ANN modeling of a two-stage industrial ATAD system for the needs of energy integration

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This study proposes an approach for Artificial Neural Network (ANN) modeling of a two-stage industrial Autothermal Thermophilic Aerobic Digestion (ATAD) system for wastewater treatment which can be incorporated in an energy-saving framework operating under uncertainties. For this purpose, ANN models with different architectures are developed for bioreactors from the first and second stages of the ATAD system. Then, they are connected in a common model of the two-stage ATAD system. Models are trained and validated using one-year records of data for a real ATAD system. Three different measures are used to assess their efficiency. The best models are used to create the model of the two-stage ATAD system which is validated with selected weekly data. The designed ATAD system model is able to capture the fluctuations in the parameters of the fresh sludge incoming into the system and to predict the expected target temperatures of the treated sludge at the end of each batch. The latter makes it suitable for use in energy-saving framework under uncertainties.

Keywords: Modeling, Artificial Neural Network, Two-stage ATAD bioreactor system, Uncertainties.

INTRODUCTION

Proper management and sustainability of water resources are some of the most important and talked about issues in the global water industry today. It concerns both improving the efficiency of wastewater disposal and the reduction of energy demands. An effective way to achieve these goals is implementation of Autothermal Thermophilic Aerobic Digestion (ATAD) processes for sludge treatment in urban wastewater treatment plant (WWTP) [1].

Autothermal Thermophilic Aerobic Digestion is a relatively novel technology for treatment of municipal wastewater in small towns and resorts with a population of 20000-30000, as well as of industrial wastewater mainly from dairy, food, poultry, swine facilities, etc. The end "product" is a biological sludge applied as a soil fertilizer, Class A biosolids [2]. The process is self-heating and has the ability to kill pathogens. Other ATAD advantages are its simplicity, high reaction rate and hence smaller sizes of bioreactors. Currently, numerous ATAD facilities work worldwide mainly in the USA, Canada and in the European Union – Austria, UK, Germany, Ireland, Poland, Spain, etc.

ATAD is carried out using thermophilic aerobic microorganisms which consume the biodegradable organic components of the sludge. As a result a high degree of stabilization is achieved due to the high level of degradation of volatile solids, 38% and more. This metabolic activity generates heat and elevates the temperature of the sludge. Retention of the heat in the system leads to high level of pathogen reduction.

Conventional ATAD processes are performed in a parallel series of two batch bioreactors where the wastewater is treated at different temperatures by aeration and mixing for 20-24 hours, Figure 1.

Once per day, part of the treated sludge from the last bioreactors is discharged to "product" storage tanks. Then, the partially treated wastewater from the previous stage is transferred to the next one and the system is fed with fresh sludge from the feed tanks. The required operating temperature for the bioreactors from the first stage is about 55°C, which is optimal for bacterial growth, while for the second one it is ~65°C which is the best for pasteurization. Nevertheless, both bioreactors typically operate below these temperatures.

Systematic observations of ATAD facilities have found that after filling the first stage bioreactors with fresh sludge, a sharp temperature drop occurs, which causes a thermal shock on the thermophilic microorganisms in the bioreactors and influenced the temperature conditions at both bioreactor stages due to the inability to reach the operating temperature [3]. Overcoming the thermal shock is associated with a delay in the operational time to restore the normal operating conditions in bioreactors and leads to increased air and electricity consumption for mixing and pumping. It results in increasing the total cost of energy and materials for the process.

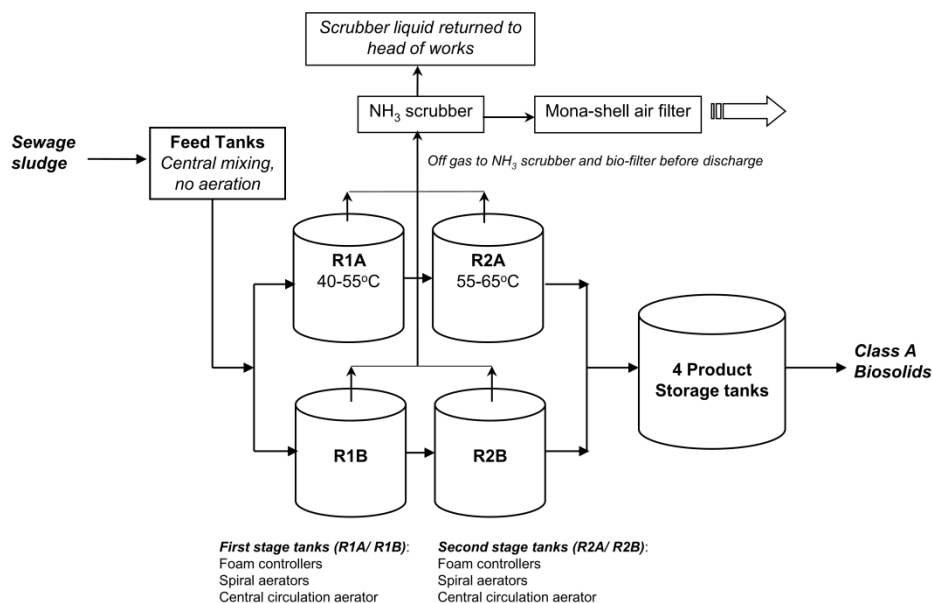* To whom all correspondence should be sent:
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Fig. 1. Configuration of a conventional two-stage ATAD facility [3].

