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Intelligent Control of an Aeration Tank Using Model Predictive Control and a Digital Twin

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Abstract

In the context of water scarcity and tightening environmental requirements, improving the energy efficiency of biological wastewater treatment processes has become particularly important. The aeration tank is one of the most energy-intensive and dynamically complex units, strongly affected by the variability in influent flow and composition. Conventional PID controllers do not provide predictive disturbance compensation and often result in excessive aeration and increased energy consumption. The study proposes an intelligent control approach based on a digital twin, neural network-based influent flow forecasting, and model predictive control (MPC). The digital twin represents a dynamic model of the biological process incorporating key state variables, including substrate, activated sludge, and dissolved oxygen concentrations. The LSTM neural network model is employed to predict the hydraulic load based on historical plant operation data, as well as to compensate for residual nonlinear dynamics that are not represented by the linearized MPC model. The predicted influent flow values are incorporated into the MPC framework as measured disturbances, enabling the generation of anticipatory control actions for the aeration system. The adequacy of the digital twin was validated using operational data from the wastewater treatment facilities of Semey city and was characterized by RMSE = 0.14 mg/L, MAE = 0.09 mg/L, R^2 = 0.94, and MAPE = 6.3%. The simulation results demonstrated that, compared with the fuzzy PID controller, the application of MPC reduced the RMSE by 57.1%, decreased the overshoot from 24% to 8%, reduced the integral absolute error (IAE) by 60.9%, and lowered the energy consumption of the aeration system by 21.1%, while maintaining the dissolved oxygen concentration within the permissible operating range. The proposed Advisory MPC architecture is compatible with existing PLC–SCADA systems and can serve as a basis for the gradual digital modernization of wastewater treatment facilities without modifying the existing automation loops.

Keywords: aeration tank; biological wastewater treatment; model predictive control (MPC); digital twin; energy efficiency; wastewater treatment plant automation; SCADA; inflow forecasting

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1. Introduction

Ensuring sustainable access to high-quality drinking water is one of the key global challenges of the twenty-first century. In this context, the energy-efficient and environmentally sustainable operation of wastewater treatment systems has become a critical requirement for modern engineering infrastructure. Rapid urbanization, increasing water consumption, stricter environmental regulations, and the aging of municipal infrastructure create a strong need for the modernization of existing wastewater treatment plants [1,2]. This problem is especially relevant for biological wastewater treatment facilities with aeration tanks, where aeration is typically the dominant consumer of electrical energy.

According to international studies, aeration processes may account for 50–70% of the total energy consumption of wastewater treatment plants [3]. In facilities equipped with outdated blowers and lacking automated control, this proportion can increase to 80–90% [4].

A further challenge is the instability of hydraulic loading. Daily and seasonal fluctuations in wastewater inflow, stormwater inflows, variations in organic load, and irregular industrial discharges result in a distinctly non-stationary operating regime in aeration tanks. Under real operating conditions, wastewater flow rates may vary by 30–50% over short time intervals [5].

The concentration of dissolved oxygen (DO) is a key parameter that determines both the efficiency of biological treatment and the associated energy consumption. Insufficient aeration impairs nitrification and deteriorates effluent quality, whereas over-aeration results in a substantial increase in energy consumption without a significant improvement in process performance [6]. Additional complexity arises from non-stationary hydraulic loads, seasonal variations in wastewater composition, parametric uncertainty in biological processes, and the degradation of aeration equipment.

From an engineering perspective, an aeration tank represents a complex nonlinear dynamic process characterized by distributed parameters, time delays, and external disturbances [7]. In most operating wastewater treatment plants, DO concentration is controlled using conventional or fuzzy PID controllers. However, these control strategies have several fundamental limitations: they are reactive in nature, do not account for predicted variations in inflow, do not provide energy consumption optimization, and do not explicitly incorporate technological constraints of actuators [8–11]. Under abrupt changes in hydraulic loading, this results in fluctuations in dissolved oxygen concentration, excessive air supply, and increased dynamic stress on blower equipment.

In this regard, model predictive control (MPC) represents a promising approach, as it allows process dynamics, predicted disturbances, and technological constraints to be considered within a unified optimization framework [12–15]. Unlike conventional PID-based approaches, MPC employs a mathematical model of the controlled process to predict system behavior over a specified prediction horizon and to generate anticipatory control actions. This is especially important for wastewater treatment plants operating under non-stationary inflow conditions and variable organic loading.

In recent years, MPC has attracted increasing research attention in the field of biological wastewater treatment, particularly for dissolved oxygen regulation, energy consumption optimization, and nitrogen emission reduction [16–18]. In parallel, increasing attention has been paid to the integration of machine learning techniques, digital twins, and intelligent forecasting methods into wastewater treatment plant control systems [9,19,20].

In recent years, Learning-Based Model Predictive Control (LMPC) has received increasing attention. In this approach, machine learning methods are integrated into MPC frameworks to improve model accuracy, enhance adaptation to uncertainty, and increase the predictive capability of MPC controllers.

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Particular attention has been given to Koopman operator-based methods, which enable nonlinear dynamics to be approximated by a system of linear equations in an extended state space. This approach makes nonlinear processes compatible with computationally efficient linear MPC algorithms.

The MAKO framework (Meta-Adaptive Koopman Operators for Learning-Based MPC) proposes an adaptive architecture that enables real-time updating of the process model under parametric uncertainty and changes in the operating regimes of the controlled system [21].

The study, Learning Predictive Control of Switched Nonlinear Systems Using Koopman Modeling, demonstrates that the use of Koopman-based models can significantly improve predictive performance and enhance the robustness of MPC when controlling nonlinear systems with switching operating modes [22].

Despite the high potential of these methods, most published studies focus on laboratory-scale setups and do not address the integration of intelligent control algorithms into the existing industrial PLC–SCADA infrastructure of wastewater treatment facilities.

Existing approaches to intelligent control of wastewater treatment facilities employ different methods and control strategies. Their comparative analysis is presented in Table 1.

Table 1. Comparison of modern intelligent control approaches for wastewater treatment facilities.

Study	Control Strategy	Forecasting Method	Digital Twin	Energy Optimization	Industrial Implementation
Alex et al. (2008) [19]	MPC	No	No	Partial	No
Yang et al. (2014) [18]	Fuzzy MPC	Fuzzy model	No	Limited	No
Wang et al. (2026) [12]	Data-driven MPC	ML-based model	No	Yes	No
Li (2023) [13]	Event-triggered MPC	Data-driven model	No	Yes	No
Shukla et al. (2025) [14]	ML-based aeration control	Neural network	No	Yes	No
Han et al. (2026) [21]	Koopman learning-based MPC	Meta-learning	No	Yes	No
Ning et al. (2025) [22]	Learning-based MPC	Koopman model	No	Partial	No
This study	Advisory MPC + PID	LSTM	Yes	Yes	Yes

A review of recent publications indicates that current research on intelligent control of wastewater treatment facilities can be grouped into several main directions:

1. The use of classical MPC;
2. The use of digital twins;
3. The integration of machine learning methods;
4. The application of Learning-Based MPC and Koopman MPC.

However, most existing studies address these technologies separately. To the best of the authors' knowledge, the available literature lacks comprehensive studies that simultaneously integrate:

1. A digital twin of the technological process;
2. Neural-network-based forecasting of the hydraulic load;
3. MPC that accounts for the constraints of real equipment;
4. Industrial implementation through existing PLC–SCADA systems;
5. Evaluation of energy efficiency using real operational data.

In addition, existing studies are mainly focused on modern wastewater treatment facilities with well-developed measurement infrastructure and do not sufficiently consider the operational characteristics of facilities with a high degree of physical equipment deterioration.

Thus, the development of an industrially oriented intelligent control system for an aeration tank remains insufficiently investigated. Such a system should integrate a digital twin, influent flow forecasting, and MPC within a unified architecture suitable for implementation at existing wastewater treatment facilities.

The modernization of wastewater treatment facilities is particularly relevant for post-Soviet countries. According to sectoral reports of the Republic of Kazakhstan, a significant

proportion of wastewater infrastructure facilities have been in operation for more than 25–30 years, while the deterioration level of individual technological units exceeds 50–60%.

At many wastewater treatment facilities, automatic control systems are limited to local PID controllers or, in some cases, operate entirely in manual mode. The absence of hydraulic load forecasting leads to blower operation with a constant reserve capacity, which increases energy consumption and operating costs.

For example, wastewater treatment facilities in medium-sized cities are typically characterized by daily influent flow fluctuations in the range of 30–60%, caused by uneven domestic water consumption and stormwater inflows. In the absence of intelligent control, this results in periodic over-aeration and inefficient use of electrical energy.

In view of the above, this study aims to develop an intelligent control system for an aeration tank that integrates a digital twin, neural-network-based inflow forecasting, and model predictive control within a unified industrially oriented architecture based on PLC/SCADA systems. The proposed approach is designed not only to improve the quality of DO regulation, but also to reduce operating costs, energy consumption, and dynamic stress on equipment under real operating conditions in wastewater treatment plants with highly deteriorated infrastructure. Unlike existing solutions, this study:

1. Explicitly incorporates the technological constraints of real-world equipment;
2. Enables intelligent control to be integrated through an Advisory MPC architecture without modifying the existing PID control loops;
3. Employs an LSTM-based correction module to compensate for nonlinear effects not accounted for by the linear MPC model;
4. Provides a fair and consistent comparison between the proposed MPC controller and a fuzzy PID controller under identical operating conditions and disturbance scenarios.

The main scientific and practical contributions of this study are as follows:

1. A nonlinear mathematical model of the aeration tank was developed based on the Activated Sludge Model (ASM) approach; the model was adapted for dissolved oxygen control tasks and designed for real-time implementation;
2. A linearized model of the aeration tank was developed for MPC controller synthesis, incorporating technological constraints and the permissible operating ranges of the aeration equipment;
3. A hybrid control architecture was proposed, in which an LSTM-based neural correction module compensates for nonlinear effects not captured by the linear MPC model;
4. A digital twin of the aeration tank was developed to support model validation, control algorithm testing, and subsequent industrial deployment;
5. An MPC algorithm was developed that incorporates predicted inflow disturbances and actuator constraints, thereby reducing DO fluctuations under abrupt changes in hydraulic loading;
6. In contrast to existing studies, this work proposes an industrially oriented hybrid control architecture based on Advisory MPC, PID control, and SCADA, which enables intelligent control to be integrated without modifying the existing PLC infrastructure;
7. A fair and consistent comparative study of the fuzzy PID controller and the MPC controller was conducted under identical constraints, identical inflow scenarios, and a unified performance criterion;
8. An assessment of energy efficiency and robustness was carried out, showing that the proposed MPC approach can reduce the energy consumption of the aeration system by preventing over-aeration while maintaining the required DO level. In addition, it reduces the amplitude of DO fluctuations and improves the operational stability of the aeration tank under non-stationary hydraulic loading conditions.

2. Materials and Methods

The following research methods were applied in the course of this work:

1. Mathematical modeling—development of a nonlinear dynamic model of an aeration tank;
2. Simulation modeling: nonlinear and linearized aeration tank systems, as well as the control system, were implemented in the MATLAB/Simulink R2025b software environment;
3. Neural network forecasting—use of a neural network model to forecast the daily inflow variability coefficient based on statistical data over a 5-year period;
4. Comparative analysis;
5. Energy analysis;
6. To assess the statistical reliability of the simulation results, each investigated scenario, namely the nominal operating mode, peak hydraulic load, and emergency overload, was simulated more than 20 times under different realizations of random influent flow disturbances and sensor measurement noise. For all control performance indicators, the mean values, standard deviations, and 95% confidence intervals were calculated. The statistical significance of the differences between the fuzzy PID controller and the MPC controller was evaluated using a two-sample Student's *t*-test at a significance level of $\alpha = 0.05$.

2.1. Modeling General Architecture of the Proposed Intelligent Control System

The general architecture of the proposed intelligent control system for the aeration tank is shown in Figure 1.

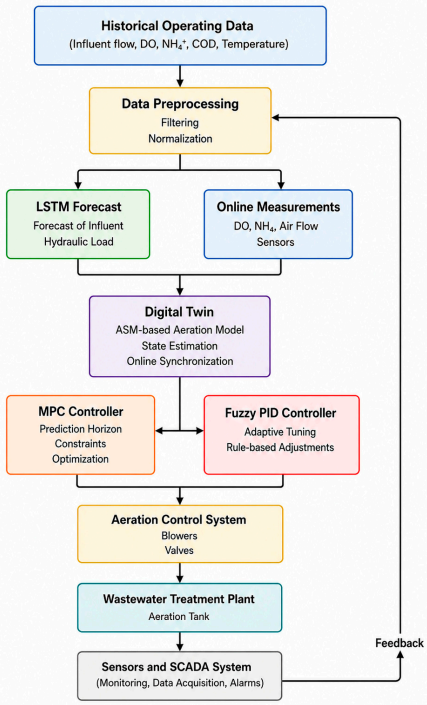


Figure 1. General architecture of the proposed intelligent control system for the aeration tank.

