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مراجعة شاملة للأدبيات حول خوارزميات تحسين عمليات معالجة مياه الصرف الصحي

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A comprehensive literature review (LR) on optimization algorithms of Sewage Water Treatment Processes

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الملخص:

يُعد تحسين عمليات معالجة مياه الصرف الصحي أمرًا بالغ الأهمية لتحسين الكفاءة وتقليل استهلاك الطاقة. تستكشف هذه الورقة البحثية تطبيق خوارزميات التعلم الآلي والذكاء الاصطناعي في تحسين العمليات الرئيسية مثل التهوية والترسيب والترشيح. من خلال الاستفادة من المراقبة الآنية والتحكم التكيفي، يمكن لهذه الخوارزميات ضبط معايير التشغيل ديناميكيًا لتعزيز كفاءة المعالجة وتقليل استهلاك الطاقة. تقدم هذه الدراسة رؤىً مفصلة حول تطبيق وفوائد التحكم في العمليات المدعومة بالذكاء الاصطناعي في معالجة مياه الصرف الصحي، مدعومة بدراسات حالة وتحليلات بيانات. تشير النتائج إلى تحسينات كبيرة في أداء المعالجة، مما يُظهر الإمكانات التحويلية للذكاء الاصطناعي في الهندسة البيئية. الذكاء الاصطناعي (AI) للتغلب على التحديات التي تواجه تقنيات معالجة مياه الصرف الصحي..

الكلمات المفتاحية: التحسين، معالجة مياه الصرف الصحي، خوارزميات الذكاء الاصطناعي، التعلم الآلي.

Abstract: Optimizing sewage treatment processes is essential for boosting efficiency and cutting down on energy utilize. This paper examines how machine learning which is associated with artificial intelligence (AI) can be applied to fine-tune critical stages like aeration, sedimentation, as well as filtration. Furthermore, via utilising real-time data as well as adaptive control strategies, these intelligent systems can continuously adjust operational settings to improve treatment outcomes while reducing energy demands. Through real-world case studies and in-depth data analysis, the research highlights how AI-driven control systems can be effectively implemented in wastewater facilities. The results demonstrate notable gains in performance, underscoring AI's potential to revolutionize environmental engineering and address long-standing challenges in wastewater treatment.