Given the wide use of ATAD systems, a number of experimental studies have been carried out to clarify and improve the process in terms of its duration and realization capabilities. Hayes *et al.* [4] have studied the microbial ecology of sludge, identifying novel bacterial strains responsible for the efficiency of the ATAD process. Liu *et al.* [5] have investigated the changes in volatile suspended solids depending on microbial diversity, conducting series of batch experiments on sewage sludge collected from a real-scale ATAD WWTP. Layden *et al.* [6] have gathered information from a number of sources and provided an insight into the actual application and experiences with a large-scale ATAD. Piterina *et al.* [7] have determined the main characteristics of the sludge, which are responsible for its poor dewatering and settleability. Piterina *et al.* [8] have investigated the bacterial community associated with ATAD treating sludge responsible for maintaining the elevated temperature at the later stages of the ATAD process.

Taking into account that the heat production and its retention in the ATAD process play a key role for its feasibility, many researchers have analyzed the opportunities to improve ATAD systems in terms of their energy efficiency. Earlier studies on ATAD systems from energy view point are focused mainly on heat balance modeling [9, 10, 11].

The latter, Gomez *et al.* [12] have presented a more detailed energy research where biodegradation and physicochemical reactions are related to the energy exchange realized in the ATAD bioreactors. Recently, Liu *et al.* [13, 14] have investigated the effect of temperature on sludge stabilization in one-stage ATAD systems and carried out a heat balance analysis that shows that the evaporation of water and discharging sludge under thermophilic conditions are the two main sources which contribute to the loss of heat.

Mathematical modeling has been used to investigate substantial aspects of the ATAD process. Many of the developed models are based on the Activated Sludge Models (ASMs), which include mass and energy balance equations for predicting either the biodegradation transformations [12] or the physico-chemical reactions and energy exchanges occurring in the ATAD bioreactors [15]. In order to minimize the energy requirement in the ATAD bioreactors, Rojas *et al.* [16] and Rojas and Zhelev [17] have created a dynamic model of ATAD and have shown that significant energy savings can be expected by appropriate altering the operating conditions while complying with the treatment objectives.

Earlier, Layden *et al.* [6] have shown that the recovery of released heat will limit the temperature fluctuations in the first bioreactor's stage. This idea is further developed by Zhelev *et al.* [18, 19]. They have proven that the energy potential of released heat from the second bioreactor's stage is sufficient to be re-used to preheat the raw sludge incoming into the first bioreactors stage. However, the heat integration process in a real industrial WWTP is complicated by the existence of many uncertainties in the parameters of the incoming raw sludge which affect the outgoing treated sludge. Therefore, in order to capture these uncertainties and to ensure effective heat recovery for the sustainable operation

of ATAD facilities, the heat integration problem should be included within a stochastic optimization framework.

For this reason, an appropriate mathematical model of the ATAD process is needed. The model should be able to predict the incoming raw sludge parameters, which are the most important ones from the point of view of energy integration, such as the maximum operating temperatures reached at the end of batches, the corresponding reduction in volatile solids and the expected thermal shock. On the other hand, it should be simple enough to be included in an optimization framework.

However, many of the models developed in the available literature include a large number of parameters, which complicates their including in the model of energy integration of the ATAD system operating under uncertainties. Given this fact, Artificial Neural Networks (ANNs) prove to be best suited to modeling the ATAD process.

The main aim of this study is to develop an ANN model of a two-stage industrial ATAD system, suitable for use in an energy-saving framework under uncertainties. The model should be able to capture the fluctuations of incoming raw sludge parameters and to predict the expected maximal temperature and reduction of volatile solids achieved at the end of each batch, as well as the resulting thermal shock.

The rest of the study is structured as follows: Section 2 provides a description of processes conducted in a two-stage industrial ATAD bioreactor system. Section 3 is devoted to developing the ANN models of bioreactors at each stage of the system and their connection in a series resulting in the design of the ANN model of the two-stage ATAD system. The results of models' validation are also shown. Finally, brief conclusions are presented.

## *Description of processes in a two-stage ATAD bioreactor system*

The typical configuration of the ATAD facility, Figure 1, includes two sequentially connected bioreactors, called stages where the reduction of volatile solids in the sludge and the pasteurization of pathogens are carried out. Both bioreactors have the same volumes. Bioreactors R1A and R2A belong to the first series, while R1B and R2B to the second series. The temperature of the sludge in the first stage should be close to 55^0 C. The maximum

disinfection is carried out in the second stage of the series where the temperature should be about 65^0 C. The ATAD bioreactors system operates within a 20-24 hours cycle. This sets up a batch operational mode of ATAD process.

For the purpose of energy integration, the operations of charging and discharging of bioreactors in the ATAD system are very important due to the fact that the integration will take place between incoming cold and outgoing hot flows. Therefore, a detailed description of these processes can be found below.

