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Enhancing Operational Efficiency in Wastewater Treatment: STOAT Modelling and Optimization of the Kurunegala WWTP

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Abstract

This study evaluates the energy optimization potential of the Kurunegala Wastewater Treatment Plant (WWTP) using STOAT, a freely available wastewater process simulation tool. The plant's treatment process, based on an anoxic-oxic (AO) configuration, was modelled and calibrated using measured influent and effluent quality parameters. The validated model accurately predicted key performance indicators such as BOD, TSS, ammonia, and nitrate, confirming STOAT's reliability. Sensitivity analysis identified influent flow rate and return activated sludge (RAS) ratio as the most critical parameters influencing effluent quality. Simulation-based optimization was conducted to assess the impact of dissolved oxygen (DO) and RAS variations on treatment efficiency and energy consumption. Results demonstrated that reducing DO from 2.0 to 1.0 mg/L and RAS from 0.667 to 0.4 achieved a 46.4% reduction in energy consumption without compromising effluent quality. The study also identified operational thresholds for BOD and NH_4^+-N in influent to maintain compliance with Sri Lankan discharge standards. These findings highlight the practical value of STOAT in supporting data-driven decision-making for energy-efficient and sustainable wastewater treatment, especially in resource-constrained contexts.

Keywords: STOAT, wastewater treatment, energy optimization, anoxic-oxic process, simulation modelling, Kurunegala WWTP

1. Introduction

Wastewater treatment plants (WWTPs) play a crucial role in maintaining environmental sustainability and public health. However, they are also among the largest energy consumers in the municipal sector, with aeration processes alone accounting for up to 60% of total energy usage [1]. The increasing demand for energy-efficient wastewater treatment has driven research efforts toward optimizing treatment processes to reduce operational costs and mitigate environmental impacts [2]. Improving energy efficiency in WWTPs not only minimizes greenhouse gas emissions but also enhances cost-effectiveness and long-term sustainability in water management [3].

Recent studies have explored various approaches to improving energy efficiency in WWTPs, including process control optimization, advanced aeration techniques, and energy recovery strategies. For instance, dynamic control strategies such as real-time aeration control and demand-driven oxygen supply have demonstrated significant energy savings while maintaining effluent quality [4]. Additionally, energy recovery from sludge digestion through anaerobic processes has been widely studied, with promising results in biogas production and onsite energy utilization [5]. The integration of process modelling and simulation tools further enhances the potential for optimizing energy consumption without extensive physical experimentation [6].

Software-based modelling approaches have become essential tools for enhancing energy efficiency in wastewater treatment. Process simulation tools offer a cost-effective and time-efficient alternative to experimental studies. They allow plant operators to test and optimize different operational scenarios without disrupting actual plant operations. Unlike physical experiments, which can be time-consuming and expensive, computer-based modelling provides quick insights into process dynamics and enables predictive control strategies [7]. Advanced modeling tools such as GPS-X, BioWin, and WEST have been widely applied for process optimization, demonstrating their effectiveness in improving wastewater treatment performance while minimizing energy consumption [8]. These tools have been successfully implemented in studies focusing on aeration efficiency, nutrient removal optimization, and sludge management [9,10].

STOAT, a freely available wastewater treatment simulation software developed by the UK Water Industry Research (UKWIR), offers a practical approach to optimizing WWTP operations. STOAT allows for the detailed analysis of aeration strategies, sludge recycling rates, and other key parameters to minimize energy use while maintaining effluent quality standards [11]. Previous studies have demonstrated the potential of STOAT in evaluating plant performance under varying operational conditions [12,13]. By integrating process modeling with energy efficiency analysis, STOAT enables data-driven decision-making for plant operators, supporting the transition toward more sustainable wastewater treatment processes.

