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The use of artificial neural networks for the assessment of the operation of settling tanks

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The aim of the research was to develop and evaluate the usefulness of artificial neural network models for predicting the key operating parameters of centrifugal settlers. Various settler structures were analyzed, taking into account such elements as internal partitions and also inlet and outlet nozzles. Neural network modeling was continued until the highest possible quality was achieved in terms of training, testing and validation, with the occurrence of errors also being minimized. This process involved multiple iterations and adjustments of the network's parameters to achieve optimal results. It was shown that artificial neural networks are characterized by having high accuracy in predicting the efficiency and damming values of centrifungal sedimentation tanks with regards to their design and hydraulic load. The designed network is able to determine both efficiency and liquid level with satisfactory accuracy.

Keywords: sedimentation tanks, artificial neural network, efficiency, liquid dammings.

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INTRODUCTION

Selecting the appropriate settling tank is an essential element in the design of processing systems in various industries such as wastewater treatment, chemical processing, mining, and many others. The selection of a settling tank is a complex process that requires an in-depth analysis of many factors. The key aspect involves the characteristics of the inlet stream. The chemical composition of the stream is important when selecting coagulation and flocculation methods that aim to increase sedimentation efficiency. The concentration and type of suspended solids are also important and directly affect the requirements for the dimensions and type of settler. The rheology of sludge, including its viscosity and density, influences the design of sludge scraping mechanisms and disposal systems[1].

In chemical engineering, assessing sedimentation tanks is crucial for ensuring the proper functioning of the entire purification process. A thorough analysis ensures that sedimentation tanks efficiently remove suspended solids and impurities from liquids while meeting specific process requirements. This is particularly important in industries such as wastewater treatment, chemical processing, and mining, where sedimentation tanks play a pivotal role in maintaining operational efficiency and compliance with environmental standards.

A settler can operate gravitationally (where heavier particles naturally fall to the bottom of the tank), can use additional forces (such as centrifugal force), or use e.g. lamella plates, deflectors, multi-stream inserts, or specific structures to accelerate the sedimentation process. The choice of technology depends on the specific requirements of a given process and the effectiveness of individual methods under given operating conditions. When designing a settling tank it is important to conduct a series of tests (including sedimentation, semi-continuous, and continuous tests) that help determine basic process parameters such as sedimentation time and separation efficiency. The dimensions and shape of the tank should be adapted to the expected volume of flow and the expected concentration of suspensions, while at the same time taking into account the possibility of future expansion and changes in the composition of the stream. The construction material must be resistant to the chemical and physical conditions that prevail in the settler – including corrosion and wear. Moreover, ease of access to key settler components for maintenance and repair purposes is crucial for ensuring operational continuity and minimizing downtime[1–3]. The efficiency of the sedimentation process directly determines the efficiency of a given settling tank. In addition to the factors influencing sedimentation, operational parameters such as hydraulic load, settling time, flow rate, settling rate, and design are also important. The basic method of assessing the efficiency of sedimentation tanks, the main task of which is to remove solid particles, is to compare the concentrations of suspended solids in sewage before and after the sedimentation process. Water samples are taken both before entering the settling tank (inlet) and again after leaving it (outlet), and then analyzed for the content of suspended solids. The difference between the concentration of suspended solids in the inlet and outlet water gives information about the degree of particle removal by the settling tank[3].

The mathematical description of sedimentation can be very complicated and requires specialized preparation. There is research that attempts to put these phenomena into a mathematical framework, but correlation equations only approximate the nature of the phenomenon. The swirl flow in centrifugal settling tanks is very complex, and its direct measurement is extremely difficult. Therefore, it is necessary to use appropriate numerical solutions to obtain accurate vortex flow characteristics[1, 4].

Hydraulic load O_h is the volumetric flow rate per unit of the cross-sectional area of the settling tank:

$$O_h = \frac{Q}{A}$$

where:

O_h – hydruailic load, [m^3/m^2*s],

Q – volumetric flow, [m^3/s],

A – cross-sectional area of the settler, [m^2].