The architecture consists of four interacting layers: the data layer, the intelligent layer, the decision-making layer, and the physical process layer. The data layer collects historical operational data together with real-time measurements from the SCADA system. After preprocessing, the measurement data are simultaneously transmitted to the LSTM forecasting model and the digital twin. The LSTM network predicts the future hydraulic load, whereas the digital twin estimates the current process state using an ASM-based mathematical model synchronized with online measurements. The predicted disturbances

and estimated process states are then supplied to the MPC controller, while the fuzzy PID controller is used as a baseline for comparative evaluation of the control algorithms. Within the MPC block, an optimization problem is solved subject to technological constraints on the dissolved oxygen concentration and aeration rate. The resulting optimal airflow command is transmitted to the blower control system. Finally, the measured process parameters are fed back to the digital twin, closing the synchronization loop and ensuring continuous model updating.

In the proposed intelligent control architecture, the LSTM neural network does not replace the ASM-based mathematical model used in the digital twin. Instead, it performs the function of correcting the predicted system states. The state evolution of the ASM can be represented as (1):

$$X_{ASM}(k+1) = f(x(k), u(k), d(k)), \quad (1)$$

where

$x(k)$—aeration tank state vector;

$u(k)$—control input (airflow rate);

$d(k)$—denotes external disturbances, including influent flow rate, ammonium concentration, and other process variables.

The LSTM module uses historical operational data to predict future load variations over the prediction horizon $\hat{d}(k+i), i = 1 \dots N_p$. At the same time, the neural network estimates the residual error of the mathematical model $\Delta x(k+i)$.

As a result, the corrected state prediction is defined as (2):

$$X_{corr}(k+i) = X_{ASM}(k+1) + \Delta x(k+i), \quad (2)$$

where

$X_{ASM}(k+1)$—prediction generated by the ASM-based digital twin;

$\Delta x(k+i)$—correction term estimated by the LSTM neural network.

The corrected state predictions are then used in the MPC optimization problem. The MPC objective function takes the following form (3):

$$J = \sum_{i=1}^{N_p} \left(X_{corr}(k+i) - x_{ref} \right)^T Q \left(X_{corr}(k+i) - x_{ref} \right) + \sum_{i=0}^{N-1} \left(\Delta u(k+i)^T R \Delta u(k+i) \right), \quad (3)$$

Thus, the MPC controller minimizes the prediction error not with respect to the original ASM output, but with respect to the corrected state forecast of the digital twin. The use of the neural network makes it possible to compensate for mathematical model errors caused by:

1. nonlinear biochemical processes;
2. uncertainty in kinetic coefficients;
3. variations in activated sludge characteristics;
4. incomplete representation of the process dynamics by the ASM.

Consequently, the LSTM module does not directly control the physical process; instead, it improves the accuracy of the prediction used by the MPC controller to compute the optimal airflow rate.

2.2. Digital Twin Synchronization and Water Quality Data Integration

The digital twin enables continuous data exchange between the virtual model and the physical system. In the proposed architecture, the digital twin operates in online mode and is synchronized with the technological process through the existing industrial PLC–SCADA infrastructure.

The input data consisted of time series obtained from the SCADA system of the wastewater treatment plant, including:

1. Dissolved oxygen concentration, measured using Yokogawa DO71 DO sensors (Yokogawa Electric Corporation, Tokyo, Japan);
2. Airflow rate, Q_{air}, measured using an EMIS-MASS 260 flowmeter (EMIS JSC, Chelyabinsk, Russia);
3. Wastewater inflow rate, Q_{in}, measured using an EMIS-MAG 270 flowmeter (EMIS JSC, Chelyabinsk, Russia).

To synchronize the digital twin with the real aeration tank, a multi-level industrial data exchange architecture is used. At the field level, dissolved oxygen sensors, flowmeters, and actuators are connected using the Modbus RTU protocol. Data exchange between the PLC, SCADA system, and digital twin is performed via OPC UA, which provides standardized, secure, and platform-independent communication. The use of OPC UA enables bidirectional synchronization between the physical object and the virtual model, including the transmission of measurements, diagnostic information, forecasts, and advisory control actions generated by the MPC controller in real time.

Since the dynamics of biological processes are significantly slower than those of the actuators, the synchronization procedure is implemented across several time scales, as presented in Table 2.

Table 2. Time scales of digital twin synchronization and control system updating.

Level	Period
PLC sensor polling	1–5 s
Data transmission to SCADA	5–10 s
Digital twin updating	30 s
MPC recalculation	1 min
LSTM retraining	Once per day

The selected update interval of 30–60 s is justified by the fact that the characteristic time constant of the aeration tank is on the order of tens of minutes or longer. Therefore, increasing the update frequency does not provide a significant improvement in control performance. The digital twin supports bidirectional information exchange between the physical process and the virtual model.

From the physical process to the digital twin, the following information is transmitted:

1. current dissolved oxygen (DO) measurements;
2. actual airflow rate;
3. influent wastewater flow rate;
4. equipment operating parameters.

These data are used to correct the model states and synchronize the digital twin with the real aeration tank.

From the digital twin to the control system, the following information is transmitted:

1. DO forecast;
2. influent flow forecast;
3. advisory MPC setpoint;
4. warnings about possible constraint violations;
5. estimated energy consumption.

As a result, a closed-loop decision-making framework is established. In addition, the digital twin provides early detection of deviations in the technological process, enabling timely identification of abnormal operating conditions.

In the case of a persistent discrepancy between the model and the real object, $|DO_{real} - DO_{model}| > \Delta DO_{crit}$, the system generates a warning indicating possible causes, including:

1. fouling of the aerators;
2. reduced blower performance;
3. degradation of activated sludge;
4. DO sensor failure;
5. abnormal influent wastewater flow.

Thus, the digital twin simultaneously performs several functions:

1. a virtual sensor;
2. a predictive model;
3. a diagnostic tool;
4. a testing environment for control algorithms;
5. an intelligent operator support system.

The main objective of the proposed intelligent control system is to optimally regulate the aeration process and reduce energy consumption. At the same time, the digital twin continuously estimates the key biological state variables that determine the quality of treated wastewater. The ASM-based process model includes dynamic relationships between dissolved oxygen (DO), biodegradable substrate concentration, heterotrophic biomass, and oxygen transfer. Therefore, variations in the influent hydraulic load predicted by the LSTM model affect not only the optimal aeration rate but also the predicted biological conversion processes inside the aeration tank. In the proposed system, dissolved oxygen is considered as the directly controlled variable, whereas ammonium concentration in the effluent and substrate removal are treated as controlled performance indicators estimated by the digital twin. Thus, aeration optimization simultaneously contributes to maintaining stable effluent quality while minimizing the energy consumption of the aeration system.

2.3. Aeration Tank

2.3.1. Process Description

The aeration tank is the main component of a biological wastewater treatment plant and is a completely mixed reactor in which biological oxidation of organic pollutants by activated sludge in the presence of dissolved oxygen takes place. The primary controlled variable is the concentration of dissolved oxygen, while the manipulated variable is the airflow rate supplied by the aeration system. The primary objective of the aeration tank is to reduce the concentration of biochemical oxygen demand and nitrogen compounds to regulatory levels prior to the discharge of treated water into a water body [20]. From the perspective of automatic control, an aeration tank belongs to the class of complex nonlinear dynamic systems, characterized by pronounced nonlinearity, time delays, parameter uncertainty and a significant external disturbance, primarily fluctuations in the inflow of wastewater [23]. In the biological treatment process, activated sludge microorganisms use organic matter as a source of nutrition; however, a certain concentration of dissolved oxygen (DO) must be maintained for aerobic reactions to take place [24].

The primary controlled variable is DO concentration, as it directly influences the rate of biochemical reactions and the stability of the activated sludge. In most practical applications, the optimal DO range is 1.5–3 mg/L, above which energy consumption increases without any significant improvement in treatment quality [10].

2.3.2. Nonlinear Dynamic Model

The mathematical model was developed on the basis of the following assumptions:

1. the aeration tank is regarded as a perfectly mixed reactor;
2. the process temperature is assumed to be constant;
3. the concentration of activated sludge changes slowly compared to the dynamics of dissolved oxygen;
4. the main controlled parameter is the concentration of dissolved oxygen (DO), and the control variable is the air supply rate.

In this study, temperature is treated as a slowly varying parameter whose influence on the dissolved oxygen dynamics is assumed to be negligible within the MPC prediction horizon.

For the aeration tank control problem, an MPC prediction horizon of approximately 1–12 h is considered.

At the same time, wastewater temperature varies much more slowly. According to the operational data from the wastewater treatment facilities of Semey city, typical temperature variations are as follows:

1. Within one day: no more than 0.5–1.5 °C;
2. Seasonally: over periods of weeks and months.

Therefore, within the MPC prediction horizon, temperature can be assumed to be a quasi-constant parameter.

Therefore, in the proposed model, the process temperature is assumed to remain constant.

The activated sludge concentration belongs to the category of slowly varying process parameters. Its characteristic time constant is on the order of tens of hours and is substantially longer than the characteristic response time of the dissolved oxygen dynamics and the aeration system. Therefore, in the synthesis of the MPC controller, the activated sludge concentration is treated as a quasi-stationary variable and is included in the model as an operating-point parameter.

The application of the time-scale separation principle makes it possible to distinguish between the fast dynamics associated with dissolved oxygen regulation and the slower biological processes related to changes in activated sludge concentration. In the considered control problem, the fast variables are described by the dynamic MPC model, whereas the influence of slow processes is treated as parametric uncertainty and compensated by the neural-network-based correction module. This approach reduces the computational complexity of the model without a noticeable loss of control accuracy.

The dynamics of the process are described by a system of nonlinear differential equations that reflect the kinetics of microbial growth, oxygen transport and mass transfer processes [23,24]:

The dynamics of dissolved oxygen concentration in the aeration tank are described by the oxygen mass balance equation (4).

$$\frac{dDO(t)}{dt} = k_L a(DO_{sat} - DO(t)) - \frac{1}{Y_0}\mu(S(t),\ DO(t))X, \tag{4}$$

where

1. $DO(t)$—dissolved oxygen concentration, mg/L;
2. DO_{sat}—oxygen saturation concentration, mg/L;
3. $k_L a$—oxygen mass transfer coefficient, s^{-1};
4. $X(t)$—concentration of active sludge, mg/L;
5. Y_0—oxygen yield coefficient of biomass;
6. $\mu(S,DO)$—microbial specific growth rate.

Microbial growth kinetics are modeled using a modified equation under oxygen-limited conditions (5):

$$\mu(S) = \mu_{max} \frac{S}{K_S + S} \frac{D_o}{K_{D_0} + D_0}, \quad (5)$$

where

1. μ_{max}—maximum specific growth rate, day^{-1};
2. S—concentration of organic substrate, mg/L;
3. K_S—substrate saturation constant, mg/L;
4. K_{D0}—oxygen saturation constant, mg/L.

The air supply to the aeration tank is related to the oxygen mass transfer coefficient (6):

$$k_L a = k_0 * u(t), \quad (6)$$

where

1. $u(t)$—airflow rate (manipulated variable);
2. k_0—an empirical coefficient that depends on the design of the aeration system.

Organic substrate balance (7):

$$\frac{dS}{dt} = \frac{Q_{in}}{V}(S_{in} - S) - \frac{1}{Y}\mu(S, DO)X, \quad (7)$$

where

1. V—aeration tank volume m^3;
2. S_{in}—influent pollutants concentration, mg/L;
3. Y—biomass concentration, mg/L.

Active sludge balance (8):

$$\frac{dX}{dt} = \mu(S, DO) * X - \frac{Q_{in}}{V}X - k_B X, \quad (8)$$

Manipulated variable—airflow rate supplied by blowers (9):

$$u(t) = Q_{air}(t), \quad (9)$$

Measurable disturbance—the outflow rate of the incoming wastewater stream, which is predictable (10):

$$d(t) = Q_{in}(t), \quad (10)$$

Controlled output—dissolved oxygen concentration (11):

$$y(t) = DO(t), \quad (11)$$

To maintain the stability of biological processes and ensure the energy-efficient operation of the aeration tank, the dissolved oxygen concentration is limited to the following range (12):

$$1.5 \leq DO(t) \leq 3.0 \text{ mg/L}, \quad (12)$$

The lower limit is determined by the need to prevent oxygen deficiency, which leads to a reduction in the rate of biochemical oxidation and a potential disruption of nitrification. The upper limit is determined by energy considerations: at DO concentrations above 3.0 mg/L, a further increase in the air supply does not lead to a significant improvement in treatment efficiency, but results in a substantial increase in energy consumption.

The selected range is consistent with established guidelines on wastewater treatment and activated sludge modeling, as reported in [25,26].

The data presented in Table 3 were used for the calculation.

Table 3. Data for calculating the aeration tank.

Parameter	Nomenclature	Typical Value	Range	Source
Maximum growth rate	μ_max	0.6 d^{-1}	0.3–1.0	[24]
Substrate half-saturation	K_S	20 mg/L	10–40	[25]
Oxygen half-saturation	K_DO	0.2 mg/L	0.1–0.5	[25]
Biomass concentration	Y	0.65	0.4–0.7	[27]
Oxygen coefficient	Y_O	1.42	1.2–1.6	[27]
Mass transfer coefficient	k_La	5–15 h^{-1}	3–20	[25]
Sludge decomposition rate	k_d	0.05 d^{-1}	0.02–0.1	[25]
Aeration tank volume	V	5000 m^3	-	Project
Influent flow rate	Q	2000 m^3/d	±50%	Operation
DO saturation	DO_sat	for Semey: Summer 9.2 mg/L Winter 7.8 mg/L	7–9.5	[26]

The biological kinetic parameters were specified according to the IWA-recommended ASM1 framework and supported by relevant literature data, whereas the hydraulic parameters were derived from the design and operational characteristics of the investigated wastewater treatment plant. The oxygen transfer coefficient and oxygen saturation concentration were selected based on typical aeration system performance and the temperature-dependent solubility of oxygen, respectively.

