J. Serb. Chem. Soc. 91 (0) 1–13 (2026) *Original scientific paper*
JSCS–13454 Published dd mm 2026

Modelling and optimisation of the activated sludge process using artificial neural networks and genetic algorithms

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(Received 9 July, revised 20 August 2025, accepted 18 February 2026)

Abstract: Mathematical modelling of the activated sludge process (ASP) was performed using multi-layer perceptron neural networks (MLP-ANN) to predict effluent water quality parameters and multi-objective genetic algorithm (MOGA) was employed to optimise influent water quality parameters so that the concentration of contaminants in the effluent stream is minimised. The study area selected was located in a central district of a southern state of India. The effluent parameters to be investigated and optimised are pH, suspended solids (*SS*) and biochemical oxygen demand (*BOD*) and oil and grease (*O&G*). The model was evaluated based on the statistical parameters of the correlation coefficient *R* and the mean square error (*MSE*). MATLAB R2019a was used for the modelling and optimisation study. It has been found that effluent *pH*, *SS* and *BOD* were predicted with an overall *R* of 0.9207 and an *MSE* of 0.0091. During optimisation of influent parameters, it was found that optimum values of the decision variables $\mathrm{pH}_{\mathrm{Inf}}$ lie between 6–8, optimum values of SS_{Inf} lie between 68–380, optimum values of BOD_{Inf} lie between 155–692 and optimum values of $O\&G_{\mathrm{Inf}}$ lie between 8–45 when the objective functions were minimised simultaneously.

Keywords: biochemical oxygen demand; suspended solids; pH; oil and grease; MATLAB.

INTRODUCTION

Wastewater facilities mimic the natural process of purifying water and send it back into the environment. Most human activities that use water produce wastewater. As the overall demand for water grows, the quantity of wastewater produced and its overall pollution load are continuously increasing worldwide. To address this,

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https://doi.org/10.2298/JSC250709008S

environmental regulations are in force worldwide, which seek to control the quality of wastewater discharged to the environment.

Treatment of wastewater through biological means has been found to be very promising and the activated sludge process (ASP) is one of the most preferred processes among them. It utilises microorganisms like bacteria to remove contaminants by digesting them. Mathematical models are required for better control of treatment plants so that treated effluent conforms to environmental standards. Additionally, the tuning of operating parameters can be studied more effectively, and alternate control strategies can be developed on computers without the need of actual systems.[1] Simulations of models using operating parameters lead to rapid responses in the event of unforeseen changes in processes.[2]

Artificial intelligence (AI) approaches mimic the human ability to learn and engage in rational problem-solving for better control of complex engineering systems. Artificial neural networks (ANNs) are employed to model the wastewater treatment process due to their high accuracy, the shorter time required for model development and the limited amount of data required.[3] Artificial neural networks require no explicit knowledge of the process or its parameters and develop knowledge through historical observations of input-output data. They learn from examples, and with suitable design, accurate predictions are obtained. However the limitation of an artificial neural network is that it does not extrapolate beyond the range of training data.[4]

In the activated sludge process, many variables are utilized to evaluate plant operation. These variables include biological oxygen demand (*BOD)*, chemical oxygen demand (*COD*), total suspended solids (*SS)*, pH, *etc.*[5,6] The literature surveyed in this study area has used these variables and found that modelling of sewage treatment plants using artificial neural networks is an effective tool for predicting effluent parameters.[7]

The outcome of this research was to find the best ANN model which represents the activated sludge process in terms of pH, *SS* and *BOD* prediction. The data fluctuated under different seasons and periods of the year. The study was conducted to model STP performance by using soft computing techniques of feed-forward multilayer perceptron artificial neural networks (FFMLP). The main aim was to find the best network structure of the artificial neural network for predicting effluent parameters. Finally, the optimisation of the influent parameters indicates in advance what control actions are necessary to conform to environmental discharge standards.

Artificial neural networks

Model of an artificial neuron

The human brain is a complex structure that is thought to consist of a densely interconnected network of processing units called neurons. It is depicted by the model in Fig. 1, which is referred to as an artificial neuron due to its resemblance to a biological neuron. Artificial neural networks are built on the foundation of this concept.

Hence, the total input I received by the artificial neuron is given by Eq. 1.

$$I = \sum_{1}^{n} w_i x_i + b_i \tag{1}$$

where w_1, w_2, *etc*. are the weights of the input connections, x_1, x_2, *etc*. are the inputs to the artificial neuron and b_i is the bias signal.

The sum is passed into a non-linear filter φ, also known as an activation function or transfer function, to produce the final output, which is given by Eq. 2.

$$Y = \varphi(I) \tag{2}$$

Non-linear statistical data modelling techniques, such as neural networks, are used to identify patterns in data or to represent intricate interactions between inputs and outputs. An ANN is often an adaptive system that modifies its architecture in response to internal or external data passing through the network while it is learning. Put another way, the network learns by experience, and the connections among its components record the knowledge that it gains.[8]

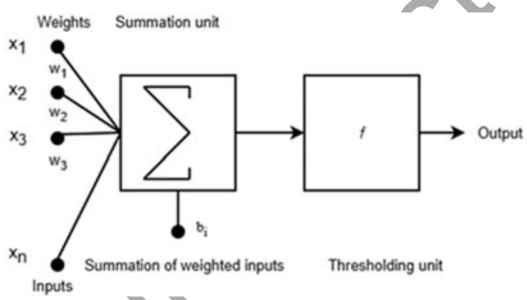

Fig. 1. Model of artificial neuron.

