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Application of the model of sludge volume index forecasting to assess reliability and improvement of wastewater treatment plant operating conditions

Bartosz Szeląg[a,*], Krzysztof Barbusiński[b], Jan Studziński[c]

[a]*Kielce University of Technology, Tysiąclecia Państwa Polskiego 7 Av., 25-314 Kielce, Poland, Tel. +41 342 47 35; email: bszelag@tu.kielce.pl*
[b]*Silesian University of Technology, Konarskiego 18 Street, 44-100 Gliwice, Poland, Tel. +32 237 11 94; email: krzysztof.barbusinski@polsl.pl*
[c]*Systems Research Institute PAN, Newelska 6 Street, 00-001 Warszawa, Poland, Tel. +22 381 02 75; email: Jan.Studzinski@ibspan.waw.pl*

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ABSTRACT

The article presents a mathematical model for the analysis of operational reliability of a wastewater treatment plant, in which sedimentation of activated sludge and removal of biogenic compounds were taken into account. The presented model allows for continuous control and monitoring of both processes, even in the case of measurement discontinuities. In the presented approach, the values of quality indicators can be determined using selected data mining methods on the basis of wastewater flow and temperature measurements. The paper proposes an innovative indicator that takes into account the interaction between the quantity, the quality of inflowing wastewater expressed by means of physicochemical parameters and the susceptibility of activated sludge for bulking. Based on the presented calculation algorithm, an exemplary concept of controlling the biological process (mixed liquor suspended solids, oxygen concentration and the amount of coagulant dosed) is presented, taking into account the variable conditions at the inflow to the bioreactor.

Keywords: Wastewater treatment plant; Sludge volume index; Reliability; Control; Neural network

1. Introduction

An effective method of municipal wastewater treatment in a wastewater treatment plant (WWTP) is a biological treatment system using activated sludge. This is possible under diverse operating conditions of a biological reactor, which is influenced by the quantity and quality of wastewater, atmospheric conditions [1], the share of particular groups of microorganisms in the activated sludge and the design of the bioreactor [2]. Achieving the assumed level of pollution reduction, and thus maintaining adequate reliability of operation, is conditioned by a properly designed technological process, but also by proper operation of the plant. The optimal reduction of pollutants in wastewater can be achieved by using mathematical models [3] and controlling the selection of settings in the bioreactor [4] or secondary settling tank [5]. The required purification effects and proper course of processes occurring in the bioreactor can be achieved by controlling the composition of the population of microorganisms in the activated sludge [6]. In practice, in order to maintain the reliability of WWTP performance at the required level, it is necessary to evaluate and analyze at the same time the processes taking place in technological facilities, characterized by values of biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), total nitrogen (TN) and total phosphorus (TP), loading of activated sludge contaminants, oxygenation, etc. For this purpose, the so-called reliability coefficients are used in practice, which can be defined as the quotient of the measured value to its permissible value

* Corresponding author.

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[7]. The sludge volume index (SVI) is one of the indicators that have a significant impact on the efficiency of the plant's operation (assessed on the basis of the quality of wastewater discharged from the WWTP, of the process of clarification in the secondary settling tank and the process of treatment of sediments). The increase in its value above 150 cm^3/g is usually associated with an excessive increase in the amount of filamentous bacteria in the sludge, which leads to so-called sludge bulking.

In order to improve the reliability of the wastewater treatment plant and to avoid problems with sedimentation of the activated sludge, the bioreactor performance parameters are adjusted by changing the oxygen concentration in nitrification chambers, internal and external recirculation rate, mixed liquor suspended solids, activated sludge loading by contaminants, and in some cases the amount of dosed external carbon source or coagulants (iron or aluminum compounds). Setting values in many facilities are determined based on the quantity and quality of wastewater and weather conditions (rainfall depth, air temperature) based on the experience of the technologist. However, this approach is not always optimal and it is usually possible to reduce the cost of the wastewater treatment plant operation and to improve the quality of the receiving water. To achieve this goal, mathematical models are increasingly being used, but in order to develop them it is necessary to collect large amounts of measurement data. The co–called black box models are successfully used for the modelling of activated sludge settle – ability, in which, without knowing the physics of the investigated process, a model structure is generated, based on historical data at the so-called learning stage, which forms the basis for further simulations. The black box models include artificial neural networks (hierarchical and probabilistic) [8,9], hybrid models (consisting of a combination of classification model and regression model) and models based on the theory of fuzzy logic of Flores-Alsina et al. [10]. An alternative approach to black box models are classification models such as logistic regression [11–13], probit regression [14], Gompertz regression [15], etc. Their advantage with regard to regression models of black box type is the fact that they are transparent, the obtained coefficients have physical interpretation and there is no need to implement complex numerical algorithms and extend the existing control and monitoring system on the wastewater treatment plant in order to put them into practice. However, literature data indicate that despite numerous analyses, a clear-cut criterion has not yet been developed, taking into account the variability and interactions between random variables included in the models (number and quality of wastewater, atmospheric conditions), which would make it possible to identify problems causing activated sludge bulking. In process models (intended to determine BOD_5, COD, TN, TP on effluent from the treatment plant and to control the process flow in individual reactor chambers), there is a significant impact on the quality of wastewater effluent from the WWTP and on the performance parameters of the biological reactor (SVI, mixed liquor suspended solids, etc.) induced by the indicators of wastewater quality at the inlet. Currently, the parameters of activated sludge chambers are monitored on-line, and the quality of wastewater is usually measured in accordance with the applicable regulations, that is, periodically. There are a number of wastewater treatment plants on which automatic wastewater quality measurement devices are also installed, but they need to be calibrated from time to time and they are relatively often damaged. However, this approach is costly and does not provide 100% data continuity in the measurement series. Therefore, it is necessary to search for new solutions allowing for the implementation of process models when there are cases of discontinuities in time series with measurements of wastewater quality indicators.

Taking this into account, the paper presents an innovative mathematical model for prognosis and control of reliability of WWTP performance with respect to sedimentation of activated sludge and removal of C, N and P compounds, taking into account discontinuities in wastewater quality measurements. The analysis of the processes under consideration in the biological reactor was based on reliability factors. In addition, the paper attempts to determine an universal parameter allowing for optimal selection of the reactor control strategy and identification of problems with sludge bulking on the basis of variability and interaction between random variables that force values of settings in the reactor.

2. Object of investigation

The analysis was conducted at the WWTP with a nominal capacity of 72,000 m^3/d, located in the southern part of Poland on the outskirts of the city of Kielce. Its catchment area covers the area of the city and surrounding towns and villages, from which the wastewater inflows to the WWTP. The wastewater is mechanically treated on the bar screen (1) and in the aerated grit chamber (2) and then discharged to the primary settling tanks (4) from which it flows to the biological part (Fig. 1). Biological reactors consist of separated pre-denitrification (5), dephosphatation (6), denitrification (7) and nitrification (8) chambers, in which organic pollutants

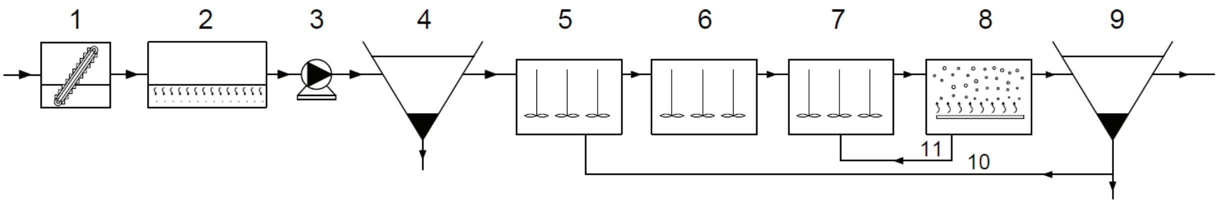

Fig. 1. Diagram of the process line for wastewater treatment: 1 – bar screen, 2 – aerated grit chamber, 3 – main pumping station, 4 – primary settling tank, 5 – separated pre-denitrification reactor, 6 – dephosphatation reactor, 7 – denitrification reactor, 8 – nitrification reactor, 9 – secondary settler, 10 – external recirculation, 11 – internal recirculation.

and nitrogen and phosphorus compounds are removed. After biological treatment, the wastewater flows to four secondary settlers (9), from where it flows to the Bobrza River.