By maintaining a constant volume of the treated wastewater in the bioreactors, every day, Q_N % from the wastewater treated discharges from the second bioreactor R2 and the first bioreactor R1 feeds with the same amount of raw sludge from feed tanks, as the opening of the ATAD bioreactors system starts from the second bioreactor (R2). The discharged from R2 batch N has a temperature equal to the maximal operating temperature (Tmax2) reached inside the second bioreactor before its opening and the ratio of the volatile solids (VS2) is equal to the one at the end of the ATAD process in R2. However, both the operating temperature and the reduction of the volatile solids reached in R2 are results of implementation of the previous batch, N-1, what follows that produced in the beginning of cycle N outgoing from R2 flow has parameters (Q_N, $Tmax2_{N-1}$, $VS2_{N-1}$). Then, Q_N % from the treated raw sludge in the first bioreactor is transferred into the second bioreactor R2.

Likewise, the operating temperature and the composition of the wastewater treated in R1 measured before its opening is $Tmax1_{N-1}$, and $VS1_{N-1}$. They also are results of implementation of the previous batch N-1 and the outgoing from R1 to R2 flow has parameters Q_N, $Tmax1_{N-1}$, $VS1_{N-1}$. The raw sludge incoming to the first bioreactor R1 has inlet temperature TAD_N, and ratio of both, total solids and volatile solids TS_N and VS_N. However, due to destroying the bioreactors' insulations in the beginning of the cycle N, incoming and outgoing flows from and to R1 and R2 and mixing the inflows with the rested there wastewater, the temperatures in the bioreactors dramatically drop to the minimum ones, named $Tmin1_N$ and $Tmin2_N$, which causes the above mentioned thermal shock on the thermophilic microorganisms and takes time to restore the required operating temperatures.
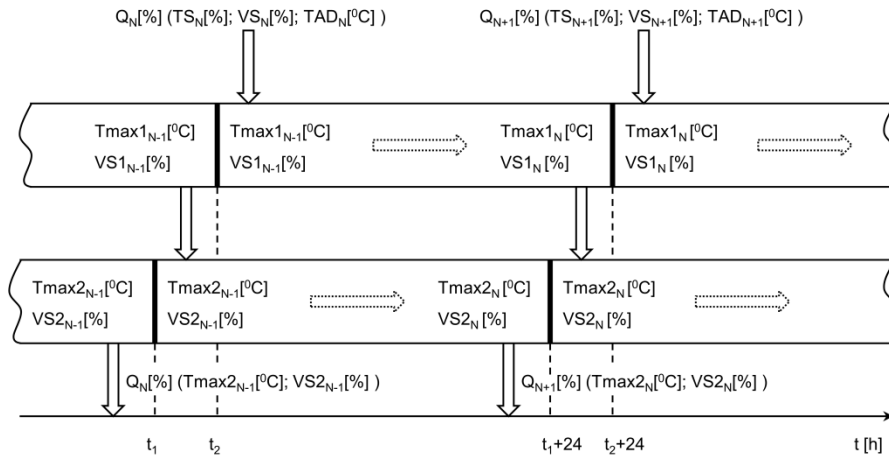
Fig. 2. Flow transfer between batches in a two-stage ATAD bioreactors system.

Then, the bioreactors are closed and isolated to conduct the ATAD process. The next day (at the end of cycle N) the bioreactors are opened and operating temperatures and the respective reduction of the volatile solids are measured which are $Tmax1_N$, and $Tmax2_N$ and $VS1_N$ and $VS2_N$, respectively. The provided brief description illustrates the interconnections in implementation of the consecutive batches that must be taken into account in modeling. It is represented in Fig.2.

Modeling of two-stage ATAD bioreactor system using artificial neural network

General Description of ANN models. Artificial Neural Networks are mathematical models inspired by the way biological neurons transmit and process information. They comprise a large number of highly interconnected artificial neurons which receive input data and process them so as to obtain output. They are applicable for modeling wide range phenomena in physics, computers science, biochemistry, mathematics, sociology, economics, telecommunications, bio-medical instrumentation and many other fields. They take into consideration only available data about the systems, developing conditional nonlinear functions based on the extraction of data.

Generally, a feed-forward ANN consists of *inputs* (like synapses through which natural neurons receive the signals from other ones), *outputs* and one or more *hidden layers* with multiple neurons in them. Connections between them are modified by *weights* (strength of the respective signals). In addition, each neuron has an extra input that is assumed to have a constant value of one. The weight that modifies this extra input is called the *bias*.

An illustration of ANN architecture, comprising several hidden layers with a different number of neurons in each one of them is shown in Fig. 3.
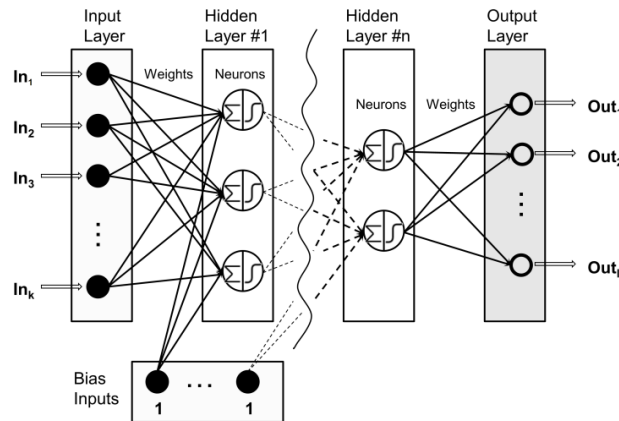
Fig. 3. Typical feed-forward ANN.

All data propagate along the connections in the direction from the network inputs to the network outputs, hence the term *feed-forward*.

