optimizes nutrient removal in SBR systems, meeting regulatory standards while lowering operational costs (Casellas, Dagot, and Baudu 2006).

Corominas *et al*. investigate enhancing Sequencing Batch Reactors (SBRs) for wastewater treatment by using model-based evaluations of an online control strategy that utilizes Oxygen Uptake Rate (OUR) and Oxidation-Reduction Potential (ORP) measurements. This approach addresses stricter effluent regulations and aims to reduce treatment costs. Employing a calibrated ASM1 model, the study compared SBR performance with and without control strategies, focusing on effluent quality, aeration energy needs, and treated wastewater volume. Results showed that an online control strategy optimizing aerobic and anoxic phase durations significantly improved effluent quality and reduced aeration energy by up to 35%. The model-based method allows testing various control strategies without extensive experiments, potentially enhancing SBR efficiency. However, the authors emphasize the need for careful monitoring of microbial communities to ensure model predictions remain valid. Future real-world implementation is necessary to confirm the model's effectiveness (Corominas *et al*. 2006). Table 1 provides a summary of articles that focus on the application of AI in SBR.

Table 1: Summary of article related to applying AI in SBR

Researcher	Method	Finding
(Dey *et al*. 2024)	Advanced control strategies	FPI controller improved nutrient levels, 11.04% reduction in air volume usage, enhanced effluent quality
(Heo *et al*. 2023)	Mathematical modeling and AI-based optimization	Developed a PN model, optimized NH4, NO2, NO3 levels, saved 31.38% energy with AI-OpAS strategy
(Kwon *et al*. 2023)	IoT integration with automatic mechanical decanter	-Reduced Time for Settling and Discharging (TRSD) to 1 hour (27-59% reduction), improved nitrogen removal to 92-93% using the step-feed method.
(Zhou *et al*. 2021)	Multi-way principal component analysis (MPCA)	Developed fault diagnosis method for SBR in paper mill, demonstrating viability and reliability of MPCA technique.
(S. Li *et al*. 2021)	A real-time management approach utilizing Dissolved Oxygen (DO) and Oxidation-Reduction Potential (ORP	Maintained N-NH4+ < 2 mg/L with 97% removal efficiency, and 98% nitrite accumulation rate.
(Salari, Ataei, and Bakhtiyari 2017)	Performance evaluation of SBR for petrochemical wastewater	Optimal 7-hour cycle time, reaching to maximum removal efficiencies of 84% COD, 67% TS, and 92% TSS, improvement in aeration.
(Ranieri, Goffredo, and Schroeder 2011)	Comparison of 'React Fill' and 'Static Fill' methods	'Static Fill' outperformed 'React Fill' in storage products production for cheese factory wastewater with high- strength properties.
(Aguado *et al*. 2008)	SOM and PCA for data analysis	Effective in diagnosing and optimizing EBPR processes in SBR, enhancing phosphor treatment efficiency.
(Marsili-Libelli 2006)	Real-time control system of pH, ORP, and DO	Achieved 91% nitrogen removal efficiency, 14-32% reduction in aeration energy, and improved substrate removal.
(Casellas, Dagot, and Baudu 2006)	Real-time monitoring and dynamic adjustments by controlling pH, ORP, and OUR	Achieved pollutant removal efficiencies of 94% for carbon, 96% for nitrogen, and 88% for phosphorus, reduced treatment time by 45%.
(Corominas *et al*. 2006)	Model-based online control strategy	Improved effluent quality, and reduced aeration energy by 35% through OUR and ORP optimization.

3.0 AI Application in Sequencing Batch Reactor

The SBR tank can serve many functions in treating wastewater if the operation and cycle time has been optimized correctly.

- **Equalization**

Many WWTPs require equalization tanks due to organic and hydraulic shock from influent, the designer set an equalization tank before the SBR tank to reduce these shocks. The application of small-scale treatment systems can be beneficial for industrial wastewater management and in small communities, particularly where conventional sewer infrastructure is lacking. These systems can adapt to both daily fluctuations and seasonal variations in wastewater characteristics (Metcalf, Eddy, and Tchobanoglous 1991). By leveraging artificial intelligence (AI), adjustments to system configurations and operational strategies in Sequencing Batch Reactors (SBR) can be seamlessly implemented. For instance, in Dakar, where only 24% of residents are connected to a sewage treatment facility, small treatment systems could effectively address sanitation challenges. The experimental approach employed an automated SBR treatment system, demonstrating adaptability to varying wastewater flow rates (Barsan *et al*. 2017).

Furthermore, when treated wastewater from smaller plants is directed to a larger SBR-operated facility, it's essential to optimize operational cycles to manage fluctuations in inflow. AI-driven models can be created to forecast reactor performance under different loading conditions, allowing operators to proactively modify their operational approaches or enhance pre-treatment processes before the wastewater enters the SBR (Kwon *et al*. 2023).