The model sensitivity analysis showed that the oxygen mass transfer coefficient kLa and the dissolved oxygen half-saturation coefficient KDO have the greatest influence on the dissolved oxygen dynamics and the performance of the MPC controller. Variations in these parameters directly affect the rates of oxygen transfer and consumption and, consequently, the energy consumption of the aeration system. The parameters Y, YO, and kd characterize slower biological processes and have a substantially lower impact on control performance within the MPC prediction horizon. Therefore, variations in kLa represent the main source of model uncertainty, which further justifies the use of a neural-network-based correction module to compensate for these variations during the operation of the wastewater treatment plant.

The model under consideration exhibits several properties that significantly influence the choice of control method:

1. significant nonlinearity;
2. the presence of parametric uncertainty;
3. the dependence of the dynamics on anticipated disturbances in the inflow;
4. strict technological and energy constraints.

These characteristics limit the applicability of classical linear controllers and justify the use of model predictive control (MPC), which is capable of taking into account process dynamics, constraints and anticipated disturbances within a single optimization framework.

The aeration tank is one of the highest energy-intensive components of a wastewater treatment plant, as the aeration system accounts for a significant proportion of the plant's total energy consumption. Therefore, even a partial optimization of the airflow regime results in a significant economic and environmental benefits [28].

The availability of DO measurements, the ability to regulate airflow, and the predictable nature of the influent make the aeration tank a suitable candidate for MPC implementation,

particularly when combined with a digital twin that enables the consideration of uncertainties and the assessment of the control system stability under various operating conditions.

2.3.3. Implementation in MATLAB/Simulink

In this study, a linear MPC controller synthesized based on a linearized process model is used.

The linear MPC provides:

1. guaranteed constraint satisfaction;
2. closed-loop system stability;
3. predictable computational performance;
4. compatibility with industrial PLC systems.

This approach is preferable for industrial applications, as it ensures computational robustness, predictable control performance, and integration capability with real-time PLC/SCADA systems. However, biological wastewater treatment processes exhibit pronounced nonlinearity caused by microbial kinetics, variations in the oxygen mass transfer coefficient, seasonal temperature fluctuations, and the stochastic nature of hydraulic loading [29].

Accordingly, within the proposed digital twin architecture, the neural-network-based model forecasts the influent wastewater flow rate Qin(t), which is then incorporated into the MPC framework as a measured disturbance.

The use of an LSTM network is motivated by the presence of pronounced temporal dependencies and time-delay effects in aeration tank dynamics. The LSTM architecture is capable of capturing:

1. diurnal variability of wastewater inflow;
2. inertial behavior of biological processes;
3. cumulative effects associated with activated sludge;
4. slow time-varying changes in system parameters.

In the proposed control structure, the neural network module does not replace the MPC controller; instead, it complements it. The neural network correction module serves as an adaptive supervisory layer that compensates for effects not captured by the linear model.

From an engineering perspective, this architecture combines the advantages of:

1. Linear MPC, which provides:
   - closed-loop stability;
   - explicit constraint handling;
   - feasibility for industrial implementation.
2. Neural network modeling, which enables:
   - approximation of nonlinear process dynamics;
   - adaptation to varying operating conditions;
   - compensation for model uncertainties.

In contrast to classical adaptive MPC, where the parameters of the linear model are updated online, the proposed approach reduces the computational burden by keeping the linear model fixed and assigning nonlinear compensation to the neural network module.

From a structural perspective, the digital twin is organised as a modular architecture comprising three levels:

1. Physical layer, which includes:
   - aeration tank;
   - air blowers;
   - dissolved oxygen (DO) sensors.
2. Model layer, which comprises:

- a mathematical model of the aeration tank that describes the dynamics of dissolved oxygen (DO) concentration;
- a disturbance generation module that simulates variations in wastewater inflow and organic loading.

3. Intelligent layer, which includes:
   - a control module implementing the MPC algorithm in an advisory mode;
   - a visualization and performance analysis module intended to assess the effectiveness of the control strategy.

The block diagram of the digital twin is shown in Figure 2.

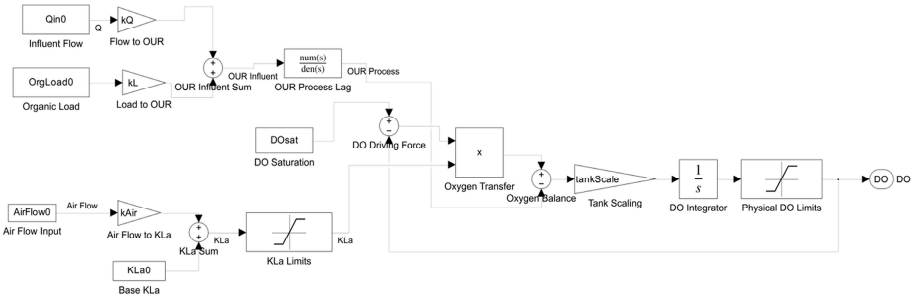


Figure 2. Block diagram of the digital twin implementation for the aeration tank in MATLAB/Simulink R2025b.

Thus, the neural network correction module adapts the linear MPC controller to the real nonlinear dynamics of the aeration tank without complicating the baseline control algorithm. This allows the system to retain its industrial applicability while simultaneously improving control quality and energy efficiency.

To verify the adequacy of the developed digital twin, validation was performed using historical operational data from the wastewater treatment plant in Semey.

The overall dataset covered 30 days of operation with a sampling interval of 5 min. The data were divided into two subsets:

1. a calibration dataset covering 20 days, used for model parameter tuning;
2. a validation dataset covering 10 days, used for independent verification of model adequacy.

The selected time interval includes:

1. Daily water consumption cycles;
2. Morning and evening load peaks;
3. Working days and weekends;
4. Random hydraulic disturbances;
5. Changes in aeration operating modes.

Thus, the dataset covers a wide range of dynamic operating conditions necessary for assessing the adequacy of the proposed control model.

At the same time, seasonal effects, including wastewater temperature variations, changes in influent pollutant composition, and long-term equipment degradation, were not considered as direct validation factors for the digital twin in the present study. Instead, these effects were incorporated at the level of the LSTM-based forecasting subsystem, which was trained using a five-year archive of operational data and applied to predict the influent flow non-uniformity coefficient.

Thus, short-term validation of the digital twin and long-term training of the neural-network-based predictor serve different purposes and are mutually complementary within the unified intelligent control system.

The accuracy of the digital twin in representing the real aeration tank was assessed using standard statistical performance metrics:

1. Root Mean Square Error (RMSE);
2. Mean Absolute Error (MAE);
3. Coefficient of determination, (R^2);
4. Mean Absolute Percentage Error (MAPE).

The statistical performance metrics used to validate the aeration tank digital twin are presented in Table 4.

Table 4. Statistical performance metrics for validating the aeration tank digital twin.

Metric	Value
RMSE	0.14 mg/L
MAE	0.09 mg/L
R^2	0.94
MAPE	6.3%
Maximum error	0.28 mg/L

The correspondence between the digital twin model and the real aeration tank is presented in Figure 3.

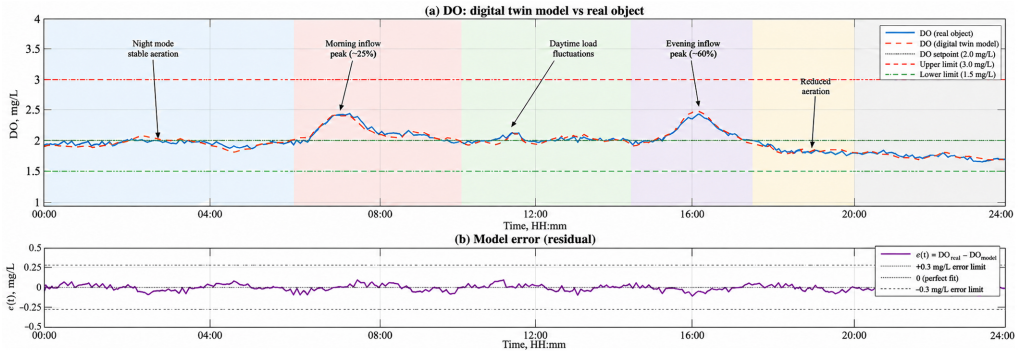


Figure 3. Validation of the aeration tank digital twin against the real process.

The obtained values indicate a high degree of agreement between the digital twin and the real process. The coefficient of determination R^2 = 0.94 shows that the model explains approximately 94% of the observed variability in dissolved oxygen concentration. The values of RMSE = 0.14 mg/L and MAE = 0.09 mg/L are substantially lower than the permissible technological DO control range of 1.5–3.0 mg/L, while the mean absolute percentage error (MAPE) does not exceed 6.3%.

The main limitation of the conducted validation is that it was based on data from a single operating season. Further confirmation of the model generalizability requires extended cross-seasonal validation using an annual dataset that includes both summer and winter operating conditions of the wastewater treatment plant. This issue is considered by the authors as an important direction for future research.

2.3.4. Linearization and MPC Design

The nonlinear model is linearized around the nominal operating point corresponding to the plant's steady-state operation. Linearization is performed in Simulink using predefined input–output linearization points and a linearization function.

Linearization is performed directly on the Simulink model of the nonlinear aeration tank using the "linearize" function. For this purpose, linearization points are specified at the inputs and outputs of the controlled object within the model.

The model is defined in the state space (13) [19]:

$$\begin{aligned} \Delta\dot{x} &= A\cdot\Delta x(t) + B\cdot\Delta u(t) + Ed(t) \\ \Delta y(t) &= C\cdot\Delta x(t) + D\cdot\Delta u(t), \end{aligned} \tag{13}$$

where

1. $\Delta x = x - x_0$—State deviations from the operating point;
2. $\Delta u = u - u_0$—Control deviation (aeration);
3. $\Delta y = y - y_0$—Output deviation (DO concentration);
4. $d(t) = \Delta Q_{in}(t)$—External disturbance caused by variations in wastewater inflow rate.

The resulting continuous-time state-space model is discretized, and the sampling time is chosen in accordance with the dominant time constants of the process. The linearized model is shown in Figure 4.

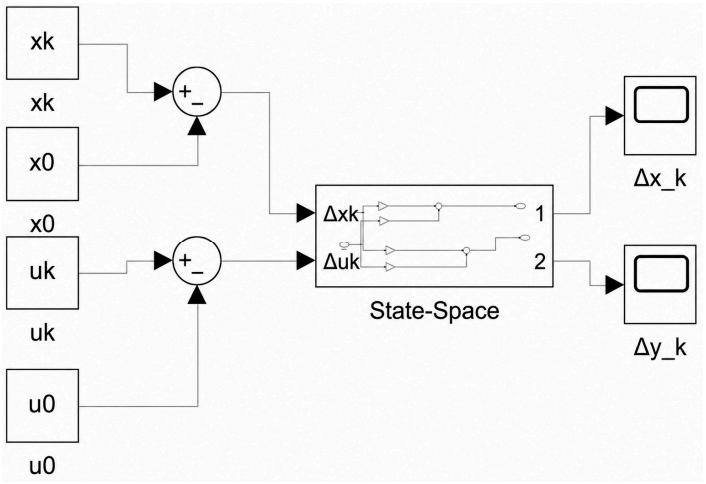


Figure 4. Linearized model of an aeration tank in Simulink.

The model is calculated using experimental data obtained from the wastewater treatment facilities in the city of Semey (Kazakhstan).

Linearization is performed at the operating point DO = 2 mg/L.

Given that the optimal dissolved oxygen (DO) concentration range for an aeration tank is 1.5–3 mg/L, a value of 2 mg/L lies at the midpoint of this range and represents a typical setpoint for most wastewater treatment plants. This ensures effective biological treatment without excessive energy consumption. Furthermore, it enables the derivation of a linearized model that most accurately describes the process dynamics in the vicinity of the desired operating regime. Maintaining DO at 2 mg/L avoids both oxygen limitation (below 1.5 mg/L) and excessive aeration (above 3 mg/L), which directly affects the energy consumption of the aeration system.

At present, the Monod model [25] is used to describe the kinetics of microbial growth, which is generally understood as the dynamics of substrate consumption, biomass production, and metabolite formation in wastewater treatment processes.

The linearized Monod model is given by (14):

$$\mu(S) = \mu 0 + \frac{\partial \mu}{\partial S}(S - S_0) + \frac{\partial \mu}{\partial DO}(DO - DO_0), \tag{14}$$

This quantity is then used as an input to the MPC controller after linearization. The matrices of the linearized model are then determined.