Depending on the hydraulic load, the height of liquid damming in the tank can be determined, which in turn allows for calculating the flow resistance that occurrs during the separation process:

$$\xi = \frac{\Delta h * 2g}{w_c^2}$$

where:

ξ – flow resistance, [N/m^2],

Δh – liquid level difference in the settler, [m],

g – Gravitational acceleration, [m/s^2],

w_c – Liquid flow velocity, [m/s].

Research shows that liquid damming (liquid level) has a significant impact on the performance of a centrifugal settler, especially in terms of its efficiency and performance. Damming levels are defined as the difference in height between the liquid levels both at rest and during flow in the sedimentation tank. Analysis of the obtained results allows for the determination of the optimal design that minimizes the occurrence of liquid damming, even at high flow rates. This aspect is crucial because damming can disturb sedimentation processes[5].

The measure of the effectiveness of sedimentation tanks is the content of suspensions in water or sewage after the sedimentation process – the degree of suspension removal, which is determined by the following formula[3, 6]:

$$E = \frac{c_0 - c}{c_0} * 100\%$$

where:

E – settling tank operation efficiency, [%],

c_0 – concentration of pollutants in the water flowing into the settling tank, [kg/m^3],

c – concentration of pollutants in the water flowing from the settling tank, [kg/m^3].

In recent years, many attempts have been made to understand and optimize the operation of centrifugal settlers. In chemical engineering, evaluating sedimentation tanks plays a critical role in ensuring the effective functioning of purification processes. Comprehensive analysis ensures that sedimentation tanks remove suspended solids and impurities efficiently while meeting specific technological requirements. The obtained research results resulted mainly in correlation equations, which only approximate the relationships between the efficiency of devices and their design and operational parameters. The diversity of these results comes from the use of different proprietary concepts and device geometries, and therefore each tested structure is characterized by a different efficiency. The location of structural elements is significant and may result in an increase or decrease in the efficiency of the centrifugal settler[1, 7].

Despite these efforts, the process of selecting an appropriate sedimentation tank remains inherently complex and requires an in-depth analysis of numerous factors. Recent studies have primarily focused on developing correlation equations to approximate the relationships between tank performance and operational parameters. However, such approaches often fail to fully capture the nonlinear and multidimensional nature of these systems, especially in the context of varying designs and structural modifications.

In light of the complexity of problems related to the optimization of centrifugal settlers, the decision was made to use artificial neural networks (ANN) as an analytical tool. Neural networks offer advanced modeling capabilities, allowing for the capture of complex relationships between various parameters that are difficult to identify using traditional methods.

As highlighted in the review by Aglodiya[8], ANNs have found extensive applications in chemical engineering due to their ability to model nonlinear, multidimensional, and dynamic relationships. Their adaptability and predictive capabilities make them an invaluable tool in optimizing processes, reducing experimental costs, and improving system efficiencies[8]. Compared to alternative machine learning methods, ANN excels in modeling nonlinear and multidimensional relationships, making it particularly suitable for predicting the performance of settling tanks. Although there are many studies regarding the application of ANNs in various fields, there is a lack of research that connects specific structural changes of settlers with their performance using advanced modeling methods. Research conducted by various authors[9–14], such as Din et al.[9] and Taloba[13], confirms the effectiveness of using artificial neural networks in modeling various processes employed in process engineering. However, these studies overlook the impact of design variables.