A neural network is made up of layers of neurons with connection weights between them. These layers are called the input layer, hidden layers and the output layer, and the weights between them are called the input-hidden layer weights and the hidden-output layer weights. The network's weights are changed throughout training until it responds within the necessary accuracy limits.[9]

Multi-objective genetic algorithm (MOGA)

In single objective function optimisation, we find the best solution, which is usually the global minimum (or maximum). However, most real-world problems involve the simultaneous optimisation of multiple objective functions. In multiple objective function optimisation, there may not be a solution that is the best (global optimum) with respect to all objectives. Instead, there could exist a complete set of optimal solutions that are equally good, called pareto-optimal solutions. A pareto set, for example, for a two-objective function problem, is described by a set of points such that when one moves from one point to any other, one objective function improves, while the other worsens. Since none of the non-dominated solutions in the Pareto set is superior to any other, any one of them is an acceptable solution. The Pareto front is a set of non-dominated solutions that are equally optimal.

A multi-objective genetic algorithm involves a system whereby an individual's rank corresponds to the number of individuals within the current population by which it is dominated. For the non-dominated solutions, it preserves diversity. Rank--based population sorting is the first phase in a multi-objective genetic algorithm, or MOGA. The individuals who have the highest level of fitness are ranked 1. A rank of 1 is given to every non-dominated individual. A linear function is used to determine an individual's fitness level. Srinivas & Deb (1994) proposed a modified version of the MOGA algorithm, called the non-dominated sorting genetic algorithm (NSGA).[10] All non-dominated individuals are classified into one category. Subsequently, the categorized individuals are eliminated from the population, and a new layer of non-dominated individuals are taken into account. This procedure keeps going until every member of the population has been classified. The people in the first front will receive more copies than the other people since they have the highest fitness value. This eventually leads to convergence and makes it possible to look for non-dominated regions. In this study, NSGA was used to find the pareto front.

EXPERIMENTAL

Description of the study area

The sewage treatment plant is located in a central district of Kerala, India. It commenced its operation in 1970 and has a capacity to treat 5 MLD of water.

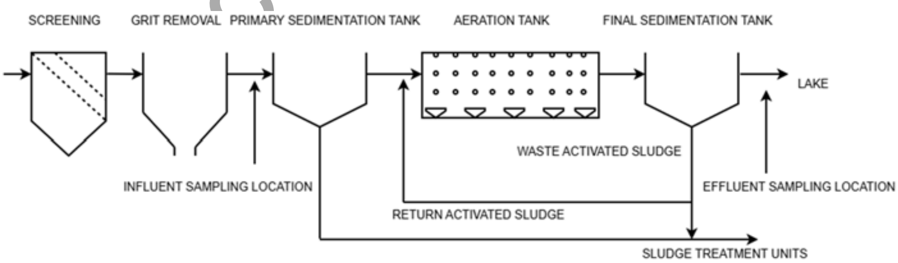

Fig. 2. Schematic of the sewage treatment plant.

The adjacent river receives the process's effluent discharge. The treatment plant uses the activated sludge process, as seen in Fig. 2. It consists of a screen and grit chamber where grit and large particles are removed. After that, the wastewater enters the primary sedimentation tank, which filters out oil, grease, and other impurities and provides a uniform liquid for second-dary treatment. The organic matter present in the sewage can be effectively removed by secondary treatment.

An aeration tank and a final sedimentation tank make up the secondary treatment facility, to which the flow next proceeds. To aid waste digestion, diffusers supply oxygen to the mixture of primary wastewater and activated sludge in the aeration tank. After being separated from the treated water in the final settling tank, part of the sludge is transferred to sludge treatment and disposal, while the remaining part is returned to the aeration tank. After treatment, the water is released into a neighbouring lake. Low *BOD*, low nutrients, low suspended particles and low turbidity are the outcomes of the treatment process.

Data collection and analytical methods

Data pertaining to the sewage treatment plant, collected over a 13-year period, from October 2008 to January 2022, were collected. There were sufficient variations in the influent parameters over the extended period of time. The location after the grit chamber was used to collect the influent parameter data, and the location after the final settling tank was used to collect the effluent data. The parameters were selected according to the rules and regulations in force in the sewage treatment plant. According to the regulations in force in India, it has been specified that for STPs, parameters considered are pH, *BOD*, *SS* and faecal coliform. Of these, effluent pH, *BOD* and *SS* were measured in the plant and were included in the modelling study.

The inputs were $\mathrm{pH}_{\mathrm{Inf}}$, oil and grease ($O\&G_{\mathrm{Inf}}$) suspended solids ($SS_{\mathrm{Inf}}$) and biochemical oxygen demand (BOD_{Inf}). The output parameters modelled and simulated in this study were $\mathrm{pH}_{\mathrm{Eff}}$, suspended solids ($SS_{\mathrm{Eff}}$) *and* biochemical oxygen demand (BOD_{Inf}). All parameters were measured according to IS 3025, and a total of 113 data points were collected for this study.[11]

Further data normalising was done according to Eq. 3:

$$Y_{\mathrm{Norm}} = (Y - Y_{\mathrm{Min}}) / (Y_{\mathrm{Max}} - Y_{\mathrm{Min}}) \tag{3}$$

where Y is the variable studied, Y_{Max} is the maximum value of the variable, Y_{Min} is the minimum value of the variable and Y_{Norm} is the normalised value of the variable.

