Activated sludge model no. 1 calibration for a paper mill wastewater treatment plant in Finland

Hussain Ahmed*, Matti Vilkko

Automation Technology and Mechanical Engineering, Tampere University, Tampere, 33720, Finland

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ABSTRACT

The Wastewater Treatment Plant (WWTP) in the paper industry faces challenges in controlling and estimating Chemical Oxygen Demand (COD) to improve monitoring and optimize the process under varying operational and environmental conditions. However, maintaining the COD content at the desired level becomes difficult due to constantly changing environmental conditions and stricter regulations. A common method in WWTP to remove organic COD is aeration treatment. For simulating the aeration process, Activated Sludge Model No.1 (ASM1) is a widely used tool, but it requires an abundance of influent COD concentration samples to estimate the effluent COD. Collecting these samples is costly both in terms of time and human resources. This study aims to use limited wastewater samples to generate artificial data for the ASM1 model using linear regression techniques. The objective is to reduce costs associated with COD concentration sample collections for a WWTP processing wastewater of a Finnish paper mill, while still providing reliable estimations for effluent COD over an extended period by identifying the optimal tuning parameters for the ASM1.

1. Introduction

Enhancing the internal water circulation is crucial in water-intensive industrial processes, aiming to minimize the consumption of fresh water, energy, and wastewater generation [1,2]. Additionally, industrial stakeholders are keen on reducing energy and resource usage while removing unwanted components from wastewater [3]. As a result, simple innovative solutions are necessary to achieve an optimal and resource-efficient process operation, secure the quality of the discharged wastewater, and ensure compliance with stringent wastewater regulations [4].

Paper production in a paper mill requires a significant amount of water, making it highly water-intensive [1,5,6]. As a result, this process generates a substantial volume of wastewater during production, which must be purified before releasing into water basins. The quality of this wastewater varies depending on changes in the production environment, such as alterations in the type of paper being manufactured [7]. To process this wastewater, wastewater treatment plants (WWTPs) are employed.

The variability of paper mill wastewater influenced by the production environment, places WWTPs at a higher risk of encountering more stringent regulations regarding wastewater treatment. Furthermore, WWTPs face regulations from water governance, biodiversity, and circular economy policies, which further adds complexity to the operational procedures of the WWTPs [8–10]. Therefore, WWTPs require new process monitoring tools to enhance efficiency, meet regulations, and achieve carbon neutrality and sustainability goals. Through advanced modelling and simulations of WWTP, it is possible to achieve optimal process operation, regulatory compliance, and sustainable practices, thus enabling the process operator to tackle emerging challenges during WWTP operations.

Fig. 1 illustrates a schematic diagram of a WWTP designed to process wastewater from the paper mill to eliminate organic substances from the wastewater. The concentration of organic substances is referred to as Chemical Oxygen Demand (COD), measuring the oxygen required for their chemical oxidation [11]. In a typical WWTP, the COD is measured at various points to control its concentration in the wastewater. Furthermore, it is influenced by factors such as wastewater type, weather conditions, and environmental variables, emphasizing the necessity of a comprehensive understanding of the COD removal process.

Due to the high levels of COD present in paper mill wastewater, the aeration treatment is intricate and demands significant energy consumption due to continuous air pumping, a concern amplified by the current trend of increasing global energy costs [10]. Such issues

* Corresponding author.
E-mail addresses: hussain.ahmed@tuni.fi (H. Ahmed), matti.vilkko@tuni.fi (M. Vilkko).

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highlight the importance of exploring cost-effective aeration treatment modelling approaches that reduce energy usage while maintaining optimal WWTP performance. Furthermore, the diverse sources of wastewater and evolving environmental regulations necessitate the aeration treatment models for comprehending and optimizing COD removal processes within WWTP operations.

COD in wastewater can generally be categorized into two groups: biodegradable and non-biodegradable. In paper mill wastewater, non-biodegradable COD is present in relatively small amounts and can often be eliminated using physical techniques. However, the biodegradable COD constitutes the primary portion of the total COD and requires aeration treatment for its removal. This large amount of biodegradable COD significantly contributes to the complexity of process operations and the cost associated with COD removal in WWTPs [12]. In the aeration treatment, biomasses consume biodegradable COD in multiple intricate biological processes. These intricate biological processes are responsible for removing various components of biodegradable COD from the influent. Consequently, a comprehensive understanding of the aeration process becomes crucial for comprehending the factors that influence effluent COD levels.