The SBR system offers considerable operational flexibility, including internal equalization. The duration of idle periods can be adjusted based on influent flow rates and operational strategies, facilitating equalization during these intervals.

- **Selector**

Regarding sludge management, a phenomenon known as sludge bulking occurs when excessive suspended solids in the effluent diminish the efficiency of treatment plants (Salari, Ataei, and Bakhtiyari 2017). This issue can arise from operational conditions such as low dissolved oxygen levels, low food-to-microorganism (F/M) ratios, and fully mixed operations, increasing filamentous bacteria that do not settle well. To mitigate this, bioreactors, often referred to as bio-selectors or selectors, are integrated into the SBR process. These systems are specifically designed to promote the growth of floc-forming heterotrophic bacteria over filamentous species (Zhao *et al*. 2016). In SBR operations, the activated sludge is returned to a floc-forming unit, where it is combined with incoming wastewater in a designated selection zone, a process that can also be enhanced through the use of AI.

- **Reducing the effect of design assumptions**

Change of design assumption in real wastewater treatment plant and need to adapt with the real conditions such as change in influent characteristics prediction or weather condition.

Table 2 outlines the standard design parameters for sequential batch reactors (SBR) that are commonly utilized by designers. However, these assumptions may not reflect real-world conditions and can change as new information becomes available.

Table 2: Typical design criteria parameter of SBR (Metcalf, Eddy, and Tchobanoglous 1991)

SRT, d	**F/M, kg BOD/ kg MLVSS•d**	**Volumetric loading, kg BOD/m^3. d**	**MLSS, mg/L**	**Total hydraulic retention time, d**
15-30	0.04-0.1	0.1-0.3	2000-5000	15-40

Research by Zhao and his team investigated how varying salinity levels (ranging from 0 to 3% w/w) influenced the performance of microbes in a sequential batch reactor (SBR). The results indicated that the best biological nutrient removal occurred in the absence of salinity. Various studies on saline wastewater have shown that higher salinity concentrations lead to a reduction in oxygen transfer rates (OTR), which in turn negatively influences the activated sludge microbial communities (Zhao *et al*. 2016).

Improve operational conditions in the initial years

Operating a Sequencing Batch Reactor (SBR) during its initial years, especially when the influent is lower than the design capacity, requires careful management to ensure efficient treatment and system stability. For adjusting operational parameters with lower influent flows, it may be necessary to adjust the operational cycles to optimize treatment efficiency.

Predictive Maintenance:

AI can also enhance the maintenance of SBR systems by predicting equipment failures through data analytics. By analyzing patterns in operational data, AI can forecast when maintenance is needed, reducing downtime and ensuring consistent treatment performance.

Sludge bulking is a significant challenge faced by more than 50% of wastewater treatment plants (WWTPs) utilizing the activated sludge process (ASP). This problem primarily arises from the excessive proliferation of filamentous bacteria. The occurrence of sludge bulking hampers the efficient separation of activated sludge, leading to the loss of solid materials in the treated effluent. Consequently, this situation not only escalates operational expenses but also diminishes the overall effectiveness of the treatment facility (Liu *et al*. 2016).

In a study by Yao, implementing a 30-minute anaerobic stirring phase after the inflow of wastewater into a sequencing batch reactor (SBR) system significantly reduced sludge bulking within just 10 cycles. The sludge volume index (SVI) decreased notably from 222 to 74 $mL \cdot g^{-1}$. Additionally, high-throughput sequencing results revealed that this anaerobic phase effectively inhibited the growth of filamentous bacteria, which improved sludge concentration and promoted the settling of activated sludge (Yao JunQin *et al*. 2019).

Resiliency Improvement

Resilience refers to a wastewater system's ability to foresee, endure, bounce back from, and adapt to various challenges posed by climate change and other occurrences. It is also recognized as an ongoing process that seeks to find a balance between risks and resources, leading to the development of flexible and innovative strategies for anticipating, managing, responding to, recovering from, and adjusting to events either before or after they occur (Asghari *et al*. 2023).

AI-operated SBR systems can offer greater flexibility in scaling operations up or down based on real-time demands and influent characteristics. This adaptability is particularly useful in industries like petrochemicals, where wastewater composition can vary significantly.

Energy Efficiency and Sustainability

Enhancing energy efficiency and sustainability in wastewater treatment presents significant opportunities for optimization through AI, given the substantial energy demands of these processes.

The research indicated that while longer aeration times improved treatment efficiency, they also increased energy costs. AI can help find the right balance between energy consumption and treatment efficacy by analyzing energy usage patterns alongside treatment outcomes, potentially suggesting more energy-efficient operational protocols.

