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Artificial neural network approach to modelling of HMW PAHs removal under fluctuating BOD loading rate in anaerobic and aerobic phases of GSBR reactor

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ABSTRACT

The paper presents models of artificial neural networks (ANN) approximating the benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene concentrations after anaerobic and aerobic phases of the sequencing batch reactor operating with aerobic granular activated sludge (GSBR). Selected technological parameters of active sludge and concentration of benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene at the beginning of anaerobic or aerobic phase were the input variables layer in ANN models. Variables set depended on the approximation algorithm purpose. The models were characterized by determination of coefficients ranging from 0.995 to 0.999 and showed a good adjustment to changes trend of studied high molecular weight (HMW) PAHs. All ANN models were the most sensitive to benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene at the beginning of modelled GSBR reactor phase. The activated sludge technological parameters showed less influence on the approximation process of individual HMW PAHs.

Keywords: HMW PAHs; GSBR; Artificial neural network; Aerobic activated granular sludge

1. Introduction

Aerobic granular activated sludge is a new element in wastewater treatment technology. According to the definition proposed by the International Water Association, these aggregates are not coagulated as a result of hydrodynamic shear forces and have better sedimentation capacity than flocked sludge [1]. The key features of granular activated sludge are, among others, high resistance to changes of organic compound loading in the reactor [2] and resistance to substances potentially toxic to the microorganisms present in activated sludge [3–5]. Examples of such compounds are polycyclic aromatic hydrocarbons containing more than four aromatic rings in their structure, which are referred to as high molecular weight PAHs [6]. In the literature, there are reports on the degradation of this compounds group by a number of microorganisms, including a consortium of microorganisms present in activated sludge [7,8]. It should be noted that the PAHs removal mechanism from wastewater is complex and consists of biosorption, anaerobic and aerobic decomposition processes [9]. Diversity and different character of above mentioned unit processes of PAH decomposition requires taking into account many variables related not only to the technological parameters of activated sludge but also to the wastewater treatment conditions in GSBR reactors. It should be emphasised that the degradation of PAHs containing four and more aromatic rings is relatively problematic in wastewater treatment systems as these compounds are more toxic to PAHs with less than four rings in their structure. This fact contributes to the increased complexity of static models and may affect their accuracy [10]. Therefore, artificial neural networks are one of the tools to describe such complexities [11]. This method allows for arbitrary parameters selection at the stage of phenomena modelling and seeking the simplest relations between variables, hence to reflect the nature

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of changes in the approximated variable set as accurately as possible [12]. In the literature on the modelling of activated sludge processes with the use of ANN, the results obtained for flocked sludge are most often taken into account. The issue of modelling of HMW PAH removal in reactors operating with granular sludge is not often discussed, while the research studies focus mainly on modelling changes in the concentration of nitrogen, phosphorus and carbon compounds expressed as chemical oxygen demand (COD). Therefore, an attempt was made to describe the process of benzo(a)pyrene (B(a)P), indeno(c,d)pyrene (I(cd)P), dibenzo(a,h)anthracene (D(ah)A) and benzo(g,h,i)perylene (B(ghi)P) removal in the anaerobic and aerobic phases of GSBR reactor.

The aim of the study was to develop models of ANNs approximating benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene concentrations after the anaerobic and aerobic phases of GSBR reactor and to identify the most important variables influencing the algorithms approximating the concentrations of individual compounds.

2. Materials and methods

Studies were carried out in a model GSBR reactor made of reinforced polyethylene. The experiment assumed that a single reactor cycle would be 12 h and consist of five unit phases, including separate filling, mixing (anaerobic), aeration (aerobic), sedimentation and decantation phase. The reactor was equipped with a slow-running agitator with a mixing speed of 70 rpm, which worked during the mixing and aeration phases to prevent the formation of blind spots in the reactor volume contributing in activated sludge biomass rotting. The work of wastewater dosing pump, agitator, aerator and duration of individual GSBR unit phases was coordinated with the Siemens LOGO! type 230RC PLC programmable logic controller. The technological and hydraulic parameters of the GSBR reactor, which were maintained during the experiment, are presented in Table 1.