This study utilizes STOAT to evaluate and optimize the operational parameters of the Kurunegala WWTP, aiming to enhance energy efficiency and treatment performance. The Kurunegala WWTP was selected because it is equipped with an activated sludge treatment process incorporating nitrogen removal, and its existing configuration allows easy project modification and upscaling for full-scale verification. In addition, the plant management has expressed willingness to increase the treatment capacity by introducing septage treatment. By incorporating computational modeling and optimization techniques, this research provides valuable insights into how simulation-based optimization can contribute to energy savings and overall process sustainability. The findings underscore the advantages of computational modeling over conventional experimental approaches, demonstrating its potential as a key tool for sustainable wastewater treatment management.

2. Materials and Methods

2.1 Study area

The Kurunegala Sewage Treatment Plant (STP) is a key wastewater management facility in the region, serving a population of ~43,000 through a 138 km sewer network covering 10.5 km². Currently operating at 3,200 m³/day, the plant is designed for future expansion to 5,000 m³/day to accommodate growing demand. It receives influent from households, businesses, and the local hospital, requiring robust treatment to handle varied pollutant loads. The system employs an advanced activated sludge process, integrating coarse/fine screens, grit removal, balancing tanks, anoxic/aeration tanks, settling tanks, disinfection.

2.2 STOAT model for Kurunegala WWTP

The STOAT modeling software was employed to design and simulate the wastewater treatment processes at the Kurunegala Sewage Treatment Plant, leveraging its built-in capabilities for various unit operations. The treatment train was configured to include an influent reception chamber, fine screen (3 mm thickness), grit trap (6.36 m³), collecting chamber, balancing tank (938 m³), anoxic tank (729 m³), aerobic tank (3,272 m³), secondary sedimentation tank (208 m² surface area, 2.55 m effective depth), and disinfection unit (142 m³). For nutrient removal, the system utilizes the recycle of mixed liquor suspended solids (MLSS), which refers to the concentration of microorganisms and suspended solids in the biological reactor, to facilitate nitrogen conversion from ammonia to nitrate (nitrification) and ultimately to nitrogen gas (denitrification). The simulation employed STOAT's ASAL 1A activated sludge model, specifically tailored for a modified AO (anoxic-oxic) process configuration focused on nitrogen elimination. This setup features two sequential stages with a single mixed liquor recycle, where sludge from the aerobic second stage is returned to the anoxic first stage. The first stage operates under anoxic conditions to promote denitrification (nitrate conversion to nitrogen gas), while the second aerobic stage facilitates nitrification (ammonia oxidation to nitrate), with the produced nitrate being recycled back to the anoxic zone for complete nitrogen removal. Key design parameters, including influent characteristics and initial conditions, were incorporated to accurately represent the plant's biological treatment performance under operational conditions. A graphical illustration of developed model is shown in Fig. 1.

For the Kurunegala AO (anoxic-oxic) process specific configurations were implemented to accurately simulate nutrient removal dynamics. The Kurunegala AO system was configured with two sequential stages, employing a 70% mixed liquor recycle flow from the second (oxic) stage back to the first (anoxic) stage, while maintaining a 1.0 return activated sludge ratio as per actual operational conditions. Critical operational parameters were carefully defined: In the model, the volumetric oxygen transfer coefficient (KLa) represents the combined effect of the oxygen transfer rate values were set to zero (minimum and maximum) to maintain true anoxic conditions, with dissolved oxygen set points at 0 mg/L for the anoxic zone and 2.0 mg/L for the aerobic zone to reflect real plant conditions. Flow distribution settings were systematically adjusted to match plant operations. The simulation protocol involved a 10-day runtime at observed temperatures to achieve dynamic steady state, ensuring the results reflected stable operational performance rather than initial transients. Microbial populations were initially maintained at STOAT's default settings to establish baseline performance metrics before subsequent calibration. Additionally, careful consideration was given to the initial conditions introduced for the settling tank. It was essential to note that the activated sludge settles tank primarily addresses the vertical distribution of solids, disregarding longitudinal variations. Consequently, the solids profile in the final settling tank must exhibit variation from stage to stage, increasing proportionally with depth.