Matrix A:

$$A_{11} = \frac{\partial\left(\frac{dS}{dt}\right)}{\partial S} = -\frac{1}{Y}X\frac{\partial\mu}{\partial S} - \frac{Q_{in}}{V} = -\left(\frac{1}{0.65}\right) * 3000 * 0.0065 - \frac{20,000}{5000} = -34,$$

$$A_{12} = \frac{\partial\left(\frac{dS}{dt}\right)}{\partial DO} = -\frac{1}{Y}X\frac{\partial\mu}{\partial S} = -\left(\frac{1}{0.65}\right) * 3000 * 0.13 = -600,$$

$$A_{21} = \frac{\partial\left(\frac{dDO}{dt}\right)}{\partial S} = -\alpha X\frac{\partial\mu}{\partial S} = -1.2 * 3000 * 0.0065 = -23.4,$$

$$A_{22} = \frac{\partial\left(\frac{dDO}{dt}\right)}{\partial DO} = -K_L\alpha - \alpha X\frac{\partial\mu}{\partial S} = -5 - 1.2 * 3000 * 0.13 = -473,$$

$$A = \begin{bmatrix} -34 & -600 \\ -23.4 & -473 \end{bmatrix},$$

The control input matrix B is defined as:

$$\frac{\partial\left(\frac{dDO}{dt}\right)}{\partial Q_{air}} = K_1(DO_{sat} - DO_0) = 20 * (8 - 2) = 120,$$

$$B = \begin{bmatrix} 0 \\ 120 \end{bmatrix},$$

The measured outputs are S and DO:

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, D = \begin{bmatrix} 0 \\ 0 \end{bmatrix},$$

The resulting state-space model is given by (15):

$$\dot{x} = \begin{bmatrix} -34 & -600 \\ -23.4 & -473 \end{bmatrix} \cdot x + \begin{bmatrix} 0 \\ 120 \end{bmatrix} \cdot u + \begin{bmatrix} 0.04 \\ 0 \end{bmatrix} \cdot d, \quad (15)$$

In contrast to traditional ASM models, which are primarily intended for technological analysis of biological treatment processes, this study proposes a reduced-order control-oriented aeration tank model integrated with a digital twin, neural-network-based influent flow forecasting, and model predictive control. This approach enables the real-time implementation of optimal control algorithms using existing PLC–SCADA systems while maintaining an adequate representation of the process dynamics. The main distinctions between the approaches are summarized in Table 5.

Table 5. Comparison between the ASM1 model and the proposed control-oriented model.

Characteristic	Classical ASM1 Model	Proposed Model
Purpose	Technological process modeling	Control and optimization
Number of states	13	3 main states
Applicability for MPC	Limited	Specifically adapted
Consideration of equipment constraints	No	Yes
Influent flow forecasting	No	LSTM-based forecasting
Digital twin	No	Yes
Neural-network-based correction	No	Yes
Real-time operation	Difficult	Oriented toward PLC–SCADA implementation
Energy optimization	No	Yes
Advisory MPC	No	Yes

3. Results

3.1. Comparison of MPC and Fuzzy PID Controllers

To assess the effectiveness of the proposed model predictive control (MPC) strategy, a comparative study was conducted with a fuzzy PID controller. The comparison was carried out to determine the best control strategy for the same nonlinear aeration tank model under identical operating conditions, disturbances and constraints, which ensures the validity of the conclusions drawn.

For an objective evaluation of the effectiveness of model predictive control (MPC), a comparative analysis was carried out between MPC and a conventional fuzzy PID controller. The comparison was performed under identical simulation conditions, with the same constraints on the controlled and control variables.

Both control systems were developed and tested under the following identical conditions:

1. controlled object—the same nonlinear aeration tank model;
2. controlled variable—dissolved oxygen concentration (DO);
3. manipulated variable—airflow rate (Qair);
4. DO setpoint—2.0 mg/L;
5. disturbances—non-steady-state wastewater inflow (including step changes and random fluctuations);
6. constraints:
   - $1.5 \leq DO \leq 3$ mg/L;
   - $Q_{airmin} \leq Q_{air} \leq Q_{airmax}$;
   - rate-of-change constraint ΔQ_{air}

A fuzzy PID controller was selected to handle continuously varying flow conditions entering the treatment plant, both in terms of volume and the amount of substrate. A system with such a regulator acts directly to resolve any arising issues.

A standard fuzzy PID structure was employed:

1. input variables:
   - control error e(t) = DOref − DO(t);
   - derivative of the error $\dot{e}(t)$;
   - output variable—corrective effect on airflow ΔQair.

The tuning criteria for the fuzzy PID were:

1. minimizing the mean squared error DO from the setpoint;
2. reduction in abrupt changes in the control signal.

A linearized model of the aeration tank, derived from Monod nonlinear kinetics, was used to design the MPC controller. The linearization was performed at an operating point corresponding to the nominal operating conditions of the wastewater treatment plant. The classical Monod model, taking into account the effects of substrate concentration and dissolved oxygen, is adopted as the kinetic equation. The partial derivatives of the growth function with respect to the relevant variables are derived analytically and used to form the state matrices of the linearized model. This approach ensures that the MPC controller is implemented correctly in accordance with MathWorks standards and allows for the physical constraints of the technological process to be taken into account.

The aeration tank operates close to steady-state conditions, and the MPC recalculates the control at each step, therefore linearization at the operating point is acceptable and widely used in industrial practice.

At each sampling step, the MPC controller predicts the change in dissolved oxygen (DO) concentration using the calibrated mathematical model of the technological process and a short-term influent wastewater flow forecast generated by the LSTM neural network.

Based on this prediction, the optimal trajectory of the airflow rate is calculated while satisfying all technological and operational constraints.

The prediction horizon was set to Np = 12 steps. With a sampling time of Ts = 1 min, the controller predicts the process dynamics over a 12 min interval.

The selected value represents a compromise between prediction accuracy and the computational complexity of the optimization algorithm. A shorter prediction horizon does not fully account for the inertial behavior of oxygen mass transfer processes in the aeration tank, whereas a substantial increase in the horizon leads to higher computational costs without a noticeable improvement in control performance.

The control horizon was set to Nc = 5 steps. Thus, only the first five control actions are independently optimized: $Q_{air}(k)$, $Q_{air}(k + 1)$. . .$Q_{air}(k + 4)$.

After the end of the control horizon, the control input is assumed to remain constant according to the above expression. This approach significantly reduces the dimensionality of the optimization problem while maintaining sufficient control flexibility. The controller operates with a fixed sampling time of Ts = 1 min.

This value was selected taking into account the following factors:

1. the data update period of the SCADA system;
2. the response time of the dissolved oxygen sensors;
3. the dynamic characteristics of the blower equipment;
4. the computational time required by the optimization algorithm.

The one-minute sampling interval is significantly shorter than the characteristic time scale of dissolved oxygen concentration dynamics and is commonly used in automated control systems for wastewater treatment plants. At each control step, a quadratic objective function (16) is minimized [18,29,30]:

$$J = \sum_{i=1}^{N} \left(\Delta y_{k+t}^{T} Q \Delta y_{k+t} \right) + \sum_{i=0}^{N-1} \left(\Delta u_{k+1}^{T} R \Delta u_{k+i} \right), \quad (16)$$

where

1. y—predicted dissolved oxygen concentration, g/m^3;
2. r—reference dissolved oxygen concentration, g/m^3;
3. u—airflow rate, m^3/h;
4. Δu—control input increment;
5. Q, R—weighting matrices.

The first term of the objective function minimizes the tracking error of the dissolved oxygen concentration with respect to its reference value, whereas the second term penalizes abrupt changes in the airflow rate, thereby reducing the mechanical load on the blower equipment and decreasing energy consumption.

The following weighting coefficients were used in this study: $Q = 5$ and $R = 0.1$. The increased value of Q ensures high accuracy in maintaining the dissolved oxygen concentration, whereas the relatively small value of R allows the controller to respond promptly to load variations without generating excessive oscillations in the control signal.

The sensitivity analysis showed that increasing Q above 10 results in more aggressive control with only a minor improvement in regulation quality, while increasing R above 1 significantly slows down the system response to external disturbances.

Physical constraints of the technological process are taken into account when solving the optimization problem. The dissolved oxygen concentration is constrained as follows (17):

$$1.5 \leq DO \leq 3.5 \text{ mg/L}, \quad (17)$$

The lower bound prevents oxygen deficiency and deterioration of the biological wastewater treatment process, whereas the upper bound prevents excessive aeration and unjustified energy consumption.

The airflow rate is constrained according to the technical characteristics of the blower equipment used at the wastewater treatment plant (18):

$$100 \leq Q_{air} \leq 600 \text{ m}^3/\text{h}, \tag{18}$$

To avoid abrupt changes in blower capacity, the rate of change in the airflow rate is also limited (19):

$$-20 \leq \Delta Q_{air} \leq 20 \text{ m}^3/\text{h}, \tag{19}$$

This constraint reduces mechanical wear of the equipment, ensures smooth control action, and improves the operational reliability of the aeration system.

The optimal control action was computed using the MATLAB Model Predictive Control Toolbox. The quadratic programming problem was solved using the Active-Set Quadratic Programming algorithm. According to the simulation results, the average solution time of the optimization problem was 0.09 ± 0.02 s. This value is significantly lower than the sampling time of Ts = 60 s, which confirms the feasibility of implementing the developed algorithm in real time.

The main tuning parameters of the MPC controller used in the proposed intelligent control architecture are summarized in Table 6.

Table 6. Main tuning parameters of the MPC controller.

Parameter	Value
Prediction horizon, Np	20 steps
Control horizon, Nc	5 steps
Sampling time, Ts	1 min
Controlled variable	Dissolved oxygen concentration (DO)
Control input	Airflow rate Q_{air}
Objective function	Minimization of DO tracking error and airflow rate variations
Weighting coefficient, Q	5
Weighting coefficient, R	0.1
DO constraint	1.5–3.5 mg/L
Airflow rate constraint	100–600 m^3/h
Airflow rate change constraint	$\pm$20 m^3/h per min
Solver	Active-Set Quadratic Programming
Average optimization time	0.09 ± 0.02 s

A fuzzy PID controller was used as the baseline algorithm for comparison. This controller provides adaptive adjustment of the controller gains depending on the current state of the aeration process.

In contrast to a conventional PID controller with fixed parameters, the fuzzy controller adjusts K_P, K_I, and K_D in real time based on an expert rule base. This makes it possible to improve control performance under varying technological load conditions.

Before applying fuzzy correction, the initial PID gains were determined using the extended frequency response characteristics method. The initial coefficients were selected considering the dynamic characteristics of the biological wastewater treatment process. The aeration tank is characterized by high inertia, a significant time delay, and slowly varying parameters. For such processes, excessively high gain values may lead to oscillations in dissolved oxygen concentration and increased energy consumption of the aeration system.

Therefore, the initial controller tuning was performed in two stages.

Stage 1. Obtaining the linear model.

The nonlinear aeration tank model was linearized around the nominal operating point corresponding to DO = 2.0 mg/L and an average airflow rate of $Q_{air} = 0.6Q_{max}$. The obtained dynamics were well approximated by a first-order plus time-delay model (20):

$$W(p) = \frac{Ke^{-p\tau}}{Tp+1}, \quad (20)$$

where

1. K = 0.83—process gain;
2. T = 14.2 min—time constant;
3. τ = 2.8 min—transport delay.

These parameters were identified based on the step response of the digital twin.

Stage 2. Initial PID tuning

To obtain the initial controller gains, the Ziegler–Nichols tuning method for first-order plus time-delay (FOPDT) models was used, followed by manual adjustment.

After the initial tuning, the following PID gains were obtained:

1. K_P = 1.8;
2. K_I = 0.12 min^{-1};
3. K_D = 3.6 min.

These values ensured stable controller operation, with no self-sustained oscillations, a settling time of less than 25 min, and an overshoot of less than 10%.

However, when the technological load varied, the control performance deteriorated due to changes in the process gain. For this reason, the obtained PID gains were used exclusively as baseline values for subsequent adaptation using fuzzy logic.

The fuzzy controller adjusts the gains K_P, K_I, K_D in real time relative to their nominal values (21):

$$K_P = K_{P0} * f_P(e, \Delta e) K_I = K_{I0} * f_I(e, \Delta e) K_D = K_{D0} * f_D(e, \Delta e), \quad (21)$$

The functions f_P, f_I, and f_D are generated by the fuzzy inference system based on the current control error $e(t) = DO_{set} - DO$ and the error increment $\Delta e(t)$.

After selecting the initial PID gains, parametric optimization was performed. The optimization was carried out by minimizing the following objective function (22):

$$J = \omega_1 IAE + \omega_2 TV + \omega_3 E, \quad (22)$$

where

1. IAE—integral absolute error;
2. TV—total variation in the control signal;
3. E—energy consumption of the blowers.

The weighting coefficients ω_1, ω_2, and ω_3, were selected based on the results of sensitivity analysis. The combinations considered in this study are presented in Table 7.

Table 7. Combinations of weighting coefficients used in the sensitivity analysis.

№	ω_1	ω_2	ω_3
1	0.7	0.2	0.1
2	0.6	0.2	0.2
3	0.5	0.3	0.2
4	0.4	0.4	0.2
5	0.4	0.3	0.3

The analysis showed the following:

1. when $\omega_1 > 0.6$, the system reached the setpoint faster, however, the airflow rate increased significantly;
2. when $\omega_2 > 0.4$, the control action became excessively smooth, which deteriorated control performance under step changes in load;
3. when $\omega_3 > 0.3$, a noticeable reduction in energy consumption was observed; however, the DO tracking error increased.