Keywords : Optimization, Sewage Treatment, AI Algorithms, machine learning

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1. INTRODUCTION

Water vital for both human life and industrial operations is under growing threat from harmful pollutants originating from human activities which is associated with natural sources alike. Ensuring access to clean, safe water remains one of the most pressing global challenges of recent time. A key step in addressing this issue is the consistent classification and monitoring of water quality. However, existing techies often fall short in delivering comprehensive and reliable water quality measurements (Ray, 2023). As the global population continues to rise, so too does human interaction with aquatic environments particularly through practices like aquaculture, aquaponics, as well as hydroponics. These activities have significantly increased the levels of nutrients, especially nitrogen which is associated with phosphorus, entering waterways. This nutrient overload disrupts delicate aquatic ecosystems, often triggering problems like algal blooms as well as oxygen depletion (Hou, 2023). To mitigate these impacts, there's an urgent need for more effective wastewater management strategies. Specifically, sustainable which is associated with innovative approaches are required to treat effluent from aquaculture systems. Embracing modern techies offers a promising path toward cleaner water and healthier ecosystems (Shen, 2023). Treating sewage effectively is essential not only to safeguard public health which is associated with meet environmental regulations but also to prevent pollution of natural water systems. Rapid population growth, urban expansion, as well as industrial development have dramatically increased the volume of wastewater, straining current treatment infrastructure. Conventional treatment methods often struggle with high energy demands, inconsistent removal of contaminants, and costly maintenance (Spellman, 2018). As clean water becomes scarcer as well as environmental rules grow stricter, there’s a clear need for smarter, more sustainable wastewater solutions. Many traditional systems operate with static settings, making them poorly suited to handle fluctuating wastewater characteristics. In response, researchers as well as engineers are turning to artificial intelligence (AI) and machine learning (ML) to modernize these processes. ML, a key component of AI, excels at uncovering hidden patterns in complex data, offering practical tools without requiring deep knowledge of underlying physical or biological mechanisms. Its adaptability, speed, which is associated with precision have made it increasingly popular across environmental engineering applications. Via learning from past operational data, AI-driven systems can fine-tune treatment parameters in real time. This leads to better performance, lower energy utilize, as well as a reduced ecological footprint ushering in a new era of intelligent wastewater management. Recent studies highlight the growing role of machine learning in modernizing wastewater treatment. For instance, Ekinci et al. (2023) applied ML algorithms to forecast influent flow rates with high accuracy, allowing treatment plants to anticipate changes which is associated with adjust operations ahead of time. Bhagat et al. (2023) conducted an in-depth review showing how ML can fine-tune key operational factors , for instance, sludge retention time, chemical dosing, as well as energy utilize leading to more efficient plant performance. Meanwhile, Phorah et al. (2024) stressed that the success of these models hinges on high-quality data as well as thorough preprocessing to ensure reliable outcomes. At its core, optimizing sewage treatment is about doing more with less: improving efficiency while cutting energy utilize which is associated with environmental impact. Conventional approaches, which depend on manual oversight as well as rudimentary controls, often fall short in responding to the constantly shifting nature of wastewater streams. These outdated methods struggle to adapt to real-time variations in flow, composition, or treatment demands. In contrast, AI as well as machine learning offer a smarter, more responsive alternative. Via learning from data patterns, these techies enable dynamic, real-time decision-making in sewage treatment plants (STPs). This shift marks a significant step forward in making wastewater management more resilient, sustainable, as well as future-ready. Artificial intelligence (AI) is transforming sewage treatment via utilizing advanced algorithms that analyze data in real time as well as adapt operations on the fly. Key processes like aeration, sedimentation, as well as filtration can be fine-tuned for better performance which is associated with lower energy utilize. For example, aeration essential for feeding oxygen to microbes in biological treatment is often inefficient with traditional controls, leading to wasted energy or poor treatment. AI systems can track dissolved oxygen levels continuously as well as adjust airflow precisely, maintaining ideal conditions without excess power consumption. In sedimentation, where solids are separated from water, AI helps optimize variables like sludge blanket depth which is associated with chemical dosing via interpreting incoming water quality as well as settling behavior, improving clarity as well as reducing sludge volume. Filtration, the final polishing step, also stands to gain: instead of rigid schedules, AI dynamically manages backwashing which is associated with flow rates based on real-time filter performance, as noted via Aghdam et al. (2023). This responsiveness prevents clogging, extends filter life, which is associated with cuts maintenance needs addressing issues highlighted via Nagpal et al. (2024) regarding variable influent quality. This paper dives into how AI is applied across these core treatment stages, examining the methods utilized, real-world hurdles, as well as tangible benefits. Supported via case studies which is associated with data-driven insights, analysis shows that AI-enabled control doesn’t just refine existing systems it redefines what’s possible in sustainable, efficient wastewater management.

2. Significance of Optimizing Sewage Treatment Processes

Optimizing sewage treatment systems facilitates more efficient resource utilization, enhances pollutant removal efficacy, which is associated with mitigates environmental impacts. Advanced optimization techniques can effectively address challenges associated with fluctuating wastewater characteristics, reduce energy consumption, as well as ensure compliance with stringent environmental regulations (Singh & Srivastava, 2021).

3. Objective and Scope

This review explores how artificial intelligence (AI) and machine learning (ML) can address the shortcomings of traditional sewage treatment systems. While studies highlight the need for high-quality data, thoughtful algorithm selection, as well as a balance between model accuracy which is associated with interpretability, they also show that integrating ML with conventional controls can lead to smarter, more adaptive treatment processes. Realizing AI’s full potential improved efficiency, lower energy utilize, as well as reduced environmental impact depends on overcoming practical hurdles like data reliability, computational demands, as well as seamless real-time deployment.