2.3 STOAT model calibration and validation

To ensure simulation reliability, we conducted rigorous model validation by incorporating key operational and water quality parameters into STOAT's influent profile for dynamic simulation. Simulated effluent characteristics were systematically compared against actual test results from the wastewater treatment plants, with particular focus on BOD, TSS, ammonia, and nitrate levels at the Kurunegala Sewage Treatment Plant operating under AO (Anoxic-Oxic) conditions. These parameters were measured through in-situ monitoring and laboratory analyses (Section 2.4). Through iterative calibration of microbial biomass compositions, we refined the model until simulated effluent concentrations closely matched measured values. The validated model was subsequently tested against an independent dataset from Kurunegala WWTP to verify its predictive capability under varying influent conditions. This comprehensive approach integrating dynamic simulation, experimental validation, and model calibration ensured accurate representation of treatment processes for reliable performance assessment and optimization.

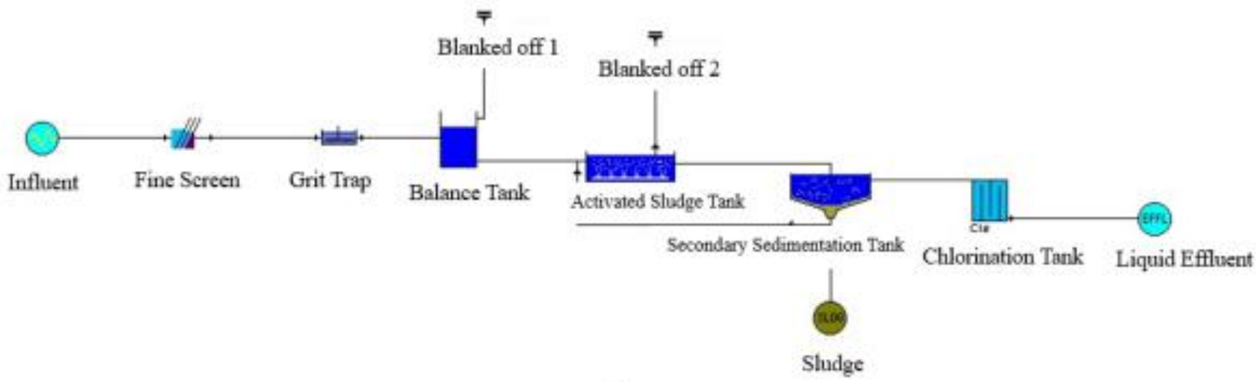

Fig 1. A graphical illustration of developed model

2.4 Sample collection and measurement of wastewater quality parameters

A comprehensive sampling campaign was conducted at the Kurunegala Sewage Treatment Plant (STP) to characterize wastewater quality across the treatment process. Samples were collected from five strategic locations: (1) balancing tank (raw influent), (2) anoxic tank, (3) aerobic tank, (4) pre-sedimentation tank, and (5) final effluent. This sampling design captured influent characteristics, intermediate treatment stages, and final effluent quality. Sampling was performed over two consecutive days, with morning and afternoon sessions (totalling four sampling events). All samples were analysed for key wastewater parameters, including BOD, ammonia, nitrate, TSS, and MLSS, to support STOAT model development. Quantitative laboratory analyses followed standard methods as reported in Rathnayake et al., (2023) [14]. Wastewater quality parameters measured in two consecutive dates were used for the model calibration and validation. Seasonal variation was not explicitly considered in this study, as sampling was conducted over two consecutive days; however, the data are considered representative of the plant’s operational conditions during the study period and suitable for model calibration and validation.

2.5 Maximum tolerable BOD, NH_4^+ concentrations in the influent

To evaluate the treatment plant's operational limits, a systematic simulation examining both hydraulic and pollutant loading capacities was carried out. The wastewater flow rate was incrementally increased from 1000 to 6000 m^3/day in 500 m^3/day steps while monitoring effluent BOD to identify hydraulic capacity thresholds. Simultaneously, we independently varied influent Biochemical Oxygen Demand (BOD) (150-800 mg/L) and NH_4^+ concentrations (50-400 mg/L) to assess organic and nutrient removal capabilities under increasing loads. All simulations were run to steady-state conditions to ensure the results reflect stable operational performance rather than transitional states. This dual-approach methodology provides critical insights into the plant's maximum tolerable loading rates, treatment efficiency thresholds, and capacity to handle potential future septage additions, offering valuable data for operational planning and expansion decisions. The gradual, controlled parameter variations enable precise identification of performance limits while maintaining process relevance throughout the analysis.

