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

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

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Treatment of waste water through biological means has been found very promising and activated sludge process (ASP) is one of the most preferred processes among them. It utilizes 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. Also 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 human ability of learning and rational problem solving for better control of complex engineering systems. Artificial neural networks (ANN) are employed to model wastewater treatment process due to high accuracy, less time for model development and limited amount of data required.[3] Artificial neural networks require no explicit knowledge of process and parameters and develop knowledge through historical observations of input output data. They learn by examples and with suitable design accurate predictions are obtained. However the limitation of artificial neural network is that they do not compute outside the range of training data.[4]

In 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] Literature surveyed done in this study area have used these variables and found that modeling of sewage treatment plants using artificial neural networks are effective tools in predicting effluent parameters.[7]

The outcome of this research was to find the best ANN model which represents the activated sludge process in term of *pH, SS* and *BOD* prediction. The data collected were fluctuating under different seasons and periods of a 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 tells us beforehand what control actions are necessary to conform to environment 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 Equation 1.

$$I = \sum_1^n w_i x_i + b_i \tag{1}$$

where w_1 , w_2 etc are the weights to 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 nonlinear filter φ, also known as an activation function or transfer function, to produce the final output, which is given by Equation 2.

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

Non-linear statistical data modelling techniques like 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]

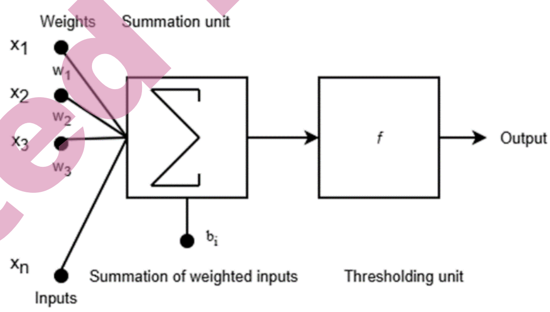

Fig. 1. Model of artificial neuron.

A neural network is made up of layers of neurons with connection weights between them. These layers are called input layer, hidden layers and output layer and the weight between them are called input-hidden layer weights and 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 optimization, we find the best solution, which is usually the global minimum (or maximum). However, most real-world problems involve the simultaneous optimization of multiple objective functions. In multiple objective function optimization, there may not exist 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.

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 nondominated 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 nondominated 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 is used to find the pareto front.

EXPERIMENTAL

Description of study area

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

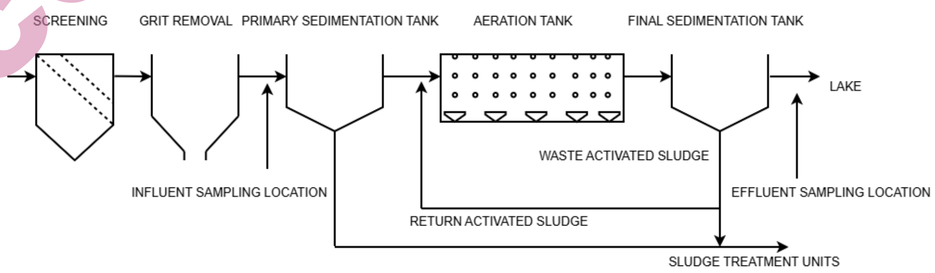

Fig.2. Schematic of sewage treatment plant.

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 the grits and big 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 secondary 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 where the flow next proceeds. To aid waste digestion, diffusers supply oxygen into 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 results 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 enough 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 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 STP, parameters considered are *pH*, *BOD*, *SS* and Faecal Coliform. Out of this, effluent *pH*, *BOD* and *SS* were measured in the plant and were included in modelling study.

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

Further data normalising was done according to Equation 3

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

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

The statistical indices of the variables of STP are given in Table I, Y_{Mean}=mean value Sd= standard deviation, Cv= variance, Med=Median, Z=Mode, Sk=Skewness

Table I. Statistical indices of parameters

	pH_{Inf}[a]	SS_{Inf}[b] / $\mathrm{mgL^{-1}}$	BOD_{Inf}[c] / $\mathrm{mgL^{-1}}$	$O\&G_{\mathrm{Inf}}$[d] / $\mathrm{mgL^{-1}}$	pH_{Eff}[e]	SS_{Eff}[f] / $\mathrm{mgL^{-1}}$	BOD_{Eff}[g] / $\mathrm{mgL^{-1}}$	$O\&G_{\mathrm{Eff}}$[h] / $\mathrm{mgL^{-1}}$
Y_{Max}[i]	6.6	624	937	56	8.2	139	79	8.4
Y_{Min}[j]	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}[k]	7.089	130.59	336.9	11.77	7.11	39.44	20.74	1.91
C_v[l]	31.79	7586	1E+05	85.96	0.24	2067	437.9	360.5
Sd[m]	5.63	87.1	317.1	9.27	0.49	45.46	20.93	18.98
Med[n]	6.58	139	224	9.6	7.15	30	18	1.5
Z[o]	5.9	68	80	6.4	7.2	16	22	0.8
Sk[p]	-0.049	2.024	0.899	2.357	0.504	1.434	3.026	2.513