Process modelling has consistently proven to be the most effective and economical approach for comprehending the aeration treatment within WWTPs. By utilizing process modelling, it becomes possible to provide a detailed description of the biological processes involved in aeration treatment, estimate the effluent COD, and conduct a thorough analysis of the factors influencing its effectiveness. This in-depth analysis of the aeration process can empower process operators to make more precise decisions, ultimately enhancing effluent quality and reducing energy requirements. As a result, this approach helps minimize the economic and environmental impact associated with WWTP operations, significantly reducing the overall footprint.

For modelling the aeration treatment, one effective tool is the use of Activated Sludge Model No.1 (ASM1) [13–15]. This model estimates the effluent COD and energy consumption and can help the operator simulate the aeration treatment for various operating conditions. This model describes in detail the complex nature of the aeration treatment that can potentially help the process operators in decision-making.

ASM1 has found diverse applications in industrial wastewater treatment plants. Brault et al. [16] adapted ASM1 to address pulp and paper effluents, focusing on operational challenges and nutrient transformations, especially bulking issues. Their findings indicated that ammonification in the aeration process was negligible, while phosphatization was associated with settling problems as indicated by the sludge volume index. In a different study, Amin et al. [17] utilized ASM1 to describe filamentous bulking sludge and examined the impact of incorporating an aerobic selector. This study expanded ASM1 by incorporating four theories, including slowly biodegradable organics hydrolysis, kinetic selection, substrate diffusion limitation, and filamentous backbone theories. These additions allowed for differentiation between substrate uptake by filamentous and floc-forming organisms, and they established a filamentous score for predicting filamentous bulking outcomes.

Maryns and Bauwens [18] extended the ASM1 model for use in a river ecosystem. They modified and expanded the traditional ASM1 matrix to create an ASM1-based water quality model. Sensitivity analyses highlighted the critical role of parameters governing hydrolysis in the ASM1 formulation of biological decay. While this model effectively estimated biochemical oxygen demand concentrations, it exhibited reduced accuracy in predicting dissolved oxygen concentrations due to model parameter uncertainties in river conditions. Additionally, Jiang et al. [19] employed ASM1 for modeling a side-stream MBR system and compared it to other activated sludge processes. Calibration of ASM1 parameters relevant to long-term biological behavior in MBR systems was crucial. Accurate characterization of influent wastewater was essential during calibration, with the chemical–biological method proving superior to the physical–chemical method. Sensitivity analysis for steady-state operation and DO dynamics underscored the high sensitivity of MBR system biological performance, including sludge concentration, effluent quality, and DO dynamics, to these parameters.

Despite the numerous applications of ASM1, one drawback of ASM1 is that it requires a substantial number of influent COD concentration samples to ensure accurate estimation of effluent COD levels. Obtaining a large amount of COD concentration sample collection can be expensive and time-consuming without the assistance of automatic sampling systems. Consequently, a challenge arises in estimating the effluent COD over an extended period using a few COD concentration samples and determining the optimal ASM1 calibrated parameters.

Motivated by the accurate COD estimation, this study focuses on reducing the costs associated with COD concentration data collection for the ASM1 model to estimate effluent COD levels. The objective of this study is threefold: first, collecting and analyzing a limited number of influent COD concentration samples from a Finnish paper mill; second, employing simple linear regression techniques to generate artificial influent COD concentration data for the ASM1 using the limited number of COD concentration samples; and third, identifying and calibrating the ASM1 model parameters to enable precise estimation of effluent COD levels. This calibrated ASM1 model provides the ability to estimate effluent COD levels, and it can serve as a valuable tool for process operators for decision-making, especially when effluent COD levels exceed permissible limits, ensuring effective wastewater treatment and compliance with regulatory standards.
2. Materials and methods

This study is subject to several assumptions and limitations. The quality of discharged wastewater from a WWTP processing paper mill wastewater is influenced by various parameters, including COD, Biological Oxygen Demand (BOD), and microplastics. In a typical WWTP, the process operator is required to calculate and monitor these parameters to ensure that they remain within acceptable limits. Additionally, the quality of paper mill wastewater depends on the paper grade produced, directly affecting the levels of these parameters.