Among the many different artificial neural networks used for prediction, the Multilayer Perceptrons (MLP) is commonly used. In the Multilayer Perceptrons, signals pass through several layers of neurons. Each layer processes the output signals from the previous layer and forwards them to the next one. This process allows the network to learn complex relationships and patterns in the data. In this architecture, neurons are arranged in layers: an input layer, hidden layers and an output layer. There may be a different number of neurons in each layer. In the input layer, the number of neurons usually corresponds to the number of parameters describing the input data – each parameter is encoded in one neuron. The number of neurons in the layers depends on the complexity of the task – the more complex the task, the more neurons in the hidden layers. The number of neurons is most often selected experimentally. However, if the number of neurons is too large, the network may start learning "by heart" instead of modeling the function properly. If the network is used for regression (e.g. predicting numerical values), then it will only have one output neuron. This neuron will return the predicted numerical value. Neurons are usually only connected between adjacent layers, and within one layer there are no connections between neurons. Connections between adjacent layers are usually implemented on a peer-to-peer basis[15, 16].

Artificial neural networks (ANNs) undergo a learning process that adjusts the weights of input connections for individual neurons and the parameters of the activation functions declared for each neuron. There are numerous learning algorithms available. Below are examples of such methods[17]:

1. Backpropagation
2. Variable metric

3. Levenberg-Marquardt algorithm
4. Conjugate gradients.

A backpropagation algorithm was developed to train multilayer neural networks. The backpropagation algorithm was chosen for this study due to its well-documented effectiveness in training feedforward neural networks, such as Multilayer Perceptrons (MLPs). The algorithm's ability to handle large datasets and capture nonlinear relationships between variables makes it ideal for modeling the complex interactions present in the sedimentation tank processes[18]. Furthermore, backpropagation is widely supported by neural network software, such as Statistica Neural Networks, enabling its seamless implementation. The algorithm uses a gradient search technique to minimize a function that is equal to the mean squared difference between the desired and actual results. This requires a continuous differentiable nonlinearity to be used by the neurons as an activation function.

The backpropagation algorithm includes several steps:

1. All weights have initial small random values assigned to them.
2. Input data is propagated by the network in a feedforward manner while generating output data according to the weights and activation function.
3. The obtained output data is compared with the target results, which are known in advance.
4. The generated errors are then propagated back by the network to adjust the current weights. This is accomplished using two factors: learning rate and testing rate.
5. This procedure is repeated for each training example in the training set; a cycle represents one pass through the entire training set. Many cycles are required, and the neural network "learns" from examples - it changes its internal parameters so that the calculated result is as satisfactory and as close to the real one as possible. Neural networks require huge amounts of data to train. This is necessary so that they can learn to recognize complex patterns and relationships in data. Small data sets can lead to the problem of overfitting, where the model learns training data "by heart"[11, 14, 15, 19].

The study aims to demonstrate the potential of neural networks, particularly MLP models, in addressing gaps in the predictive modeling of centrifugal settling tanks, which has traditionally relied on correlation equations. The research focuses on developing and evaluating artificial neural network models to predict key operational parameters of centrifugal settling tanks, such as efficiency and damming, depending on their design and hydraulic load. The analysis utilized data from experimental studies on various designs of centrifugal settlers presented in[1].

MATERIALS AND METHODS

This work uses the experimental research of various designs of vortex settling tanks conducted by Markowska[1]. Various designs of centrifugal settlers were analyzed to examine how individual design elements affect the efficiency of the process. Particular attention was paid to the geometry and location of the outlet nozzle, the geometry of the outlet nozzle, the suspension height, the position of the longitudinal partition, and the presence or absence of a cylindrical partition. The constant parameters were the internal diameter of the tank D = 0.19 m, height H = 0.69 m, and the diameters of the nozzles d = 0.28 m. Figure 1 shows a diagram of a standard centrifugal settling tank, with design parameters being marked. It formed the basis for further modifications. The first modification was the introduction of an immersed profiled nozzle located tangentially to the settling tank axis. This is how the ZW type construction was created, in which a 135° elbow pipe was used to direct the stream towards the tank wall, thus causing a swirling motion. In the next design (ZM), the nozzle was placed radially. In this case, a 135° elbow pipe was also used. The ZMP settling tank is a modernized version of the ZM settling tank, and is equipped with an additional longitudinal partition. This partition can be placed in the axis of the device or moved towards the outlet by a certain distance l_b. All the structures are described in detail in[1].