Then, the neurons of hidden layers aggregate these weighted values to single values, as follows:

$$net_i = \sum_j w_{i,j} \cdot x_j + b \qquad (1)$$

$$\forall i, i \in k, \qquad \forall j, j \in In \ ,$$

where i are indices for the neurons; j are indices for the inputs; $w_{i,j}$ are the weighted coefficients of input-to-hidden connections and hidden-to-output connections; x_j are the inputs to the neurons for a given layer of the neural network; b are the bias inputs for each one of the neurons from the hidden layers;

Then, an *activation function* is applied to the aggregated weighted value to produce an individual *output* for the specific neuron (like activated natural neuron which emits a signal through the axon which might be sent to another synapse, and might activate other neurons). For the purpose of ATAD bioreactors modeling the following sigmoid function is used:

$$F(x)_i = \frac{1}{1 + e^{-a \cdot net_i}} \ , \qquad (2)$$

where a is a coefficient which determines the slope of sigmoid function. In this case $a = 2$ is used.

Using *a least-square function* (LSF) as an optimization criterion, the weights of the artificial neurons are adjusted in a way so as the required outputs for specific inputs are thus obtained to minimize the optimization criteria. For this purpose a *powerful optimization tool* should be applied. This process is called *supervising*.

Having in mind existing interconnections between the bioreactors and the batches described in Section 2, two models about the bioreactors from the first and second stages are designed. After that both models are connected creating the ANN model of the two-stage ATAD system through correct transfer of the calculated data from R1 to R2 and from batch to batch.

The performance of ANN is influenced substantially by the number of inputs and outputs for the model, as well as its architecture, i.e. the number of hidden layers and neurons in each hidden layer.

The purpose of ANN modeling of each bioreactor is to determine the expected temperature drop, maximal operating temperature reached at the end of batch and the respective reduction of volatile solids, as a function of the parameters of the flow incoming to the bioreactor. Thus, required inputs and outputs for modeling the bioreactors are selected and they are listed in Table 1.

The choice of ANN architecture is preceded by an analysis of the collected data, such as to clearly reveal the relations between inputs and outputs and to choose samplings for ANN learning and validation of designed models.

Table 1. Selected inputs and outputs for modelling.

	Bioreactor 1 (R1)		Bioreactor 2 (R2)	
	Inputs	Outputs	Inputs	Outputs
Feed amount, [%]	Q_N		Q_N	
Ratio of the total solids, [%]	TS_N		-	
Ratio of the volatile solids, [%]	VS_N		$VS1_{N-1}$	
Temperature of the feed, [˚C]	TAD_N		$Tmax1_{N-1}$	
Temperature inside the bioreactor before opening in a current day, [˚C]	$Tmax1_{N-1}$		$Tmax2_{N-1}$	
Volatile solids the next day, [%]		$VS1_N$		$VS2_N$
Temperature drop in the bioreactor, [˚C]		$Tmin1_N$		$Tmin2_N$
Temperature inside the bioreactor before opening the next day, [˚C]		$Tmax1_N$		$Tmax2_N$

Data analysis

For the purpose of ANN modeling one-year records of an industrial two-stage ATAD facility in Ireland were used. Beside the measured amounts, temperatures and compositions of the raw sludge fed in the first bioreactor, they also include records about the changes in operating conditions in both bioreactors such as temperatures drop, maximal temperatures reached after that and degradation rates of the volatile solids.

Given that charging and discharging operations in the considered ATAD system are carried out from Monday to Friday, while only temperature measurements are performed on Saturdays and Sundays, these temperature measurements are excluded from existing data sets.

By assuming a confidence interval of 95%, the upper and lower confidence limits for each set of measured data are determined:

$$\overline{X} \pm 1.96 \frac{S}{\sqrt{n}}, \qquad (3)$$

where $\overline{X}$, S and n are average, standard deviation and size of the data set under consideration. In this way, only the data contained within the defined limits are used for modeling, the remainder is excluded from further consideration due to the presence of noise.

Then, full weekly data sets (Monday through Friday) are selected for six randomly selected weeks from different seasons for simulation and validation of the two-stage ATAD model. The remaining data set is used to determine the number of samplings for training and validation of the ANN models for the first and the second bioreactors stages.

The number of samplings for training is determined on the basis of a well-known empirical rule such as they should be at least twice as high as the number of weighting coefficients. Thus, for the validation of the designed ANN models for the first and second bioreactors stages, two sets of 27 and 26 samplings were determined.

ANN architecture

The number of available data allows us to investigate two architectures for each model with one (H1) and two (H2) hidden layers, which differ in the number of neurons in each layer.

The number of neurons selected for the chosen architectures is determined based on the following empiric rule:

$$NN \approx 2 \cdot \sqrt{In \cdot Out}, \qquad (4)$$

where In is the number of inputs; Out is the number of outputs.

According to that, for the first bioreactor R1 the acceptable number of neurons is 6-9, and for the second bioreactor R2 – 5-9.

Thus, the investigated architectures ((I,H1,O) and (I,H1,H2,O)) for modeling of R1 are (5,6,3); (5,7,3); (5,5,3,3) and (5,6,3,3), while for R2 they are (4,5,3); (4,6,3); (4,7,3); (4,5,3,3) and (4,6,3,3).

Training and validation of ANN models for both bioreactors

To design ANN with different architectures, an original software code was developed in MATHCAD environment, while for their training, BASIC genetic algorithm [20] was used to obtain the values of the weighting coefficients (models'

parameters) at which the criterion LSF has a minimum value.