TABLE I. Statistical indices of the parameters; $\mathrm{pH}_{\mathrm{Inf}}$ – pH influent; SS_{Inf} – Suspended solids influent; BOD_{Inf} – Biochemical oxygen demand influent; $O\&G_{\mathrm{Inf}}$ – Oil and Grease influent; $\mathrm{pH}_{\mathrm{Eff}}$ – pH effluent; SS_{Eff} – suspended solids effluent; BOD_{Eff} – biochemical oxygen demand effluent; $O\&G_{\mathrm{Eff}}$ – oil and grease effluent; Y_{Max} – maximum value of the variable Y; Y_{Min} – minimum value of the variable Y; Y_{Mean} – mean value of the variable Y; C_V – variance; Sd – standard deviation; Med – Median; Z – Mode; Sk – Skewness

	pH_{Inf}	SS_{Inf} / $\mathrm{mgL^{-1}}$	BOD_{Inf} / $\mathrm{mgL^{-1}}$	$O\&G_{\mathrm{Inf}}$ / $\mathrm{mgL^{-1}}$	pH_{Eff}	SS_{Eff} / $\mathrm{mgL^{-1}}$	BOD_{Eff} / $\mathrm{mgL^{-1}}$	$O\&G_{\mathrm{Eff}}$ / $\mathrm{mgL^{-1}}$
Y_{Max}	6.6	624	937	56	8.2	139	79	8.4
Y_{Min}	5.1	16	42.6	0.8	5.8	4	5.6	0
Sum	801.1	14757	38070	1330	803.9	4457	2344	216.3
Y_{Mean}	7.089	130.59	336.9	11.77	7.11	39.44	20.74	1.91
C_v	31.79	7586	1E+05	85.96	0.24	2067	437.9	360.5
Sd	5.63	87.1	317.1	9.27	0.49	45.46	20.93	18.98
Med	6.58	139	224	9.6	7.15	30	18	1.5
Z	5.9	68	80	6.4	7.2	16	22	0.8
Sk	–0.049	2.024	0.899	2.357	0.504	1.434	3.026	2.513

ANN Modelling strategy

ANN software

Neural network modelling and simulation were carried out using MATLAB 9.6 software (Version–R2019a, MathWorks, Inc., USA). The data were split in the ratio 60:20:20, with 60% going toward training, 20% going toward validation and 20% going toward testing. The application of multilayer perception ANNs (MLP-ANNs) was justified by their ease of coding and simplicity.

ANN training

The available data were divided into three parts. The training set is the first component, and it is used to update the network's weights and biases by calculating the difference between the expected and actual outputs. The validation set, which is the second component, determines when neural network training should end. During training, the training error and validation error are calculated, and it is typically seen that both errors first start to reduce. Nevertheless, training is halted when validation error increases and the network overfit. The network parameters corresponding to the minimum validation error are fixed, and the optimum number of neurons in the hidden layer are returned. The third part of the data is called the testing data tests how the model generalises to new data. Ideally the testing error should be minimal. Overfitting issues can be avoided when there are fewer hidden layer neurons and, thus, fewer network parameters than training data points.[12]

A multi-output model of effluent parameters was implemented for the optimisation study as the entire plant is to be optimised with the three effluent parameters pH, *SS* and *BOD* simultaneously. Also, one hidden layer has been shown to be to be a universal approximator.[13]

The Levenberg-Marquardt backpropagation algorithm was employed by the ANN network to train its single hidden layer.[13] The backpropagation algorithm adjusts the connection weights and biases by returning the error generated by the neural networks. The Levenberg-Marquardt (LM) back-propagation training algorithm is employed in the current study since it is the fastest and converges most quickly.[14] The learning rate parameter, which keeps the network from being stuck in a local minimum instead of a global minimum, is set at 0.01. A trial-and-error procedure was employed to determine the optimal trained model.

ANN training for predicting *BOD*, *SS* and pH is shown in Fig. 3. Eq. 4 for the hyperbolic tangent function is utilised in the hidden layer, while Eq. 5 for the linear activation function is employed in the output layer.[15]

$$f(x) = \frac{2}{1+\mathrm{e}^{-2x}} - 1 \tag{4}$$

$$f(x) = x \tag{5}$$

Multi objective optimisation

MOO Software

The MATLAB 9.6 (Version–R2019a) program was utilised to carry out the multi objective optimisation using artificial neural networks, which were then utilised to simultaneously optimise pH, *SS* and *BOD* in the effluent stream.

Initialization

The first step in the algorithm was the creation of an initial population. The algorithm creates the population, or an initial of partial initial population can be provided using the Initial population matrix option. The number of individuals in the population was set according to the value of the PopulationSize option. The algorithm evaluates the objective function and constraints for the population, and uses those values to create scores for the population. A snapshot of the Rank histogram, which shows the distribution of individuals in each pareto tier is shown in Fig. 4.

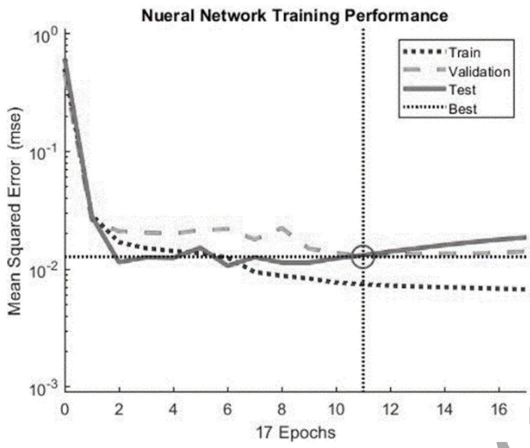

Fig. 3. ANN training.