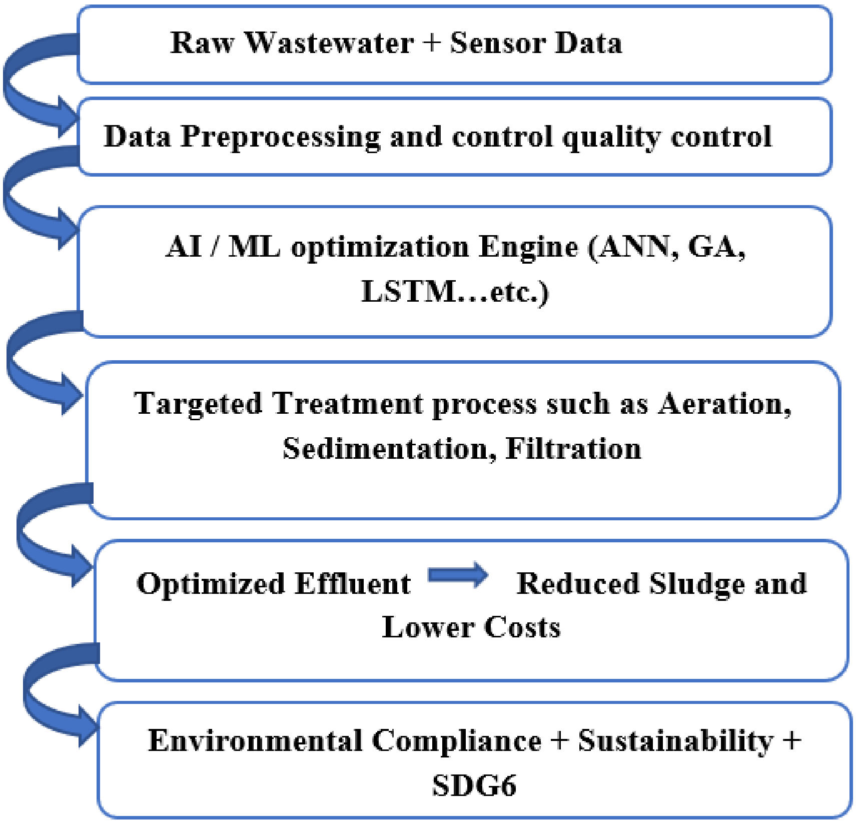

Figure.1. The Conceptual framework of AI-Driven Sewage Treatment Optimization

4. Sewage Management

Sewage refers to wastewater mixed with various types of waste generated from homes, factories, farms, as well as rainwater runoff. It carries a complex mix of pollutants, including human excreta, food scraps, grease, detergents, which is associated with industrial chemicals that pose serious risks if left untreated. Properly managing as well as treating this wastewater is essential to protect both community health as well as the natural environment.

5. Components of Sewage

Household wastewater from toilets, sinks, showers, which is associated with laundry is a daily byproduct of domestic life, while industrial sewage often carries harsher, potentially toxic chemicals from factories. Add to that stormwater, which washes pollutants like oil, dirt, as well as fertilizers off roads as well as land during rain or snowmelt, as well as get a complex mix that demands careful treatment to protect both people as well as the planet.

6. Sewage Treatment Process

The treatment of sewage involves a systematic series of processes aimed at eliminating contaminants as well as producing treated water (effluent) that is safe for environmental discharge or reuse. The standard stages of sewage treatment encompass the following:

6.1. The Utilization of AI in Sewage Treatment Optimization

Artificial Intelligence (AI) has emerged as a transformative techy across various domains, including environmental engineering. AI algorithms, for instance, Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), as well as Fuzzy Logic, provide innovative solutions for optimizing complex processes like sewage treatment. In this context, AI can predict treatment outcomes, optimize process parameters, as well as adapt to varying wastewater characteristics in real-time. (Singh & Srivastava, 2021).