Research conducted by Ku and associates emphasizes the ability of AI to optimize the performance of wastewater treatment systems, increase their resilience, and lower operational expenses. The study indicates that AI methodologies could be utilized to manage various other factors, thereby fostering more sustainable operations in Sequencing Batch Reactors (SBR) (Heo *et al*. 2023).

The overall design and functionality can include the capability to share mechanical equipment among the reactors to minimize the need for extra equipment for instance, blowers can alternate between reactor modules.

Qua *et al*. conducted an analysis focusing on the economic implications of Sequencing Batch Reactors (SBRs) for municipal wastewater treatment in developing nations. This analysis was performed using the Environmental Protection Agency's (EPA) computer- assisted tool, as illustrated in Figure 4.

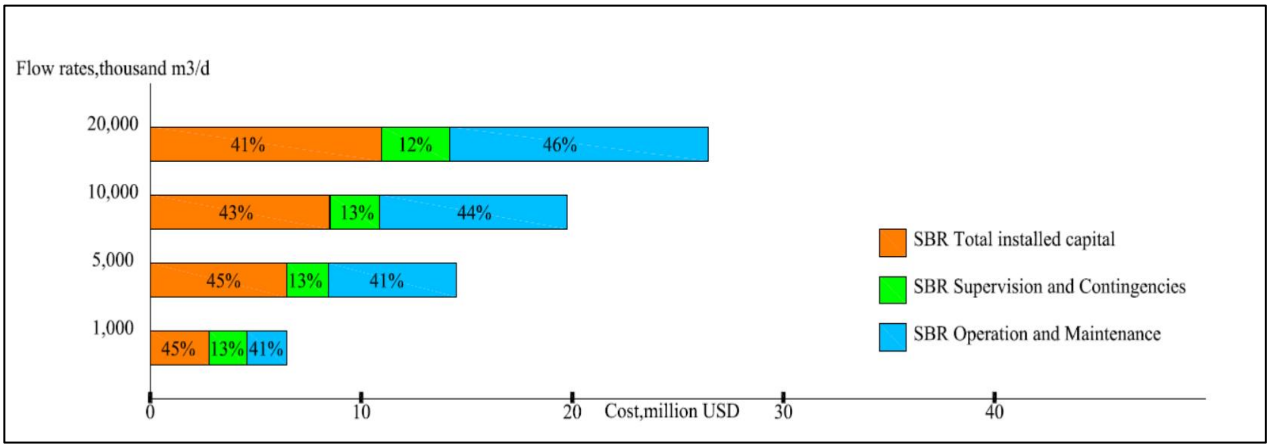


Figure 4: Economic aspects associated with Sequencing Batch Reactors (SBRs) in developing countries

The graph illustrates that a significant proportion of the SBR treatment systems' costs are attributed to operational and maintenance expenses, independent of the capacity of the wastewater treatment facility (Quan and Gogina 2021). Consequently, implementing effective operational strategies is essential for minimizing expenses.

Other benefits

Additionally, AI can play a significant role in effectively addressing the following challenges in SBR wastewater treatment systems.

- Impacts of climate change.
- Presence of emerging pollutants.
- Introduction of new knowledge, resulting in a mismatch between prior designs and current best practices.
- Quantitative and qualitative shocks caused by unauthorized and industrial discharges into the sewage networks.
- Improving effluent quality during operation, including adjustments to Sludge Retention Time (SRT), Hydraulic Retention Time (HRT), sludge return flow rates, sludge loading rates during the sedimentation phase, Nor/NOx.
- The necessity for upgrading as the treatment plant approaches the end of its operational lifespan.

4.0 Challenges of AI in Sequencing Batch Reactor

Despite the advancements in predictive modeling techniques, several limitations persist that hinder their effectiveness in bioremediation applications. Typical challenges in the application of AI in SBR wastewater treatment plants are listed below.

Data Limitations

One major challenge is the heavy dependence of these models on the selected data. Effective models typically emerge from a thorough learning and training process, which requires an appropriate dataset. However, wastewater treatment facilities often face constraints in historical data availability, and many communities lack the necessary data management and storage capabilities to support these models (Joel, Doorsamy, and Paul 2022).

Additionally, missing data poses another significant challenge, as the performance and reliability of AI and machine learning (ML) models are closely tied to the quality of the data utilized (Joel, Doorsamy, and Paul 2022). Sensor data is often susceptible to inaccuracies and uncertainties, which complicate the development and training of precise AI models (Salem, Saraya, and Ali-Eldin 2022)

Sensor faults can be categorized into two types: sudden failures (characterized by abrupt, noisy, and random errors) and deterioration failures (involving bias, drift, and gain issues) (D. Li *et al*. 2020).