The aerobic granular activated sludge used in the study has been inoculated and treated for a period of 30 d prior to the beginning of main experiment. The length of this period allowed for sludge retention time stabilization and microorganisms present in sludge adapted to new oxygen conditions. The considered technological parameters of the activated sludge were calculated based on the equations used for flocked activated sludge:

Sludge volume index:

$$\mathrm{SVI} = \frac{V_{30}}{G}\,\mathrm{cm}^3/\mathrm{g} \tag{1}$$

Hydraulic retention time:

$$\mathrm{HRT}\,\frac{V_{\mathrm{GSER}}G}{G}[\mathrm{d}] \tag{2}$$

Sludge retention time:

$$\mathrm{SRT} = \mathrm{HRT}\cdot\frac{t_R}{t_C}[\mathrm{d}] \tag{3}$$

BOD load of activated sludge mass:

$$A' = \frac{Q_d\cdot S_{\mathrm{BOD}}}{V_{\mathrm{GSBR}}\cdot G}\cdot\frac{t_R}{t_C}[\mathrm{kg\,BOD/\,kg.d}] \tag{4}$$

Activated sludge growth rate:

$$\mathrm{ASG} = L_{\mathrm{BOD}}\cdot\left(0.75+\frac{0.6}{S_{\mathrm{BOD}}}-\frac{0.102\cdot\mathrm{SRT}\cdot 1.072^{T-15}}{1+0.17\cdot\mathrm{SRT}\cdot 1.072^{T-15}}\right)[\mathrm{mg/d}] \tag{5}$$

In presented equations, V_{30} stands for activated sludge velocity after 30 min of sedimentation, V_{GSBR} is defined as actual GSBR capacity, G is activated sludge dry mass in GSBR reactor, ΔG defines activated sludge daily growth rate, Q_d is the amount of raw wastewater inflowing to GSBR reactor in 1 d, S_{BOD} represents BOD concentration in raw wastewater, L_{BOD} stands for BOD loading rate inflowing to GSBR reactor, t_R is defined as duration of GSBR aeration phase, t_C stands for duration of single GSBR reactor cycle and T is temperature in Celsius degrees. Activated sludge technological parameters, which were observed during the experiment, are presented in Table 2.

Wastewater used in the studies was prepared from casein peptone (0.113–4.520 g/L), enriched dry broth (0.076–3.040 g/L), NH_4Cl (0.010–0.400 g/L), NaCl (6.59 g/L), $CaCl_2{\cdot}6H_2O$ (0.004–0.160 g/L), $MgSO_4{\cdot}7H_2O$ (0.001–0.040 g/L), KH_2PO_4 (0.008–0.320 g/L), K_2HPO_4 (0.020–0.800 g/L) and oily substances solution (0.032 μL/L). An oily wastewater solution

Table 1
GSBR reactor hydraulic and technological parameters

GSBR technological parameter	Value range
Aerator capacity, L/h	550.0
Total GSBR capacity, L	16.0
Actual GSBR capacity, L	15.0
Volume exchange factor	0.33
Filling phase duration, min	30.0
Mixing phase duration, min	90.0
Aeration phase duration, min	540.0
Sedimentation phase duration, min	30.0
Decantation phase duration, min	30.0

Table 2
Activated sludge technological parameters

Activated sludge technological parameter	Range
Activated sludge dry mass (G), kg/m^3	3.9–4.1
Sludge volume index (SVI), cm^3/g	59–70
Hydraulic retention time (HRT), d	31–60
Sludge retention time (SRT), d	21–42
Activated sludge growth rate (ASG), mg/d	0.05–1.48
BOD loading rate (L_{BOD}), kg BOD/kg d	0.05–1.40

was prepared on the basis of naphtha (60%), burned-out car oil (30%) and petroleum oil (10%) and was used as a base PAH solution. Similar wastewater composition was used in previous studies [13,14]. The components of oily solution were selected so that HMW PAHs group constitute the dominant part of polycyclic hydrocarbons.