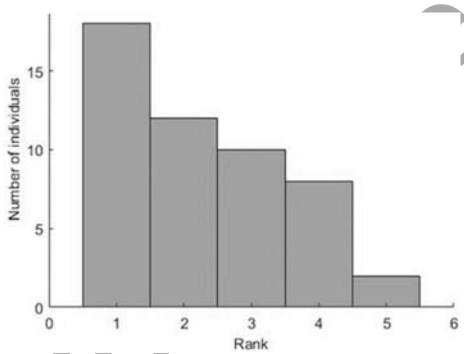

Fig. 4. Rank histogram.

Iterations

The main iteration of the gamultiobj algorithm proceeded as follows.

Select parents for the next generation using the selection function on the current population. The only built-in selection function available for gamultiobj is the binary tournament.

Create children by mutation and crossover from the selected parents.

By calculating their objective function values, children were scored.

The extended population was generated by combining the current population and the children into one matrix.

Rank and crowding distance were calculated for all individuals in the extended population.

By retaining the appropriate number of individuals of each rank, the extended population was reduced to have Population size individuals.

Stopping conditions

The algorithm was terminated when any of the specified termination criteria were met, such as when the maximum number of generations was exceeded or time limit was exceeded.

Effluent regulations

In order to meet the regulatory standards for sewage treatment plants in India, the effluent stream's pH concentration should be between 6.5 and 9, its *SS* concentration should be less than 100 mg L^{-1}, and its *BOD* concentration should be less than 30 mg L^{-1}.

Decision variables for optimisation

The decision variables associated with the process are the influent variables pH, *SS*, *BOD* and *O&G* which were optimised. This study minimised the concentration of pH, *SS* and *BOD* in the effluent and satisfied the regulations on the effluent stream. All the three pollutants are simultaneously minimised.

MOO modelling strategy

The four-input model of pH, *SS*, *BOD* and *O&G* was used to predict the three outputs pH, *SS* and *BOD* simultaneously. The neural network structure is shown in Fig. 5.

Optimisation strategy

This study's goal was to minimize the effluent stream's pH, *SS*, and *BOD* concentrations while meeting all applicable regulations. The pH, *SS*, *BOD* and *O&G* of the influent stream were the process's decision variables.

The fitness function or objective function consisted of the optimised neural network outputs of pH, *SS*, and *BOD*.[16] After entering the variable's upper and lower bounds from Table II, optimisation was initiated. The limits that the regulatory organisations have placed on the effluent quality are the constraints to be fulfilled. To comply with the regulations, the concentration of pH in the effluent stream should be between 6.5 and 9, the concentration of *SS* in the effluent stream should be below 100 mg L^{-1}, the concentration of *BOD* in the effluent stream should be below 30 mg L^{-1} and the concentration of the pollutants should not be negative. Therefore, the concentration of all four pollutants should be greater than zero.

A penalty term of 134 was added to *SS* and 38 to *BOD* so that the effluent pH, *SS* and *BOD* (objective functions) are all greater than zero.[17] If this is not done objective function values would yield negative values for *SS* and *BOD*. The output from the software was the optimum influent values of the decision variables pH, SS, *BOD* and *O&G* of the influent stream.

The lower and upper bound values of the decision variables are shown below.

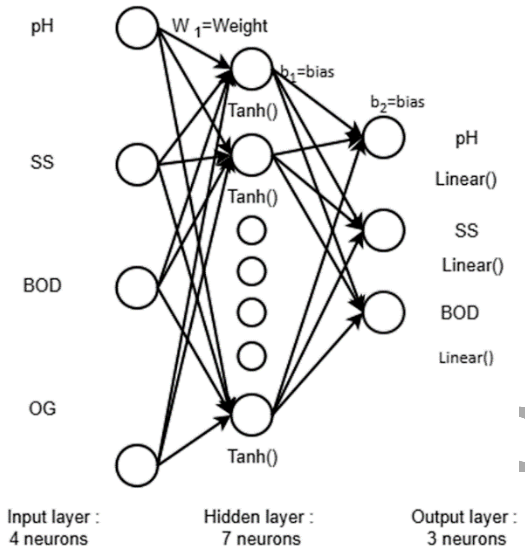

Fig. 5. Neural network for predicting pH, *SS* and *BOD*.

TABLE II. Bounds of the variables; pH_{Inf} – pH influent; SS_{Inf} – Suspended solids influent; BOD_{Inf} – Biochemical oxygen demand influent; $O\&G_{Inf}$ – Oil and Grease influent

Decision variable	Lower bound	Upper bound
pH_{Inf}	5.1	8.3
SS_{Inf} / mgL^{-1}	16	624
BOD_{Inf} / mgL^{-1}	42.6	977
$O\&G_{Inf}$ / mgL^{-1}	0.8	56

RESULTS AND DISCUSSION

Analysis of ANN modelling Results.

ANN modelling performed well for predicting pH, *SS* and *BOD*. Therefore, the four input model of pH, *SS*, *BOD* and *O&G* was used to predict the three outputs pH, *SS* and *BOD*. The neural network was trained and the network with seven hidden-layer neurons was found to give a correlation coefficient of 0.9207 and an MSE of 0.0091, with a training regression of 0.9371, a validation regression of 0.8932, a testing regression of 0.8644 and training MSE of 0.0074, validation MSE of 0.0128 and testing MSE of 0.0131. The regression plots are shown in Fig. S1. Literature surveyed on the application of ANN for modelling WWTPs found that the ANN could predict the plant performance in terms of BOD, COD and SS together with a correlation coefficient of 0.903.[6]

MOO Results and Discussion

Pareto front

The three-objective pareto front of pH, *SS* and *BOD* effluents were plotted as shown in Fig. S2. Also, two-objective pareto fronts of pH_{Eff} and SS_{Eff}, SS_{Eff} and BOD_{Eff}, and BOD_{Eff} and pH_{Eff} were plotted in Figs. S3-5 respectively. It was found that after the 102^{nd} iteration, there was no further improvement in the front.