In order to assess the efficiency of ANN models and their ability for precise prediction three different measures to quantify the accuracy of the modeling: root mean square error (RMSE); mean absolute percentage error (MAPE); and linear correlation coefficient (R) were used.

The root mean square error (RMSE) represents the square root of the average of the summing square predicting errors and is defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - M_i)^2} \qquad (5)$$

Where P_i and M_i are calculated and measured values of Tmax; Tmin and VS, respectively, and n is the number of data samplings.

The second measure is the absolute percentage error (MAPE). It represents the percentage of the mean ratio of the error related to the measured data. MAPE is defined as:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{P_i - M_i}{M_i} \right| \cdot 100 \qquad (6)$$

The lower values for RMSE and MAPE, the more accurate the prediction is.

The linear correlation coefficient R represents a measure of the strength of the straight-line or linear relationship between measured data and data calculated by the model. The best match between measured and calculated values corresponds to $R = \pm 1$. The linear correlation coefficient R is given by:

$$R = \frac{n \cdot \left(\sum_{i=1}^{n} P_i \cdot M_i \right) - \left(\sum_{i=1}^{n} P_i \right) \cdot \left(\sum_{i=1}^{n} M_i \right)}{\sqrt{\left[\left(n \cdot \sum_{i=1}^{n} M_i^2 - \left(\sum_{i=1}^{n} M_i \right)^2 \right) \cdot \left(n \cdot \sum_{i=1}^{n} P_i^2 - \left(\sum_{i-1}^{n} P_i \right)^2 \right) \right]}} \qquad (7)$$

The trained ANN models with selected architectures were validated by using the above measures. The values of RMSE, MAPE and R for the chosen models are listed in Table 2.

Concerning the models of bioreactors from the first stage, a very good consistency between different measures of ANN performance is seen for these with the architectures (5,6,3) and (5,7,3). The RMSE and MAPE values are almost equal and the values of the correlation coefficients tend to 1, indicating a very high correlation between measured and calculated data for Tmax, Tmin and VS.

However, the situation for the models with two hidden layers is quite different. There is a big

difference between the measures for the two studied architectures. It can be seen that for the architecture (5,5,3,3) the values of RMSE, MAPE and R are closer to the same measures for the models with one hidden layer, while for the architecture (5,6,3,3) RMSE and MAPE are 3-4 times higher and R shows a weak to modest correlation for Tmax, Tmin and VS. What follows, assuming a confidence level of 95% these correlation

coefficients are compared with the critical value for R of 0.3809. It can be seen that R for VS is less than this, which means that this correlation coefficient is not significant. That is why the ANN model with the architecture (5,6,3,3) is excluded from further consideration, although R for Tmax and Tmin exceeds the critical value, they together with VS are outputs of the same model.

Table 2. Values of RMSE, MAPE and R for the considered ANN models.

ANN architectures for modeling of both bioreactors		RMSE			MAPE			R		
		Tmax	Tmin	VS	Tmax	Tmin	VS	Tmax	Tmin	VS
R1	(5,6,3)	2.072	1.242	0.144	2.757	2.046	4.019	0.972	0.987	0.953
	(5,7,3)	2.069	1.198	0.137	2.721	1.929	4.051	0.971	0.988	0.965
	(5,5,3,3)	1.728	1.334	0.355	2.202	2.268	12.77	0.976	0.972	0.753
	(5,6,3,3)	5.865	5.837	0.437	8.947	9.17	13.66	0.452	0.449	0.339
R2	(4,5,3)	1.614	0.915	0.082	2.393	1.200	2.495	0.875	0.903	0.690
	(4,6,3)	1.622	0.9186	0.0917	2.355	1.209	2.873	0.88	0.903	0.632
	(4,7,3)	1.597	0.898	0.078	2.362	1.171	2.365	0.877	0.907	0.731
	(4,5,3,3)	1.432	1.033	0.1412	2.047	1.348	4.923	0.885	0.875	0.454
	(4,6,3,3)	1.443	0.854	0.105	2.124	1.072	3.496	0.886	0.918	0.66

Note: The darkened data are excluded from further consideration.

Table 3. Values of the coefficient of determination for the second stage ANN models.

ANN architectures		$R^2.100\%$		
		Tmax	Tmin	VS
R2	(4,5,3)	76.56	81.54	47.61
	(4,6,3)	77.44	81.54	39.94
	(4,7,3)	76.91	82.26	53.43
	(4,5,3,3)	78.32	76.56	20.43
	(4,6,3,3)	78.49	84.27	43.56

Note: The darkened data are excluded from further consideration.

As far as the models for the second stage bioreactor are concerned, RMSE and MAPE have promising values. By analyzing the values of the correlation coefficients, it can be concluded that there is a large correlation between measured and calculated data for Tmax and Tmin. Whereas for VS the correlation can be assumed to be moderate to high without the model (4,5,3,3) where R for VS is 0.454. The latter is close to the critical value of 0.3882 within a confidence level of 95%. Therefore, for all models for the second stage bioreactor, the determination coefficients - R2.100% were calculated, which provides information about the percentage of the data closest to the line of best match between measured and calculated data, see Table 3. It can be seen that the coefficient of determination for VS for the model with the architecture (4,5,3,3) is very low - barely 20.43%. This is the reason, this model to be excluded from further consideration.