In this study, priority was given to maintaining a stable dissolved oxygen concentration; therefore, the highest weight was assigned to the IAE criterion, $\omega_1 = 0.5$. The TV criterion characterizes the smoothness of airflow rate variation and is associated with the mechanical load on the actuators; therefore, an intermediate weight was assigned to this term, $\omega_2 = 0.3$. Minimization of energy consumption was considered as an additional optimization objective, and its weight was set to $\omega_3 = 0.2$. In addition, a sensitivity analysis was performed, which showed that varying the weights within the range of ± 0.1 did not change the qualitative nature of the results and did not affect the advantage of the proposed method over the baseline control algorithms.

The control objective is to maintain the dissolved oxygen concentration at a set point, while minimizing fluctuations in airflow rate and adhering to operational constraints. The MPC model includes: the manipulated variable (airflow rate), the controlled output (dissolved oxygen concentration), and the measured disturbance (predicted inflow rate). Constraints on oxygen concentration and airflow rate are explicitly included in the optimization problem.

1. Simulation results.
2. A comparative analysis of the performance of an MPC controller and a fuzzy PID controller.

For non-stationary operating conditions, fuzzy PID and MPC controllers represent suitable control strategies. A comparative analysis (Figure 5) of these approaches is carried out. Furthermore, the control input and energy consumption are evaluated. The results are presented below.

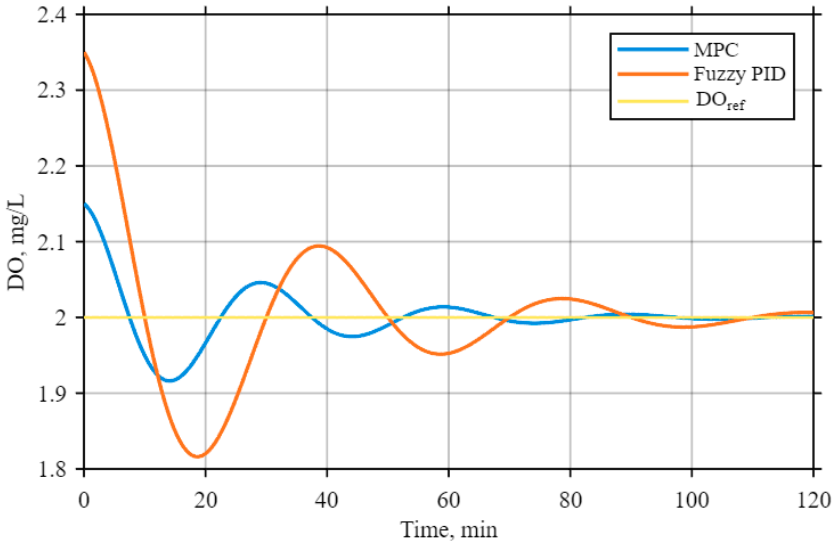


Figure 5. Comparison of DO dynamics under fuzzy PID and MPC during a sudden increase in wastewater inflow.

The behavior of a fuzzy PID controller

1. Following the disturbance, a significant overshoot is observed:

- DO rises above 2.4–2.5 mg/L;
- this indicates an excess air supply.

2. Characteristic oscillation:
   - the fluctuations persist throughout the entire interval;
   - the amplitude decays slowly.
3. Reasons:
   - fuzzy PID controller reacts only to the current error;
   - fuzzy logic rules do not take into account future inflow dynamics;
   - lack of explicit consideration of energy consumption in the control objective.

As a result, excessive aeration leads to a 10–25% increase in the energy consumption of the air blowers.

Performance of the MPC controller:

1. The response to the disturbance is smooth and predictable:
   - DO does not exceed 2.15–2.2 mg/L;
   - No abrupt peaks are observed.
2. Fast settling to the setpoint:
   - the system stabilizes without fluctuation;
   - DO smoothly converges to 2.0 mg/L.
3. Reasons:
   - MPC uses an aeration tank model;
   - incorporates influent flow forecasts over the prediction horizon;
   - optimizes control based on the following criteria: DO deviation + aeration costs.

As a result: the exact required volume of aeration is supplied—energy savings of 15–30% (Figure 6).

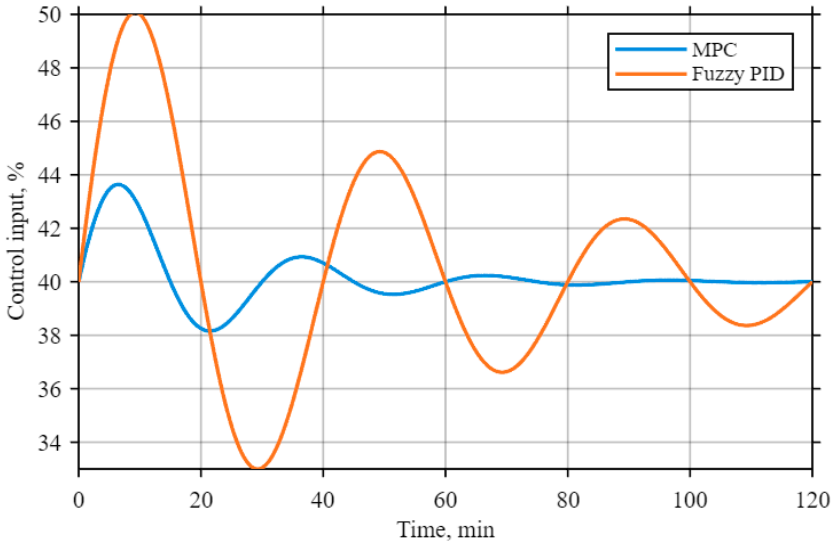


Figure 6. Comparison of control actions between MPC and a fuzzy PID controller.

The graphical results indicate that the MPC controller generates a smooth control action without abrupt fluctuations, while ensuring compliance with the specified technological constraints on the minimum and maximum airflow rates. When a fuzzy PID controller is used, the control action has a higher amplitude and is characterized by frequent corrective adjustments, which potentially increases the dynamic load on the air blower equipment.

A joint analysis of the DO(t) and u(t) plots leads to the conclusion that the MPC controller provides a better trade-off between control quality, control constraints and power consumption than a fuzzy PID controller.

Simulation experiments are carried out under conditions of a time-varying inflow, including periodic oscillations and step disturbances. The predicted influent flow data is fed into the MPC controller in the form of measured disturbances—predicted values derived using neural networks based on five years of monthly measurements of the volume of water entering the aeration system.

To predict the daily non-uniformity coefficient of influent wastewater flow, a recurrent neural network based on Long Short-Term Memory (LSTM) architecture was employed. LSTM networks are well suited for time-series processing and for capturing long-term temporal dependencies.

The choice of the LSTM architecture is justified by the fact that the hydraulic load of wastewater treatment plants is characterized by:

1. pronounced daily periodicity;
2. weekly seasonality;
3. seasonal climatic variations;
4. random short-term disturbances;
5. a nonlinear relationship between past and future flow values.

In contrast to conventional recurrent neural networks (RNNs), the LSTM architecture incorporates a memory mechanism that allows information to be retained over extended time intervals and enables the model to account for cumulative temporal effects.

The LSTM model was trained using historical operational data collected from the wastewater treatment facilities of Semey city over a five-year observation period.

To forecast variations in the hydraulic load, a recurrent neural network based on the Long Short-Term Memory (LSTM) architecture was employed. The LSTM model was selected because it is capable of capturing long-term temporal dependencies in the technological process. The input variables of the network included the influent wastewater flow rate (Q_{in}), dissolved oxygen concentration (DO), ammonium concentration (NH_4^+), chemical oxygen demand (COD), and the previous airflow rate (Q_{air}).

Before training, all input variables were normalized using the Min–Max normalization method. The structure of the LSTM network used in this study is presented in Table 8.

Table 8. LSTM model architecture and training hyperparameters.

Parameter	Value
Network type	LSTM
Number of LSTM layers	2
Number of neurons in the first layer	64
Number of neurons in the second layer	32
Dropout	0.2
Fully connected layer	16 neurons
Output layer	1 neuron
Activation function of hidden layers	tanh
Activation function of the output layer	linear
Optimizer	Adam
Learning rate	0.001
Batch size	64
Number of epochs	100
Early stopping	Yes

The 64–32 architecture provided the best compromise between forecasting accuracy, computational complexity, and real-time implementation capability. Increasing the number of layers did not lead to a statistically significant improvement in forecasting performance, but substantially increased the training time and the risk of overfitting.

The first LSTM layer extracts long-term patterns in hydraulic load variations, whereas the second LSTM layer refines the nonlinear process dynamics. The dropout layer reduces overfitting, and the fully connected layer generates the final influent wastewater flow forecast.

For the validation dataset, the following forecasting performance indicators were obtained: RMSE = 0.047, MAPE = 3.4%, and R^2 = 0.97. These results indicate high accuracy of short-term hydraulic load forecasting, which supports more effective operation of the subsequent MPC controller.

The Adam optimization algorithm (Adaptive Moment Estimation) was used to train the LSTM model. For the task of forecasting wastewater treatment plant parameters, Adam is one of the most suitable algorithms for the following reasons:

1. it provides fast convergence during training;
2. it automatically adapts the learning rate for each weight;
3. it is robust to noise in operational SCADA data;
4. it works effectively with long time series used in LSTM networks.

Compared with classical stochastic gradient descent, Adam automatically adapts the learning rate for each network parameter based on estimates of the first and second moments of the gradient, which ensures faster and more stable convergence. The initial learning rate was set to 0.001, which corresponds to the commonly recommended value proposed by the developers of the Adam algorithm and is widely used in training recurrent neural networks [31]. The choice of this optimizer is justified by its high robustness to noise in experimental data and its efficiency in processing multidimensional time series typical of wastewater treatment control systems.

The input sequence length was set to N = 288 samples. Given a sampling interval of 5 min, this corresponds to 1440 min, or 24 h, of historical observations. Therefore, the LSTM model uses the complete daily influent flow profile to predict the subsequent time interval.

The input vector has the following form (23):

$$X = [Q(t-287), Q(t-286), \ldots Q(t)], \tag{23}$$

where $Q(t)$ is the influent wastewater flow rate. The output of the LSTM network is the one-step-ahead influent wastewater flow forecast $\hat{Q}(t+1)$, which is then incorporated into the MPC framework as a measured disturbance. The obtained forecast is not used directly for blower control.

The LSTM-based module performs two main functions. First, it predicts the future influent wastewater flow rate $\hat{Q_{in}}(t+k)$, which is supplied to the MPC controller as a measured disturbance. This enables the controller to take into account anticipated variations in the hydraulic load.

Second, the LSTM-based module is used for residual error compensation. After the MPC calculation, the discrepancy between the real process and the digital twin is evaluated. Based on the history of this residual error, the network generates a correction signal, which is defined as (24):

$$\begin{gathered} e_m(t) = y_{real} - y_{model}(t) \\ u_{kor} = f_{LSTM}(e_m), \end{gathered} \tag{24}$$

The generated correction signal is then used to compensate for residual nonlinearities and unmodeled process dynamics that are not represented in the linearized MPC model.

Thus, the same LSTM-based architecture is used as:

1. an influent flow forecasting module;
2. a nonlinear correction module for the digital twin.

To evaluate the effectiveness of the LSTM model, a comparative analysis with commonly used time-series forecasting methods was carried out, as presented in Table 9.

Table 9. Comparative analysis of influent wastewater flow forecasting models.

Model	Nonlinearity Handling	Long-Term Memory Handling	RMSE	MAPE	Features
ARIMA	No	Limited	0.31	12.4%	Performs well for stationary processes
MLP	Partial	No	0.25	9.8%	Does not account for temporal structure
GRU	Yes	Yes	0.18	7.1%	More compact architecture
LSTM	Yes	Yes	0.14	6.3%	Best forecasting performance

The obtained results indicate that the ARIMA model can adequately capture the general trend of the influent flow, but it is less effective in reproducing abrupt variations in the hydraulic load.

The multilayer perceptron (MLP) can capture nonlinear process relationships; however, it lacks a memory mechanism and therefore provides less accurate representation of daily cycles.

The GRU model demonstrates forecasting performance comparable to that of LSTM, but it performs worse in the presence of long-term seasonal dependencies.

The LSTM model demonstrated the best forecasting performance among the considered approaches.

The high accuracy of the forecast enabled the LSTM output to be incorporated into the MPC framework as a measured disturbance, thereby providing anticipatory control of the aeration system.

The performance of the proposed forecasting model is illustrated in Figure 7.

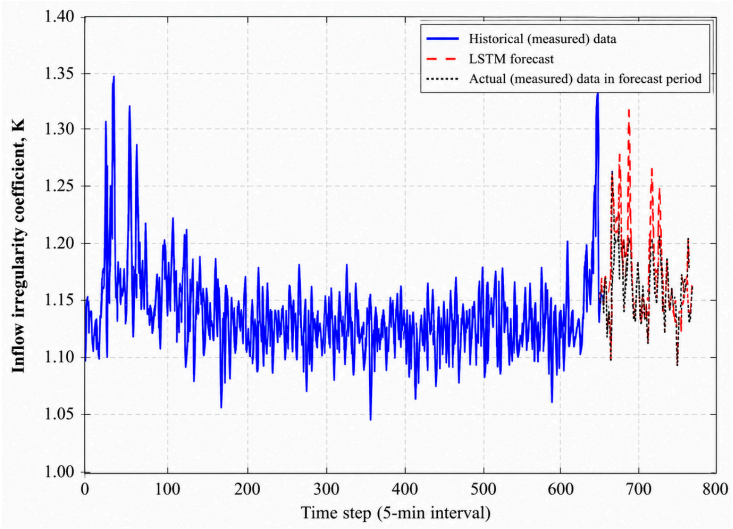


Figure 7. Input data, predicted values, and actual values of the influent flow non-uniformity coefficient over the forecasting horizon.