Plot of decision variables and pH_{Eff}, SS_{Eff} *and* BOD_{Eff}.

The optimum values of the decision variables obtained are given in Table III. The optimum influent variables pH, *SS*, *BOD* and *O&G* were determined by employing genetic algorithms resulting in 18 (50*0.35) decision variables as the population size was 50 and the pareto front population fraction was 0.35. The optimum values of the four decision variables are plotted against pH_{Eff} SS_{Eff} and $BOD_{Eff.}$ to show the relationship between the variables.[16]

When the decision variables are plotted against pH_{Eff} it was observed that the optimum values of pH_{Inf} varied from 6–8 which were closer to the upper bound values, optimum values of SS_{Inf} varied from 68–380 mg L^{-1}, which were closer to the upper bound values. The optimum values of BOD_{Inf} varied from 155–692 mg L^{-1} and optimum values of $O\&G_{Inf}$ varied from 8–45 mg L^{-1}. Figs. S6–9 show the variation of decision variables with pH_{Eff}.

When the decision variables are plotted against $SS_{Eff.}$, the optimised values of the influent parameters were predominantly concentrated near their respective upper bounds. Specifically, the optimal pH_{Inf} ranged between 6 and 8 and SS_{Inf} ranged from 68 to 380 mg L^{-1}, while BOD_{Inf} varied between 155 and 692 mg L^{-1}, and $O\&G_{Inf}$ ranged from 8 to 45 mgL^{-1}. Figs. S10–13 show the variation of decision variables with SS_{Eff}.

When the four-decision variables are plotted against BOD_{Eff}, the optimised influent parameter values were found to cluster predominantly near the upper limits of their respective ranges in the case of pH_{Inf} where it ranged between 6 and 8 and SS_{Inf} where it ranged from 68 to 380 mg L^{-1}. BOD_{Inf} lied between 155 and 692 mg L^{-1}, and $O\&G_{Inf}$ values varied from 8 to 45 mg L^{-1}. Figs. S14–17 show the variation of decision variables with BOD_{Eff}.

From the literature surveyed, it was found that the optimal values of *pH* inf ranged between 7.8–8.1, the optimal values of BOD_{Inf} varied between 175–475 mg L^{-1}, the optimal values of *SS* Inf lay close to 850 mg L^{-1} when *BOD*, *SS* and total phosphorous *TP* were minimised simultaneously.[16]

TABLE III. Optimum values of the decision variables. pH_{Inf} – pH influent; SS_{Inf} – suspended solids influent; BOD_{Inf} – biochemical oxygen demand influent; $O\&G_{Inf}$ – oil and grease influent

pH_{Inf}	SS_{Inf} / mgL^{-1}	BOD_{Inf} / mgL^{-1}	$O\&G_{Inf}$ / mgL^{-1}
6.0109	73.5756	244.8432	16.6149
6.6443	265.7488	692.2355	7.9727
8.0089	379.6842	263.4342	18.3982
6.6822	256.6529	683.3599	9.2286

5.7030	158.3825	680.4012	10.4858
6.5795	167.5787	674.3457	10.2858
7.0111	81.5747	217.7412	15.9524
6.6225	185.6128	680.6632	9.9630
5.9477	252.6379	683.367	9.4305
6.7325	217.2645	209.909	13.6525
6.2953	77.8575	202.5866	18.8731
6.8540	334.2789	294.5785	18.0587
6.3737	67.4801	155.2362	45.4133
6.6313	205.9524	206.6183	16.0169
7.8411	353.9885	245.7956	17.1385
6.8289	285.1475	543.4304	10.0868
6.3881	67.5123	155.1961	45.3586
6.0075	173.3748	598.5686	11.3049

CONCLUSIONS

Artificial neural networks were found to model the complex nonlinear process occurring in sewage treatment plants. The model developed in the research work was found to predict effluent pH, *SS* and *BOD* with a correlation coefficient value of 0.9207.

Multi-objective optimisation was proposed to minimise the concentration of pollutants pH, *SS* and *BOD* in the effluent stream in the STP. A genetic algorithm was employed to minimise the concentration of pH, *SS* and *BOD* simultaneously in the effluent stream.

The goal of this research work was to find the optimum values of the decision variables that satisfy the objectives and constraints. The decision variables involved in this process are the pH, *SS*, *BOD* and *O&G* in the influent stream. The constraints imposed are in accordance with the regulatory requirements for the effluent quality of treated wastewater. It was observed that optimum values of the decision variables pH_{Inf} lay between 6–8, the optimum values of SS_{Inf} lay between 68–380 mg L^{-1}, the optimum values of BOD_{Inf} lay between 155–692 mg L^{-1} and the optimum values of $O\&G_{Inf}$ lay between 8–45 mg L^{-1}, when all the effluent concentrations are minimised simultaneously.

SUPPLEMENTARY MATERIAL

Additional data are available electronically at the pages of journal website: https://www.shd-pub.org.rs/index.php/JSCS/article/view/13454, or from the corresponding author on request.