[a]*pH* influent; [b]suspended solids influent; [c]biochemical oxygen demand influent; [d]oil and grease influent; [e]*pH* effluent; [f] suspended solids effluent; [g] biochemical oxygen demand effluent; [h] oil and grease effluent; [i] maximum value of the variable Y; [j] minimum value of the variable Y; [k] mean value of the variable Y; [l] variance; [m] standard deviation; [n] Median; [o] Mode; [p] Skewness

ANN Modelling strategy

ANN software

Neural network modelling and simulation are carried out using the software MATLAB 9.6 (Version–R2019a) (Math Works, Inc., USA). The data is 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 is 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 expected and actual outputs. The validation set, which is the second component, is what determines when neural network training should end. During training, the training error and validation error are found out, and it is typically seen that both errors first start to reduce. Nevertheless, training is halted when validation error increases and the network overfits. The network parameters corresponding to minimum validation error are fixed and 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 minimum. Overfitting issues can be avoided when there are fewer hidden layer neurons and, thus, fewer network parameters than there are training data points.[12]

Multi output model of effluent parameters is implemented for optimisation study as the entire plant is to be optimised with the three effluent parameters *pH, SS* and *BOD* simultaneously. Also one hidden layer was said 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 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 is employed to determine the optimal trained model.

ANN training for predicting biochemical oxygen demand (*BOD*), suspended solids (*SS*) and *pH* is shown in Fig. 3. Equation 4 for the tangent hyperbolic function is utilized in the hidden layer, while Equation 5 for the linear activation function is employed in the output layer.[15]

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

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

Multi objective optimisation

MOO Software

MATLAB 9.6 (Version–R2019a) program was utilized to carry out the multi objective optimization using artificial neural networks, which is then utilized to simultaneously optimize *pH*, suspended solids (*SS*), and biochemical oxygen demand (*BOD*) in the effluent stream.

Initialization

The first step in the algorithm is creating an initial population. The algorithm creates the population, or we can give an initial population or a partial initial population by using the Initial population matrix option. The number of individuals in the population is set 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. An snapshot of the Rank histogram which shows the distribution of individuals in each pareto tier is shown in Fig. 4.

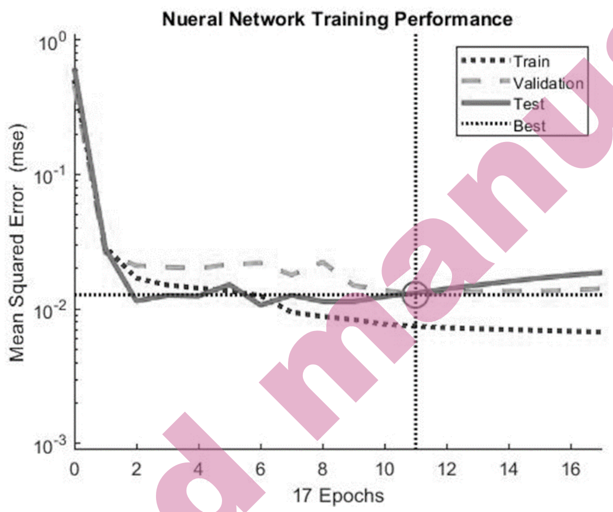

Fig. 3. ANN Training

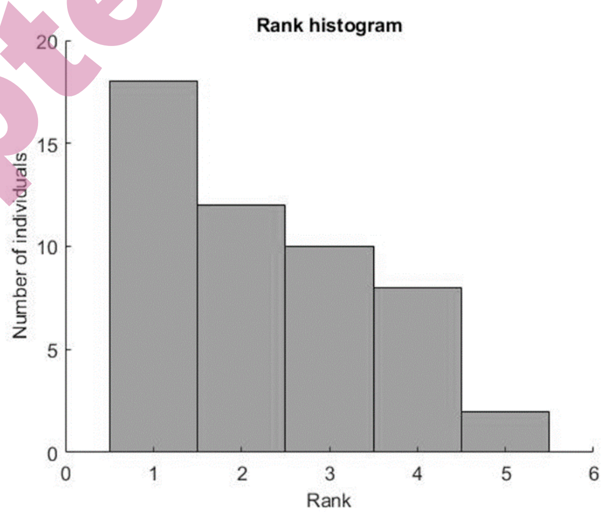

Fig. 4. Rank histogram

Iterations

The main iteration of the gamultiobj algorithm proceeds as follows.