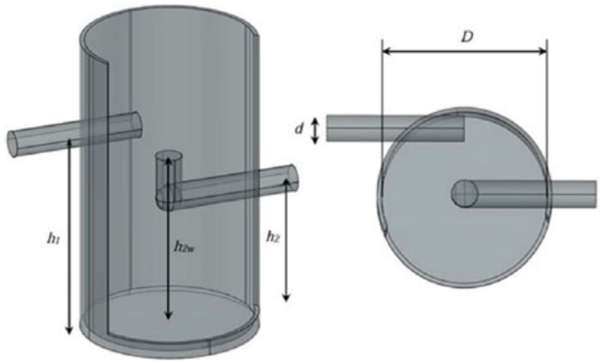

Figure 1. Diagram of a standard centrifugal settler (S)

Before proceeding with neural network training, a linear regression analysis was conducted for each input variable to assess the presence of linear relationships between the input and output data. This analysis was performed using the built-in Data Analysis ToolPak in Microsoft Excel. Key regression metrics were calculated, including the coefficient of determination R2, the F-statistic, and p-values for both the overall model and the slope of the regression line. For each input variable, the dependent (output) variable was regressed against the independent (input) variable. Summary statistics were generated to evaluate the strength of linear relationships and the assumptions of linear regression. Residual plots were analyzed for patterns that could indicate model misfit, while normality plots of residuals were used to assess the assumption of normally distributed errors. A significance level of 0.05 was established to determine whether the relationships were statistically significant. The F-statistic assessed the overall model fit, while the p-value for the slope coefficient indicated the strength of the relationship for each variable. It is important to note, however, that linear regression analysis evaluates only individual relationships between input variables and the output variable. It does not account for complex interactions between multiple variables, which can significantly influence the resulting model.

Artificial neural networks (ANNs) are particularly well-suited for modeling such multidimensional and complex interactions, as they do not require predefined assumptions about the form of the relationships. By employing neural networks, it was possible to capture both individual dependencies and their combinations, providing a more realistic representation of the analyzed system. The results of the preliminary analysis confirmed the appropriateness of using ANNs in this study.

An attempt was then made to use artificial neural networks to predict the efficiency of various centrifugal sedimentation tanks and the levels of the damming occurring in the tanks. These variables are key for determining the efficiency of centrifugal settlers. The Multilayer Perceptron (MLP) was chosen as the type of neural network for this task due to its ability to approximate nonlinear relationships between input and output variables. MLPs are characterized by a feedforward architecture consisting of an input layer, one or more hidden layers, and an output layer. This structure allows for capturing complex dependencies, which are often present in sedimentation processes.

In order to investigate the possibility of using artificial neural networks, the Statistica 13 Neural Networks program from StatSoft was used. The process included selecting input data that was critical for the accuracy of the model. Afterwards, the neural network training process began, which included using the regression method to model the relationship between the input and output variables. The training process utilized the BFGS (Broyden–Fletcher–Goldfarb–Shanno) optimization algorithm, which iteratively adjusts the weights and biases to minimize the error function. The selected error function for this study was the sum of squares, calculated as the Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2$$

where

y_i – actual values,

$\widehat{y_i}$ – predicted values.

The quality of the neural networks, as reported by the Statistica Neural Networks software, refers to the correlation coefficient r between the actual and predicted values. The correlation coefficient measures the strength and direction of a linear relationship between two variables and is calculated using the formula:

$$r = \frac{\sum_{i=1}^{n}(y_i - \widehat{y_m})(\widehat{y_i} - y_m)}{\sqrt{\sum_{i=1}^{n}(y_i - \widehat{y_m})^2 \sum_{i=1}^{n}(\widehat{y_i} - y_m)^2}}$$

where

y_i – actual values,

$\widehat{y_i}$ – predicted values

y_m – mean of the actual values

$\widehat{y_m}$ – mean of the predicted values.