In this study, it is assumed that the paper grade remains constant throughout the simulations, and thus, the effect of the paper grade on wastewater quality is not considered in the model formulation. Furthermore, it is assumed that BOD and microplastics already remain within acceptable limits due to prior actions taken. Therefore, COD is the sole criterion for assessing the quality of wastewater in this study. Consequently, only COD concentration samples are collected during the campaign period that are used to calibrate the ASM1 to estimate COD in the discharged wastewater.

For the ASM1, a large sample size is preferable to enhance the robustness of the model. However, the collection of a substantial number of samples is challenging due to logistical or financial constraints. Considering these constraints, this study utilizes only a limited number of COD concentration samples for model calibration. To strengthen the validity of the results and enhance the robustness of the model, artificial data is generated, which is used for model calibration. This study treats this artificial data as an estimation of the original COD data.

The ASM1 model comprises two parts: the anoxic for nitrogen removal, and the aerobic removes organic substances from the influent wastewater. WWTP processing paper mill wastewater, nitrogen removal is not the primary objective due to nitrogen deficiency. Consequently, the ASM1 model has been modified by excluding the anoxic part and focusing solely on the aerobic part. Also, this study assumes that the secondary clarifier operates at maximum capacity and effectively eliminates all biomass and other particulate matter from the flow originating from the aeration process. As a result, the secondary clarifier model is not considered in this study. Fig. 2 presents a schematic diagram depicting the ASM1 model configuration for this study.

This study conducted a sampling campaign to collect influent and effluent wastewater samples to determine various COD concentrations. Three composite samples were obtained during weeks 23–25 in June 2022. The samples were collected using a composite sampler HACH AS950. The sampling process involved taking grab samples at intervals of 4 h and 40 minutes over a 24-h period, which were then combined to create a composite sample. Each grab sample had a volume of 1 L, resulting in a total composite sample volume of 6 L. After sampling, the samples were stored at a temperature of 4 °C for a maximum of two days.

The ASM1 model requires the concentration of various components in the influent COD. To quantify these concentrations, the collected samples are analysed in the laboratory. These samples were meticulously separated into their original and soluble constituents, employing molecular size as the guiding principle for segregation. This fractionation process

<table>
<thead>
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<th>Table 1 Influent COD concentration.</th>
<th>component</th>
<th>description</th>
<th>week 23</th>
<th>week 24</th>
<th>week 25</th>
</tr>
</thead>
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<tr>
<td>$S_e$</td>
<td>easily biodegradable COD</td>
<td>778.6</td>
<td>404.4</td>
<td>558</td>
<td></td>
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<tr>
<td>$X_e$</td>
<td>easily slow biodegradable COD</td>
<td>885.1</td>
<td>506.6</td>
<td>259</td>
<td></td>
</tr>
<tr>
<td>$S_i$</td>
<td>easily non-biodegradable soluble COD</td>
<td>386.6</td>
<td>404.4</td>
<td>220.3</td>
<td></td>
</tr>
<tr>
<td>$X_i$</td>
<td>easily non-biodegradable inert COD</td>
<td>347.3</td>
<td>404.4</td>
<td>263.4</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 2. Simplified ASM1 model.
facilitated a thorough assessment of the COD concentrations, which were subsequently computed and recorded. Table 1 provides various influent COD concentrations. For a more comprehensive understanding of the sampling campaign, please refer to Ref. [20].

After collecting the COD concentration samples, the subsequent step involves calibrating the ASM1 model for the collected samples. The primary objective of this calibration process is to determine suitable parameter values that align the estimated value of the model with the sample results obtained during the sampling campaign. Given that the wastewater from a paper mill is nitrogen-deficient, urea is introduced to supply the necessary ammonia for biomass growth and reproduction during the aeration process. Since nitrogen removal is not the primary focus of this study, ASM1 model parameters related to nitrogen removal are set to a minimum value during the calibration process. The calibrated model results are depicted in Fig. 3, and the calibrated parameters are reported in Table 2. Given that carbon is the predominant component in the influent COD, only carbon-based substrates are presented here.