During the summer period, phosphorus is mainly removed from wastewater using the biological method without chemical support. Only in wet periods, which may cause disturbances in the functioning of the activated sludge chambers, occasional dosing of coagulant is expected. On the other hand, in winter, due to the lower temperature and slower reactions of biochemical changes, the process of phosphorus removal is supported chemically – a coagulant in the form of iron compounds is injected. At the same time, problems with sedimentation of activated sludge usually occur at this time – the SVI value is then greater than 150 cm^3/g, which indicates the sludge bulking. In order to prevent this, the settings in the biological reactor need to be controlled, which is difficult without adequate simulation calculations. Hence the need to develop mathematical models that enable monitoring and correcting of sedimentation capabilities.

3. Methodology used

In the paper, a mathematical model was developed, allowing for continuous simulation and correction of sedimentation capacity of activated sludge and control of the process of nutrient removal in case of discontinuity of measurements concerning wastewater quality indicators. The calculation scheme of the developed algorithm is presented in Fig. 2. This method is based on the evaluation of the course of two processes – sedimentation of activated sludge and removal of organic and biogenic compounds measured by BOD_5, COD, TN, TP indices. In the process of wastewater treatment, one of the important parameters informing about the correctness of the process of reduction of C, N and P is the value of food to mass ratio (*F*/*M*) of the activated sludge. The model development methodology provides for the use of data collected at the wastewater treatment plant in terms of quantity, quality of wastewater and performance parameters of the biological reactor to develop a model for forecasting sludge sedimentation and wastewater quality. Sedimentation forecast was based on the classification model [12,13], because despite a smaller number of explanatory variables included in such models in comparison with regression models, they are physically interpreted and may be used as the basis for control of settings in a biological reactor. An interesting solution is also models developed on the basis of fuzzy logic, in which determined dependencies can be interpreted without the need to implement complex algorithms [10]. In order to

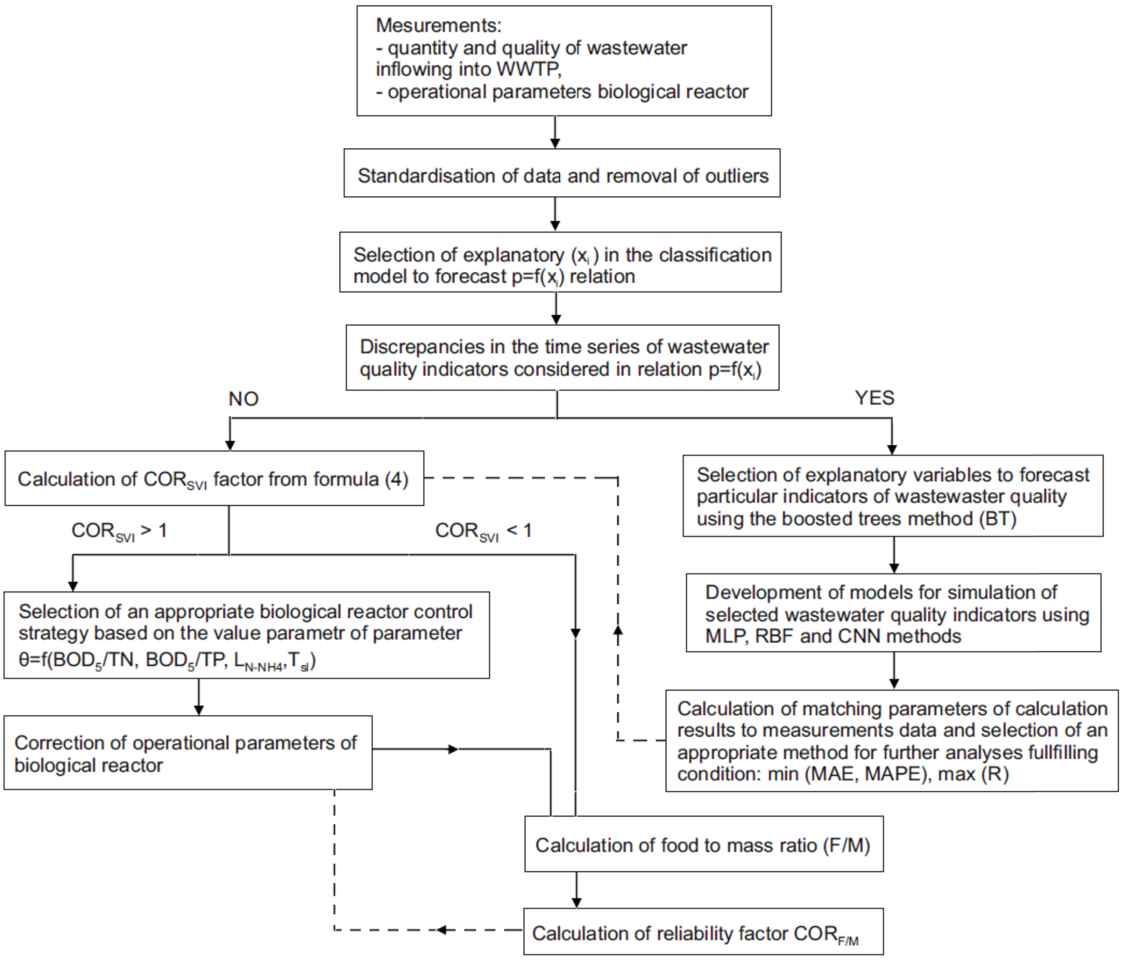

Fig. 2. Algorithm for model setting for simulation and control of activated sludge sedimentation.

ensure continuity of data on wastewater quality in case of lack of measurements of indicators due to, for example, failure of analyzers, it is envisaged to use data mining methods for their forecasting. For the selection of settings, a developed mathematical model is selected for which the determined mean absolute error (MAE) and mean relative error (MAPE) values are minimal.

The reliability of the plant's operation analyzed on the basis of evaluation of the course of the processes of C, N and P removal and of sludge sedimentation, was evaluated using the reliability coefficient (COR), described in detail below. On the basis of the obtained models for the forecast of sludge sedimentation and wastewater quality, the probability of exceeding the SVI (p) using Eq. (3) is calculated and, on this basis, the reliability coefficients COR_{SVI} and $COR_{F/M}$ are computed. Appropriate settings values for the biological reactor will be determined on the basis of the determined reliability coefficient values and the developed control strategy.