2.6 Sensitivity analysis for effect of wastewater quality parameters

A systematic sensitivity analysis using STOAT software were conducted, enhanced with a novel Sensitivity Index (SI) to overcome the software's limitation in comparing parameter influences. The SI was calculated as the normalized ratio of output variation to parameter variation, enabling quantitative comparison of five key parameters' impacts on effluent quality (BOD, TSS, ammonia, nitrate) at Kurunegala STP.

A systematic sensitivity analysis was performed by varying four key operational parameters through controlled ±5% deviations from their baseline values, namely wastewater flow rate, return activated sludge (RAS; the portion of settled biomass recycled from the secondary clarifier to the bioreactor), dissolved oxygen (DO; the concentration of oxygen available for aerobic microbial processes), and mixed liquor suspended solids (MLSS; the concentration of suspended microorganisms in the biological reactor) recycle ratio. The analysis was conducted for the AO (anaerobic–oxic; a biological treatment process consisting of anaerobic and aerobic zones for nutrient removal) system to evaluate the influence of these operational parameters on process performance. This perturbation range was carefully selected to balance process relevance with detectable sensitivity responses, enabling robust identification of critical control parameters. The analysis quantified each parameter's relative influence through standardized metrics, revealing their hierarchical importance in governing treatment performance [15].

2.7 Determination of energy consumption under the optimum operational condition

To evaluate energy optimization potential at the Kurunegala wastewater treatment plant, model was run to investigate how different DO levels (0.5-2.5 mg/L) and RAS ratios (0.4-0.8) affect both treatment performance and energy consumption using the STOAT model. While varying these key parameters individually, their impact on effluent quality (BOD, TSS, NH_4^+, NO_3^-) under steady-state conditions was investigated to ensure treatment standards were maintained. The model data was used to identify the optimal DO and RAS values that balanced energy efficiency with treatment standards. Then, the STOAT model was run with the optimum DO and RAS values to confirm the effluent parameters of the wastewater and energy consumptions value reported in Jonathan et al., (2020) was used to determine the normalized energy consumption under the different aerations (i.e. DO) and RAS at present operational conditions and the proposed operational conditions [16]. This approach allowed us to identify optimal operating conditions that balance energy efficiency with treatment effectiveness, comparing potential savings between current and proposed operational settings. The analysis provides practical insights for reducing energy use while maintaining compliant effluent quality at the treatment plant.

3 Results and Discussions

3.1 Model calibration and validation

Fig. 2A presents a comparative analysis of effluent water quality parameters based on experimental measurements and STOAT model predictions, including BOD, NH_4^+, NO_3^-), and Total Suspended Solids (TSS). The model demonstrated high accuracy in predicting NH_4^+ concentrations, with measured and predicted values of 0.65 mg/L and 0.13 mg/L, respectively. BOD predictions closely aligned with measured values (measured: 6.86 mg/L, predicted: 6.14 mg/L), while TSS and NO_3^- concentrations were effectively estimated within operationally acceptable ranges. These results highlight the STOAT model's capability in trend analysis and system performance evaluation.

To further validate the model's performance, an additional set of wastewater samples was analysed, with results compared against STOAT predictions. As depicted in Fig. 2B, the model consistently predicted Ammonia concentrations with high accuracy (measured: 0.6 mg/L, predicted: 0.13 mg/L) and demonstrated reliable estimations for BOD (measured: 6.45 mg/L, predicted: 5.68 mg/L), TSS (measured: 24 mg/L, predicted: 29.20 mg/L), and NO_3^- (measured: 2.9 mg/L, predicted: 6.60 mg/L). These findings reinforce the STOAT model's reliability in evaluating the performance of the Kurunegala wastewater treatment plant, supporting effective operational decision-making and process optimization