The value of r ranges from –1 to 1, where values close to 1 indicate a strong positive correlation and high predictive accuracy of the model. For the networks used in this study, quality values close to 1 indicate the high accuracy of the predictions.

To prevent overfitting, the training process included an early stopping mechanism, which terminated training once the validation error stabilized. Additionally, the dataset was divided into training (80%), validation (10%), and test (10%) subsets to ensure the generalizability of the model. The assignment was performed manually using unique sample identifiers.

Training consisted of iteratively adjusting the network weights in such a way as to minimize the difference between the model's predictions and the actual values from the training set. The following method of describing the ANN architecture was used: the abbreviation of the network name - a multi-layer perceptrons (MLP), the number of neurons in the input layer, the number of neurons in the hidden layer, and the number of neurons in the output layer. All the numbers are separated by dashes, e.g. MLP 6-19-1. At the stage of selecting the data for the neural network, it was necessary to define variables - output and input, quantitative and qualitative. Before using the data in the neural network, all input parameters were normalized using the min-max normalization technique to ensure their values fell within the range (0, 1). Normalization was conducted before dividing the dataset into training, testing, and validation subsets to ensure consistency across all data splits. This step was particularly important to eliminate scale discrepancies between variables, which could have negatively affected the learning process. The normalization was performed using the formula:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where:

X – the original value,

min(x) – minimum values of the dataset,

max(x) – maximum values of the dataset.

Normalization is a critical preprocessing step in neural network modeling. Its purpose is to bring all input features to a common scale, which helps prevent dominance by variables with larger magnitudes and reduces numerical instabilities during training. This process improves the network's stability, speeds up convergence, and enhances its ability to generalize to unseen data. In this study, the input parameters were scaled using this technique. This ensures that the learning process remains efficient and that the network focuses on the relative relationships between the variables rather than their absolute magnitudes. Normalization is particularly important when using activation functions like the hyperbolic tangent (tanh), as it ensures the inputs fall within the sensitive range of the function. This technique is widely recommended in neural network modeling[20].

In the next step, an "automatic network search" option was selected as a way to create the model. This in turn allowed for optimal adjustment of the neural network without the need for the user to manually design the structure. In the research, due to the specificity of the analyses, all input parameters were quantitative. It is important to avoid creating false relationships between parameters, which could in turn lead to incorrect conclusions and a reduction in the model's quality. Afterwards, in the "selection of subsets" tab, the sampling method was defined. Instead of random assignment, the sample's identificator was chosen, where each measurement point had a T/T/V (Training/Test/Validation) value manually and randomly assigned. The next step in the process was the configuration of the automatic neural network's design. In this step, the type of network was selected, with the parameters related to its structure and learning being determined. At each stage, the MLP network type was chosen, while the remaining parameters were modified to find the optimal network. Although there are no clear rules on the exact number of hidden layers, an empirical approach is usually taken by testing different configurations to find the optimal network architecture. In practice, the number of hidden layers depends on the complexity of the problem, the amount of available data, and the specifics of the task. In the training process, the number of neural networks that will be trained is defined, and then only those models (the number of retained networks is also defined) that achieved the best results are retained. To determine the best-performing neural network, various configurations of the MLP network were tested with different numbers of hidden neurons, ranging from 4 to 20 in a single hidden layer. This range was chosen based on the complexity of the problem and the amount of available data. Testing architectures with a significantly higher number of neurons (e.g., 100 or more) would likely lead to overfitting, as the network would have too many parameters to train relative to the size of the dataset. Additionally, the chosen range is consistent with similar studies in the field, which demonstrate that fewer neurons are sufficient for capturing the relationships between variables in problems of this scale. These configurations were evaluated based on the minimization of Mean Squared Error (MSE) for both validation and test datasets[21].