4. Logistic regression

In the developed methodology for simulation of sludge sedimentation process, the logistic regression classification model was used, which generates values from the range of 0–1 as the results of calculations, thus enabling determination of the probability of exceeding the threshold of a tested variable, for example, SVI. This method has already been used in medicine and social sciences and for modelling the sedimentation of activated sludge, but the resulting dependencies did not allow for control of the operational parameters of the biological reactor. Bayo et al. [11] demonstrated the seasonal nature of sedimentation changes. Bezak-Mazur et al. [12] confirmed the differentiated effect of filamentous bacteria on the sedimentation capacity of the activated sludge. Szeląg and Siwicki [13] omitted in their studies that in some cases at the exploitation stage there is a need to dose chemicals in order to improve the settling of activated sludge flocs. Logistic regression used in the calculations done is a special case of generalized model of linear form:

$$g(\mu) = \alpha_0 + \alpha_1 \cdot X_1 + \alpha_2 \cdot X_2 + \alpha_3 \cdot X_3 + \ldots + \alpha_k \cdot X_k \tag{1}$$

where $g(\mu)$ – so called binding function describing the relationship between the mean value of the variable explained $\mu = E(Y|X_1 = x_1, X_2 = x_2, X_k = x_k)$ and the linear combination of predictors: α_0 – free coefficient; $\alpha_1, \alpha_2, \ldots \alpha_k$ – regression coefficients, x_i – dependent variables (predictors): wastewater inflow (Q), wastewater quality indicators (BOD_5/TN, BOD_5/TP, $L_{N\text{-}NH4}$ – load ammonium nitrogen), activity indicators of activated sludge chambers (temperature – T_{sl}, oxygen concentration – DO, mixed liquor suspended solids – MLSS, amount of dosed m_{PIX} coagulant).

In the model under consideration, a binding function called logit is described by the equation:

$$g(p) = \text{logit}(p) = \ln\left(\frac{p}{1-p}\right) \tag{2}$$

where $p = \mu = P(Y|X_1 = x_1, X_2 = x_2, X_3 = x_3, X_k = x_k)$.

Based on Eqs. (1) and (2), a new logit model form results:

$$p = P\left(Y = 1| X_1 = x_1, X_2 = x_2, \ldots, X_k = x_k\right) = \frac{\exp\left(\alpha_0 + \sum_{i=1}^{k} \alpha_i \cdot x_i\right)}{1 + \exp\left(\alpha_0 + \sum_{i=1}^{k} \alpha_i \cdot x_i\right)} \tag{3}$$

where p – probability of exceeding the accepted limit value of the variable under consideration.

In the developed logit model (Eq. (3)), the value of the SVI equal to SVI_{lim} = 150 cm³/g [13] was used as a criterion for the assessment of the influence of biological reactor settings and the quality of effluent on the activated sludge sedimentation. In order to select appropriate explanatory variables for the model, which determine its satisfactory predictive abilities, standard model matching measures used in classification models were used, that is, specificity (SPEC), sensitivity (SENS) and calculation error (R_z^2), described in Harrell's [16] paper and expressing the correctness of the process progress identification for SVI < 150 cm³/g and SVI > 150 cm³/g.

5. Reliability of wastewater treatment plant operation

One of the most commonly used indicators to evaluate the functioning of WWTP is the reliability coefficient (COR), which expresses the ratio of the concentration of the tested parameter in wastewater on the effluent to its admissible value [7]. This factor is normally used for the simultaneous assessment of organic and nutrient removal (BOD_5, COD, TN, TP). In the paper to evaluate the process of sedimentation of activated sludge and pollution reduction (in accordance with the binding guidelines and legal regulations) in wastewater inflowing to WWTP, reliability coefficients COR_{SVI} and $COR_{F/M}$ described by formulas:

$$COR_{SVI} = \frac{p}{p_{SVI_{lim}}} \tag{4}$$

$$COR_{F/M} = \frac{F/M}{F/M_{lim}} \tag{5}$$

were introduced, where F/M_{lim} – food to mass ratio value, the excess of which leads to problems with the removal of C, N and P compounds; the calculations are based on F/M_{lim} = 0.15 g BOD_5/g MLSS·d; p_{SVIlim} – the probability of exceeding the SVI value, the exceedance of which leads to problems with sludge sedimentation; the calculations are based on p_{SVIlim} = 0.50, what corresponds to the linear combination of the variables analyzed (x_i):

$$\begin{aligned}\alpha_0 + \alpha_1 \cdot T_{sl} + \alpha_2 \cdot \frac{\text{BOD}}{\text{TN}} + \alpha_3 \cdot \frac{\text{BOD}}{\text{TP}} + \alpha_3 \cdot L_{\text{N-NH}_4} \\ + \alpha_4 \cdot \text{MLSS} + \alpha_5 \cdot \text{DO} + \alpha_6 \cdot m_{\text{PIX}} = 0\end{aligned} \tag{6}$$

Therefore, in order to maintain an adequate reliability of WWTP operation, it is essential to maintain the values COR_{SVI} ≤ 1 and $COR_{F/M}$ ≤ 1, which allows to eliminate sludge bulking and to maintain the correctness of the removal process of C, N and P compounds. In case of exceeding the given values of reliability coefficients COR_{SVI} and $COR_{F/M}$, operational problems will occur in the treatment plant.

6. Forecast of wastewater quality indicators

Since in most of the process models being developed (modelling the removal of C, N and sedimentation of sludge, etc.) the basic explanatory variables are indicators of wastewater quality, therefore in order to achieve high operational efficiency of the facility it is necessary to keep their values at a constant level, and in order to achieve this, it is necessary to optimize the settings in technological objects. In the developed calculation algorithm (Fig. 2), the above problems have been taken into account and the values of the wastewater quality indicators included in Eq. (1) will be projected based on the results of measurements of inflowing wastewater quantity and temperature, using the following equation [17]:

$$C(t)_n = f\left(Q(t), Q(t-1), Q(t-j), \ldots, T_{\text{in}}(t), T_{\text{in}}(t-1), T_{\text{in}}(t-m)\right) \tag{7}$$

where $C(t)_n$ – values of n indicators of wastewater quality, that is, BOD_5, TN, TP and $N\text{-}NH_4$, measured at the inflow to WWTP.

Eq. (7) shows that indicators of the quality of wastewater influent into the treatment plant can be modelled on the basis of the measured degree of wastewater dilution (e.g., rainfall) and kinetics of biochemical transformations occurring in the wastewater flowing through the wastewater system, which was confirmed in Lubos et al. [17], Ahnet et al. [18], Rousseau et al. [19] and Szeląg and Studziński [20]. This relationship is very important from a practical point of view, as it indicates that based on the results of simple measurements carried out in WWTP, it is possible to model the indicators of wastewater quality. In practical considerations, this fact may translated into an appropriate strategy of biological reactor control, and thus into lowering operating costs of the plant.

In the paper for modelling the wastewater quality indicators (BOD_5, TN, TP, $N\text{-}NH_4$) based on Eq. (7), the method of artificial neural networks of multilayer perceptron (MLP) type was used. MLP – based mathematical models are generally characterized by satisfactory predictive performance and the calculation results are generally not significantly different from those obtained using more complex models, such as SVM (support vector machines), adaptive neuro fuzzy neural network or hybrid models. When the performance of the MLP networks does not meet expectations, modifications of the original model are generally made, which does not necessarily lead to improved performance, but other types of networks are rarely used which could be more useful to solve the problem. These other types of networks are, for example, radial basis function (RBF) or cascade neural networks (CNNs). In order not to make such a mistake, various types of neural networks, that is, MLP, RBF and CNNs, were used to estimate the quality indicators of wastewater, and the results obtained were compared with the results obtained by Szeląg et al. [21,22] by means of other types of models, such as k-NN (k-nearest neighbour), BT (boosted tree), MARS (multivariate adaptive regression spline) and SVM.