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SAURABH SAHADEV[1], GUPTA MADHU[2] ¦ ROY M. THOMAS[2]

[1]Ddb'qsl dmsneBgdl hb'kEmfhmddqhmf, Gnudqml dmsEmfhmddqhmf Bnkkdfd, Tgqhrrtq, Jdq'k', Hmch' ¦ [2]Sbgnnkne Emfhmddqhmf, Bnbghm Umhudqrhsx neSbhdmbd 'mc Tdbgmnknfx, Jnbgh, Jdq'k', Hmch'

œ ½µÐý ½µ¦ÑþÇ ý ÇíÐÃÇú½" Ð ñðÇõÐÅ½ ½þµ¦úÁÇé ý Ù, ½ÅñðÇúÐíÐÁÇ Ð þÇð¦Ú »Ð" Ðý ú¦Ú Ð-ÅÃÇ Á¦Š ñÐðõÐñµðÇÁÅþ¦Š ÁÐÙðÇÁÅþ¦Š ý ðÐî ½ Ù õ¦, Ù ñðÐíú¦›½" ½ ñ½ð½ý Ðµ½ð½ þú½Ã¦µÐµ½ ¦®Ã½®ÁÐ úÇíÐ, íÇþ Ðú¦Ú Ðõ¦, Á¦ éÐÁÐµÅþ¦ ½ÃéÇð¦µ½ý ñð¦ý Ð" ÐÁ ®½Çñµ¦ý ¦®½õ¦ Ùñ½ð½ý Ðµ½ð½ ÙÃ½®ÁÐ úÇíÐ þ½þÇ õ¦ ÅÐ ý ¦Á¦ý ¦®Çú½Ã½ þÇÁõÐÁµð½õ¦ ½ ®½é½›ÙÙ»¦Š ý ½µÐð¦ ½ Ù ¦®Ã½®ÁÇý µÇþÙ. œ ½µÐý ½µ¦ÑþÇ ý ÇíÐÃÇú½" Ð Ð ¦®úðÚ ÐÁÇ þÇð¦Ú »Ð" Ðý ñÇí½µ½þ½ ñÇÅµðÇ Ð" ½ ®½ ñðÐÑ¦- Ú »½ú½" Ð Çµñ½íÁ¦Š úÇí½ ¦® õÐÁµð½ÃÁÇé ÇþðÙé½ Ùî ÁÐ Å½úÐ®ÁÐ íðî ½úÐ ı Áí¦ Ð. ı Åñ¦µ¦ú½Á¦ ñ½ð½ý Ðµð¦ ¦®Ã½®ÁÐ úÇíÐ ÅÙ oH úðÐíÁÇÅµ, þÇÁõÐÁµð½õ¦ ½ ÅÙÅñÐÁíÇú½Á¦Š ý ½µÐð¦ ½ ¦ õ¦ÇŠÐ-ý ¦ Åþ½ ñÇµðÇÚ " ½þ¦ÅÐÇÁ¦þ½, íÇþ ÅÙ ñ½ð½ý Ðµð¦ ÙÃ½®ÁÐ úÇíÐ þÇ˘¦ ÅÐ Çñµ¦ý ¦®ÙÙ oH úðÐíÁÇÅµ, þÇÁõÐÁµð½õ¦ ½ ÅÙÅñÐÁíÇú½Á¦Š ý ½µÐð¦ ½, õ¦ÇŠÐý ¦ Åþ½ ñÇµðÇÚ " ½þ¦ÅÐÇÁ¦þ½ ¦ Å½íðî ½˘Ù, ½ ¦ ý ½Åµ¦. œ ÇíÐÃ Ð Ðú½ÃÙ¦ð½Á Á½ ÇÅÁÇúÙ Åµ¼µ¦Åµ¦Ñþ¦Š ñ½ð½ý Ðµ½ð½ þÇÐÈ ¦õ¦ ÐÁµ½ þÇðÐ-Ã½õ¦ Ð ¦ ÅðÐí" Ð þú½íð½µÁÐ éðÐÚ þÐ. æ½ ý ÇíÐÃÇú½" Ð ¦ Çñµ¦ý ¦®½õ¦ Ù þÇð¦Ú »ÐÁ Ð œ —Öø—Æ °2019½. öµúð›ÐÁÇ Ð í½ ÅÙ oH, þÇÁõÐÁµð½õ¦ ½ ÅÙÅñÐÁíÇú½Á¦Š ý ½µÐð¦ ½ ¦ õ¦ÇŠÐý ¦ Åþ½ ñÇµðÇÚ " ½þ¦ÅÐÇÁ¦þ½ ¦®Ã½®ÁÐ úÇíÐ ñðÐíú¦›ÐÁ¦ Å½ÙþÙñÁ¦ý þÇÐÈ ¦õ¦ ÐÁµÇý þÇðÐÃ½õ¦ Ð Çí 0,9207 ¦ ÅðÐí" Çý þú½íð½µÁÇý éðÐÚ þÇý Çí 0,0091. ÖÇþÇý Çñµ¦ý ¦®½õ¦ Ð ñ½ð½ý Ðµ½ð½ ÙÃ½®ÁÐ úÇíÐ ÙÅµ½ÁÇú, ÐÁÇ Ð í½ ÅÐ Çñµ¦ý ½ÃÁÐ úðÐíÁÇÅµ¦ ñðÇý ÐÁ, ¦ú¦Š þðÐ»Ù Ù ÇñÅÐéÙ: oH 6·8, þÇÁõÐÁµð½õ¦ ½ ÅÙÅñÐÁíÇú½Á¦Š ý ½µÐð¦ ½ 68·380 l fL^{-1}, õ¦ÇŠÐý ¦ Åþ½ ñÇµðÇÚ " ½þ¦ÅÐÇÁ¦þ½ 155·692 l fL^{-1}, Å½íðî ½˘Ù, ½ ¦ ý ½Åµ¦ 8·45 l fL^{-1}, Ù ÅÃÙÑ½Ù ¦ÅµÇúðÐý ÐÁÇé ý ¦Á¦ý ¦®Çú½" ½ ÈÙÁþõ¦ ½õ¦, ½.