These models are selected based on the lowest testing and validation error values. The error function chosen for minimization in the training process was the sum of squares. Then, different configurations of the MLP network with different numbers of hidden neurons were obtained. Furthermore, to avoid overfitting, early stopping was implemented during training, monitoring the validation error to terminate training when performance began to degrade. The use of early stopping ensured that the network did not memorize the training data but instead focused on learning generalizable patterns.

RESULTS

In the process of modeling the neural network, the aim was to obtain the lowest possible values of the testing error and validation error. After training the model, additional tests were conducted to evaluate its performance on a dataset that was randomly selected from the training set. If the results are similar but not identical, it may indicate that the network is capable of generalization.

Process efficiency

The efficiency of the centrifugal settler was determined as the output signal (Fig. 2). The following were selected as input signals: the height of the axis of the outlet from the inlet nozzle inside the settling tank (h_{1w}), the height of the axis of the outlet nozzle at the intersection with the tank wall (h_2), the height of the partition suspension (h_b), the position of the partition in relation to the settling tank axis (l_b), the average diameter of the particles (d_s), and the hydraulic load of the settling tank (O_h). To ensure that nonlinear relationships existed between the selected input variables and the output signal, a linear regression analysis and RESET test were conducted. The analysis examined the statistical significance of linear dependencies between the variables. The results (Tables 1 and 2) confirmed that most relationships were nonlinear, as evidenced by p-values below the significance level of 0.05 for variables such as h_{1w}, h_2 and O_h, justifying the application of artificial neural networks for this study. The average diameter of solid particles refers to two ranges: 125 μm for particles ranging from 100 to 150 μm, and 175 μm for particles ranging from 150 to 200 μm. The inclusion of both particle diameter ranges is intended to increase the number of measurement points, which in turn makes the analysis more representative. Particle diameter plays a key role in determining the cleaning efficiency of a centrifugal settler, so it was included as a dependent variable. Parameters such as settler diameter were omitted in the construction due to their invariability in each case, which meant that they had no impact on the analysis. The dataset consisted of 316 measurement points and was divided into three sets: training (approximately 253 points), testing (approximately 32 points), and validation (approximately 31 points), corresponding to percentage shares of 80%, 10%, and 10%, respectively. The point counts were rounded to the nearest integer for practical purposes. This distribution is widely recommended in neural network modeling as it allows sufficient data for training while reserving enough samples for independent evaluation of model performance[15, 22]. While the number of data points may seem limited, it is a consequence of the slow nature of the sedimentation process, which makes collecting experimental data time-consuming. Each measurement requires significant preparation and monitoring to ensure accuracy, emphasizing the practical challenges of experimental research in this domain. The study involved various designs of centrifugal settling tanks, each differing in their geometric and structural parameters. Some designs incorporated specific elements, such as partitions or modified outlet nozzles, while others omitted these features entirely. For instance, in several cases, parameters such h_b and l_b as were set to zero, reflecting the absence of a partition in the design[1].

The conducted analyzes showed that the best network quality (with the lowest errors) was obtained by the MLP 6-19-1 network. The training, testing, and validation quality were approximately 97%, 96% and 97%,

Table 1. Statistical characteristics of input parameters used in the neural network modeling

Variable	Min	Max	Mean	Median	Standard deviation	CV
h_{1w} [mm]	80.0000	400.0000	174.4304	200.0000	64.4695	36.9600
h_2 [mm]	300.0000	400.0000	379.7468	400.0000	40.1886	10.5830
h_b [mm]	0.0000	360.0000	183.7975	220.0000	145.4918	79.1588
l_b [mm]	0.0000	55.0000	10.4430	0.0000	21.5710	206.5591
d_s [μm]	125.0000	175.0000	150.0000	150.0000	25.0000	16.6667
O_h $[\frac{m^3}{m^2 * h}]$	21.1726	65.2822	45.3156	42.3452	12.4272	27.4236