Calibrating the ASM1 model using 2 weeks of data samples requires 1344 influent COD concentration samples with a sampling period of 15 minutes. For this study, collecting this amount of COD concentration samples was challenging due to the unavailability of logistical and human resources. Therefore, only three influent COD concentration samples are collected that are used as a basis for the artificial data generation for the ASM1 model. This artificial data is generated by assuming that the percentage of various COD concentrations does not change significantly. The average percentage of influent COD concentration is given in Table 3.

For the artificial data generation, this study utilizes the available influent COD concentration samples, and industrial online and laboratory data and uses linear regression techniques. The artificial data sample for weeks 23 and 24 of June 2022 is shown in Fig. 4. To ensure model robustness, the ASM1 model is simulated for this artificial data sample to find the optimal calibrating parameters. The calibrated model parameters are given in Table 2.

3. Results and discussion

Table 1 implies that the COD concentration of various components varies during the sampling campaign. This variation could happen due
to changes in the operating conditions of the paper mills, seasonal variations, and the performance of the clarifier [21,22]. Furthermore, the unavailability of data related to the wastewater streams entering the WWTP can also contribute to variations in COD concentrations.

During the aeration process, the slowly biodegradable substrate exhibits slight variations in concentration, as shown in Table 1. However, the biomass rapidly consumes the readily biodegradable substrate, resulting in relatively stable concentrations of this substrate. This indicates a consistent supply of oxygen and ammonia for the biomass during the sampling campaign. The absence or minimal presence of non-biodegradable particulate COD suggests that the secondary clarifier is functioning at maximum efficiency, effectively removing such components. On the other hand, the soluble inert COD remains unaffected by both the aeration process and the secondary clarifier. As a result, it constitutes the largest portion of the effluent COD.

In the calibration process using artificial data, this study initializes the ASM1 model with values obtained during the ASM1 calibration process for the three collected COD concentration samples. Throughout each iteration, the model calibration process involves identifying the most sensitive parameter and carefully fine-tuning it until its optimal value is achieved. Following that, the next most sensitive parameter is selected, and its optimal value is determined. This iterative refinement continues until the optimal values for the model parameters are determined, which minimizes the difference between the effluent COD estimated by the ASM1 model and the online measured COD.

For this case study, the objective is to calibrate the ASM1 model until it reaches a level of optimality, characterized by an error margin of less than 20%. Such a criterion ensures that the model closely aligns with the online measured data, enhancing its predictive accuracy. The unfolding of the calibration process follows a sequenced approach, as illustrated in Fig. 5. This iterative and systematic refinement process is crucial for achieving a robust and reliable calibration of the ASM1 model. Fig. 6 presents a comparison between the estimated effluent COD generated by the ASM1 model and the actual effluent COD measured through the online monitoring system in the WWTP. This comparative analysis effectively demonstrates the ASM1 model’s capability, highlighting its accuracy in estimating effluent COD. Utilizing artificial data derived from only three influent wastewater samples through linear regression techniques, the ASM1 model exhibits its ability to accurately predict effluent COD levels, emphasizing its potential for robust predictions. This calibrated ASM1 model can be confidently employed to predict COD concentrations during the aeration process, which provides an accuracy rate exceeding 85%.

4. Conclusion

This study introduces a novel yet remarkably efficient approach for
generating artificial data to calibrate the ASM1 model, especially in situations where the availability of influent data samples is limited. The methodology of this study is grounded in the analysis of three influent COD concentration samples to calculate the average composition of various COD components in the influent wastewater. Utilizing linear regression techniques, artificial influent COD concentration data is generated, which is used in achieving calibration of the ASM1 model.

The simulation results underscore the novelty of this methodology, revealing that even with only three influent COD concentration samples, the derived artificial influent COD concentration data enables highly accurate calibration of the ASM1 model. This calibrated model, in turn, proves to be a reliable tool for estimating effluent COD levels, particularly in the context of paper and other industrial wastewater processes. The simulation results further demonstrate that the proposed artificial data-generating techniques have potential utility in scenarios where the availability of influent data is constrained, providing a pragmatic solution for accurate modelling and estimation in wastewater treatment applications.

CRediT authorship contribution statement

Hussain Ahmed: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Conceptualization. Matti Vilkko: Visualization, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Matti Vilkko reports financial support was provided by Business Finland. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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