The quantities of reagents used in the preparation of model wastewater increased with the increase of activated sludge BOD load. Presented wastewater mixture contained both easily and hardly decomposable carbon compounds, nitrogen and phosphorus compounds. The aim of this approach was to adjust the laboratory conditions as closely as possible to those that may occur in real objects. Activated sludge BOD load was increased when after 2 d (four complete cycles) any changes in the efficiency of wastewater treatment were observed. The studies were carried out at room temperature (20 °C ± 2 °C). Parameters of raw wastewater inflowing to the reactor are presented in Table 3. The analysis of individual wastewater parameters, including HMW PAHs, was carried out in accordance with methodology described in the previous paper [14]. HMW PAHs were determined by means of gas chromatography coupled with mass spectrometer (GC/MS) with a DB-5MS column. The stationary phase of column was polydimethylsiloxane with 5% phenyl groups.

In order to observe quantitative changes of studied HMW PAHs, a sample of raw wastewater and wastewater after filling phase, after anaerobic phase (mixing) and after aerobic phase (mixing and aeration) was collected for analyses. Each wastewater sample was filtered through the quantity filter to determine changes in the concentration of studied PAHs in the wastewater. The aim of this approach was to omit the processes of biodegradation, biotransformation and biosorption of PAHs retained in the structure of activated sludge aerobic granules in developed ANN models. ANNs are characterized by flexibility in the selection of variables. The principle of this type of calculation algorithm allows to find the simplest relations between variables. Consequently, this type of approach leads to a relatively accurate description of the phenomena described by the collected database. The structure of a neural network can be divided into three main layers. These include the input layer, which constitutes the variables used to describe a given phenomenon. The next element is the hidden layer, in which the calculation process is carried out in a discreet way and the simplest and most accurate reflection of variables in the output layer is obtained. In turn, the output layer includes variables that are subject to the modelling process.

Table 3
Raw wastewater parameters range

Parameter	Range	Standard deviation
BOD, mg/L	36–1,000	303.74
COD, mg/L	57–1,618	461.89
Total N, mg/L	5.89–166.56	50.72
Total P, mg/L	1.49–43.84	13.35
B(a)P, μg/L	10.42	0.01
I(cd)P, μg/L	12.61	0.01
D(ah)A, μg/L	8.58	0.01
B(ghi)P, μg/L	11.23	0.01

Input variables in ANN models describing changes of individual HMW PAHs were selected on the basis of Pearson's linear correlation coefficients. Only technological parameters of activated sludge were considered in the analysis. Variables describing the technological and hydraulic parameters of GSBR reactor were skipped due to the fact that they were constant during the experiment. Therefore, the parameters of GSBR reactor are the criteria, for which ANN models can be used in further research. Correlation coefficients observed between the technological parameters of activated sludge and the concentrations of HMW PAHs after individual phases are presented in Table 4.

ANN models were developed using Statistica 13.1 software running on Windows 10 Home Edition platform. The database used to develop ANN models was divided into three sets, including a learning set, which constituted 75% of all measurement results, a test and validation set, which contained 15% of all measurement results each. Dividing all results into individual data sets made it possible to verify the obtained approximation results. The Broyden–Fletcher–Goldfarb–Shanno algorithm (BFGS) was selected during the learning phase of the individual models. Selection of this machine learning algorithm was based on the experience from previous studies, where the best learning results of the neural network were obtained with its use [15,16].

It was assumed that the number of epochs in a single model could not exceed 200 during the learning phase. Such an approach minimized the risk of neural network overturning, which would result in a good adjustment to changes trends in particular approximated variables, but would prevent from accurate approximation of variables introduced outside the learning scope. When developing a single model, 500 networks were sampled, from which the algorithm best describing the behaviour of a particular compound in a given

Table 4
Correlation between activated sludge technological parameters and selected PAHs concentration after anaerobic and aerobic phase