Figure 4 shows a comparison between the measured values for Tmax, Tmin, VS and the

calculated values obtained in the architectures (5,7,3) for R1 and (4,6,3,3) for R2.

According to that, seven models that provide a very good match between measured and calculated values were chosen as the most prospective for modeling the two-stage ATAD system. Three of them, with architectures (5,6,3), (5,7,3) and (5,5,3,3) are related to the first stage, while the rest with architectures (4,5,3), (4,6,3), (4,7,3) and (4,6,3,3) – to the second stage.

Modeling of two-stage ATAD system

In order to model the two-stage ATAD system, the selected ANN models for R1 and R2 were connected in series. The transfer of data toward and between ANN models for the first and second stage bioreactors was organized according to the description of the real system flows given in Section 2. Thus, the organized models calculate $Tmin2_N$, $Tmax2_N$ and $VS2_N$ of outgoing flow from the second bioreactor at the end of each batch N. So, 12 possible models for the two-stage ATAD system were created.

Simulation of the performance of the two-stage ATAD system was carried out based on already selected data for six-week data from different seasons. During simulation, the Tmax, Tmin, and VS of the outgoing flows were tracked in each batch from both bioreactors stages, the calculated results to be verified with the measured values.

Then, RMSE and R and also coefficients of determination - $R^2.100\%$ were calculated for Tmax, Tmin, and VS. The results for the best four models, including individual models with the following architectures R1(5,7,3)-R2(4,5,3); R1(5,7,3)-R2(4,6,3); R1(5,7,3)-R2(4,7,3) and R1(5,7,3)-R2(4,6,3,3) are summarized in Table 4.
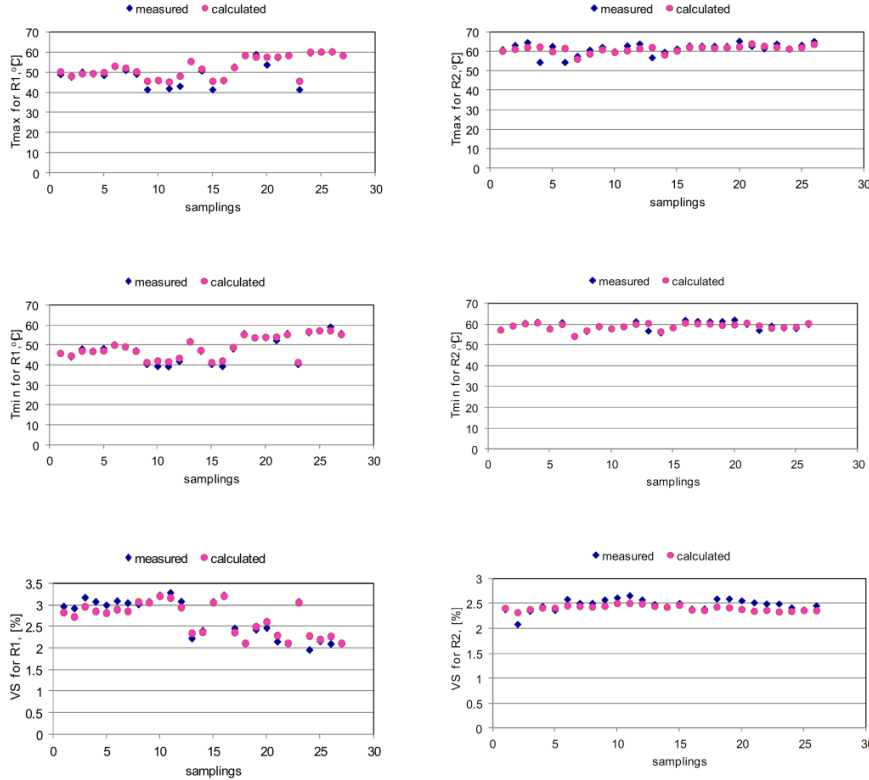

Fig. 4. Comparison between measured and calculated values for Tmax, Tmin and VS for R1 and R2.

Table 4. Values for RMSE, R and R^2 for the best ANN models of a two-stage ATAD system.

| ANN models of a two-stage ATAD system	*RMSE*			*R*			*$R^2.100\%$*		
	Tmax	Tmin	VS	Tmax	Tmin	VS	Tmax	Tmin	VS
R1 (5,7,3)	1.64	1.51	0.245	0.913	0.955	0.881	83.34	91.2	77.63
R2 (4,5,3)	2.74	2.27	0.195	0.619	0.482	0.616	38.34	23.26	38.02
R2 (4,6,3)	2.71	2.25	0.194	0.62	0.503	0.639	38.44	25.33	40.79
R2 (4,7,3)	2.17	1.91	0.192	0.639	0.534	0.656	40.79	28.57	43.06
R2 (4,6,3,3)	2.67	2.25	0.206	0.6538	0.5484	0.6526	42.75	30.07	42.57

Note: The darkened data are related to the selected ANN model R1(5,7,3)-R2(4,6,3,3).

Table 4 clearly shows the increase in RMSE values and the decrease in R values for $Tmax2_N$, $Tmin2_N$ and $VS2_N$. They go out of the created two-stage ATAD models compared to the same measures for the individual models of second stage bioreactors. The latter can be explained by the errors accumulated in the input data for the second bioreactor stage resulting from the simulation of the first stage. Correlation coefficients obtained show moderate correlations between measured and calculated data.