As shown in the plot, the forecast closely follows the actual consumption, almost completely reproducing its dynamics. This indicates the strong capability of the LSTM model to capture complex nonlinear dependencies. The model successfully predicts both the overall trend and local peaks and troughs with minimal lag.

The forecasting performance of the LSTM model was evaluated using regression analysis between the target and predicted values. The accuracy of the forecast is demonstrated by the regression plots presented in Figure 8.

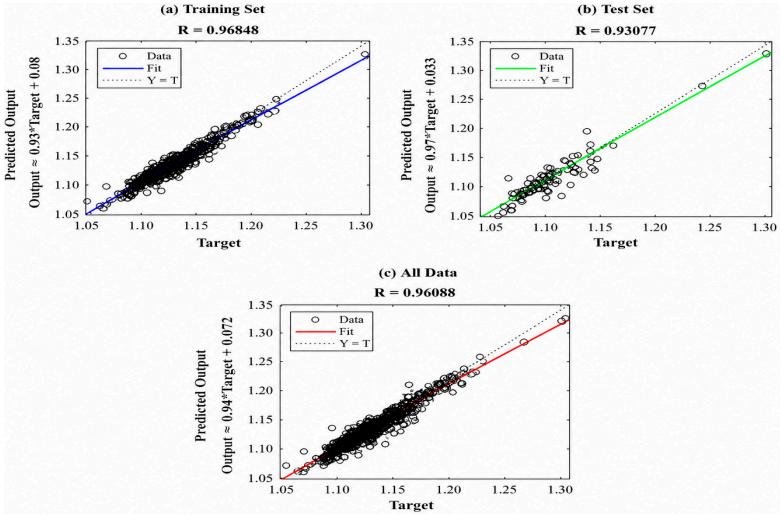


Figure 8. Regression plots of target and LSTM-predicted influent flow values for the training, test, and entire datasets.

The regression analysis showed a high correlation between the predicted and target values. The correlation coefficient was R = 0.97 for the training dataset, R = 0.93 for the test dataset, and R = 0.96 for the entire dataset. For the considered forecasting task, the test-set correlation coefficient of R = 0.93 can be regarded as satisfactory, indicating an adequate generalization capability of the LSTM model. Therefore, additional retraining of the network was not required.

The error histogram also confirms the adequacy of the obtained forecasting results. As shown in Figure 9, the prediction errors are distributed close to a normal distribution, which indicates the absence of pronounced systematic bias and confirms the satisfactory performance of the trained neural network.

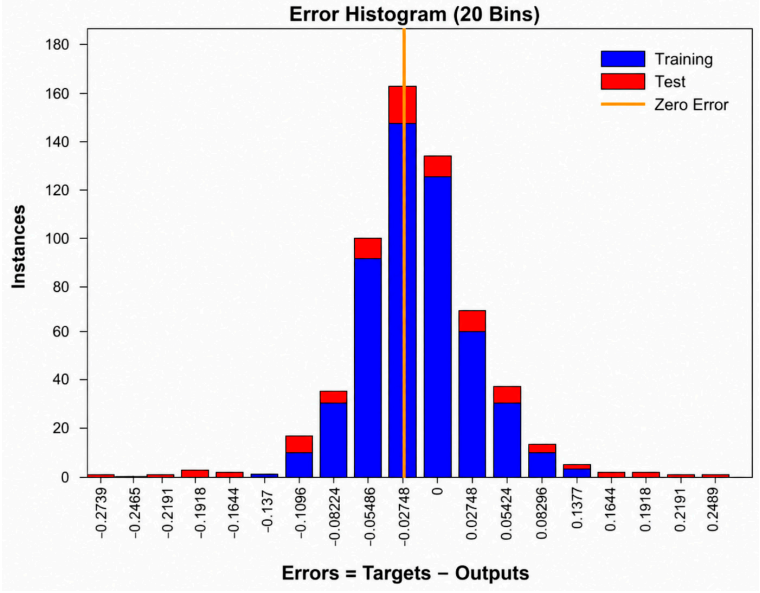


Figure 9. Error distribution histogram of the LSTM forecasting model.

The results show that the MPC controller anticipates an increase in the influent flow and adjusts the aeration rate in advance. As a result, the dissolved oxygen concentration remains within acceptable limits, with only a minimal overshoot.

When subjected to a predicted non-steady-state influent wastewater flow, this system ensures proactive adjustment of the air supply, thereby stabilizing the dissolved oxygen concentration and minimizing the impact of disturbances on the biological treatment process.

The system outputs include the dynamics of wastewater inflow, dissolved oxygen concentration, and the control action generated by the MPC controller, as presented in Figure 10.

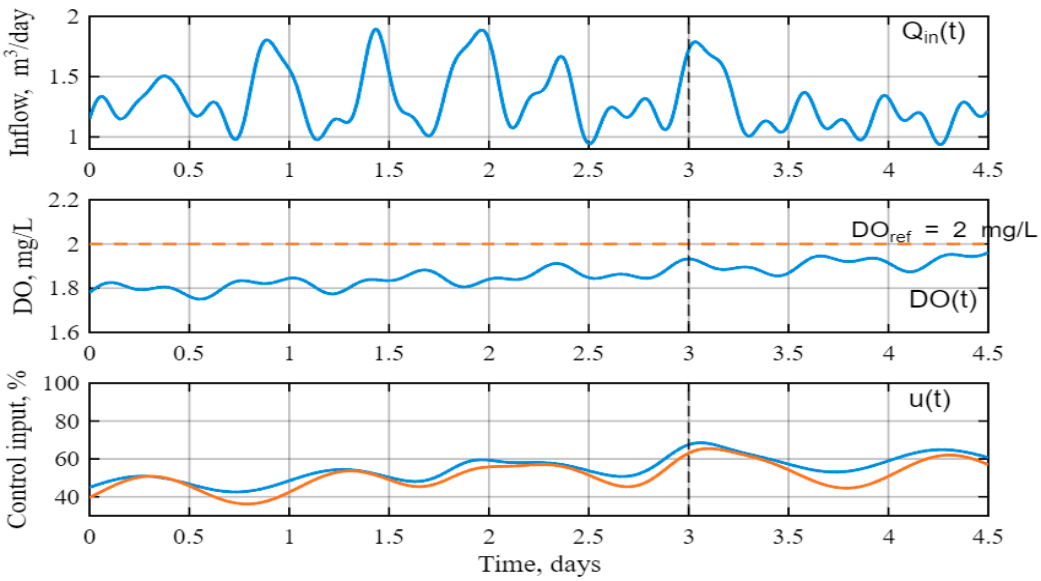


Figure 10. Comparison of the trends in wastewater inflow, dissolved oxygen concentration and control action when using an MPC controller.

The upper plot shows disturbances in the inflow, the middle plot shows that DO re-mains stable, and the bottom plot shows how MPC proactively changes aeration. This clearly demonstrates the principle of predictive control.

Despite pronounced fluctuations in influent flow, short-term load peaks and the lack of clear periodicity, when using predictive MPC, fluctuations in influent flow do not lead to corresponding fluctuations in dissolved oxygen concentration. Through predictive adjustment of aeration, the DO plot is characterized by smooth dynamics and is maintained close to the set value.

To ensure the scientific validity of the results and to define the applicability limits of the proposed methodology, an extended statistical analysis of the control system performance under various operating scenarios was carried out. Each simulation scenario was repeated 30 times with different realizations of stochastic inflow disturbances and measurement noise. Mean values and standard deviations were calculated for all performance metrics.

The primary objective of this analysis is to evaluate the robustness of the MPC controller under various operating regimes. For this purpose, two scenarios are considered:

1. Scenario 1: Peak hydraulic loading, considered to evaluate the robustness of the controller under abrupt changes in hydraulic load.

A short-term increase in wastewater inflow rate of 40–60% was simulated to represent morning and evening peak inflow conditions, as presented in Figure 11.

2. Scenario 2: Emergency overload.

This scenario was designed to evaluate the fault tolerance of the control system. It simulates an abrupt increase in wastewater inflow, a short-term blower failure, and a disturbance in the dissolved oxygen regime, as presented in Figure 12.

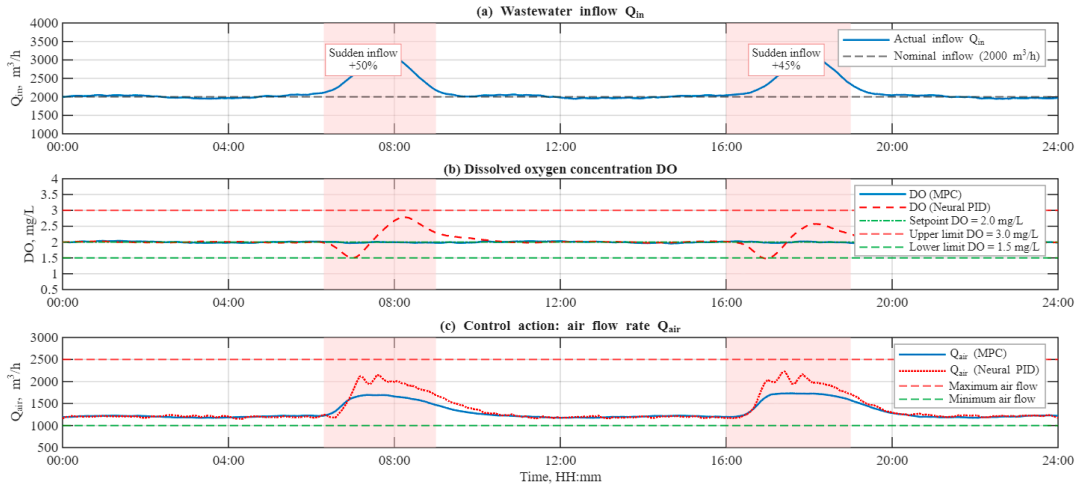


Figure 11. Peak hydraulic loading scenario.

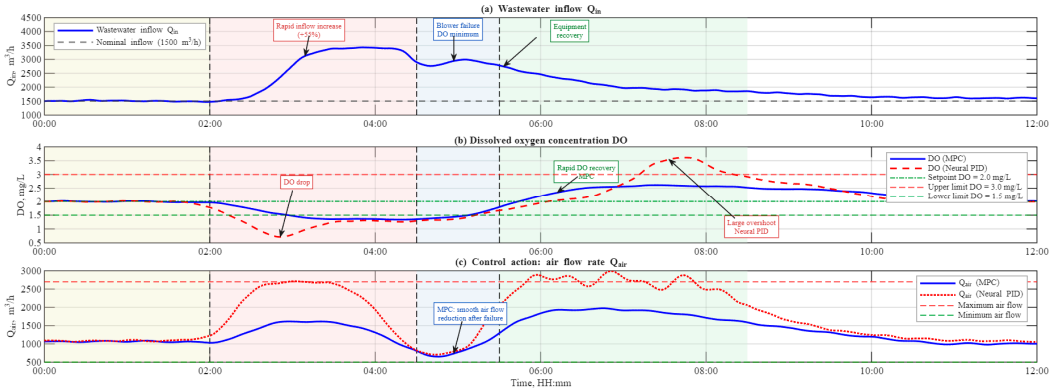


Figure 12. Emergency overload.

3.2. Energy Consumption Analysis of the Aeration System

As part of the experimental studies, the energy consumption was quantitatively assessed for the aeration system when using a fuzzy PID controller and MPC predictive control. The main focus of the analysis was on the air blowers, which, according to data on the operation of the treatment plant, account for up to 50–70% of the plant's total energy consumption [3].

The instantaneous electrical power of the aeration system was evaluated using the standard engineering expression (25), in which power is proportional to the product of airflow rate and pressure drop, accounting for equipment efficiency [32]:

$$P(t) = \frac{Q_{air}(t) * \Delta p}{\eta}, \tag{25}$$

where

1. Δp—pressure drop, kPa;
2. Q_{air}—airflow rate, m^3/s;
3. η—Combined efficiency of the blower and electric motor.

The daily energy consumption of the aeration system was determined by integrating the instantaneous electrical power over time (26), which corresponds to the standard definition of electrical energy and is widely used in the energy analysis of wastewater treatment plants and when comparing control strategies:

$$E_{day} = \int_0^{24} P(t)dt, \tag{26}$$

Substituting the expression for power from Equation (25) into Equation (26) gives (27):

$$E = \frac{\Delta p}{\eta} \int_0^{24} Q_{air}(t)dt, \tag{27}$$

Thus, aeration energy consumption is directly proportional to the time-integrated airflow over the considered period, enabling a consistent comparison of different control algorithms under identical process constraints.