Anaerobic					Aerobic				
Variable	B(a)P	I(cd)P	D(ah)A	B(ghi)P	Variable	B(a)P	I(cd)P	D(ah)A	B(ghi)P
BOD load	0.88	0.88	0.88	0.88	BOD load	0.88	0.88	0.88	0.88
SVI	–0.69	–0.69	–0.69	–0.69	SVI	–0.68	–0.68	–0.68	–0.68
HRT	–0.60	–0.60	–0.60	–0.60	HRT	–0.59	–0.59	–0.58	–0.59
SRT	–0.62	–0.62	–0.62	–0.63	SRT	–0.61	–0.61	–0.61	–0.61
ASG	0.88	0.88	0.88	0.88	ASG	0.88	0.88	0.87	0.88

process phase of a GSBR reactor was selected. The error function in the developed models was the sum of squares. Activation functions of neurons in the hidden and output layer were selected automatically by the program. The best describing parameters from obtained ANN models are presented in Table 5.

3. Results and discussion

The developed ANN models were characterized by a good representation of benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene both in the anaerobic and aerobic GSBR reactor phases. The determination coefficients between the observed and approximated values in individual data sets (learning, test and validation) were greater than or equal to 0.993. Determination coefficient values can be interpreted as a linear adjustment of observed to approximated values. This means that the approximation of both the concentration and changes trend of individual compounds in individual phases have been reflected with an accuracy of more than 99%. The achieved level of accuracy was additionally confirmed by relatively small values of approximation error in individual data sets. Table 6 presents determination coefficients values and estimation errors of individual ANN models approximating the concentrations of benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene in anaerobic and aerobic phases of the GSBR reactor.

The sensitivity analysis of developed ANN models was an important element in modelling studies of PAHs changes. All ANN models showed the highest sensitivity to concentration of modelled compound at the beginning of GSBR reactor process phase. In case of models approximating benzo(a) pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene concentrations in the anaerobic phase, the input variables were the concentrations of these compounds after the filling phase, whereas in case of ANN models describing changes in the aerobic phase, the concentrations of these compounds after the anaerobic phase were assumed.

In the experiment, the HWM PAHs concentrations inflowing with raw wastewater into each GSBR cycle were constant values and the activated sludge BOD loading was regularly increased. It should be noted that an increase in the active sludge BOD loading indirectly resulted in increased amount of easily available carbon compounds supplied with enriched broth and casein peptone. Therefore, the removal effectiveness of individual compounds from the HMW group decreased with the increase of BOD load. As a result, the amount of benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene present in the reactor gradually increased. On the other hand, a progressive increase in the amount of these compounds resulted in their higher concentrations after the filling and anaerobic phases (Figs. 1–4). Therefore, this phenomenon may have directly contributed to the highest sensitivity of benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)

Table 5
Summary of developed ANN models

HMW PAH	GSBR phase	ANN topology	Machine learning algorithm and epochs	Error function	Hidden layer activation function	Output layer activation function
B(a)P	Anerobic	MLP 6-6-1	BFGS 36	SOS	Exponential	Tanh
I(cd)P		MLP 6-6-1	BFGS 22	SOS	Exponential	Tanh
D(ah)A		MLP 6-6-1	BFGS 33	SOS	Exponential	Tanh
B(ghi)P		MLP 6-10-1	BFGS 14	SOS	Logistic	Sinus
B(a)P	Aerobic	MLP 6-5-1	BFGS 18	SOS	Exponential	Tanh
I(cd)P		MLP 6-5-1	BFGS 128	SOS	Logistic	Tanh
D(ah)A		MLP 6-7-1	BFGS 17	SOS	Exponential	Tanh
B(ghi)P		MLP 6-10-1	BFGS 14	SOS	Logistic	Sinus

Table 6
Matching the quality of individual ANN models

HMW PAH	GSBR phase	Learning quality	Test quality	Validation quality	Learning error	Test error	Validation error
B(a)P	Anaerobic	0.997	0.999	0.999	0.043	0.019	0.025
I(cd)P		0.997	0.999	0.999	0.070	0.018	0.051
D(ah)A		0.997	0.999	0.999	0.032	0.012	0.021
B(ghi)P		0.995	0.993	0.999	0.068	0.122	0.103
B(a)P	Aerobic	0.998	0.999	0.999	0.024	0.012	0.010
I(cd)P		0.997	0.999	0.999	0.052	0.017	0.007
D(ah)A		0.998	0.999	0.999	0.019	0.005	0.016
B(ghi)P		0.995	0.993	0.999	0.068	0.122	0.103