6.2. Aeration Process Optimization within artificial intelligences

6.2.1. Monitoring as well as Control within Real-Time

AI helps wastewater plants breathe smarter not harder. Via constantly adjusting airflow based on real-time conditions, it keeps microbes working efficiently, cuts energy utilize via up to 25%, as well as prevents both wasted power which is associated with poor treatment. It's like giving the system a brain that learns as well as adapts, ensuring cleaner water with less waste.

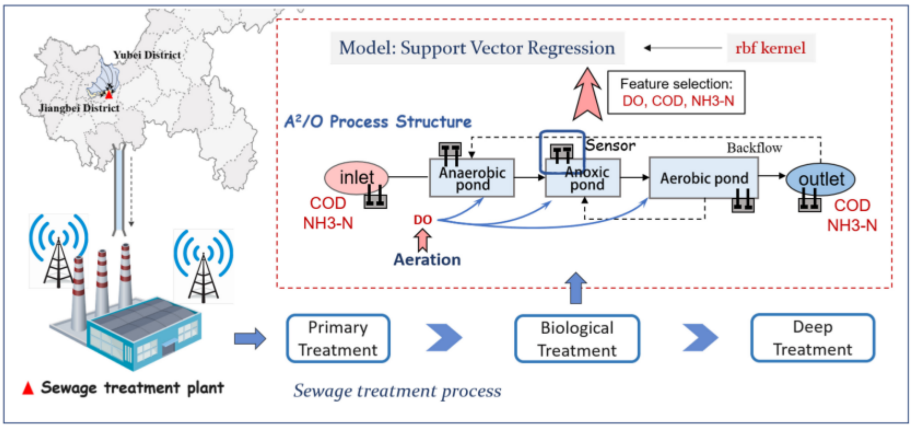

Figure. 2. Problem scene of the wastewater treatment as well as intelligent aeration research (source : Guo et al., 2024).

6.2.2. Adaptive Aeration Control

Machine learning–powered adaptive control systems can forecast oxygen needs via learning from past as well as live data, allowing them to fine-tune aeration before problems arise. This proactive approach has helped treatment plants boost effluent quality via 20% which is associated with cut energy costs significantly (Sheel et al., 2023; Alprol et al., 2024), while AI's predictive insight ensures aeration stays efficient amid both sudden shifts as well as gradual changes in wastewater makeup.

Table 1. compares traditional as well as AI-driven approaches for optimizing the aeration process in sewage treatment.

Aspect	Traditional Approach	AI-Driven Approach
Real-Time Monitoring	Manual monitoring, fixed adjustments	Automated real-time monitoring, dynamic control
Energy Consumption	High due to inefficiencies	Reduced via 15-35%
Oxygen Demand Prediction	None	Predictive, based on historical and real-time data
Adaptability	Low adaptability to fluctuations	High adaptability, proactive adjustments

Innovations like membrane bioreactors (MBRs), advanced oxidation processes (AOPs), as well as anaerobic membrane bioreactors (AnMBRs) offer smarter, more efficient ways to treat sewage tackling shortcomings of older methods, for instance, high energy utilize which is associated with incomplete contaminant removal (Abbas et al., 2009). Yet conventional optimization still leans on mathematical models, trial-and-error rules, as well as lab experiments (Fu, Butler, & Khu, 2008), which, while useful, often struggle to adapt quickly to the ever-changing nature of real-world wastewater.

6.2.3. The enhancement based on Energy Efficiency

Aeration alone can gobble up to 60% of a sewage treatment plant's energy utilize (Liu, 2024), but AI-driven control systems are proving to be a game-changer cutting energy consumption via 15% to 35% across European plants, depending on setup as well as conditions. These savings come from AI's ability to fine-tune airflow precisely when as well as where it's needed, avoiding waste while keeping treatment effective, as clearly illustrated in the comparative data presented via Alprol et al. (2024) in Table 2.