(–ð¦ý, ÐÁÇ 9. ÙÃ½, ðÐú¦í¦ð½ÁÇ 20. ½úéÙÅµ½ 2025, ñð¦Šú½»ÐÁÇ 18. È ÐÕðÙ½ð½ 2026)

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Journal of the Serbian Chemical Society
JSCS@tmf.bg.ac.rs • www.shd.org.rs/JSCS
J. Serb. Chem. Soc. 91 (0) S1–S4 (2026) *Supplementary material*

SUPPLEMENTARY MATERIAL TO

Modelling and optimisation of activated sludge process using artificial neural networks and genetic algorithms

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J. Serb. Chem. Soc. 91 (0) (2026) 000–000

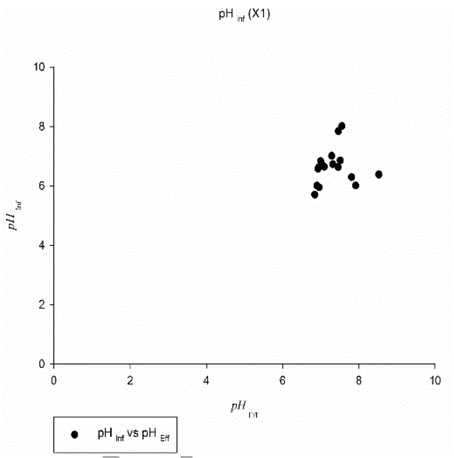

Fig. S1. Relationship between pH_{Inf} and pH_{Eff}

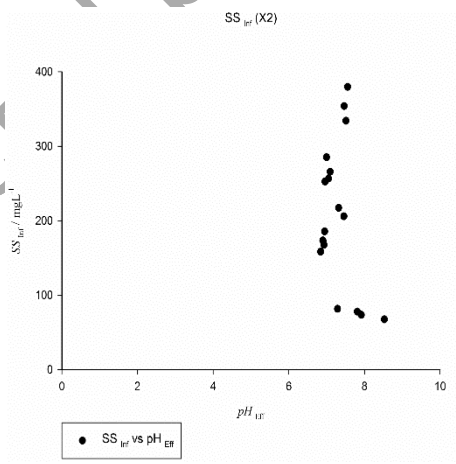

Fig. S2. Relationship between SS_{Inf} and pH_{Eff}

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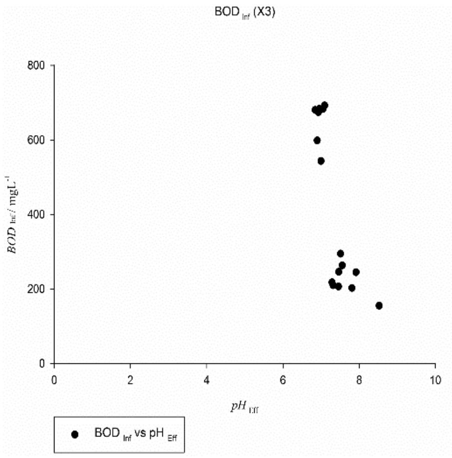