In a three-layer MLP neural network with one output, the x_i input signals are multiplied by the weight values w_{ij} and transferred to the hidden layer neurons, where they are added together. The sums received shall be transformed using the activation function f( ) and transferred to the output neuron (Fig. 3). The estimation of the weight values in the model is carried out at the network learning stage using special numerical algorithms. The output values obtained in this way are calculated from the formula:

$$y = \sum_{j=1}^{J} w_{j1} f\left(\sum_{i=1}^{I} w_{ij} \cdot x_i + b_j\right) \tag{8}$$

where I – number of inputs of the model, J – number of neurons in the hidden layer, w_{ij} – weight values between inputs and neurons of the hidden layer, b_j – threshold values activating the neurons on the hidden layer, w_{j1} – weight values between neurons of the hidden layer and the single output of the model, f(-) – activation function. A RBF network is a modification of a MLP network in which the activation function on the hidden layer neurons is the Gauss function.

The CNN is a modification of MLP network, in which additional weights have been added to the additional connections between the input neurons and the output neuron as well as the hidden layer neurons (Fig. 3).

The analysis carried out showed that additional links lead to an acceleration of the learning process and improvement of predictive abilities of the CNN model in comparison with the MLP model. This is confirmed by the results of simulations performed by Capizzi et al. [23], modelling the quality of atmospheric air, and Setti and Rao [24] dealing with the simulation of stress–strain dependence for titanium alloy. The simulation results obtained with the CNN model may be described by the following formula:

$$y = \sum_{j=1}^{J} w_{j1} f\left(\sum_{i=1}^{I} w_{ij} \cdot x_i + b_j\right) + \left(\sum_{i=1}^{I} w_{i1} \cdot x_i + b_1\right) \tag{9}$$

The optimal structure of neural networks of MLP and CNN type was determined on the basis of fitting parameters

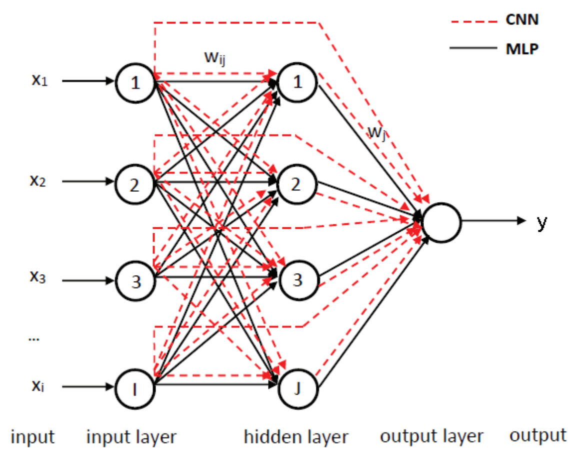

Fig. 3. Comparison of MLP and CNNs.

values (MAE, MAPE) calculated for the assumed number of neurons in the hidden layer (from the range 3–30) and its activation function (selected from the linear, exponent, sinusoidal, sigmoid and hyperbolic tangent functions). In the CNN model two hidden layers were adopted, while for both types of models a linear activation function was adopted for the output layer neuron. The adopted assumptions are confirmed by the results of simulations performed by Szeląg et al. [22], who modelled activated sludge, Al-batah et al. [25] modelling landslides, and Setti and Rao [24] predicting stresses in titanium alloys. The structure of the models was considered to be optimal when the calculated fitting parameters reached the lowest value. Calculations of the structure of the neural networks of MLP, RBF and CNN were performed with the use of MATLAB (Toolbox Neural Network) program, in which the optimal model structure (referring to the number of neurons and activation functions) for forecasting the quantity and quality of wastewater was determined using the "trial and error" method. The Broyden–Fletcher–Goldfarb–Shanno method [26] was used to estimate the weights in the networks.

In order to limit the number of explanatory variables in mathematical models described by Eq. (4), the boosted tree (BT) method was used. It was used to establish a ranking of the predictors, allowing to determine the influence of individual independent variables (x_i) on the dependent variable. This approach is often used, because it allows to reduce the number of explanatory variables with minimal loss of predictive capability of the model. This approach was presented by Szeląg et al. [22] on the example of creating a mathematical model of activated sludge, as well as by Wei et al. [27] forecasting wastewater inflow to a WWTP.

7. Identification of typical operating conditions of biological reactors

Due to the complex influence of quantity (which results, among others, from daily, weekly and monthly seasonality) and quality (physicochemical parameters including temperature and pH of wastewater as well as values of quality indicators such as BOD_5, COD, TN, $N\text{-}NH_4$, etc.) of wastewater on the inflow to WWTP and of weather conditions (rainfalls, air temperature [28]) on the operation of the facility, it is advisable to separate the typical periods of its operation.

This is important because the technologist does not have to select the bioreactor settings by means of a "trial and error" method, but rather follow the typical patterns for dynamically changing operating conditions, ensuring that the object's efficiency and reliability of its operation are achieved (which means in the examined case that there is no bulking of activated sludge and an undisturbed process of removing C, N and P). Practical considerations for this purpose use classification (supervisory) methods where the investigator accepts a number of classes with similar characteristics. However, because of the fact that this may lead to ambiguous solutions, unsupervisory methods have been used where, at the calculation stage, a set of attributes is classified into certain classes also called clusters [29]. One of the simplest and most effective methods of identifying similarities in multidimensional sets of features is hierarchical cluster analysis (HCA). The result of the calculation obtained, that is, dendrogram, allows for unequivocal determination of different objects. Some distance measures are used to assess the diversity of objects. One of the most common measures used is Euclidean distance.

In order to determine distances between objects, in the paper, the Ward method has been used, in which variance is the basis for the assessment of similarity of variables in a given class. Taking into account the advantages of the HCA method, it has been used to identify periods of time during which the pollution load and process kinetics are similar. For the analysis of clusters, the independent variables in the logit model (Eq. (3)), describing quantity (Q), wastewater quality (BOD_5, TN, TP, $N\text{-}NH_4$) and kinetics of biochemical processes (T_{sl}) were used. The MLSS, DO and m_{PIX} values were omitted from the calculations, as the values used for the existing state of operation of the object investigated do not ensure the required reliability of the biological reactor. This is confirmed by calculations made by Han and Qiao [8], Han et al. [9], Szelag and Siwicki [13], Szeląg et al. [21], and Luo and Zhao [30], who developed mathematical models for the simulation of activated sludge sedimentation based on the quantity and quality of wastewater and the operational parameters of the bioreactor. Since a large amount of data is required to perform cluster analysis for the development of a reactor control strategy, an attempt was made to define a universal parameter whose value would allow an assessment to be made of how to select settings in the reactor to reduce problems with sedimentation of activated sludge in it. Using Eq. (3) and dividing analyzed independent variables into independent random and controlling variables, the following relationship was formulated:

$$X = \left(\alpha_1 \cdot \frac{\mathrm{BOD}_5}{\mathrm{TN}} + \alpha_2 \cdot \frac{\mathrm{BOD}_5}{\mathrm{TP}} + \alpha_3 \cdot L_{\mathrm{N\text{-}NH_4}} + \alpha_4 \cdot T_{\mathrm{sl}}\right)_r + \left(\alpha_0 + \alpha_{1,1} \cdot \mathrm{MLSS} + \alpha_{1,2} \cdot \mathrm{DO} + \alpha_{1,3} \cdot m_{\mathrm{PIX}}\right)_c \tag{10}$$

where $\alpha_1 \cdot x_1 + \ldots \alpha_i \cdot x_i)_{r,c}$ – independent random and control variables, respectively.