AI Training Concerns

AI systems may inherit biases from their training datasets, leading to potentially unfair outcomes. In the field of wastewater treatment, these biases can have a disproportionate effect on marginalized communities that are already facing environmental disparities (Sun *et al*. 2022). A study highlighted that forecasting a variable using machine learning involves adjusting model parameters based on a training set created by Machine Learning Methods Modeling (Rodríguez-Rángel *et al*. 2022).

Challenges in AI Learning and Reproducibility

Many AI methodologies utilize customized datasets for training and testing, which can result in poor reproducibility (Nagpal *et al*. 2024). This variability complicates the process for businesses attempting to apply a single AI technique across diverse industry applications and poses challenges for researchers aiming to replicate and validate previous studies and results (Adadi 2021). Historically, monitoring nutrients (such as BOD, COD, NH_4–N, NO_3-N, and $PO4_3^-$) in bioreactors in real-time has been both challenging and costly. Consequently, studies with online controls have typically relied on factors that indicate biological states, such as pH levels, oxidation-reduction potential (ORP), and dissolved oxygen (DO) (Kwon *et al*. 2023).

Data challenges

The reliance of these models on selected datasets poses a significant challenge. Effective model development typically involves a thorough learning and training process, underscoring the importance of choosing an appropriate dataset wastewater treatment facilities often face limitations in historical data availability, while many communities lack the necessary resources for data management and storage, which are crucial for the successful implementation of these models (D. Wang *et al*. 2022).

Moreover, the issue of incomplete data can exacerbate the situation, as the effectiveness of AI and machine learning models largely relies on the quality of the input data. Sensor data, in particular, may be prone to inaccuracies and uncertainties, hindering the development and training of dependable AI models (Salem, Saraya, and Ali-Eldin 2022). Sensor faults can be categorized into two types: sudden failures, which are abrupt and erratic, and deterioration failures, which involve bias, drift, or gain issues (D. Li *et al*. 2020).

Training the AI

AI systems can adopt biases present in their training datasets, resulting in outcomes that may be unjust. In the context of wastewater treatment, these biases could disproportionately affect marginalized communities that already face environmental injustices (Nagpal *et al*. 2024). A study indicated that the process of forecasting variables using machine learning involves adjusting the model's parameters based on a training dataset created through machine learning methods (Rodríguez-Rángel *et al*. 2022).

AI learning and reproducibility

Many AI techniques rely on customized datasets for training and validation, which can result in challenges related to reproducibility (Adadi 2021). This limitation complicates the ability of companies to apply a single AI method across various industry contexts and hinders researchers’ efforts to replicate and verify previous studies and findings (Sun *et al*. 2022).

Historically, managing nutrients such as BOD, COD, NH_4^-N, NO_3-N, and PO_4^{3-}, in bioreactors through online control was both complex and costly. Consequently, online studies often utilized indicators of biological states, such as pH, oxidation-reduction potential (ORP), and dissolved oxygen (DO) (Kwon *et al*. 2023).

Reliability

Achieving reliable and consistent performance from AI-driven systems in real-world applications presents substantial challenges, as wastewater treatment processes are influenced by complex dynamics, seasonal changes, and unforeseen disturbances (Abdalrahman *et al*. 2022).

According to Rajaee and colleagues, the evaluation of the model's performance is typically conducted through a range of metrics, including the coefficient of correlation (R), root mean square error (RMSE), and coefficient of determination (R^2) (Rajaee, Khani, and Ravansalar 2020).

Based on Rajaee *et al*., the predictions made by AI tools may not always align with actual results in specific scenarios. It is crucial to improve the predictive abilities of these tools so that they can function effectively across various situations and adjust to unexpected changes in input factors. For example, sudden alterations in wastewater quality and operational parameters can result in inaccurate forecasts by AI tools (Alam *et al*. 2022).

Current predictive modeling techniques may lack generalizability across different conditions and pollutants. A model trained on a specific dataset may perform poorly when applied to different contexts, limiting its applicability. This challenge underscores the importance of developing adaptable modelling frameworks that can be tailored to varying conditions while still providing reliable predictions (J. Li *et al*. 2020).

Sophisticated Computations

High computational demands are often required for advanced predictive modeling techniques, especially those using machine learning and simulation-based approaches. This can limit the accessibility of these models, particularly for smaller organizations or researchers with limited resources. Developing more efficient algorithms and leveraging cloud computing can help alleviate these computational constraints, making predictive modeling tools more widely available.