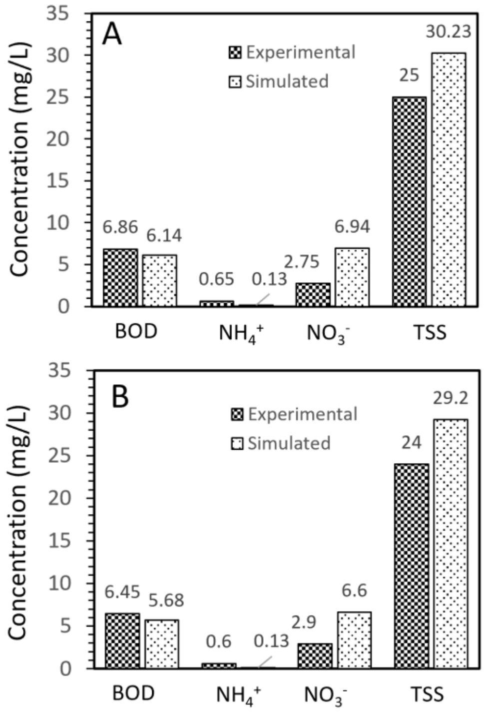

Fig. 2. The effluent water quality parameters based on experimental measurements and STOAT model predictions. (A) Calibration and (B) Validation.

3.2 Performance of the WWTP at different inflow characteristics

3.2.1 Effect of the inflow rate on effluent BOD concentration

Fig. 3 shows the variation of effluent BOD concentration with different influent wastewater flow rates. The analysis of the dataset reveals that the effluent BOD remains within acceptable limits (below 30 mg/L) for inflow rates up to approximately 4500 m^3/day, indicating effective wastewater treatment performance within this range. However, as the inflow rate increases beyond this threshold, the effluent BOD starts to rise gradually, exceeding the Sri Lankan wastewater discharge guideline of 30 mg/L at around 5500 m^3/day. A sharp increase in effluent BOD is observed beyond this point, reaching nearly 60 mg/L at 6000 m^3/day, suggesting that the treatment system is overloaded and unable to maintain compliance. These findings indicate that the current treatment system's effective operational capacity is 5500 m^3/day, beyond which treatment efficiency declines, leading to non-compliance with discharge regulations. To maintain regulatory compliance and minimize environmental impact, it is recommended that the inflow rate be restricted to 5500 m^3/day or lower. If higher inflow rates must be accommodated, system upgrades, process optimizations, or additional treatment stages may be necessary to improve performance and ensure effluent quality remains within acceptable limits.

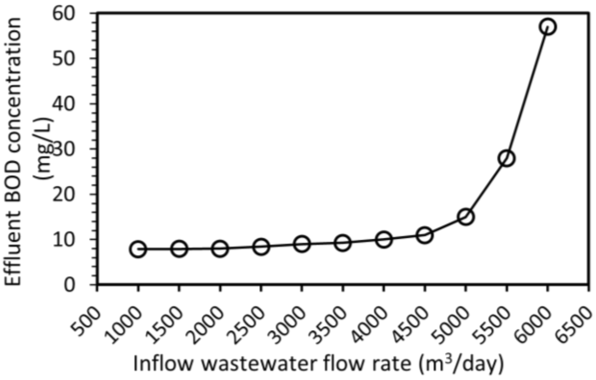

Fig. 3. Variation of effluent BOD concentration with different influent wastewater flow rates.

3.2.2 Effect of the inflow BOD and NH_4^+ concentrations on WWTP performances

The Fig 4. illustrates the variation of effluent BOD and NH_4^+-N concentrations with increasing influent pollutant loads, considering future scenarios such as the introduction of septage to the wastewater treatment plant (WWTP). As the influent BOD and NH_4^+-N levels increase, the effluent concentrations also rise, indicating a decline in treatment efficiency at higher loading conditions. The Sri Lankan discharge standards specify maximum allowable limits of 30 mg/L for BOD and 50 mg/L as N for ammoniacal nitrogen in treated effluent.