Based on Eq. (10) and by introducing appropriate symbols, an innovative parameter (θ) taking into account interactions between random variables:

$$\theta = \alpha_1 \cdot \frac{\mathrm{BOD}_5}{\mathrm{TN}} + \alpha_2 \cdot \frac{\mathrm{BOD}_5}{\mathrm{TP}} + \alpha_3 \cdot L_{\mathrm{N\text{-}NH_4}} + \alpha_4 \cdot T_{\mathrm{sl}} \tag{11}$$

and control parameter Γ, expressed by relation:

$$\Gamma = \alpha_0 + \alpha_{1,1} \cdot \mathrm{MLSS} + \alpha_{1,2} \cdot \mathrm{DO} + \alpha_{1,3} \cdot m_{\mathrm{PIX}} \tag{12}$$

were introduced.

Parameters θ and Γ described by Eqs. (9) and (10) fulfil the following condition:

$$\theta + \Gamma = \ln\left(\frac{p}{1-p}\right) \tag{13}$$

what results from the relations describing the logit model.

Indicators described by Eqs. (11) and (12) are general relationships in which determining α_i coefficients require relevant measurement data. The given equations are universal and the variables included in them are typical for biological reactors based on activated sludge technology. If the independent variables in indexes θ or Γ are not measured, then the values $\alpha_i \cdot x_i$ are equal to 0.

8. Control and optimization of the biological reactor operation

When operating a wastewater treatment plant, it is important that the designed control system operates in a dynamic mode and takes into account the changing amount and quality of inflowing wastewater and weather conditions when selecting the bioreactor settings. Fulfilling these conditions should ensure high efficiency of the process, that is, no sludge bulking and continuous removal of C, N and P. Problems with the sedimentation of activated sludge occur in the examined wastewater treatment plant, therefore the conducted analyses were aimed at improving the reliability of its operation. It has been done by eliminating sludge bulking, ensuring of the process of removal of C, N and P from the wastewater and minimizing the amount of chemical reagents added which was dosed unreasonably during the period under consideration. The task described by the following conditions had, therefore, to be solved:

$$\sum_{t=1}^{242}\left(m_{\text{PIX}}\left(\theta,\text{MLSS},\text{DO}\right)\right)_{\varnothing z} \to \min \tag{14}$$

$$\text{COR}_{\text{SVI}}\left(t=1,2,3,\ldots 242\right) \le 1 \tag{15}$$

$$\text{COR}_{F/M}\left(t=1,2,3,\ldots 242\right) \le 1 \tag{16}$$

where m_{PIX} (θ, MLSS, DO)$_{ø}$ – the dosing function of PIX coagulant depending on the quantity and quality of wastewater and on weather conditions, as well as on the method of adjustment of DO and MLSS dependent on $Ø_z$ control [30]. In the longer term, it is planned to optimize the process aimed at minimizing costs of facility operating, which is the main subject of many studies. At the moment, the possibility of performing the analyses is limited due to insufficient data obtained from the air blowers operation.

Achievement of conditions, that is, Eqs. (14)–(16) is achieved by controlling MLSS and DO values in appropriate ranges (min – max) depending on the quantity and quality of wastewater and on weather conditions. When for the limit values of MLSS and DO, the calculated values $\text{COR}_{\text{SVI}} > 1$ or θ + Γ > 1, then PIX is given in following quantity:

$$m_{\text{PIX}} = \frac{-\theta - \alpha_{1,1}\cdot\text{MLSS} - \alpha_{1,2}\cdot\text{DO}}{\alpha_{1,3}} \tag{17}$$

In the case of continuous control of MLSS and DO values, it is necessary to comply with the condition that the value of MLSS must be increased accordingly with the increase of DO. This condition may be expressed by the formula:

$$\text{DO}\left(t+1\right)-\text{DO}\left(t\right)<0 \to \text{MLSS}\left(t+1\right)=\text{MLSS}\left(t\right)+\Delta\text{MLSS}\left(\theta\left(t+1\right)\right) \tag{18}$$

or otherwise:

$$\text{MLSS}\left(t+1\right)=\text{MLSS}\left(t\right)-\Delta\text{MLSS}\left(\theta\left(t+1\right)\right) \tag{19}$$

where ΔMLSS(θ) – change in mixed liquor suspended solids between time steps (t) and (t + 1).

In order to implement the calculation algorithm discussed above (Fig. 2), the possibility of its application at the concerned wastewater treatment plant in the period January–August 2016 was analyzed. In the summer months of March–August, the total precipitation was 552 mm and the number of rainfall days was 50. Using mathematical models for the prediction of sludge sedimentation and wastewater quality indicators on influent and set-point measurements (MLSS, DO, m_{PIX}) of the biological reactor, COR_{SVI} and $\text{COR}_{\text{F/M}}$ values were calculated for the actual condition of the plant operation. Then, solving the task described by conditions (i.e., Eqs. 14–16), optimization of MLSS, DO and m_{PIX} coagulant doses was carried out using the Nelder-Mead Simplex method [31].

9. Results and discussion

For the measurements data concerning the wastewater quantity and quality as well as technological indicators of wastewater treatment plant operation, ranges of their variability have been determined (Table 1).

On their basis, a large variability of quantity and quality of wastewater influent into the WWTP was found, which combined with different weather conditions significantly influenced the values of operating parameters of the bioreactor and sedimentation of the sludge. Based on the values of SVI > 150 cm^3/g and F/M < 0.05 g BOD$_5$/g MLSS·d,

Table 1
Range of variability of quantity and quality of wastewater and operational parameters of activated sludge chambers [22]

Variable	Minimum	Mean	Maximum
Q, m^3·d	32,564	40,698	86,592
T_{in}, °C			
T_{sl}, °C	10	15.9	23
pH	7.2	7.7	7.8
MLSS, kg/m^3	1.98	4.26	6.59
PIX, m^3/d	0	0.8	1.93
F/M, g BOD$_5$/g MLSS·d	0.03	0.07	0.17
DO, mg/L	0.55	2.56	5.78
SVI, cm^3/g	95	186	320
BOD$_5$, mg/L	127	309	557
NH_4^+-N, mg/L	24.4	49.4	65.9
TN, mg/L	39.9	77.7	124.1
TP, mg/L	4.3	7.8	12.6

it can be seen that in the analyzed period there was a sludge bulking. Furthermore, the measured maximal F/M value confirms that during the period under investigation problems with removal of C, N and P compounds were encountered. On the basis of the results of measurements of quantity and quality of influent and set-points of the biological reactor, a logistical regression model was developed for forecasting SVI, in which vector X is a linear combination of independent variables described by the formulas:

$$X = \theta + \Gamma \tag{20}$$

$$\theta = 0.02 \cdot \frac{\mathrm{BOD}_5}{\mathrm{TN}} + 0.32 \cdot \frac{\mathrm{BOD}_5}{\mathrm{TP}} + 0.0012 \cdot L_{\mathrm{N\text{-}NH_4}} - 0.37 \cdot T_{\mathrm{sl}} \tag{20a}$$

$$\Gamma = 14.38 - 0.37 \cdot T_{\mathrm{sl}} - 1.36 \cdot \mathrm{MLSS} - 1.76 \cdot m_{\mathrm{PIX}} - 1.18 \cdot \mathrm{DO} \tag{20b}$$

The resulting logistical regression model (Eq. (20)) has satisfactory predictive capabilities. This is indicated by the value of SPEC = 0.900 indicating that 72 events were correctly classified out of 80 cases when SVI > $\mathrm{SVI}_{\mathrm{lim}}$, and by the value of SENS = 0.867 indicating that 87 events were correctly classified out of 100 cases when SVI < 150 cm^3/g. As a result, out of 180 analyzed events, the assigned model appropriately classified 169 cases. The model's validation showed that the model correctly classified 8 out of 10 events. The obtained values of parameters for matching calculation results to measurements data (SENS, SPEC and R_z^2) indicate that the obtained logit model is characterized by better predictive abilities than the models given by Belanche et al. [32] and Bayo et al. [11] who used as explanatory variables the operational parameters of the biological reactor, measurements of bacterial microflora, temperature and pH in the activated sludge chambers.