Staff Training

It's important to note that operators and managers of WWTPs might not possess the required skills to successfully implement, maintain, and assess AI technologies. It is crucial to facilitate collaboration between wastewater treatment specialists and data science professionals to enhance the successful deployment of these solutions. Additionally, tailoring AI applications to meet the unique operational needs and limitations of each wastewater treatment plant can be a challenging and lengthy process (Di Maria, Daskal, and Ayalon 2020).

Typically in an SBR WWTP, an average operator needs at least a year before becoming confident to operate an SBR process, while the process for learning the system operated by AI could be more challenging (de Silva 2003).

Besides, many predictive models are complex and require sophisticated algorithms, which can lead to challenges in interpretation and implementation. Users may struggle to understand the underlying mechanics of these models.

Compatibility with Existing Infrastructures

Integrating AI with the existing WWTP infrastructure might also necessitate modifications and upgrades, resulting in further expenses. Regular maintenance and updates are crucial for ensuring the AI systems function optimally, leading to ongoing costs for software updates, hardware upkeep, and troubleshooting. However, AI has the potential to significantly improve the efficiency of these facilities in a cost-effective manner.

Cost-Benefit Analysis:

Incorporating artificial intelligence (AI) into wastewater treatment demands a thorough assessment of both costs and advantages. Generally, implementing AI technologies entails a considerable initial investment in the required infrastructure, including sensors, data storage, and computational resources, along with continuous expenses for maintenance and system enhancements. It is crucial to balance these financial commitments with the prospective benefits, which could encompass enhanced operational efficiency, lower operational costs, and improved adherence to environmental regulations.

The implementation and advancement of artificial intelligence in wastewater treatment facilities may result in higher energy usage and an increase in electronic waste. Although AI enhancements, such as optimizing aeration control, are designed to lower energy consumption, the necessary infrastructure—including servers and sensors—can significantly impact the environment. Therefore, it is crucial to evaluate and address these negative environmental effects to ensure the sustainable application of AI technologies (Bolón-Canedo *et al*. 2024).

The research should prioritize the creation of detailed cost-benefit models to assist decision-makers in evaluating the financial feasibility of AI technologies across various wastewater treatment facilities, especially smaller plants that might face budget limitations. (Ly *et al*. 2022).

Additionally, assessing the cost-effectiveness of integrating AI into wastewater treatment plants (WWTPs) can be difficult, as it varies based on numerous factors, including the facility's size and complexity, the nature of the wastewater being processed, and the specific AI technologies utilized. Furthermore, there are significant initial costs associated with deploying AI, such as acquiring the necessary software, hardware, sensors, and other critical equipment. Training staff to effectively operate these AI systems also contributes to both time and financial investments.

Regulation

It is essential that discussions on regulating AI applications in social infrastructure keep pace with this rapid development. However, the legal implications and potential risks associated with using AI for managing critical services such as wastewater treatment have not been thoroughly examined (Takeda *et al*. 2021a).

Copyright

As AI technology continues to advance, the question of copyright in AI-generated content becomes increasingly complex. Because the training of AI models demands significant human resources and time. Moreover, as the program's accuracy is influenced by the training methods used, this training process is deemed a critical aspect of intellectual property. It is important for those looking to profit from AI system development and sale. As a result, establishing clear guidelines and protections for AI-generated works is essential to encourage innovation while safeguarding the interests of creators and investors in this rapidly evolving field (Takeda *et al*. 2021b).

Ethical Issue

When applied to wastewater treatment plants (WWTPs), AI introduces a range of ethical challenges that must be addressed to ensure these technologies are used responsibly and equitably. It's important to uphold transparency and accountability in the AI systems employed in WWTPs to build trust with stakeholders and regulatory bodies.

It is essential to offer thorough documentation of the decision-making processes behind AI systems, making it accessible to stakeholders. This level of transparency is crucial for ensuring accountability among both developers and operators regarding the outcomes produced by AI systems (Nagpal *et al*. 2024).

5.0 CONCLUSION

Incorporating AI technologies into Sequencing Batch Reactor (SBR) operations can significantly enhance the efficiency, cost-effectiveness, and management of wastewater treatment processes, thus upgrading traditional systems. The implementation of AI marks a transformative shift in SBR wastewater treatment facilities, facilitating improved management and sustainability through the use of data and sophisticated algorithms. This transition not only contributes to better environmental outcomes but also promotes public health.

This approach offers significant potential for sustainable wastewater treatment by effectively lowering operational costs and safeguarding the environment. In addition to forecasting the efficiency of wastewater treatment processes, AI technologies can be employed to develop an integrated wastewater treatment system. This system encompasses various elements, including wastewater discharge, sludge management, environmental impacts, economic factors, and policy development. It is crucial to present data accurately, ensuring that details regarding data sources, locations, operational contexts, and dataset structures are included (Lowe, Qin, and Mao 2022). Ongoing research in this field is anticipated to yield additional innovative solutions.