Table 2. Linear regression analysis of input parameters

Variable	R^2	F-statistic	p-value (Slope)	Interpretation
h_{1w}	0.0015	0.4812	0.4884	The relationship may be linear
h_2	0.0014	0.4312	0.5119	The relationship may be linear
h_b	0.0352	11.444	0.0008	The relationship is not linear
l_b	0.0033	1.0595	0.3041	The relationship may be linear
d_s	0.1113	39.3784	<0.0001	The relationship is not linear
O_h	0.5857	443.8665	<0.0001	The relationship is not linear

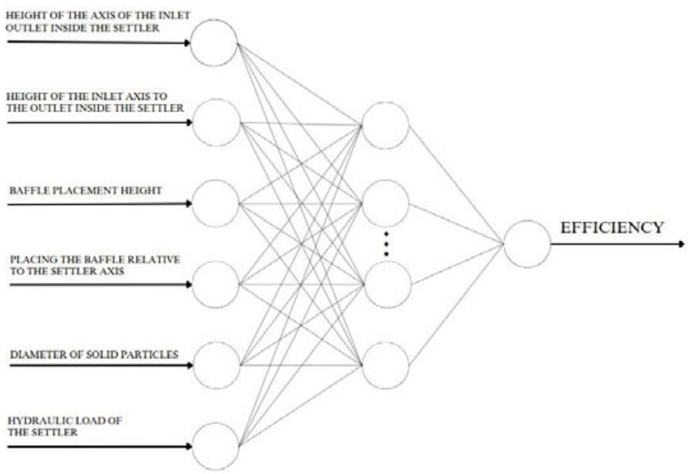

Figure 2. Structure of the neural network. In this diagram, the 19 neurons are symbolized collectively, and their exact count is abstracted with the "..." to emphasize the hidden layer's role rather than displaying all neurons individually

respectively. The learning algorithm used in the analysis was BFGS (Broyden-Fletcher-Goldfarb-Shanno). The activation function in the hidden layer was an exponential function, while in the output layer it was a hyperbolic tangent function. When comparing these values with other neural network structures, MLP 6-19-1 achieved the best results, which confirmed its effectiveness in the analyzed problem. Detailed information about the network is summarized in Table 3.

Table 3. Summary of the results for the selected neural network

Network	MLP 6-19-1
The training quality	0.9730
The testing quality	0.9558
The validation quality	0.9711
The training error MSE	<0.0001
The testing error MSE	<0.0001
The validation error MSE	<0.0001
The learning algorithm	BFGS 94
The error function	SOS
Activation (hidden)	Exponential
Activation (output)	Tahn

A small control group was randomly selected from the training set for the verification process. For these cases, a prediction sheet was prepared using their input variable values. This analysis aimed to assess the model's stability and its ability to generalize patterns within the training data. Although this step is not a standard evaluation method, it provided experimental insights into the network's behavior, particularly its capacity to capture relationships in the data without overfitting.

The detailed comparison of the prediction results on the test and validation samples remains, however, the primary method of assessing the model's generalization ability. The additional analysis, conducted using this small subset of training data, demonstrated that the MLP 6-19-1 network achieved predictions close to the experimental values in most cases, with some deviations[23]. Notably, the network did not produce identical predictions for training samples, indicating that it learned meaningful patterns in the data rather than memorizing specific examples.

Figure 3 shows the distribution of the dependent variable of the neural network for the test and validation sample. The red line is the ideal regression line, where the predictions perfectly match the actual values. The spread of the actual and predicted values is up to 15%. Data points are generally clustered close to the red regression line, which suggests that the neural network model predicts the efficiency values well.

Figure 4 shows a histogram of the distribution of residuals (differences between experimental data and the prediction of the neural network). The residual values are close to zero, which means that the model's predictions are usually very close to the actual values. The residuals are distributed between about –0.1 and 0.8, which means that the differences between the actual values and those predicted by the model rarely exceed 10%. The histogram resembles a normal distribution.