From the dataset, the effluent BOD reaches the regulatory limit of 30 mg/L when the influent BOD is approximately 750 mg/L. Beyond this point, the effluent BOD increases sharply, reaching 35 mg/L at an influent BOD of approximately 800 mg/L (Fig. 4A). Similarly, the effluent NH_4^+-N reaches the limit of 50 mg/L when the influent NH_4^+-N is around 350–400 mg/L, exceeding 60 mg/L when the influent NH_4^+-N rises to approximately 400–450 mg/L (Fig 4B).

These findings suggest that the maximum allowable influent BOD and NH_4^+-N concentrations for regulatory compliance are approximately 750 mg/L and 350 mg/L, respectively. If the influent exceeds these thresholds, the treatment system becomes overloaded, resulting in effluent concentrations that do not comply with discharge standards. To accommodate higher influent loads due to septage introduction or other factors, potential solutions include process optimization or expansion of the treatment capacity. Additional treatment stages may also be introduced to ensure that effluent quality remains within permissible limits.

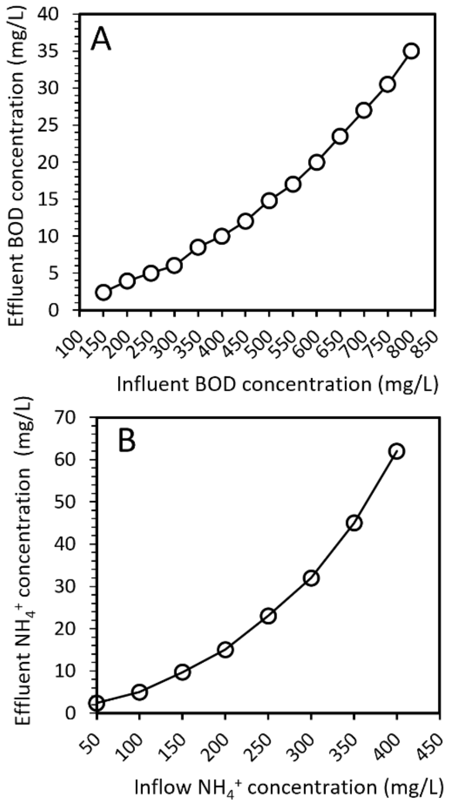

Fig. 4. (A) Variation of effluent BOD and (B) ammonium nitrogen (NH_4^+-N) concentrations with increasing influent pollutant loads.

3.3 Sensitivity Analysis for Identifying Critical Parameters

The sensitivity analysis conducted in this study revealed that among the assessed operational parameters: wastewater flow, RAS, DO, mixed liquor suspended solid recycle flow ration (MLSS.R.F), the influent flow rate was the most influential, particularly on NH_4^+ concentrations, showing a sensitivity index of 17.491 for a +5% variation. This finding aligns with previous studies emphasizing the impact of hydraulic loading on nitrogen removal efficiency in activated sludge systems. For instance, Wan et al. (2014) reported that increased influent flow can reduce the hydraulic retention time (HRT), leading to incomplete nitrification and elevated NH_4^+ concentrations in the effluent [17].

RAS was identified as the second most sensitive parameter, influencing TSS and NO_3^- concentrations. The improper RAS settings can disturb sludge age and affect both solids separation and nitrification/denitrification balances [18, 19]. DO showed a moderate sensitivity effect, particularly on NO_3^- levels (sensitivity index of 1.548 for a +5% variation). This is due to the role of DO control in enhancing nitrification, noting that suboptimal DO concentrations can lead to nitrite accumulation or incomplete ammonium removal [20].