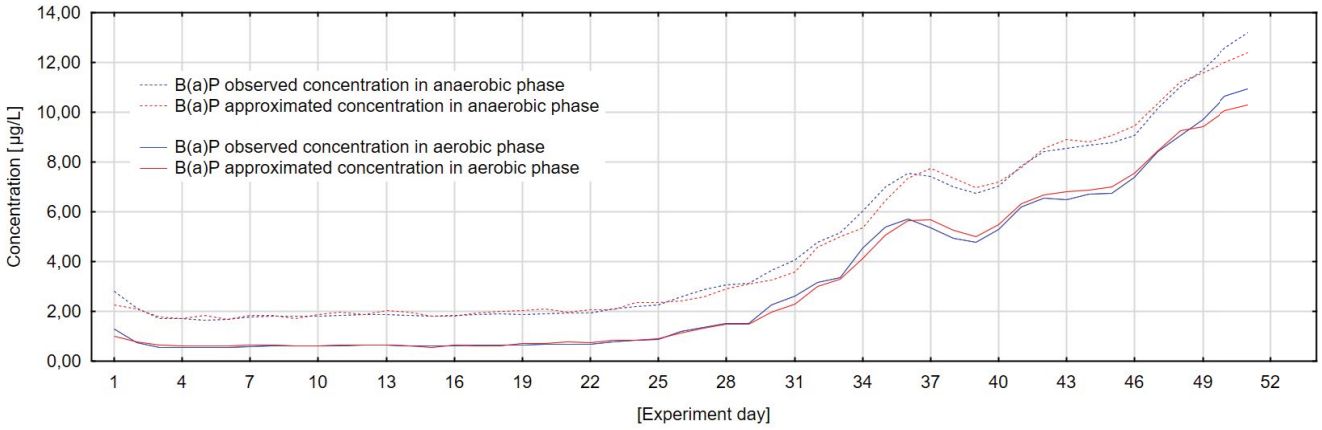

Fig. 1. Observed and approximated values of B(a)P in anaerobic and aerobic GSBR phases.

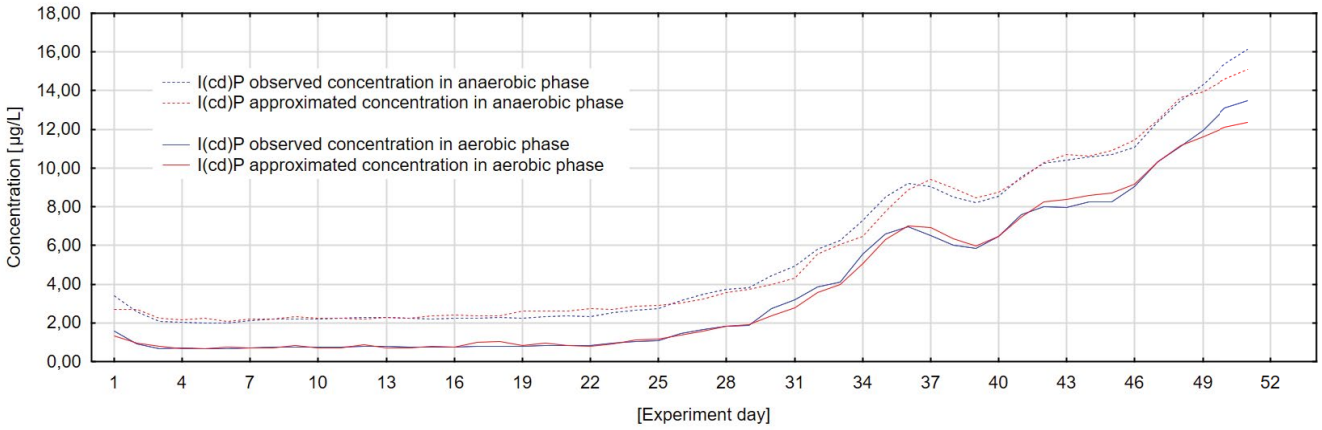

Fig. 2. Observed and approximated values of I(cd)P in anaerobic and aerobic GSBR phases.