In this case, the coefficients of determination are an additional option to evaluate the results

calculated by the models. It can be seen that the percentage of data closest to the line of best match between measured and calculated data is the most promising for the model R1(5,7,3)-R2(4,6,3,3). This is the reason for selecting the R1(5,7,3)-R2(4,6,3,3) model for incorporation in the ATAD energy integration framework. A comparison of measured and calculated values of R1(5,7,3)-R2(4,6,3,3) for $Tmax2_N$, $Tmin2_N$ and $VS2_N$ for one winter and one summer week is shown in Figure 5.
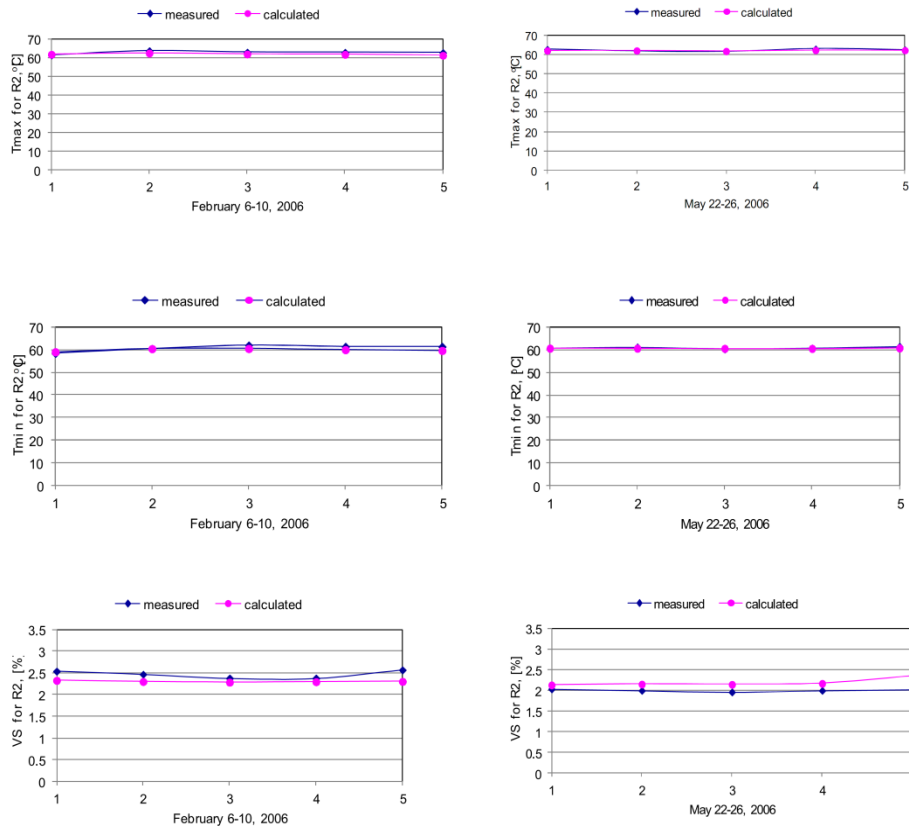
Fig. 5. Comparison between measured and calculated data by the model of two-stage ATAD system for one winter and one summer week.

CONCLUSIONS

This study presents a way to model a two-stage industrial ATAD system that can be included in an energy-saving working frame under uncertainties. Due to uncertainties in the incoming raw sludge parameters, Artificial Neural Networks are used for modeling ATAD bioreactors of each stage. Twelve different ANN architectures are investigated. One-year records of the environmental conditions and resulting operating conditions in ATAD bioreactors are used for training and validation of the ANN models. During validation of the ANN's architectures, three different measures such as root mean square error (RMSE), mean absolute percentage error (MAPE) and linear correlation coefficient (R) are used to assess their performances. The best models for the first and the second bioreactor in the ATAD system are selected based on the values obtained for the measures. Then, the selected models are connected in series by organizing the correct transfer of the calculated data between them. Thus, the constructed models of the two-stage ATAD bioreactor system are also validated with weekly data from different seasons, using the same performance measures. It was shown that there is a good consistency between the implementation measures not only for the two bioreactors models but also for the designed model of the two-stage ATAD system. The latter gives us reason to believe that the ANN model for a two-stage ATAD system is applicable to predict, with sufficient accuracy, the expected temperature drop, the maximal operating temperature reached at the end of batch and the respective reduction of volatile solids.

In future, the already developed ANN models of the two-stage ATAD bioreactors system will be included in analytical models of energy integration of the processes carried out in ATAD systems. The resulting hybrid model will be involved in an optimization framework under uncertainties.