REFERENCES

1. Abdalrahman, Ghada, Sai Hin Lai, Pavitra Kumar, Ali Najah Ahmed, Mohsen Sherif, Ahmed Sefelnasr, Kwok Wing Chau, and Ahmed Elshafie. 2022. "Modeling the Infiltration Rate of Wastewater Infiltration Basins Considering Water Quality Parameters Using Different Artificial Neural Network Techniques." *Engineering Applications of Computational Fluid Mechanics* 16 (1): 397–421. https://doi.org/10.1080/19942060.2021.2019126.
2. Adadi, Amina. 2021. "A Survey on Data-efficient Algorithms in Big Data Era." *Journal of Big Data* 8 (1): 24. https://doi.org/10.1186/s40537-021-00419-9.
3. Aguado, Daniel, Tatiana Montoya, L. Borras, Aurora Seco, and José Ferrer. 2008. "Using SOM and PCA for Analysing and Interpreting Data from a P-Removal SBR." *Engineering Applications of Artificial Intelligence* 21 (6): 919–30.

4. Ahmad, Abdul Latif, Jing Yi Chin, Mohd Hazarel Zairy Mohd Harun, and Siew Chun Low. 2022. “Environmental Impacts and Imperative Technologies towards Sustainable Treatment of Aquaculture Wastewater: A Review.” *Journal of Water Process Engineering* 46:102553.
5. Alam, Gulzar, Ihsanullah Ihsanullah, Mu Naushad, and Mika Sillanpää. 2022. “Applications of Artificial Intelligence in Water Treatment for Optimization and Automation of Adsorption Processes: Recent Advances and Prospects.” *Chemical Engineering Journal* 427:130011.
6. Asghari, Fatemeh, Farzad Piadeh, Daniel Egyir, Hossein Yousefi, Joseph P. Rizzuto, Luiza C. Campos, and Kourosh Behzadian. 2023. “Resilience Assessment in Urban Water Infrastructure: A Critical Review of Approaches, Strategies and Applications.” *Sustainability* 15 (14): 11151.
7. Baarimah, A.O., M.A. Bazel, W.S. Alaloul, M.Y. Alazaiza, T.M. Al-Zghoul, B. Almuhaya, A. Khan, and A.W. Mushtaha. 2024. “Artificial Intelligence in Wastewater Treatment: Research Trends and Future Perspectives through Bibliometric Analysis.” *Case Stud. Chem. Environ. Eng* 100926.
8. Barsan, N., V. Nedeff, A. Temea, E. Mosnegutu, A.D. Chitimus, and C. Tomozei. 2017. “A Perspective for Poor Wastewater Infrastructure Regions: A Small-Scale Sequencing Batch Reactor Treatment System.” *Chem. J. Mold,* 61–66.
9. Bolón-Canedo, Verónica, Laura Morán-Fernández, Brais Cancela, and Amparo Alonso-Betanzos. 2024. “A Review of Green Artificial Intelligence: Towards a More Sustainable Future.” *Neurocomputing*, 128096.
10. Casellas, M., C. Dagot, and M. Baudu. 2006. “Set up and Assessment of a Control Strategy in a SBR in Order to Enhance Nitrogen and Phosphorus Removal.” *Process Biochemistry* 41 (9): 1994–2001.
11. Corominas, Ll, Gürkan Sin, S. Puig, A. Traore, M. Balaguer, J. Colprim, and P. A. Vanrolleghem. 2006. “Model-Based Evaluation of an on-Line Control Strategy for SBRs Based on OUR and ORP Measurements.” *Water Science and Technology* 53 (4–5): 161–69.
12. Dey, Indranil, Seshagiri Rao Ambati, Prashant Navnath Bhos, Shirish Sonawane, and Sridhar Pilli. 2024. “Effluent Quality Improvement in Sequencing Batch Reactor-Based Wastewater Treatment Processes Using Advanced Control Strategies.” *Water Science & Technology* 89 (10): 2661–75.