Identical conditions were set for all controllers:

- the same dissolved oxygen setpoint DO_{set} = 2.0 mg/L;
- the same airflow constraints;
- the same influent disturbance scenario (a sudden increase of 30–50%).

The pressure drop Δp in the aeration system is taken to be 55 kPa, which corresponds to typical values for fine-bubble aeration systems with an aeration tank depth of 4–6 m, taking into account hydrostatic pressure and losses in the diffusers and piping.

Typical design values for the operating pressure of air blowers used in fine-bubble aeration range from 45 to 70 kPa, as confirmed by manufacturers' data and technical publications on the energy efficiency of aeration systems.

In engineering practice, the specific efficiency of air blowers (the overall system efficiency) is typically around η = 0.60–0.70, which takes into account losses in the electric motor and compressor. A value of η = 0.65 is adopted. These assumptions are consistent with current practice in optimizing energy consumption at wastewater treatment plants in Russia and Europe [26,28].

The average airflow rate was defined as the time-averaged control signal over the daily simulation interval. The maximum airflow rate corresponded to the highest value of the control signal occurring during the compensation of peak supply air disturbances. Both indicators are derived directly from the simulation results under identical technological constraints and are used to assess the energy efficiency of various control strategies.

The benefits of the proposed MPC–LSTM control strategy are clearly illustrated by the airflow rate distribution shown in Figure 13.

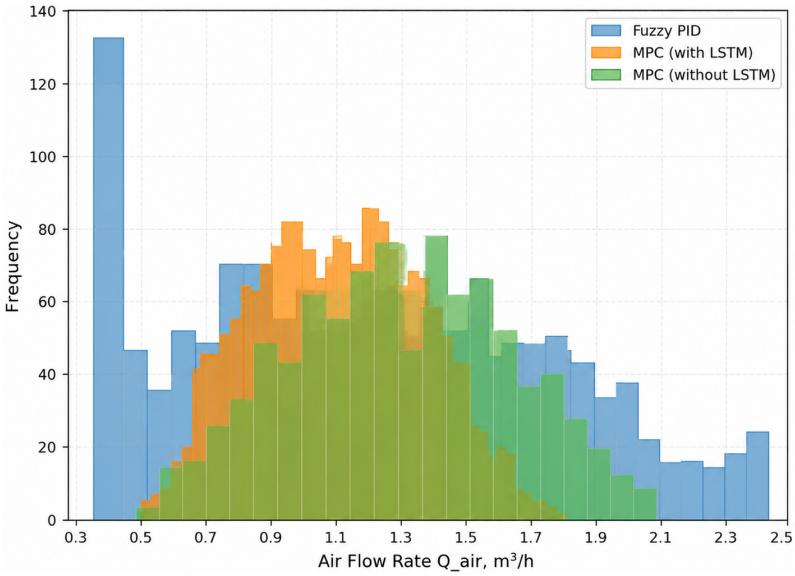


Figure 13. Distribution histogram of the airflow rate Qair(t) under different control strategies.

The obtained histograms demonstrate that the integration of the LSTM forecasting block substantially changes the operating pattern of the aeration control system. In contrast to conventional MPC, which uses only current information about the process state, the MPC–LSTM approach generates proactive control actions based on the predicted hydraulic load. This results in a narrower distribution of the airflow rate, reduced variability of the control signal, and a lower frequency of operating modes with increased air supply.

Thus, the main contribution of the LSTM module is not limited to improving the accuracy of dissolved oxygen control; it also enables the formation of a more energy-efficient control strategy through the preliminary compensation of expected disturbances. The observed narrowing of the airflow rate distribution provides quantitative evidence of improved energy efficiency and operational stability compared with both the fuzzy PID controller and conventional MPC without forecasting.

To evaluate the effectiveness of the proposed control strategy, the performance of the MPC–LSTM controller was compared with conventional MPC and fuzzy PID controllers. The comparison was performed using standard control performance indicators, including IAE, ISE, ITAE, RMSE, total variation (TV) of the control signal, and daily energy consumption for aeration.

The results show that the proposed MPC–LSTM controller consistently outperforms both baseline controllers. Compared with conventional MPC, the proposed approach reduced IAE by 21%, ISE by 37%, ITAE by 19%, RMSE by 15%, and TV by 35%. These improvements indicate enhanced tracking performance and smoother actuator operation.

The most significant practical outcome is the reduction in aeration energy consumption from 1818 kWh/day to 973 kWh/day, corresponding to an average decrease of approximately 46.5%. Since these values were obtained from simulation experiments, the result should be interpreted as an estimated potential energy saving under the investigated operating conditions, rather than as a guaranteed reduction in full-scale operational costs.

4. Discussion

The proposed Advisory MPC approach, integrating a digital twin and a neural network correction module, offers several advantages over conventional industrial PID and fuzzy PID control systems for the following reasons:

1. Conventional industrial controllers are inherently reactive, as they generate control actions only after a deviation of the controlled process variable has occurred. Under wastewater treatment plant operating conditions, this leads to a delayed response to abrupt changes in hydraulic loading and may result in excessive air supply, increased energy consumption, and oscillations in dissolved oxygen concentration. By contrast, the MPC controller employs a mathematical model of the process together with a forecast of wastewater inflow, allowing anticipatory control actions to be generated before a critical deviation develops. This enables more stable maintenance of dissolved oxygen concentration within the permissible range while substantially reducing energy consumption.
2. Classical PID-based systems do not explicitly account for technological constraints. Constraints on airflow rate, control signal variation rate, and permissible DO concentration ranges are typically adjusted empirically, which does not guarantee optimal equipment operation. In contrast, the MPC controller directly incorporates these constraints into the optimization problem, thereby simultaneously ensuring treatment quality, energy efficiency, and actuator protection.
3. Combining linear MPC with a neural network correction module enables nonlinear process effects to be compensated for without the need for computationally demanding nonlinear MPC. The linear model provides computational robustness and feasibility

for industrial implementation, while the LSTM-based correction module adaptively compensates for residual nonlinearities arising from variations in activated sludge kinetics, seasonal temperature fluctuations, and changes in wastewater composition.

A key advantage of the proposed approach is its industrial deployability. In contrast to fully centralized MPC systems that require complete modernization of the PLC infrastructure, the proposed Advisory MPC architecture can be integrated as a supervisory layer over existing PID control loops and SCADA systems without modifying the underlying automation structure. This significantly reduces implementation costs, mitigates failure risks, and supports the gradual digital modernization of wastewater treatment plants.

A further advantage is the use of a digital twin, which allows controller tuning, control algorithm testing, emergency scenario prediction, and energy consumption analysis to be performed virtually without interfering with the real technological process.

The simulation results indicate that the proposed control architecture can potentially reduce the integral energy consumption of the aeration system by an average of 21.1% compared with the fuzzy PID controller. The 95% confidence interval for this reduction is 17.4–24.8%. Since this result was obtained using the digital twin and scenario-based simulation, it should be interpreted as an expected energy-saving effect under the investigated operating conditions. Further industrial validation at full-scale wastewater treatment facilities is required to confirm the quantitative effect.

In addition, the proposed control strategy makes it possible to:

1. reduce DO concentration overshoot by more than a factor of two;
2. reduce the settling time of the transient response;
3. decrease the dynamic load on the blower equipment;
4. enhance system robustness under non-stationary wastewater inflow conditions.

For the quantitative evaluation of the proposed MPC controller, standard integral performance indices commonly used in nonlinear process control were applied, namely IAE, ISE, ITAE, and RMSE. The indices were calculated separately for each operating scenario presented in Figures 7–9.

Energy efficiency was assessed based on the total energy consumption of the aeration system, whereas the dynamic load on the actuators was evaluated using the total variation (TV) index of the control signal.

The MPC and fuzzy PID controllers were tested under the following conditions:

1. under the same disturbance scenarios;
2. under the same technological constraints;
3. with identical DO concentration setpoints;
4. using the same aeration tank model.

The results of the quantitative comparison are presented in Table 10.

Table 10. Statistical comparison of the fuzzy PID, MPC, and MPC–LSTM controllers.

Control Performance Metric	Fuzzy PID Controller	MPC Controller	MPC–LSTM	*p*-Value
IAE	18.4 ± 3.7	7.2 ± 1.4	6.05 ± 0.7	<0.001
ISE	31.7 ± 6.5	9.5 ± 2.1	7.49 ± 1.8	<0.001
ITAE	412 ± 58	138 ± 31	95.12 ± 26	<0.001
RMSE	0.42 ± 0.08	0.18 ± 0.03	0.14 ± 0.01	<0.001
TV	8.4 ± 1.9	3.1 ± 0.7	2.35 ± 0.38	<0.001
Aeration system energy consumption	17.5 ± 1.6	13.8 ± 1.1	10.88 ± 1.06	0.002

To quantitatively assess the contribution of the forecasting module, the relative reductions in the main control performance indicators were evaluated for conventional MPC

compared with fuzzy PID and for MPC–LSTM compared with conventional MPC, as summarized in Table 11.

Table 11. Quantitative assessment of the contribution of the LSTM forecasting module to control performance improvement.

Indicator	MPC Relative to Fuzzy PID	MPC–LSTM Relative to MPC
IAE	−60.9%	−16%
ISE	−70%	−22%
ITAE	−66.5%	−31.1%
RMSE	−57.1%	−20%
TV	−63.1%	−24%
Energy consumption	−21.1%	−21.2%

Negative values indicate a reduction in the corresponding performance indicator. Therefore, lower values of IAE, ISE, ITAE, RMSE, TV, and energy consumption correspond to improved control performance.

The obtained results show that the main additional effect is provided by the LSTM forecasting module. While conventional MPC responds only after a disturbance has appeared in the measured process variables, the use of forecasting enables the system to account in advance for expected variations in hydraulic and organic loads and to adjust the airflow rate before deviations in dissolved oxygen concentration occur.

Thus, the control strategy becomes anticipatory, or proactive, rather than traditionally reactive.

The forecasting module has a particularly noticeable effect on the smoothness of control. Compared with conventional MPC, the total variation in the control signal (TV) decreases by approximately 24%, indicating smoother actuator operation, fewer abrupt changes in the airflow rate, and reduced mechanical wear of blowers and control valves.

The most significant practical effect is observed in terms of energy saving. The application of conventional MPC reduces the energy consumption of the aeration system by approximately 8% compared with the fuzzy PID controller. The integration of the LSTM forecasting module provides an additional reduction in energy consumption of approximately 13%, resulting in an overall energy saving of about 21%.

Consequently, more than half of the total energy-saving effect of the proposed intelligent control system is associated with the use of future load forecasting.

Conventional MPC improves control performance by optimizing the current control actions based on the mathematical model of the process. However, the use of LSTM-based forecasting enables proactive control, in which decisions are made with consideration of expected changes in the technological load. This leads to a statistically significant reduction in control errors, decreased oscillations of the control signal, and an additional reduction in the energy consumption of the aeration system. The obtained results confirm that the LSTM forecasting module makes an independent and quantitatively measurable contribution to improving the efficiency of the intelligent control system for wastewater treatment facilities.

4.1. Industrial Implementation

The mathematical model of the aeration tank that was developed was converted into a discrete form and directly incorporated into the structure of the digital twin implemented at the PLC level. The algorithms for calculating the dynamics of dissolved oxygen concentration have been implemented using standard Simulink modules, ensuring compatibility with industrial controllers. The linearized model is used in a model predictive control loop, which operates in advisory mode and generates setpoints for the lower-level PID control.

This architecture ensures industrial viability, fault tolerance and the ability to implement MPC in phases without disrupting existing automation systems.

For the industrial implementation of the predictive control system using an MPC controller, the following scheme was modeled (Figure 14).

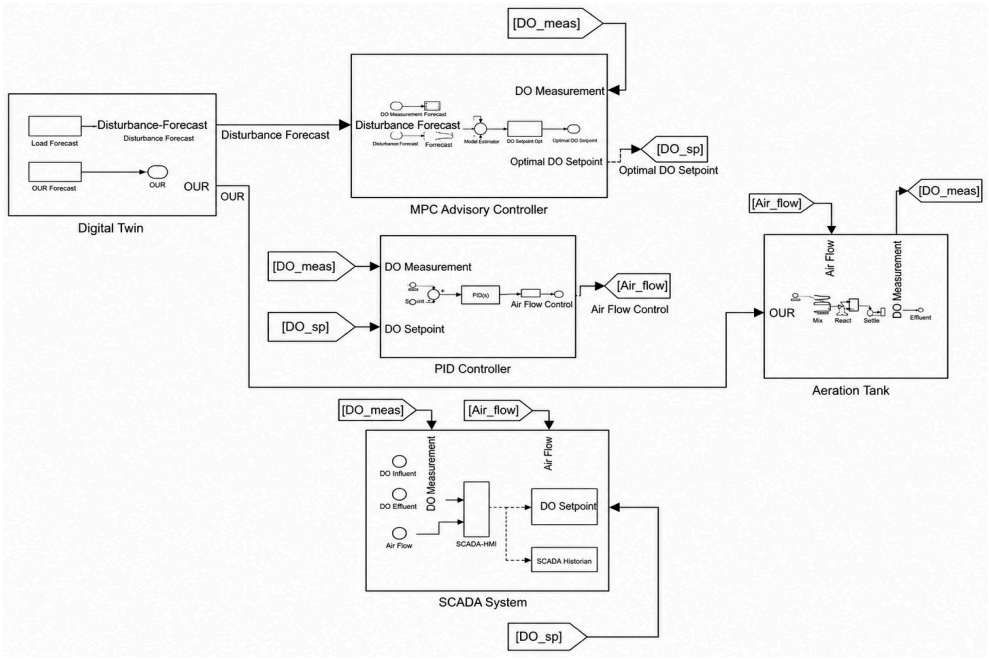


Figure 14. Aerator control system.