NOTATIONS

a – coefficient determining the slope of sigmoid function (activation function);
b – bias inputs for each neuron from the hidden layers;
F – activation function representing sigmoid function;
In – number of inputs;
M – measured values of Tmax, Tmin and VS;

MAPE– mean absolute percentage error, %;

N – number of data samplings;

net – function aggregating weighted values to a single one to each neuron in the hidden layer;

NN – number of neurons;

Out – number of outputs;

P – calculated values for Tmax, Tmin and VS;

Q – feed amount, %;

R – linear correlation coefficient;

R1 – first bioreactor in the series;

R2 – second bioreactor in the series;

S – standard deviation;

TAD – temperature of the feed, ^{0}C;

Tmax – temperature inside the bioreactor before opening in a current day, ^{0}C;

Tmax1 - temperature inside the bioreactor before opening the next day in R1, ^{0}C;

Tmax2 - temperature inside the bioreactor before opening the next day in R2, ^{0}C;

Tmin1 – temperature drop in the first bioreactor, ^{0}C;

Tmin2 – temperature drop in the second bioreactor, ^{0}C;

TS – ratio of total solids in the feed, %;

VS – ratio of volatile solids in the feed, %;

VS1 – ratio of volatile solids at the end of the process in the first bioreactor, %;

VS2 – ratio of volatile solids at the end of the process in the second bioreactor, %;

w - weighting coefficients of input-to-hidden connections and hidden-to-output connections;

x – inputs to the neurons for a given layer of the neural network;

$\overline{X}$ - mean deviation.

Subscripts

i – indices for neurons;

j – indices for inputs;

N – number of batches.

REFERENCES

1. H. G. Kelly, Proceedings of the 4th European Biosolids and Organic Residuals Conference, Chartered Institution of Water and Environmental Management, Wakefield, UK, 2011, p.1.
2. US Environmental Protection Agency, Environmental Regulations and Technology, Control of Pathogens and Vector Attraction in Sewage Sludge. Under 40 CFR Part 503. EPA Report, Cincinnati, OH 45268, 2003.
3. N. M. Layden, *J. Environ. Eng. Sci.,* **6**, 19 (2007).
4. D. Hayes, L. Izzard, R. Seviour, *Syst. Appl. Microbiol.*, **34**, 127 (2011).
5. S. Liu, F. Song, N. Zhu, H. Yuan, J. Cheng, *Bioresource Technol.*, **101**, 9438 (2010).
6. N. M. Layden, H. G. Kelly, D. S. Mavinic, R. Moles, J. Bartlett, *J. Environ. Eng. Sci.*, **6**, 679 (2007).
7. A. V. Piterina, J. Bartlett, T. Pembroke, *Wat. Res.*, **45**, 3427 (2011).
8. A. V. Piterina, J. Bartlett, T. Pembroke, *Wat. Res.*, **46**, 2488 (2012).
9. R. Vismara, *Wat. Res.,* **19(4)**, 441 (1985).
10. J. R. Messenger, H. A. De Villiers, G. A. Ekama, *Wat. Sci. Technol.*, **22**, 217 (1990).
11. J. R. Messenger, H. A. De Villiers, G. A. Ekama, *Water SA,* **19**, 193 (1993).
12. J. Gomez, M. de Gracia, E. Ayesa, J. L. Garcia-Heras, *Wat. Res.*, **41**, 959 (2007).
13. S. Liu, N. Zhu, P. Ning, L. I. Li, X. Gong, *Chem. Eng. J.*, **197**, 223 (2012).
14. S. Liu, P. Ning, N. Zhu, *Fresenius Environ. Bull.*, **22**, 1913 (2013).
15. R. Kovács, Z. Csikor, F. Házi, P. Miháltz, *Wat. Environ. Res.*, **79**, 554 (2007).
16. J. Rojas, T. Zhelev, A. D. Bojarski, *Comput. Chem. Eng.,* **34**, 802 (2010).
17. J. Rojas, T. Zhelev, *Comput. Chem. Eng.,* **38**, 52 (2012).
18. T. Zhelev, N. Vaklieva-Bancheva, D. Jamniczky-Kaszás, *Computer Aided Chem. Eng.,* **25**, 1 (2008).
19. T. Zhelev, N. Vaklieva-Bancheva, J. Rojas-Hernandes, T. Pembroke, Proc. 10th Int. Symp. on Process Systems Engineering: Part A. Computer Aided Chemical Engineering, **27**, 933 (2009).
20. E. G. Shopova, N. G. Vaklieva-Bancheva, *Comput. Chem. Eng.,* **30**, 1293 (2006).

МОДЕЛИРАНЕ ПОСРЕДСТВОМ ИЗКУСТВЕНА НЕВРОННА МРЕЖА НА ДВУСТАДИЙНА ATAD СИСТЕМА ЗА НУЖДИТЕ НА ЕНЕРГИЙНАТА ИНТЕГРАЦИЯ

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(Резюме)

Предложен е подход за моделиране на двустадийна промишлена система за автотермално термофилно аеробно разграждане (ATAD) за обработка на отпадъчни води посредством изкуствена невронна мрежа (ANN), която да се включи в енергоспестяваща рамка, работеща в условията на несигурности. За целта са разработени ANN модели с различна архитектура за биореактори от първото и второто стъпало на ATAD системата, които впоследствие са свързани в общ модел на двустадийната ATAD система. Моделите са обучени и валидирани с данни за едногодишен период, получени от реална ATAD система. Използвани са три различни мерки за оценка на тяхната ефективност. Най-добрите модели са избрани за създаване на модел на двустадийната ATAD система, който е валидиран с избрани седмични данни. Създаденият модел на ATAD системата е в състояние да обхване флуктуациите на параметрите на суровата утайка, постъпваща в системата и да предскаже очакваните целеви температури на обработената утайка в края на всяка партида. Това го прави подходящ за използване в енергоспестяваща рамка, работеща в условията на несигурности.