1) Select parents for the next generation using the selection function on the current population. The only built-in selection function available for gamultiobj is binary tournament.
2) Create children by mutation and crossover from the selected parents.
3) By calculating their objective function values, children are scored.
4) The extended population is generated by combining the current population and the children into one matrix.
5) Rank and crowding distance is calculated for all individuals in the extended population.
6) By retaining the appropriate number of individuals of each rank, the extended population is reduced to have Population size individuals.

Stopping conditions

The algorithm is terminated when any of the termination criterion specified is met like maximum number of generations exceeded or time limit 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 mgL^{-1}, and its *BOD* concentration should be less than 30 mgL^{-1}.

Decision variables for optimisation

The decision variables associated with the process are the influent variables *pH*, *SS*, *BOD* and *O&G* which are to be optimised. This study minimizes the concentration of *pH*, *SS* and *BOD* in the effluent and satisfy 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* were 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 is 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 are the process's decision variables.

The fitness function or objective function is the optimized neural network outputs of *pH*, *SS*, and *BOD*.[16] After entering the variable's upper and lower bounds from Table II, optimization is started. The limits that the regulatory organizations 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 mgL^{-1}, the concentration of *BOD* in the effluent stream should be below 30 mgL^{-1} and the concentration of the pollutants cannot be a negative number. Therefore, the concentration of all four pollutants should be greater than zero.

A penalty term 134 is 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 will give negative values for *SS* and *BOD*. The output from the software are 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 decision variables are shown below.

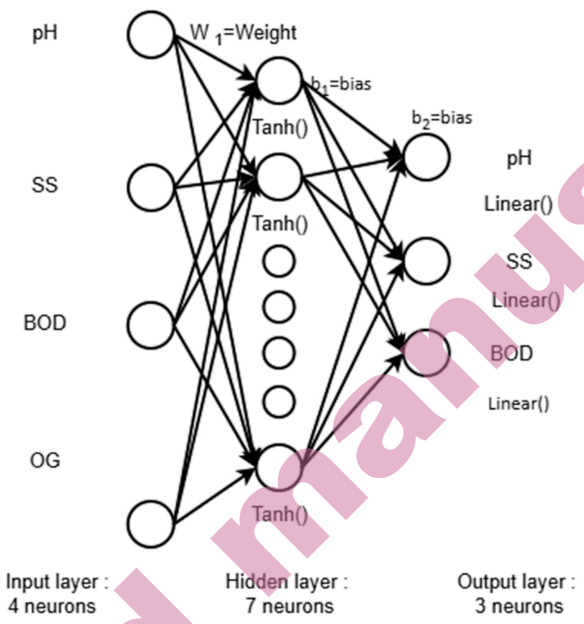

Fig. 5. Neural network for predicting pH, SS and BOD.

Table II. Bounds of variables

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

[a] *pH* Influent; [b] Suspended solids Influent; [c] Biochemical oxygen demand Influent; [d] Oil and Grease Influent

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* were used to predict the three outputs *pH*, *SS* and *BOD*. The neural network was trained and the network with seven hidden neuron layer neurons was found to give a correlation coefficient of 0.9207 and MSE of .0091 with training regression of 0.9371, validation regression of 0.8932, 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 can 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 Fig. S3, Fig. S4 and Fig. S5 respectively. It was found that after the 102 iteration there was no improvement in 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* are found by employing genetic algorithms resulting in 18 (50*0.35) decision variables as the population size is 50 and the pareto front population fraction is 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 is seen that the optimum values of pH_{Inf} varies from 6-8 which are closer to the upper bound values, optimum values of SS_{Inf} varies from 68-380 mgL^{-1} which are closer to the upper bound values, optimum values of BOD_{Inf} varies from 155-692 mgL^{-1} and optimum values of $O\&G_{Inf}$ varies from 8-45 mgL^{-1}. Fig. S6, Fig. S7, Fig. S8 and Fig. S9 show the variation of decision variables with pH_{Eff}.