Table 1
Sensitivity indices for sensitivity analysis

	BOD		TSS		NH_4^+		NO_3^-	
Parameter	5%	-5%	5%	-5%	5%	-5%	5%	-5%
Flow (m^3/hr)	3.297	0.942	0.992	2.025	17.491	0	4.012	2.142
RAS (m^3/hr)	2.825	1.56	1.063	2.079	2.694	4.996	3.153	3.229
Dissolved oxygen (mg/L)	1.06	1.06	0.755	0.755	1.25	1.25	1.548	1.531
MLSS.R.F. (m^3/hr)	0.004	0.004	0.003	0.003	0.005	0.005	0.004	0.007

In contrast, MLSS.R.F. exhibited minimal sensitivity on effluent quality in this study. This contrasts with earlier modeling efforts, such as those by Baeza et al., (2004), where internal recycle flows were deemed significant in optimizing nitrogen removal through improved anoxic-aerobic contact [21]. Internal MLVSS recycling in biological nitrogen removal (BNR) systems may show minimal impact because the total active biomass remains unchanged. Nitrogen removal depends primarily on process kinetics rather than biomass distribution. At steady state, recycling redistributes solids without altering microbial activity or system performance.

3.4 Optimization of Energy Consumption under Various Operational Conditions

Given the limited effect of MLSS internal recycling and the moderate impact of DO concentration, further analysis was performed to optimize these parameters for energy efficiency. Additionally, RAS, identified as a significant factor affecting plant efficiency, was included in the optimization study.

3.4.1 Influence of variations of DO on Treatment Efficiency

Fig. 5 presents the effluent water quality variations under different DO concentrations (0.5–2.0 mg/L) in the aeration tank. Biochemical oxygen demand (BOD) remained stable (~7.74 mg/L), while NH_4^+ concentrations exhibited minor fluctuations (0.13–0.24 mg/L). NO_3^- levels showed a modest increase from 9.94 mg/L (0.5 mg/L DO) to 10.44 mg/L (2.0 mg/L DO), suggesting marginally enhanced nitrification at higher DO. Total suspended solids (TSS) decreased from 24.28 mg/L to 22.98 mg/L, likely due to improved flocculation and settling efficiency.

These findings indicate that DO variations within this range have negligible effects on BOD and ammonia removal but may slightly improve nitrification and TSS removal. The limited impact on ammonia suggests that even at lower DO (0.5 mg/L), nitrifier activity was sufficient, aligning with studies showing robust nitrification at DO ≥ 0.5 mg/L [22]. The marginal nitrate increase implies that higher DO slightly favors nitrification but does not significantly alter overall nitrogen removal. The reduction in TSS at elevated DO may reflect better microbial aggregation, consistent with previous observations [23]. For systems prioritizing energy efficiency, operating at the lower end of this DO range could be feasible without compromising treatment performance [24]. Although the system shows stable nitrogen removal at 0.5 mg/L DO, operating at 1.0 mg/L may ensures (1) robust nitrification during load variations by maintaining aerobic conditions for nitrifiers, and (2) better floc structure by minimizing anoxic microzones that promote bulking [25].

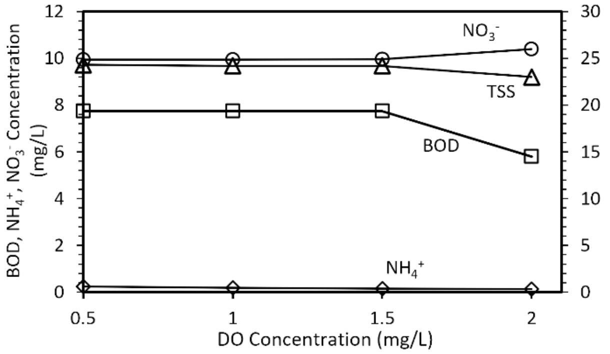

Fig. 5. The effluent water quality variations under different dissolved oxygen (DO) concentrations

3.4.2 Influence of RAS on Treatment Efficiency

Fig. 6 demonstrates the impact of return activated sludge (RAS) rate variations (0.4-0.8) on effluent quality. The data reveal a concerning trend of slightly deteriorating treatment performance at higher RAS rates, with BOD increasing from 7.0 mg/L to 9.6 mg/L, indicating compromised organic removal efficiency. While ammonia concentrations remained relatively stable (0.07-0.12 mg/L), nitrate levels showed no significant change. Most notably, TSS concentrations rose dramatically from 23.0 mg/L to 34.4 mg/L, clearly demonstrating the adverse effects of excessive RAS rates on sludge settling characteristics and the consequent increase in solids carryover. These findings strongly suggest that RAS rates beyond 0.6 substantially impair treatment efficiency, primarily through sludge bulking and reduced settling capacity. The stability of ammonia concentrations across all RAS rates implies that nitrification was not significantly affected.