13. Di Maria, Francesco, Shira Daskal, and Ofira Ayalon. 2020. “A Methodological Approach for Comparing Waste Water Effluent’s Regulatory and Management Frameworks Based on Sustainability Assessment.” *Ecological Indicators* 118:106805.
14. Heo, SungKu, Juin Yau Lim, Hai-Tra Nguyen, Paulina Vilela, Usman Safder, TaeYong Woo, SangYoon Kim, TaeSeok Oh, and ChangKyoo Yoo. 2023. “End-to-End Autonomous and Resilient Operability Strategy of Full-Scale PN-SBR System: From Influent Augmentation to AI-Aided Optimal Control and Scheduling.” *Journal of Water Process Engineering* 53:103694.
15. Jing, YANG, Liang Wei-Li, and Huang Fu-Chuan. 2021. “Review of SBR Process in Effluent Treatment.” In *E3S Web of Conferences*, 233:01120. EDP Sciences. https://www.e3s-conferences.org/articles/e3sconf/abs/2021/09/e3sconf_iaecst20_01120/e3sconf_iaecst20_01120.html.
16. Joel, Luke Oluwaseye, Wesley Doorsamy, and Babu Sena Paul. 2022. “A Review of Missing Data Handling Techniques for Machine Learning.” *International Journal of Innovative Technology and Interdisciplinary Sciences* 5 (3): 971–1005.
17. Kwon, Hyuck, Hyun-Jin Kang, Yuchan Park, and Jaeho Bae. 2023. “Optimization of a Sequencing Batch Reactor with the Application of the Internet of Things.” *Water Research* 229:119511.
18. Li, Daoliang, Ying Wang, Jinxing Wang, Cong Wang, and Yanqing Duan. 2020. “Recent Advances in Sensor Fault Diagnosis: A Review.” *Sensors and Actuators A: Physical* 309:111990.
19. Li, Jun, Yanqiu Pei, Shaohua Zhao, Rulin Xiao, Xiao Sang, and Chengye Zhang. 2020. “A Review of Remote Sensing for Environmental Monitoring in China.” *Remote Sensing* 12 (7): 1130.
20. Li, Shunyi, Jiannan Mu, Yafei Du, and Zhenjun Wu. 2021. “Study and Application of Real-Time Control Strategy Based on DO and ORP in Nitritation–Denitrification SBR Start-Up.” *Environmental Technology* 42 (1): 114–25. https://doi.org/10.1080/09593330.2019.1624297.
21. Liu, Yiqi, Jianhua Guo, Qilin Wang, and Daoping Huang. 2016. “Prediction of Filamentous Sludge Bulking Using a State-Based Gaussian Processes Regression Model.” *Scientific Reports* 6 (1): 31303.
22. Lowe, Matthew, Ruwen Qin, and Xinwei Mao. 2022. “A Review on Machine Learning, Artificial Intelligence, and Smart Technology in Water Treatment and Monitoring.” *Water* 14 (9): 1384.
23. Luo, Z. Y. 2018. “Application of SBR Process in Urban Sewage Treatment. J.” *Value Engineering* 16:180–82.
24. Ly, Quang Viet, Viet Hung Truong, Bingxuan Ji, Xuan Cuong Nguyen, Kyung Hwa Cho, Huu Hao Ngo, and Zhenghua Zhang. 2022. “Exploring Potential Machine Learning Application Based on Big Data for Prediction of Wastewater Quality from Different Full-Scale Wastewater Treatment Plants.” *Science of the Total Environment* 832:154930.
25. Marsili-Libelli, Stefano. 2006. “Control of SBR Switching by Fuzzy Pattern Recognition.” *Water Research* 40 (5): 1095–1107.
26. Mazloom, M.S., F. Rezaei, A. Hemmati-Sarapardeh, M.M. Husein, S. Zendehboudi, and A. Bemani. 2020. “Artificial Intelligence Based Methods for Asphaltenes Adsorption by Nanocomposites: Application of Group Method of Data Handling, Least Squares Support Vector Machine, and Artificial Neural Networks.” *Nanomaterials* 10:890.