7. Sludge management and reduction

7.1. AI Optimization by using algorithms in Sedimentation Process

Sedimentation key for removing solids from wastewater can be significantly improved with AI, which fine-tunes variables like sludge blanket depth as well as chemical dosing in real time based on sensor data (Liu, 2024; Babu et al., 2023). At one industrial plant, this smart approach boosted sedimentation efficiency via 18%, cut down on sludge output, which is associated with made the whole process more stable as well as reliable.

Table .2. A comparative aspects between traditional linked with AI-driven approaches for optimizing the sedimentation process.

Aspect	Traditional Approach	AI-Driven Approach
Parameter Adjustment	Manual or fixed schedules	Dynamic adjustment of sludge blanket height as well as flocculant dosing
Efficiency	Moderate	Improved via 18%
Flocculant Usage	High, often inefficient	Reduced via 22% with optimized dosing
Sludge Production	Higher, increased disposal costs	Reduced via 15%

AI is proving to be a powerful ally in cutting down sludge via fine-tuning sedimentation settings as well as improving control across all treatment stages. In a real-world trial at a municipal plant, AI-driven management reduced sludge volume via 15%, lowering disposal costs which is associated with boosting the facility’s environmental footprint (Liu, 2024; Duarte et al., 2023).

7.2. Filtration Optimization Process via utilizing AI

Filtration plays a vital role in polishing treated wastewater via removing lingering solids as well as harmful pathogens especially important when water is reutilized or released into sensitive ecosystems. AI boosts this process via continuously monitoring conditions which is associated with intelligently adjusting filtration rates as well as backwash cycles in real time, as highlighted via Nagpal et al. (2024). Unlike traditional methods which often backwash too early or too late, causing unnecessary wear or poor performance (Jepsen et al., 2019; Alufasi et al., 2017) AI predicts the ideal moment for cleaning based on actual filter data. This smart approach has improved filter efficiency via 20%, prolonged media life, cut maintenance needs, as well as ensured more reliable pathogen removal through dynamic, data-driven control.

Table 3. A comparative between traditional as well as AI-driven approaches based on optimizing the filtration process.

Aspect	Traditional Approach	AI-Driven Approach	Author and years
Monitoring	Periodic, manual	Continuous, real-time	Markov et al., (2018)
Backwash Scheduling	Fixed intervals	Adaptive, based on performance data	Jepsen et al., (2019)
Pathogen Removal	Suboptimal under variable conditions	Enhanced via 25%	Alufasi et al., (2017)
Filter Media Life span	Reduced due to premature wear	Extended via 10%	Duffy et al., (2004)

8. AI in Process Control Implementation

A major municipal wastewater plant boosted its overall efficiency via 20% via weaving AI into its existing SCADA infrastructure a move that included upgrading sensors, designing tailored control algorithms, as well as training staff to utilize the new system confidently (Oruganti et al., 2023). To ease the transition, several plants rolled out hands-on training programs that familiarized operators with AI tools, interfaces, which is associated with troubleshooting, leading to smoother adoption as well as better performance. A thorough cost-benefit analysis showed the investment paid for itself in under three years, with expected annual savings of $200,000 from reduced energy which is associated with chemical utilize (Wongburi & Park, 2023). The evaluation also factored in upfront costs, ongoing operational gains, as well as environmental advantages, painting a clear picture of AI's strong financial as well as ecological value.

9. Types of machine learning utilized in water treatments

Machine learning encompasses the process of exposing a machine to extensive datasets, enabling it to learn, predict, identify patterns, or classify the data. The type of algorithm employed dictates the specific methodology of machine learning. Generally, machine learning can be categorized into two types: supervised learning which is associated with unsupervised learning. (Dalla and Ahmad, 2023).

9.1. Supervised learning

Supervised learning gets its name from the "guided" training process, where algorithms learn from labeled datasets meaning each input comes with the correct output enabling them to make reliable predictions on new data. This approach is especially valuable in real-world business scenarios, for instance, forecasting sales or optimizing inventory levels (Dalla & Ahmad, 2023).