A graphical interpretation of the calculation of Eq. (4) is shown in Fig. 4(a). On the other hand, Fig. 4(b) presents the results of calculation of $\%\mathrm{COR}_{\mathrm{SVI}} = (\mathrm{COR}_{\mathrm{SVI}}(x_i + \Delta x_i) - \mathrm{COR}_{\mathrm{SVI}}(x_i))/\mathrm{COR}_{\mathrm{SVI}}(x_i) = \mathrm{f}(\Delta x_i/x_i)$, which clearly shows the influence of independent variables (x_i) on the reliability coefficient.

Figs. 4(a) and (b) show that successively T_{sl}, MLSS and then DO and m_{PIX} values have the highest influence on $\mathrm{COR}_{\mathrm{SVI}}$. Among the analyzed quality indicators, the load of ammonium nitrogen pollution has the least effect on sludge sedimentation. Fig. 4(a) shows also that for $\mathrm{COR}_{\mathrm{SVI}} > 1$, there are problems with sedimentation problems in the treatment plant: sludge bulking and deterioration of wastewater quality at the effluent occur. At the same time, it is possible to maintain adequate reactor reliability ($\mathrm{COR}_{\mathrm{SVI}} > 1$) and eliminate sludge bulking provided that the MLSS, DO and m_{PIX} values are maintained on an adequate level.

In view of the fact that in the present case, the $\mathrm{COR}_{\mathrm{SVI}}$ value described by Eq. (4) is influenced, inter alia, by the wastewater quality indicators BOD_5, TN, TP, $\mathrm{N\text{-}NH_4}$, which is why models for their prognosis have been developed. As a first step, using the BT method, the so-called importance was determined to describe the impact of individual independent variables on the values of the analyzed wastewater quality indicators. These analyses made it possible to determine the variables $Q(t-j)$ and $T_{\mathrm{in}}(t-p)$ in Eq. (7), which have a decisive

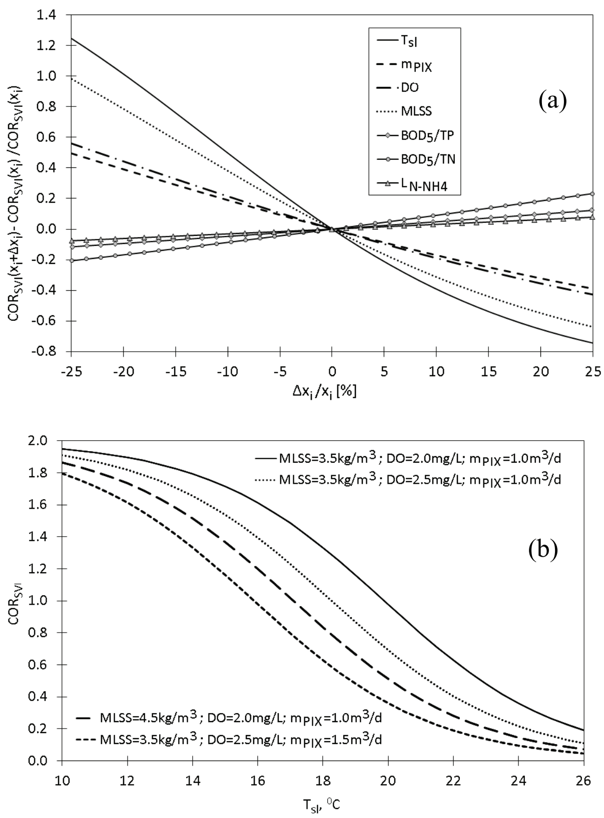

Fig. 4. (a) Relationship of the form $\mathrm{COR}_{\mathrm{SVI}} = \mathrm{f}(x_i)$, (b) effect of change of x_i by Δx_i on $\mathrm{COR}_{\mathrm{SVI}}$ value.

influence on the quality of the wastewater. Independent variables were included in the calculations for which the IMP values obtained were at least 0.90 [33,34]. Detailed calculation methodology was presented in the paper [22]. On the basis of performed analyses, using the toolbox neural network of MATLAB program, optimal structures of MLP, RBF and CNN models were determined for simulation of the analyzed wastewater quality indicators (Table 2). Table 2 shows that the lowest errors while forecasting, the quality indicators were obtained using the CNNs method, and highest simulation errors were obtained using MLP and RBF methods. The model for forecasting BOD_5 values, based on the values of $Q(t-j)$ and $T_{\mathrm{in}}(t-m)$ and using the CNN method, was characterized by better predictive capabilities (the value of the correlation coefficient R was 0.89) than the model obtained by Abyaneh [35] who used for BOD_5 simulation the MLP method and the measurements of wastewater temperature in the influent, of pH and total suspended solids, to obtain the value of R = 0.83.

The models of BOD_5 developed by means of MLP method by Dogan et al. [36] (who received R = 0.92) confirmed significant influence on the value of the concerned wastewater quality index of flow rate values, but also of concentration in inflowing wastewater to the WWTP, of TN, TP and suspended solids. In addition, it can be noted that the results of wastewater quality calculations (BOD_5, TN, TP, $\mathrm{N\text{-}NH_4}$) performed by BT and k-NN methods [20,22] were worse than those obtained by the CNN method and better than those obtained by MLP and RBF methods.

Table 2
Results of modelling of wastewater quality indicators by CNN, MLP and RBF methods

Indicators	n_{INP}	CNN					MLP					RBF			
		MAE	MAPE	R	N	f(·)	MAE	MAPE	R	N	f(·)	MAE	MAPE	R	N
		mg/dm³	%	–			mg/dm³	%	–			mg/dm³	%	–	
BOD_5	10	32.35	10.21	0.89	7	tanh	49.2	18.6	0.69	11	exp	58.21	23.12	0.48	8
TP	8	0.79	10.5	0.83	8	exp	1.15	16.5	0.38	10	sigm	1.11	15.76	0.40	16
TN	8	4.66	5.46	0.85	7	tanh	6.25	8.22	0.59	10	tanh	5.82	7.75	0.63	14
$N-NH_4$	8	2.74	5.19	0.87	8	tanh	4.08	8.33	0.68	10	exp	5.06	9.21	0.63	15

n_{INP} – number of inputs to the models described by Eq. (7) for particular indicators of wastewater quality, N – number of neurons in the hidden layer.

The HCA method was used to develop a reactor control strategy for the investigated WTP, depending on the quantity and quality of inflowing wastewater and on weather conditions. The results of obtained calculations in the form of dendrogram are presented in Fig. 5, on which we can see the presence of three clusters. Table 3 shows the average values of the independent variables considered (BOD_5/TN, BOD_5, TP, L_{N-NH4}, T_{sl}) in the clusters obtained. Analyzing the average values of the dependent variables addressed in HCA (Table 3), it was found that in C1 the T_{sl} values (mean score of 12.30°C) were lower than in C2 (mean score of 17.90°C) and C3 (mean score of 15.90°C). Hence, it follows that C1 includes events where process kinetics in the biological reactor was lower than for C2 and C3 clusters, which is typical of the winter period and is confirmed by the activated sludge temperature. In C3 (mean score of 2,550 kg $N-NH_4$/d), the L_{N-NH4} value is higher than in C1 (mean score of 1,948 kg $N-NH_4$/d) and C2 (mean score 2,150 kg $N-NH_4$/d) and at the same time the T_{sl} is lower than in C2, which may indicate the overload of the object, which is typical for WWTP operation in the dry weather.