Fig. S3. Relationship between *BOD*Inf and *pH*Eff

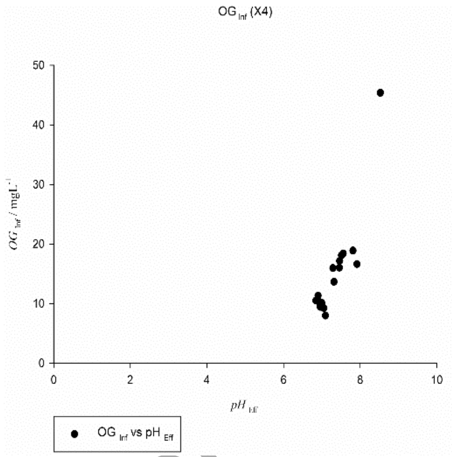

Fig. S4. Relationship between *O&G*Inf and *pH*Eff

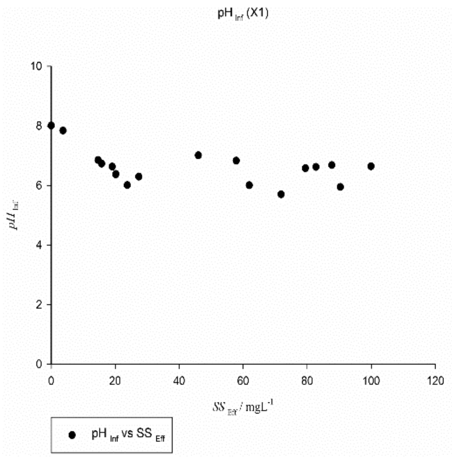

Fig. S5. Relationship between *pH*Inf and *SS*Eff

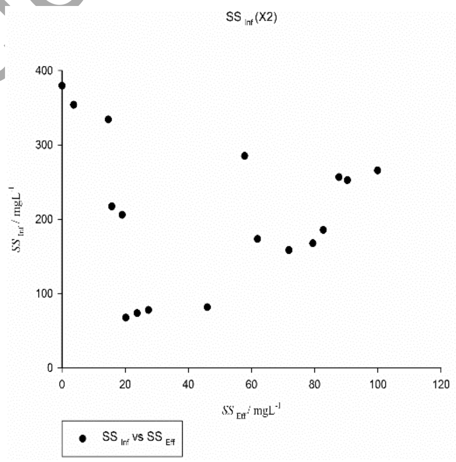

Fig. S6. Relationship between *SS*Inf and *SS*Eff

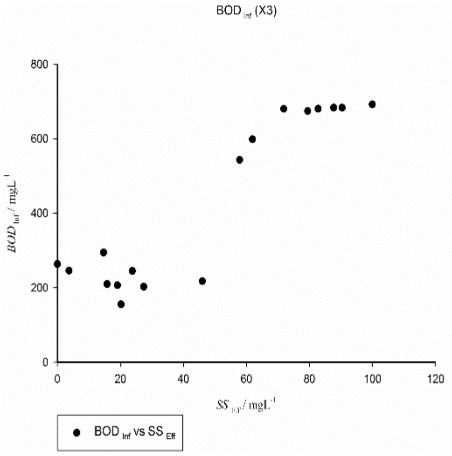

Fig. S7. Relationship between BOD_{Inf} and SS_{Eff}

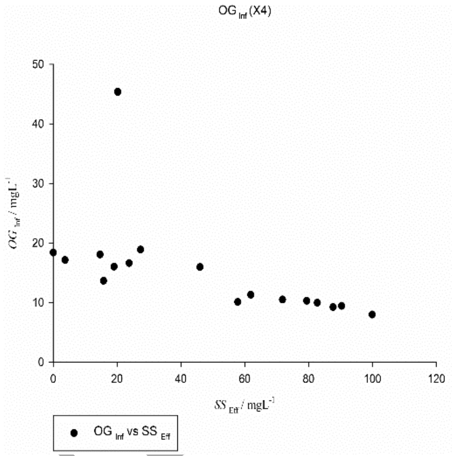

Fig. S8. Relationship between $O\&G_{Inf}$ and SS_{Eff}

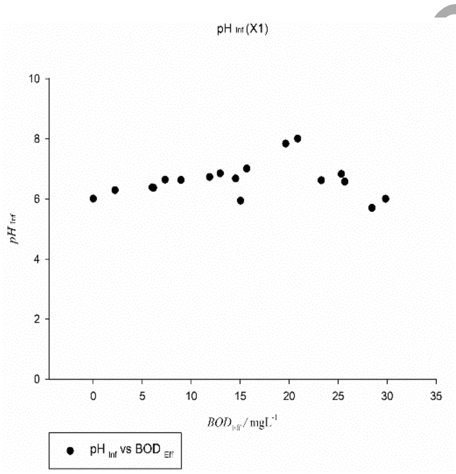

Fig. S9. Relationship between pH_{Inf} and BOD_{Eff}

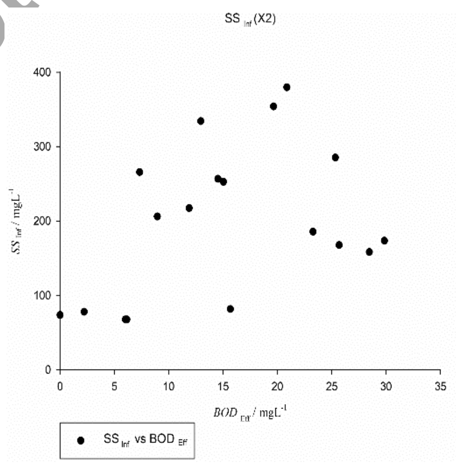

Fig. S10. Relationship between SS_{Inf} and BOD_{Eff}

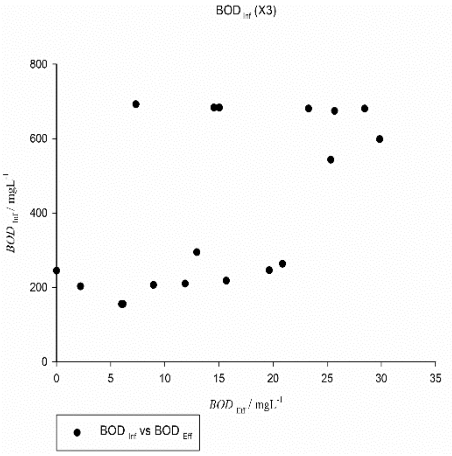

Fig. S11. Relationship between *BOD*Inf and *BOD*Eff

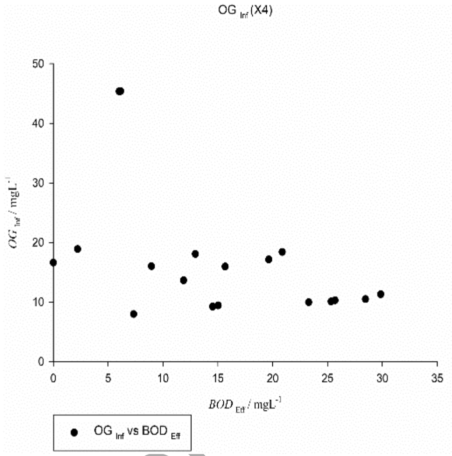

Fig. S12. Relationship between *O&G* Inf and *BOD*Eff