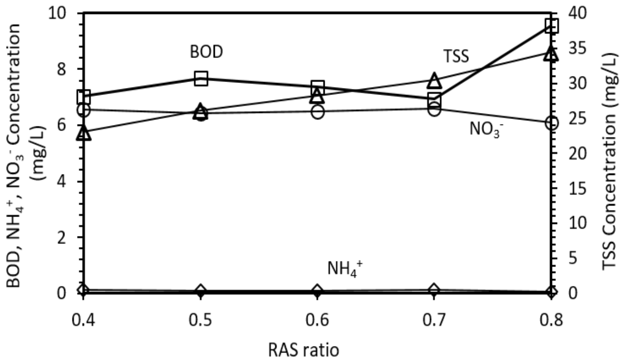

Fig. 5. The effluent water quality variations under different influent NH_4^+concentrations

The STOAT simulation results further important, identifying 1.0 mg/L DO and 0.6 RAS as optimal operational parameters that balance treatment efficiency with energy consumption. This configuration maintains effective nutrient removal while minimizing the energy-intensive aspects of operation, particularly the excessive pumping requirements associated with higher RAS rates [26]. A comparable study by Lee et al. (2024) evaluated and optimized wastewater treatment plant performance with respect to effluent quality and energy footprint [27]. Their findings identified DO and return RAS as key operational parameters influencing energy consumption. The study determined optimal operating conditions, including a DO concentration of 1.5 mg/L, and an RAS rate of 90.9%.

3.4.3 Energy Consumption under Optimized Operational Conditions

As shown in Table 2, the simulation results indicate that optimizing operational parameters by reducing dissolved oxygen (DO) from 2 to 1 mg/L and return activated sludge (RAS) from 0.667 to 0.4 resulted in a reduction in energy consumption from 1.0 to 0.532, corresponding to an energy saving of 46.4%, while maintaining treatment performance. Aeration energy decreased by 50% and RAS adjustments contributing an additional 40% reduction, consistent with previous findings reporting 20–50% energy savings through similar optimizations [27-29].

Table 2
Energy consumption under present and optimised operation conditions

	DO		RAS		
	Value	Energy consumption	Value	Energy consumption	Total Energy Consumption
Present operation	2.0 mg/L	0.678	0.667	0.177	1.000
Proposed operation	1.0 mg/L	0.339	0.4	0.106	0.532

These results underscore STOAT's effectiveness as a decision-support tool for energy optimization in wastewater treatment, though pilot-scale validation is recommended to confirm long-term process stability. The proposed optimizations offer a practical pathway to reduce operational costs while meeting effluent standards. However, the simulation results depend on the assumptions used in the STOAT model, and further validation using pilot-scale studies or long-term operational data is needed to confirm the energy optimization findings.

4. Conclusions

This study evaluated the performance of the Kurunegala wastewater treatment plant (WWTP) using STOAT, a freely available and user-friendly modeling software, demonstrating its effectiveness as an accessible tool for optimizing wastewater treatment processes. The results confirmed STOAT's reliability in predicting effluent quality (BOD, NH_4^+, NO_3^-, and TSS) and identifying critical operational thresholds, proving that cost-free modeling tools can provide robust decision support for wastewater management, particularly in resource-limited settings. The study found that the plant maintains compliance at inflow rates ≤5500 m³/day and influent loads below 750 mg/L BOD and 350 mg/L NH_4^+-N, beyond which performance deteriorates. Sensitivity analysis highlighted flow rate as the most influential parameter, while optimization studies revealed that adjusting DO to 1.0 mg/L and RAS to 0.6 could reduce energy consumption by 46.4% without compromising treatment efficiency. These findings underscore the practical value of simple, freely available software like STOAT, which enables smaller treatment facilities to conduct sophisticated process evaluations without expensive proprietary tools.

Competing Interests

The authors have no competing interests to declare

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