This fact is also confirmed by the values of BOD_5/TN and BOD_5/TP, which are smaller in C3 than in C1 and C2. Taking into account the calculation results obtained for the clusters related, it can be concluded that cluster 2 includes WWTP events for dry weather.

Taking into account the results of the calculations, some simulations of the wastewater quality indicators (BOD_5, TN, TP, $N-NH_4$) and Q were performed using CNN method. Then, based on Eq. (20) and Eqs. (4), (5), values of COR_{SVI}, $COR_{F/M}$ and of θ and Γ parameters were determined (Fig. 6). Analyzing the results of calculations obtained using the HCA method and the obtained value of variability of θ parameter (Fig. 6), three operating periods of WWTP were determined: winter, dry and wet periods, for which control of the operational parameters of activated sludge chambers (MLSS, DO and m_{PIX}) were developed in relation to sludge sedimentation and to the course of C, N and P removal. Fig. 6 shows that during the period from 21.03.2015 to 23.04.2015, covering the initial spring period, the sludge bulking occurred. It should be noted that during this period the mean activated sludge temperature was 13.3°C and this value did not differ significantly (p = 0.05) from the temperature values for the winter period, as shown by the ANOVA test. In the winter period, the values of parameter θ are the lowest and amount to 1.9–3.0. In the summer and spring periods, the values of parameter θ are higher than 3.0, but during wet they are lower by about 15% than in the dry period. Taking into account the results of the calculations, it has been concluded that θ can be an important variable to determine the appropriate control of the biological reactor regarding the sludge sedimentation and removal of C, N and P.

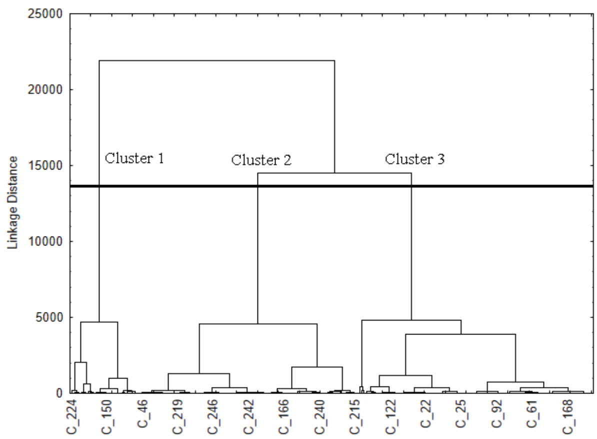

Fig. 5. Dendrogram obtained from cluster analysis, where C_1, C_2, C_p – number of measured events.

Table 3
Summary of average values of analyzed independent variables (BOD_5/TN, BOD_5, TP, L_{N-NH4}, T_{sl}) in obtained clusters (C)

Cluster	T_{sl}	L_{N-NH4}	BOD_5/TP	BOD_5/TN
C1	12.3	1,948	37.5	3.85
C2	17.9	2,150	43.8	4.07
C3	16	2,550	32.15	3.5

Fig. 6 shows that in winter, spring and summer, there were problems with the operation of the WWTP – the activated sludge bulking, which is confirmed by the values COR_{SVI} > 1. In spring and summer, these episodes appear during wet weather. Fig. 6 also shows that in the winter period COR_{SVI} values changed in the range of 1.90–3.60, and in the spring and summer period during rainfall events these values did not exceed COR_{SVI} = 1.24. During dry days in the spring – summer period, when there were no problems with the operation of WWTP in relation to sludge sedimentation (sludge bulking) (COR_{SVI} = 0.60–1.00), the object was

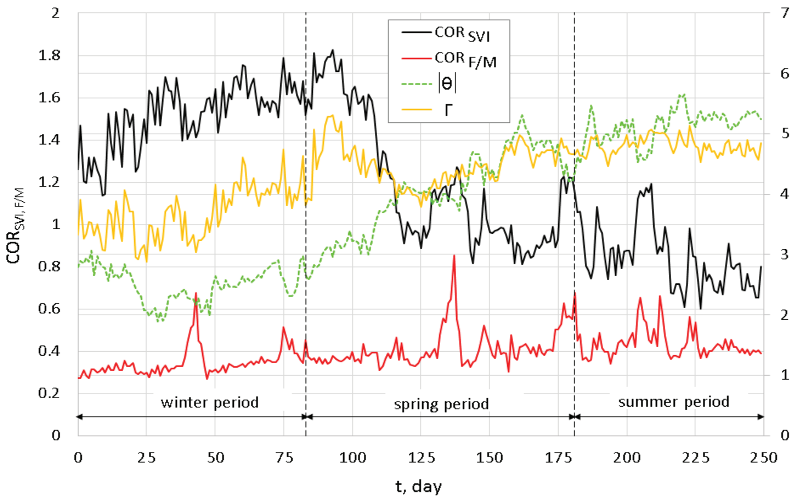

Fig. 6. Results of calculations of $COR_{SVI, F/M}$ and of θ and Γ parameters for the period 01.01.2015–08.30.2015.

characterized by high operational reliability. However, this does not mean that the facility function optimally. It seems that it is possible to limit the amount of coagulants dosed and to correct MLSS and DO in dry periods, as indicated by the values $COR_{SVI} < 1.0$ (Fig. 6).

Another problem was the MLSS values significantly exceeding the maximum values (5.0 kg/m^3) recommended for the operation of wastewater treatment systems with activated sludge chambers. Studies carried out by Barbusiński and Kościelniak [37] have shown that maintaining high MLSS values for a long period of time can lead to problems in the operation of biological reactors. Without commenting, it is not possible to leave the fact that the calculated $COR_{F/M}$ values (Fig. 6) were below 1.0 (maximum value is 0.81), which indicates that in the analyzed period there were no disturbances in the course of C, N and P removal processes.

Taking into account the recommendations for the use of WWTP with the activated sludge chamber system [32], the results of the calculations of Lou and Zhao [30] and of Flores-Alsina et al. [10], and also analyzing the variability of the values of $COR_{SVI} = f(\text{MLSS, DO}, m_{PIX})$, the following ranges of variability of operating parameters for the described WWTP operating conditions were assumed:

$$\varnothing_z = \begin{cases} \text{MLSS} \le 4.50\ \text{kg/m}^3 \vee \text{DO} \le 2.25\ \text{mg/L}, z = 1 \\ \text{MLSS} \le 4.75\ \text{kg/m}^3 \vee \text{DO} \le 2.50\ \text{mg/L}, z = 2 \\ \text{MLSS} \le 5.00\ \text{kg/m}^3 \vee \text{DO} \le 2.50\ \text{mg/L}, z = 3 \end{cases} \tag{21}$$

where z = 1 (dry period), z = 2 (wet period), z = 3 (winter period).