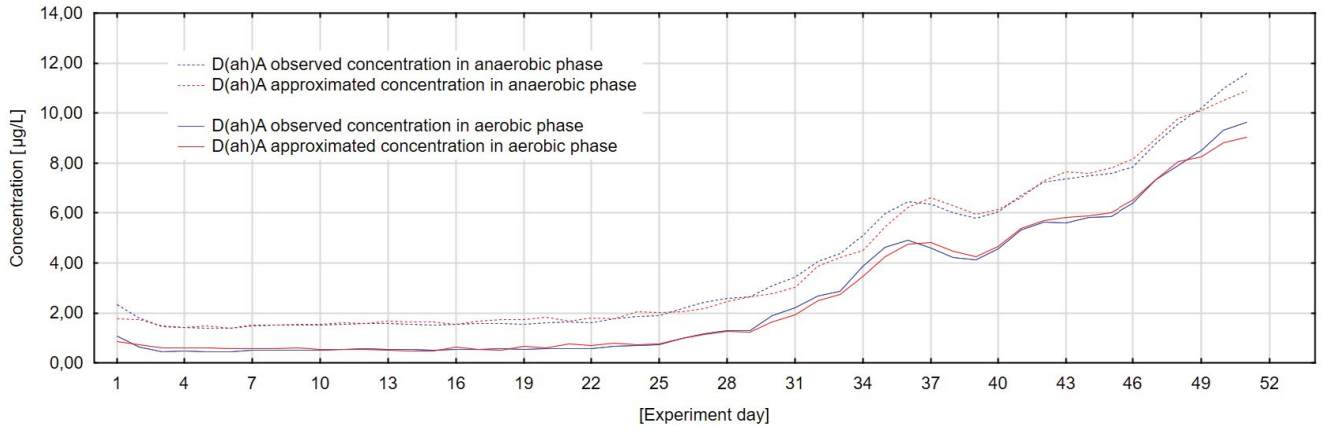

Fig. 3. Observed and approximated values of D(ah)A in anaerobic and aerobic GSBR phases.

perylene concentrations, depending on the ANN model, after the filling phase or after the anaerobic phase.

Other variables taken into account in the models were activated sludge technological parameters. It should be noted that in all models, those variables were characterized by similar influence on the calculation of ANN algorithms. Among the considered technological parameters of active sludge, the active sludge growth rate had the greatest influence on the approximation of benzo(a)pyrene and dibenzo(a,h)anthracene concentrations in the anaerobic phase, while the SRT had the greatest influence on the concentrations of indeno(c,d) pyrene and benzo(g,h,i)perylene. On the other hand, in the