9.2. Unsupervised learning

Unsupervised learning excels at uncovering hidden patterns in data whether it's grouping similar items through clustering, finding relationships between variables via association rules, or pulling key themes from text documents to support smarter decisions. As Ara et al. (2024) illustrate in Figure 3, this approach is a cornerstone of predictive modeling as well as widely utilized across diverse fields.

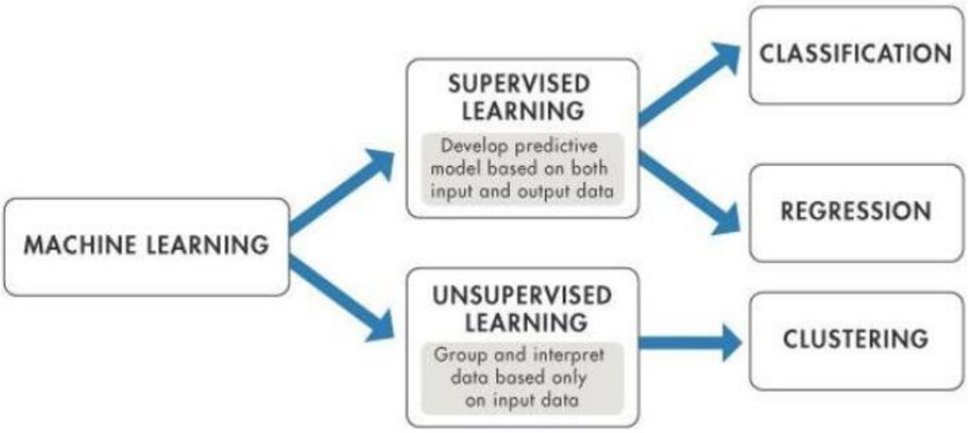

Figure.3. shows types of machine learning (Dalla and Ahmad, 2023)

AI-powered tools are transforming water management via ensuring higher water quality making it safer for drinking as well as farming while also supporting sustainability through resource recovery (Fu et al., 2023). They're also revolutionizing infrastructure care via forecasting equipment wear as well as scheduling maintenance before failures occur, which cuts costs which is associated with keeps systems running smoothly. Beyond that, AI helps the sector tackle climate change via boosting energy efficiency, lowering emissions, as well as enabling smarter water utilize in the face of growing scarcity.

10.1. High operational costs and energy demands

Sewage treatment is a cornerstone of urban infrastructure, vital for safeguarding public health which is associated with the environment but conventional systems come with steep operational costs as well as massive energy demands (Obaideen et al., 2022). From primary sedimentation to advanced disinfection, each treatment stage relies on complex machinery, chemicals, as well as skilled staff, while maintaining pumps, aerators, as well as clarifiers adds further financial pressure often straining municipal budgets which is associated with compromising performance (Ahansazan et al., 2014). Aeration alone can consume up to 60% of a plant's energy (Huang et al., 2021), as well as when paired with sludge handling as well as pumping, the environmental toll grows through higher greenhouse gas emissions which is associated with dependence on fossil fuels. To tackle these issues, innovative approaches like anaerobic digestion, energy-efficient equipment, renewable energy integration, as well as decentralized systems offer promising paths toward more sustainable, affordable, as well as resilient wastewater management especially for communities with limited resources.

10.2. Limited adaptability to fluctuating influent characteristics

Sewage treatment plants often struggle with the ever-changing nature of incoming wastewater its flow, temperature, pH, organic load, and chemical makeup can shift unpredictably, throwing traditional systems off balance (Bachand et al., 2019; Jin et al., 2014; Hartley, 2013). Conventional setups rely on fixed settings designed for stable conditions, so when real-world inputs fluctuate as they often do performance suffers, energy utilize spikes, as well as treated water quality can fall short of standards. For instance, static aeration rates may miss the mark when pollutant levels surge, while chemical dosing systems frequently under- or over-react to sudden pH changes (Ganigue et al., 2011), wasting resources as well as risking compliance. These challenges are only growing, as industrial discharges, new contaminants, as well as climate-driven variability make influent streams even more complex (Bachand et al., 2019). AI offers a smarter path forward: via utilizing real-time data as well as predictive models, it can anticipate changes which is associated with dynamically fine-tune operations though success depends on reliable sensors, quality data, as well as seamless integration with existing infrastructure.