27. Metcalf, Leonard, Harrison P. Eddy, and Georg Tchobanoglous. 1991. *Wastewater Engineering: Treatment, Disposal, and Reuse*. Vol. 4. McGraw-Hill New York. https://library.wur.nl/WebQuery/titel/1979505.
28. Nagpal, Mudita, Miran Ahmad Siddique, Khushi Sharma, Nidhi Sharma, and Ankit Mittal. 2024a. "Optimizing Wastewater Treatment through Artificial Intelligence: Recent Advances and Future Prospects." *Water Science & Technology* 90 (3): 731–57.
29. Obaideen, Khaled, Nabila Shehata, Enas Taha Sayed, Mohammad Ali Abdelkareem, Mohamed S. Mahmoud, and A. G. Olabi. 2022. "The Role of Wastewater Treatment in Achieving Sustainable Development Goals (SDGs) and Sustainability Guideline." *Energy Nexus* 7:100112.
30. Quan, Tran Ha, and Elena Gogina. 2021. "The Assessment of Technical-Economic Efficiency of Sequencing Batch Reactors in Municipal Wastewater Treatment in Developing Countries." In *IOP Conference Series: Materials Science and Engineering*, 1030:012060. IOP Publishing. https://iopscience.iop.org/article/10.1088/1757-899X/1030/1/012060/meta.
31. Rajaee, Taher, Salar Khani, and Masoud Ravansalar. 2020. "Artificial Intelligence-Based Single and Hybrid Models for Prediction of Water Quality in Rivers: A Review." *Chemometrics and Intelligent Laboratory Systems* 200:103978.
32. Ranieri, Ezio, Vito Goffredo, and E.D. Schroeder. 2011. "Shock Load Response in an SBR-Activated Sludge Process Treating High Load Wastewater." *International Journal of Environmental Engineering* 3 (2): 164. https://doi.org/10.1504/IJEE.2011.039452.
33. Rodríguez-Rángel, Héctor, Dulce María Arias, Luis Alberto Morales-Rosales, Victor Gonzalez-Huitron, Mario Valenzuela Partida, and Joan García. 2022. "Machine Learning Methods Modeling Carbohydrate-Enriched Cyanobacteria Biomass Production in Wastewater Treatment Systems." *Energies* 15 (7): 2500.
34. Salari, Mina, Seyed Ahmad Ataei, and Fereshteh Bakhtiyari. 2017. "Evaluation of Sequencing Batch Reactor Performance for Petrochemical Wastewater Treatment." *Advances in Environmental Technology* 3 (3): 133–37.
35. Salem, Ranya MM, M. Sabry Saraya, and Amr MT Ali-Eldin. 2022. "An Industrial Cloud-Based IoT System for Real-Time Monitoring and Controlling of Wastewater." *IEEE Access* 10:6528–40.
36. Silva, Viraj de. 2003. "OPERATING SBR PLANTS–ISSUES AND CONCERNS." In *WEFTEC 2003*, 91–95. Water Environment Federation. https://www.accesswater.org/publications/proceedings/-290450/operating-sbr-plants---issues-and-concerns.
37. Sun, Hong, Pouya Saeedi, Suvi Karuranga, Moritz Pinkepank, Katherine Ogurtsova, Bruce B. Duncan, Caroline Stein, Abdul Basit, Juliana CN Chan, and Jean Claude Mbanya. 2022. "IDF Diabetes Atlas: Global, Regional and Country-Level Diabetes Prevalence Estimates for 2021 and Projections for 2045." *Diabetes Research and Clinical Practice* 183:109119.
38. Takeda, Tomoko, Junko Kato, Takashi Matsumura, Takeshi Murakami, and Amila Abeynayaka. 2021. "Governance of Artificial Intelligence in Water and Wastewater Management: The Case Study of Japan." *Hydrology* 8 (3): 120.
39. Wang, Dong, Sven Thunéll, Ulrika Lindberg, Lili Jiang, Johan Trygg, and Mats Tysklind. 2022. "Towards Better Process Management in Wastewater Treatment Plants: Process Analytics Based on SHAP Values for Tree-Based Machine Learning Methods." *Journal of Environmental Management* 301:113941.
40. Wang, Yi, Yuhan Cheng, He Liu, Qing Guo, Chuanjun Dai, Min Zhao, and Dezhao Liu. 2023. "A Review on Applications of Artificial Intelligence in Wastewater Treatment." *Sustainability* 15 (18): 13557.
41. Yao JunQin, Yao JunQin, Liu JiaQi Liu JiaQi, Zhang YanJiang Zhang YanJiang, Xu Shuang Xu Shuang, Hong Ying Hong Ying, and Chen YinGuang Chen YinGuang. 2019. "Adding an Anaerobic Step Can Rapidly Inhibit Sludge Bulking in SBR Reactor." https://www.cabidigitallibrary.org/doi/full/10.5555/20193448173.
42. Zhang, Shubo, Ying Jin, Wenkang Chen, Jinfeng Wang, Yanru Wang, and Hongqiang Ren. 2023. "Artificial Intelligence in Wastewater Treatment: A Data-Driven Analysis of Status and Trends." *Chemosphere* 336:139163.
43. Zhao, Yuanyuan, Hee-Deung Park, Jeong-Hoon Park, Fushuang Zhang, Chen Chen, Xiangkun Li, Dan Zhao, and Fangbo Zhao. 2016. "Effect of Different Salinity Adaptation on the Performance and Microbial Community in a Sequencing Batch Reactor." *Bioresource Technology* 216:808–16.
44. Zhou, Jing, Feini Huang, Wenhao Shen, Zhang Liu, Jean-Pierre Corriou, and Panagiotis Seferlis. 2021. "Sub-Period Division Strategies Combined with Multiway Principle Component Analysis for Fault Diagnosis on Sequence Batch Reactor of Wastewater Treatment Process in Paper Mill." *Process Safety and Environmental Protection* 146:9–19.