When the decision variables are plotted against $SS_{Eff.}$ the optimized 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 mgL^{-1}, while BOD_{Inf} varied between 155 and 692 mgL^{-1}, and $O\&G_{Inf}$ ranged from 8 to 45 mgL^{-1}. Fig. S10, Fig. S11, Fig. S12 and Fig. S13 show the variation of decision variables with $SS_{Eff.}$

When the four decision variables are plotted against BOD_{Eff}, the optimized 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 mgL^{-1}. BOD_{Inf} lied between 155 and 692 mgL^{-1}, and $O\&G_{Inf}$ values varied from 8 to 45 mgL^{-1}. Fig. S14, Fig. S15, Fig. S16 and Fig. S17 show the variation of decision variables with BOD_{Eff}.

From the literature surveyed it is found that the optimal values of *pH* inf range between 7.8-8.1 optimal values of BOD_{Inf} vary between 175-475 mgL^{-1} the optimal values of *SS* Inf lies close to 850 mgL^{-1} when *BOD*, *SS* and total phoshorous *TP* were minimized simultaneously.[16]

Table III. Optimum values of the decision variables.

pH_{Inf}[a]	SS_{Inf}[b] / mgL^{-1}	BOD_{Inf}[c] / mgL^{-1}	$O\&G_{Inf}$[d] / 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

[a]*pH* influent; [b]suspended solids influent; [c]biochemical oxygen demand influent; [d]oil and grease influent;

CONCLUSION

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

Multi-objective optimization is proposed to minimize the concentration of pollutants pH, *SS* and *BOD* in the effluent stream in STP. Genetic algorithm is employed to minimize the concentration of *pH*, *SS*, and *BOD* simultaneously in the effluent stream.

The goal of this research work is 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 of effluent quality of treated wastewater. It is seen that optimum values of the decision variables pH_{Inf} lies between 6-8, optimum values of SS_{Inf} lies between 68-380 mgL^{-1}, optimum values of BOD_{Inf} lie between 155-692 mgL^{-1} and optimum values of $O\&G_{\text{Inf}}$ lie between 8-45 mgL^{-1} when all the effluent concentrations are minimised simultaneously.

NOMENCLATURE

AI	Artificial intelligence
ANN	Artificial neural network
ASP	Activated sludge process
BOD	Biochemical oxygen demand
COD	Chemical oxygen demand
Eff	Effluent
Inf	Influent
IS	Indian Standards
LM	Levenberg-Marquardt
MLD	Million litres per day
MLP	Mutti layer perceptron
MOGA	Multiobjective genetic algorithm
MOO	Multi objective optimisation
MSE	Mean square error
NSGA	Non-dominated Sorting Genetic Algorithm
OG	Oil and Grease
SS	Suspended Solids
STP	Sewage treatment plant
WWTP	Wastewater treatment plant

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.

И З В О Д

МОДЕЛОВАЊЕ И ОПТИМИЗАЦИЈА ПРОЦЕСА АКТИВНОГ МУЉА ПРИМЕНОМ ВЕШТАЧКИХ НЕУРОНСКИХ МРЕЖА И ГЕНЕТСКИХ АЛГОРИТАМА

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Математичко моделовање процеса активног муља спроведено је коришћењем вишеслојних перцептронских неуронских мрежа у циљу предвиђања параметара квалитета излазне воде, док је вишециљни генетски алгоритам примењен за оптимизацију параметара улазне воде како би се минимизовала концентрација загађујућих материја у излазном току. Математичко моделовање је извршено коришћењем података постројења за пречишћавање отпадних вода из централног округа јужне савезне државе Индије. Испитивани параметри излазне воде су pH вредност, концентрација суспендованих материја и биохемијска потрошња кисеоника, док су параметри улазне воде који се оптимизују pH вредност, концентрација суспендованих материја, биохемијска потрошња кисеоника и садржај уља и масти. Модел је евалуиран на основу статистичких параметара коефицијента корелације и средње квадратне грешке. За моделовање и оптимизацију коришћен је МАТЛАБ Р2019а. Утврђено је да су pH, концентрација суспендованих материја и биохемијска потрошња кисеоника излазне воде предвиђени са укупним коефицијентом корелације од 0,9207 и средњом квадратном грешком од 0,0091. Током оптимизације параметара улазне воде

установљено је да се оптималне вредности променљивих крећу у опсегу: pH 6–8, концентрација суспендованих материја 68–380 mgL^{-1}, биохемијска потрошња кисеоника 155–692 mgL^{-1}, садржај уља и масти 8–45 mgL^{-1}, у случају истовременог минимизовања функција циља.

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