The digital twin of the aeration tank has a modular structure and comprises the following main components:

1. Mathematical model of an aeration tank describing the dynamics of dissolved oxygen concentration;
2. Disturbance generation module simulating changes in inflow and organic load;
3. Control module implementing the MPC algorithm in advisory mode;
4. Module for visualizing and analyzing results, designed to assess control effectiveness.

Thus, the following conceptual scheme is obtained:

1. Real Object:
   - Serves as a source of data on the current state of the process, including dissolved oxygen (DO) concentration, airflow rate Q_{air}, and activated sludge parameters;
   - Provides accumulated historical influent data for training and operation of the forecasting model.
2. Digital twin:
   - Receives current measurements from the real object;
   - Uses a nonlinear mathematical model based on ASM to simulate the behavior of the aeration tank in real time;
   - Provides the MPC controller with information on process dynamics and current system states that may not be directly measurable.
3. Neural Network Predictor (LSTM):
   - Analyses historical influent trends;
   - Generates forecasts of external disturbances (future influent flow) over the prediction horizon;
   - Transfers forecasted values to the MPC controller for anticipatory correction.

4. MPC Controller:
    - Solves the optimization problem based on information from the digital twin and forecasts from the neural network, taking into account process and energy constraints;
    - Generates recommendations for optimal setpoints.
5. Operator:
    - Receives recommendations from the MPC controller.
    - Makes the final decision regarding the application of the setpoints.
    - Inputs the approved setpoints into the PLC, where they are implemented by the underlying PID controllers.
    - Provides feedback by adjusting system parameters when necessary.

The proposed intelligent control architecture has not yet been directly implemented at full-scale wastewater treatment facilities. Therefore, the reported improvements should be interpreted as simulation-based results obtained using a validated digital twin. Nevertheless, the digital twin used in this study was calibrated using real operational data collected from the SCADA system. Consequently, the investigated operating scenarios reproduce realistic hydraulic disturbances and process dynamics typical of municipal wastewater treatment plants. Future work will focus on pilot-scale and full-scale implementation of the proposed controller under real operating conditions in order to quantitatively assess the achievable energy savings and treatment efficiency improvements in industrial practice.

4.2. Effect of Aeration Control on Treated Water Quality

The proposed intelligent control strategy was primarily designed to optimize energy consumption in the aeration system while maintaining stable conditions for biological wastewater treatment. Since dissolved oxygen directly influences nitrification and the oxidation of organic matter, accurate DO regulation indirectly supports the maintenance of treated wastewater quality.

The digital twin continuously estimates the state of the biological process using the ASM-based model, which makes it possible to predict changes in ammonium concentration and substrate removal under varying hydraulic loads. Therefore, energy consumption is not optimized independently of treatment efficiency. Instead, the controller operates within technological constraints that ensure the required conditions for stable biological treatment are maintained.

Nevertheless, the present study does not explicitly formulate a multi-objective optimization problem that directly incorporates effluent quality indicators such as COD, BOD_5, total nitrogen (TN), and total phosphorus (TP). Although these indicators are represented through the process model, they are not directly included in the MPC objective function. Extending the proposed controller toward the simultaneous optimization of aeration energy consumption and treated wastewater quality using large-scale operational datasets remains an important direction for future research.

Although the proposed control system was investigated in a high-fidelity digital twin environment, its direct industrial implementation was not carried out within the scope of the present study. Therefore, the observed improvements in dissolved oxygen regulation, treated water quality support, and aeration energy consumption should be interpreted as simulation-based results obtained under conditions that closely approximate real operation. At the same time, the use of synchronized operational data substantially increases the practical reliability of the study compared with purely theoretical modeling.

4.3. Limitations of the Study

Despite the positive results obtained in this study, the proposed intelligent control architecture has a number of limitations that should be taken into account when interpreting the simulation results and planning its industrial implementation.

The main limitations of the present study are as follows.

1. Limited experimental dataset. The validation of the digital twin was performed using archived operational data from the wastewater treatment facilities of Semey city over a period of 30 days with a sampling interval of 5 min. This dataset is sufficient to assess the adequacy of the mathematical model and verify the performance of the control algorithms under typical operating conditions. However, it does not fully capture long-term operational variability associated with seasonal factors.
2. Simplifications of the mathematical model. The digital twin was developed using a simplified nonlinear model of the aeration tank, primarily oriented toward the control of dissolved oxygen concentration. To ensure the feasibility of real-time computation, the following assumptions were adopted:
    - the aeration tank is considered as a completely mixed reactor;
    - the temperature is assumed to be constant;
    - the activated sludge concentration changes significantly more slowly than the dissolved oxygen concentration.

These assumptions substantially reduce the computational complexity of the model while preserving sufficient accuracy for dissolved oxygen control within the MPC framework.

3. Limitations of the LSTM forecasting model. The LSTM neural network model was trained using historical data from a single wastewater treatment plant. Therefore, the forecasting performance depends on:
    - the water consumption pattern of the specific settlement;
    - the composition of the influent wastewater;
    - the operational regime of the treatment plant.

Therefore, the direct transfer of the trained LSTM model to other wastewater treatment plants may reduce forecasting accuracy unless the model is retrained or fine-tuned using local archived operational data.

4. Limitations of the energy efficiency assessment. The estimated reduction in aeration energy consumption of approximately 21% was obtained solely from simulation experiments performed using the digital twin. Although the digital twin was previously validated against operational data from the wastewater treatment plant, this result should be regarded as an estimate of potential energy savings rather than as a guaranteed operational outcome. Therefore, pilot-scale and full-scale industrial testing is required to confirm the actual energy-saving effect under real operating conditions.
5. Limitations of industrial implementation. The proposed architecture is intended for integration into existing PLC–SCADA systems in the Advisory MPC mode, in which the model predictive controller generates recommended setpoints for the existing PID controllers. This approach substantially reduces implementation risks; however, it does not allow all potential advantages of fully automatic MPC to be realized, since the final control action is generated at the lower automation level.

Therefore, the practical performance of the proposed control architecture is strongly dependent on sensor reliability, data transmission quality, and the stability of the existing automation infrastructure.

6. Limitations related to communication, measurement infrastructure, and cybersecurity. The proposed intelligent control system assumes reliable communication between field

devices, the SCADA system, and the digital twin. Communication delays, network failures, sensor faults, and cybersecurity-related disturbances were not explicitly modeled in the present study. Therefore, the reported control performance should be interpreted as corresponding to normal operating conditions with validated measurement data.

7. Limitations in the scope of applicability. The proposed digital twin is primarily oriented toward aeration process control and the maintenance of dissolved oxygen (DO) concentration in the aerobic zone of the wastewater treatment plant. Therefore, anoxic and anaerobic processes involved in modern biological nitrogen and phosphorus removal schemes are not explicitly modeled in the present study.

The mathematical basis of the digital twin is a simplified ASM-based model that describes the oxygen balance and the dynamics of aerobic oxidation of organic pollutants. This simplification is justified by the objective of the study, namely the development of an intelligent energy-efficient control system for blower operation, rather than the detailed modeling of the complete biochemical cycle of wastewater treatment. At the same time, the digital twin architecture is not inherently limited to aerobic processes. The proposed approach is modular and can be extended to more complex technological schemes.

The hydraulic residence time of approximately two days used in the present study should not be interpreted as the actual residence time of wastewater in a full-scale industrial aeration tank. This volume-to-flow ratio was selected to ensure the numerical stability of the digital twin during extended simulations and to reproduce slowly varying biological processes under variable load conditions. Since the objective of this work is to develop an intelligent control algorithm rather than to perform the hydraulic design of wastewater treatment facilities, the selected value does not affect the structure of the proposed MPC–LSTM control system. In practical implementation, the model parameters should be calibrated according to the characteristics of the specific wastewater treatment plant.

8. Future research directions. Future development of the proposed approach should be aimed at addressing the following tasks:
    - conducting long-term industrial validation of the digital twin over a full calendar year;
    - incorporating the seasonal temperature dependence of the oxygen mass transfer coefficient and model kinetic parameters;
    - investigating the fault tolerance of the digital twin under sensor faults and communication channel failures;
    - assessing the economic feasibility of implementing the proposed system at operating wastewater treatment facilities using real operational data.

Despite the aforementioned limitations, the results of this study demonstrate the potential of the proposed digital twin architecture, which integrates model predictive control with neural-network-based forecasting. The obtained results indicate that the proposed approach can substantially improve dissolved oxygen regulation and provide potential reductions in aeration energy consumption. These findings create a foundation for subsequent pilot-scale and full-scale industrial validation of the developed control strategy.

4.4. Comparison with Recent Studies

A comparison with published studies shows that current research in this field is mainly developing in three directions: the use of soft sensors in combination with MPC, the application of Koopman-based models to reduce the computational complexity of MPC, and the development of economically oriented control strategies for wastewater treatment plants [33–37].

Vasiliev et al. (2025) [33] focused primarily on the integration of a soft sensor with MPC to improve the estimation of internal process variables. However, their study does not address the forecasting of future influent load variations.

In the study by Han et al. (2024) [34], an economic MPC strategy based on a Koopman model was proposed. This approach provides a substantial reduction in computational complexity, by more than 5600-fold compared with conventional nonlinear EMPC, while maintaining high control performance. However, the forecasting of future technological load variations is not addressed in that study.

Neto et al. (2025) [35]. focused on ensuring the energy self-sufficiency of wastewater treatment plants through the optimization of biogas production and treated wastewater quality. This approach addresses a higher-level plant-wide optimization problem and does not specifically analyze the energy consumption of the aeration system.

The MAKO framework (Automatica, 2026) [21] implements a meta-adaptive Koopman model to enhance the robustness of MPC under parametric uncertainty. In contrast, the approach proposed in this study uses an LSTM-based influent flow forecasting model, allowing anticipated load variations to be considered before they affect the process. As a result, the controller can generate more proactive control actions, reduce abrupt changes in the airflow rate, and decrease aeration energy consumption.

Therefore, the scientific novelty of the present study lies not in the application of MPC itself, but in the joint integration of a digital twin, LSTM-based influent load forecasting, and model predictive control within a unified intelligent control architecture. This integration makes it possible to reduce the energy consumption of the aeration system while maintaining the required performance of dissolved oxygen regulation.

It should also be emphasized that the reported 21% reduction in energy consumption refers to simulation results obtained using the developed digital twin and should not be interpreted as a confirmed full-scale industrial effect without further experimental validation under real operating conditions.

5. Conclusions

1. The results of the study demonstrated that model predictive control (MPC) provides significantly more effective aeration tank control than conventional and fuzzy PID controllers under non-stationary hydraulic loading conditions and process constraints.
2. The key advantage of MPC is its ability to use a dynamic process model together with predicted disturbances, thereby providing anticipatory control. In contrast to PID controllers, which react only to the current control error, MPC can proactively compensate for variations in wastewater inflow and prevent critical deviations in dissolved oxygen concentration from developing.
3. The simulation results confirmed that MPC provides substantially higher control performance than the fuzzy PID controller. In particular, the proposed MPC approach reduced IAE by 60.9%, ISE by 70.0%, ITAE by 66.5%, and RMSE by 57.1%. In addition, DO overshoot was reduced from 24% to 8%, and no violations of technological constraints were observed. These results demonstrate the high robustness of MPC under abrupt changes in hydraulic loading and external disturbances.
4. A significant advantage of MPC is its ability to explicitly account for technological constraints on dissolved oxygen concentration, airflow rate, and the rate of change in the control signal. This makes it possible to simultaneously maintain treatment quality, reduce energy consumption, and protect blower equipment from overloads.
5. The statistical analysis showed that the application of the proposed MPC–LSTM strategy provides a statistically significant reduction in the energy consumption of the aeration system compared with the fuzzy PID controller ($p < 0.01$). According

to the simulation results, the average reduction in energy consumption was 21.1%, while the 95% confidence interval ranged from 17.4% to 24.8%. This result should be interpreted as a predicted energy-saving effect that requires subsequent validation under industrial operating conditions at full-scale wastewater treatment facilities.

6. The proposed Advisory MPC architecture demonstrated high potential for industrial deployment, since it can be integrated as a supervisory layer over existing PID control loops and SCADA systems without requiring complete modernization of the PLC infrastructure. This reduces implementation risks, supports fault-tolerant operation, and enables gradual deployment at existing wastewater treatment plants.
7. Overall, the results confirm that the proposed integration of MPC, a digital twin, and neural-network-based forecasting represents a promising approach for the digital modernization of wastewater treatment plants. This architecture improves the robustness of biological treatment, reduces aeration energy consumption, mitigates dynamic stress on equipment, and enhances the operational reliability of aeration tanks under non-stationary wastewater inflow conditions.

Thus, the proposed MPC-based architecture offers substantial advantages over conventional industrial control systems and can serve as an effective foundation for the development of next-generation intelligent and energy-efficient wastewater treatment plants.

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