10.3. Incomplete removal of emerging pollutants like pharmaceuticals as well as microplastics

Emerging contaminants like pharmaceuticals and microplastics are proving tough to tackle in conventional sewage treatment plants thanks to their complex chemistry as well as resistance to standard processes posing real risks to ecosystems as well as human health (Muparutsa, 2024). These pollutants enter wastewater from homes, farms, which is associated with industries; antibiotics and hormones can disrupt aquatic life as well as fuel antimicrobial resistance, while microplastics (tiny plastic fragments under 5 mm) carry toxins as well as slip through treatment systems due to their size which is associated with buoyancy. Traditional methods designed mainly for organic matter, nutrients, as well as larger solids lack the precision needed to remove such trace, persistent substances effectively. Enter AI: via analyzing real-time as well as historical data, artificial intelligence can fine-tune advanced treatments like ozone-based oxidation or membrane filtration to target these elusive pollutants more efficiently (Shahid et al., 2021). Still, realizing this potential hinges on better sensors, high-quality contaminant data, which is associated with smart integration with existing infrastructure challenges that ongoing research is steadily addressing.

10. 4. Role of Optimization in Sewage Treatment

Optimizing sewage treatment is key to making the process more efficient, cost-effective, as well as environmentally sustainable especially as plants face rising wastewater volumes, tighter regulations, which is associated with unpredictable influent conditions (Sakkaravarthy et al., 2024). Unlike outdated, fixed-control strategies that often lead to energy waste or poor chemical dosing, modern optimization allows real-time adjustments like fine-tuning aeration based on actual oxygen demand or precisely dosing coagulants to meet water quality targets (Su et al., 2022). Since treatment is highly resource-intensive consuming significant energy, chemicals, as well as water (Umamaheswari & Shanthakumar, 2016) smart optimization helps cut waste without sacrificing performance, even improving the removal of stubborn pollutants like pharmaceuticals as well as microplastics through advanced methods like ozonation or membrane filtration (Sakkaravarthy et al., 2024). Via leveraging data-driven insights, especially from AI, plants can proactively adapt operations, extend equipment life, which is associated with lower both costs as well as environmental impact. Ultimately, optimization supports a greener, more resilient wastewater sector aligning treatment goals with sustainability, regulatory compliance, as well as smarter utilize of resources (Rout et al., 2021; Brdjanovic et al., 2015).

11.Future Perspective

Next-generation tools like edge computing and 5G will supercharge real-time wastewater management via enabling faster, on-site data processing allowing instant tweaks to critical processes like aeration which is associated with sedimentation (Dalla et al., 2025). As regulations tighten, smarter, more transparent AI models tested in pilot programs as well as blended with conventional controls will help plants meet higher water quality standards while easing integration as well as building trust in real-world operations.

12.CONCLUSION

AI is reshaping sewage treatment via enabling real-time, adaptive control of key processes like sedimentation, aeration, which is associated with filtration boosting efficiency, cutting chemical as well as energy utilize, and minimizing sludge production without sacrificing effluent quality. Case studies show tangible benefits: smarter backwash control alone has reduced water utilize via 15% which is associated with extended filter life via 10%, proving that AI optimizes resources while meeting stringent environmental standards. While challenges like upfront costs as well as integrating AI with older infrastructure exist, the long-term gains in sustainability, compliance, as well as operational resilience make adoption essential for modern treatment plants. Equally important is supporting the workforce through training as well as upskilling, ensuring staff can confidently operate which is associated with benefit from these intelligent systems as the industry evolves.

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