The analyses for the precipitation period assume a higher MLSS value than for the wet period, since the influent entering the reactor may lead to a decrease in T_{sl} and MLSS values, and therefore to sludge bulking. This assumption is confirmed by the results of calculations, because Spearman's correlation coefficient (R) values between Q and MLSS/T_{sl} are $R = -0.33$ and $R = -0.32$, and are statistically significant at the assumed confidence level ($p = 0.05$). On the basis of Eqs. (4), (5) and (21) and limiting conditions Eqs. (14)–(16), the operating parameters of the biological reactor were optimized using the Nelder-Mead Simplex method.

Fig. 7 shows that optimization of the biological reactor operating parameters have had a significant impact on the reliability of the wastewater treatment plant. This is confirmed by the determined COR_{SVI} values, that do not exceed 1.0, which means that the use of the SVI modelling method described above eliminates the problems of activated sludge bulking. Based on Fig. 7, it was also found that in the winter period, in order to obtain adequate reliability of WWTP operation (COR_{SVI} reduction from $COR_{SVI} = 1.57$ for the current state of WWTP operation to $COR_{SVI} = 1.0$ level), it was necessary to increase the amount of dosed chemical reagents (up to 119.3 m^3 within 106 d) compared with the current state (46.16 m^3). Improvements in the efficiency of WWTP regarding the sludge sedimentation have led to an increase in the average daily dose of PIX from 0.44 to 1.12 m^3/d, which is economically useless, but technological considerations make this necessary. Furthermore, the values obtained from MLSS calculations do not exceed the maximum values (5.0 kg/m^3) recommended by the operation of the WWTP in the activated sludge technology. At the same time, at the optimization stage, DO values above 2.5 mg/dm^3 were eliminated in order to avoid potential overburdening of the activated sludge, which could lead to a sludge bulking. In the dry period (123 d), the optimization of activated sludge chambers parameters contributed to the reduction of MLSS and DO values in relation to the existing state, which translated into a reduction of PIX dosage from 54.24 to 42.35 m^3 (Fig. 8).

The average daily dose of PIX was reduced from 0.55 to 0.46 m^3/d and the average MLSS value decreased from 4.57 to 4.50 kg/m^3. During the wet period, the model application and optimization of reactor operating parameters improved the reliability of the plant operation, as the average COR_{SVI} value for the existing state of operation decreased from 1.08 to 1.0.

This effect was achieved by increasing the average MLSS = 4.6 kg/m^3 and DO = 2.3 mg/dm^3 compared with the existing operation state by 3.3% and 15.2%, respectively, which allowed to reduce the amount of dosed chemical reagents from 24.86 to 14.68 m^3.

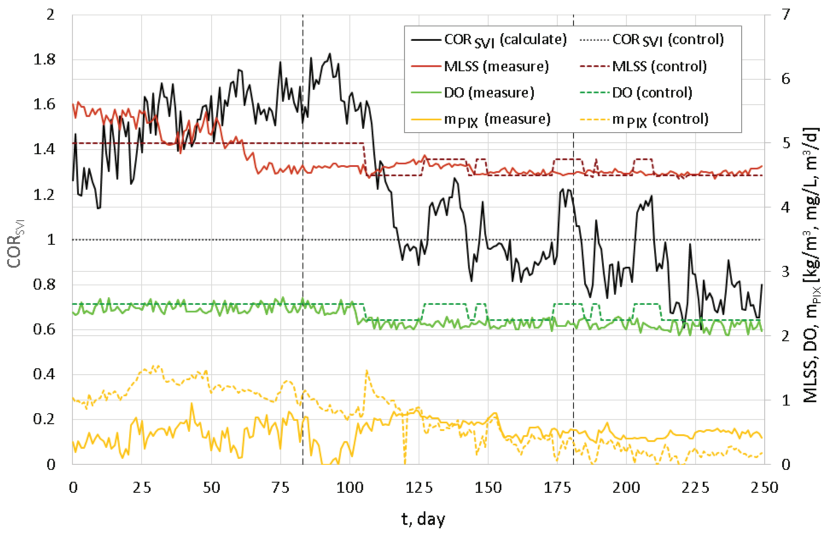

Fig. 7. Results of calculations of variability of biological reactor operating parameters (MLSS, DO, m_{PIX}) after optimization.

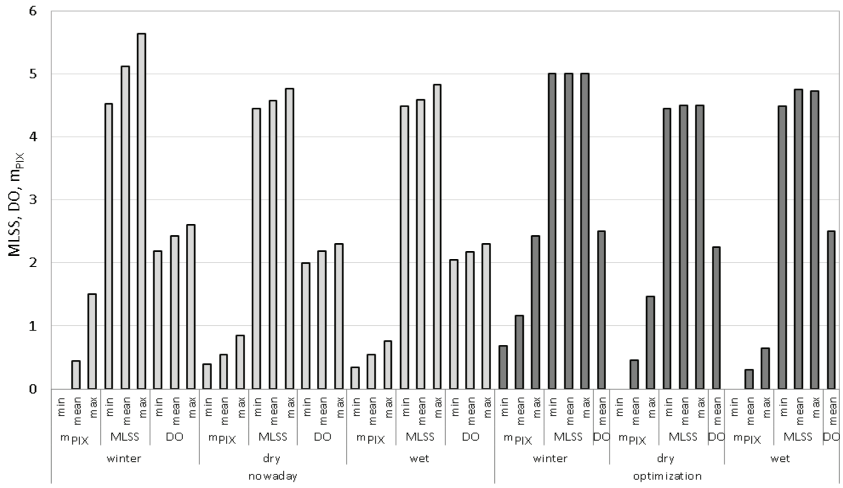

Fig. 8. Comparison of the variability of reactor operating parameters (MLSS, DO, m_{PIX}) for the existing state and after optimization.

10. Conclusions

The analyses carried out in the paper showed that the proposed COR_{SVI} and $COR_{F/M}$ reliability indices can serve as a basis for real-time evaluation of wastewater treatment plant operation. It is possible to analyze the influence of selected settings (oxygen concentration, mixed liquor suspended solid, amount of dosed PIX) on the values of the considered reliability coefficients, which so far has been limited. The presented mathematical model for reliability analysis enables simulation and control of bioreactor operating parameters even in case of lack of continuity of wastewater quality indicators determining sedimentation and wastewater quality at the effluent. This is a significant advantage of the model, as it is possible to control the operation of the plant even in the case of failure of the wastewater quality measurement system at the inflow, which has not been included in the process models so far.

Moreover, the parameter θ taking into account the variability and interactions between the quantity and quality of wastewater and weather conditions allows to identify problems with sedimentation of activated sludge. This parameter is seasonal in nature, with the lowest values for the winter period, and in spring and summer it has been found to decrease locally during intensive precipitation events. The innovation of the solution is the fact that on its basis it is possible to select operating parameters of the biological reactor in terms of obtaining high reliability of plant operation in relation to the sedimentation process and the quality of effluent. Until now it required the use of complex numerical models to simulate sedimentation and implementation of classification models (HCA). The solution presented in the paper is less complicated than the one presented by other researchers, and the possibility of its implementation in many objects seems to be simpler than before.

Taking into account the satisfactory predictive abilities of the model presented in the paper, it is necessary to verify it on other objects. Taking into account the satisfactory predictive abilities of the model to predict and control the precipitate sedimentation in the reactor, further analyses are recommended to develop a control strategy in terms of reducing operating costs in the area of aeration, precipitate recirculation and coagulant dosing. At the same time, it is necessary to run analyses aimed at assessing the impact of errors in forecasting indicators of wastewater quality on the accuracy of forecasting COR_{SVI} values. In addition, it is advisable to further reflect on the development of the model calculated by forecasting the reliability of WWTP performance with respect to the wastewater quality indicators, that is, BOD_5, TN, TP.

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