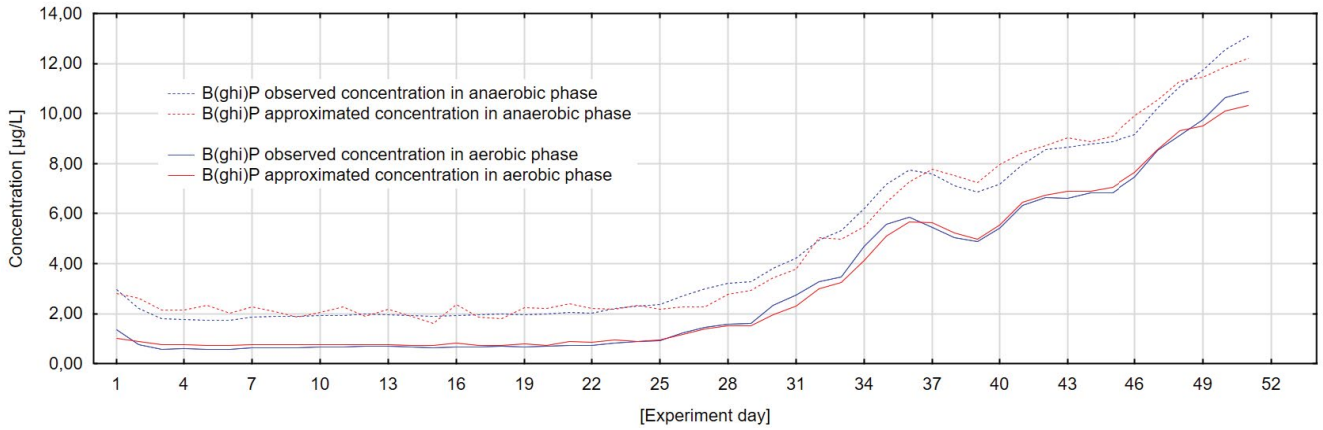

Fig. 4. Observed and approximated values of B(ghi)P in anaerobic and aerobic GSBR phases.

Table 7
Variable weights included in ANN models

HMW PAH	GSBR phase	Variable weight (w)					
		HMW PAH	ASG	HRT	SRT	BOD load	SVI
B(a)P	Anaerobic	98.55	2.24	1.83	1.78	1.42	1.07
I(cd)P		87.40	2.78	1.57	2.79	1.50	1.05
D(ah)A		98.04	2.52	1.48	1.40	1.33	1.07
B(ghi)P		23.08	2.58	2.65	4.23	2.12	1.33
B(a)P	Aerobic	193.03	1.89	4.38	2.10	1.76	1.05
I(cd)P		160.76	1.18	1.26	1.23	1.13	1.05
D(ah)A		177.98	1.76	2.57	4.76	3.32	1.06
B(ghi)P		23.08	2.58	2.65	4.23	2.12	1.33

aerobic phase, among the considered technological parameters of active sludge, the HRT influenced the approximation of benzo(a)pyrene and indeno(c,d)pyrene, whereas the SRT showed the highest sensitivity to the dibenzo(a,h)anthracene and benzo(g,h,i)perylene concentrations. Both the activated SVI and loading with organic compounds expressed as BOD did not affect the estimation process of individual PAHs from the HMW group.

Similar sensitivity of ANN models to activated sludge technological parameters may have resulted from mathematical similarity of those variables. This convergence is dictated by the use of sludge dry matter in the calculation of activated sludge growth rate, hydraulic retention time in the reactor chamber, sludge retention time and its volume index. Therefore, the individual technological parameters of activated sludge are indirectly related to this value. The sensitivity analysis of individual models could show similar weights for these variables. Another reason for this phenomenon could be the fact that individual parameters of active sludge did not show any rapid changes that would be caused by an increase in BOD load inflowing into GSBR reactor. On the other hand, no significant changes in technological parameters of activated sludge under the influence of increasing activated sludge BOD load could have resulted from the properties of studied activated sludge structure. According to the literature data, granulated activated sludge shows resistance to fluctuations of BOD load inflowing to reactor with raw wastewater [17]. Additionally, this type of sludge is characterized by a high tolerance towards contaminants potentially toxic to microorganisms present in the activated sludge including HMW PAHs [18].

Figs. 1–4 show changes in benzo(a)pyrene, indeno(c,d) pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene concentrations in anaerobic and aerobic GSBR reactor phases. Concentrations of individual PAHs in wastewater increased with increased activated sludge BOD loading. This relationship was well represented by individual ANN models. Both in the anaerobic and aerobic phases, the ANN models reflected with high accuracy the changes trend of individual compounds and their concentration during experiment. Presented trends are also reflected in basic statistics of observed and approximated data sets (Table 8). All statistical data (arithmetic mean, median, minimum, maximum and standard deviation) of the individual compounds were similar. This means that ANN models developed for approximation of benzo(a)pyrene, indeno(c,d) pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene concentrations reflected not only changes trend in individual compounds in the modelled phases of GSBR reactor but also matched well the values within the approximation range.

Static models, used to describe changes in HMW PAHs concentration occurring in the anaerobic and aerobic phases of GSBR reactors, are rarely mentioned due to the complexity

Table 8
Basic statistics on observed (O) and approximated (A) values in anaerobic (An) and aerobic (Ae) GSBR process phases

HMW PAH	Arithmetic mean	Median	Min	Max	SD
B(a)P- An (O)	4.63	2.81	1.66	13.20	3.44
B(a)P- An (A)	4.61	2.42	1.68	12.39	3.41
I(cd)P- An (O)	5.63	3.42	2.01	16.15	4.20
I(cd)P- An (A)	5.61	3.03	2.10	15.09	4.10
D(ah)A- An (O)	3.96	2.33	1.39	11.57	3.00
D(ah)A- An (A)	3.94	2.06	1.41	10.88	2.97
B(ghi)P- An (O)	4.73	2.96	1.74	13.11	3.42
B(ghi)P- An (A)	4.76	2.62	1.62	12.21	3.39
B(a)P- Ae (O)	3.12	1.28	0.54	10.94	3.14
B(a)P- Ae (A)	3.11	1.14	0.54	10.30	3.11
I(cd)P- Ae (O)	3.81	1.57	0.65	13.47	3.86
I(cd)P- Ae (A)	3.79	1.36	0.67	12.36	3.79
D(ah)A- Ae (O)	2.68	1.06	0.45	9.62	2.74
D(ah)A- Ae (A)	2.68	0.97	0.49	9.05	2.69
B(ghi)P- Ae (O)	3.18	1.35	0.56	10.90	3.16
B(ghi)P- Ae (A)	3.17	1.19	0.72	10.31	3.09

of processes occurring during wastewater treatment with aerobic granular activated sludge [19,20]. Most often, presented ANNs models focus on approximation of nitrogen, phosphorus and carbon compounds expressed as COD during wastewater treatment in batch reactors operating with activated aerobic granular sludge [21,22]. The transformation mechanism of these compounds both in anaerobic and aerobic conditions is well known. This fact is directly related to the selection of input variables to the model and the possibility of their initial narrowing without the use of additional tools [23,24]. The process of PAH modelling is additionally hindered by the fact that these compounds show different degradation mechanism under anaerobic and aerobic conditions [25], and additionally those compounds are partially subject to biosorption processes [26].

The degradation processes reflection involving microorganisms is a relatively complex process in its nature. It requires consideration of a number of factors that are not controllable and may concern only selected microorganisms [27]. In the case of activated sludge processes, mathematical description is further complicated by the fact that in the mineral-organic structure of aerobic granules, a consortium of both anaerobic and aerobic microorganisms is present, which differ in decomposition mechanism of individual HMW PAHs [28,29]. Therefore, generalized values describing the biomass behaviour in the wastewater treatment process are used for modelling. Most frequently, the papers on wastewater treatment modelling process with the use of aerobic granular activated sludge include the active sludge volume index, reactor loading with BOD or COD, sludge retention time in the chamber, active sludge growth and age of active sludge [30–32]. A similar approach was applied in the ANN models describing benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i) perylene changes in the anaerobic and aerobic phases of the GSBR reactor. Apart from activated sludge technological parameters, an important element of wastewater treatment process modelling is to take into account the technological parameters of batch reactor, in which the process is carried out. Zaghloul et al. [33] suggest that the models should take into account the duration of individual GSBR process phases, volumetric exchange coefficient and concentration of dissolved oxygen in the aeration phase. In the presented ANN models, technological parameters of the GSBR reactor were not taken into account in the input variables layer. This was due to the fact that technological parameters of GSBR reactor in conducted experiment were constant. Therefore, they are the boundary conditions of the developed ANN models.

4. Conclusions

- The developed ANN models approximated changes in benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h)anthracene and benzo(g,h,i)perylene concentration both in anaerobic and aerobic GSBR reactor phases with the accuracy exceeding 99%. The matching accuracy of individual models is also reflected in basic statistics of approximated and observed data sets, which are similar in value.
- All developed ANN models showed the highest sensitivity to benzo(a)pyrene, indeno(c,d)pyrene, dibenzo(a,h) anthracene and benzo(g,h,i)perylene concentrations at the beginning of modelled GSBR reactor process phase.
- Activated sludge technological parameters had less influence on the calculation course of ANN models. This phenomenon could be caused neither by significant influence of HMW PAHs nor increased activated sludge BOD loading rate on activated sludge technological parameters nor wastewater treatment process.

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