Liquid damming

The following were selected as input signals (Fig. 5): height of the axis of the outlet from the inlet nozzle inside the settling tank (h_{1w}), height of the axis of the outlet nozzle at the intersection with the tank's wall (h_2),

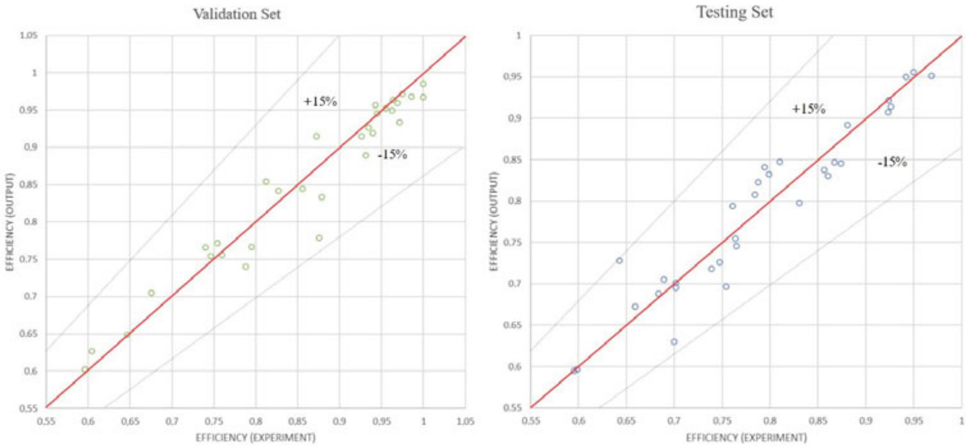

Figure 3. Distribution of the neural network model predictions

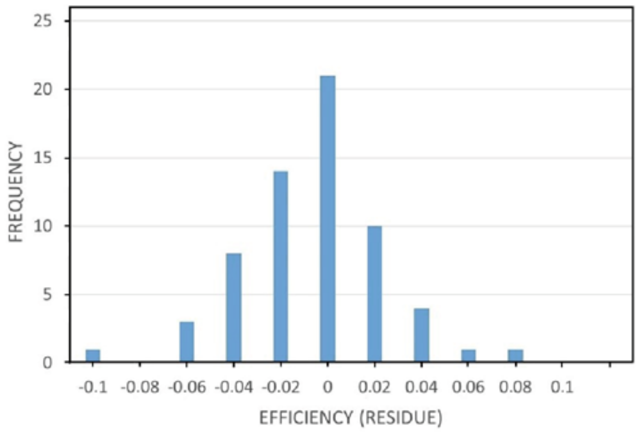

Figure 4. Histogram of the residuals of the neural network model predictions

height of the partition suspension (h_b), position of the partition in relation to the settling tank axis (l_b), hydraulic load of the settling tank (O_h). A linear regression analysis was performed for each input variable to test for linear dependencies with the output. The results showed that some variables, such as h_{1w}, exhibited significant linear relationships, while others, such as l_b, did not. This confirmed the need for using artificial neural networks to capture more complex dependencies (Tables 4 and 5). For liquid damming predictions, particle size was not included as an input parameter because the experiments were conducted with clean water, free of suspended particles. The focus of this part of the study was to evaluate liquid levels in the settling tanks under various hydraulic conditions. As in the previous case, the parameters that did not change in any modified structure were omitted from the analysis. The dataset consisted of 199 measurement points and was divided into three sets: training (approximately 159 points), testing (approximately 20 points), and validation (approximately 20 points), with percentage shares of 80%, 10%, and 10%, respectively. The point counts were rounded to the nearest integer to match the specified proportions. The limited number of data points for damming measurements stems from the experimental setup, where the liquid level was recorded under specific operating conditions—first with the device turned off and then with it running. Each measurement required precise control and repeated calibration to ensure the reliability of the recorded differences in liquid levels. This meticulous process, while essential for accuracy, constrained the total number of observations.

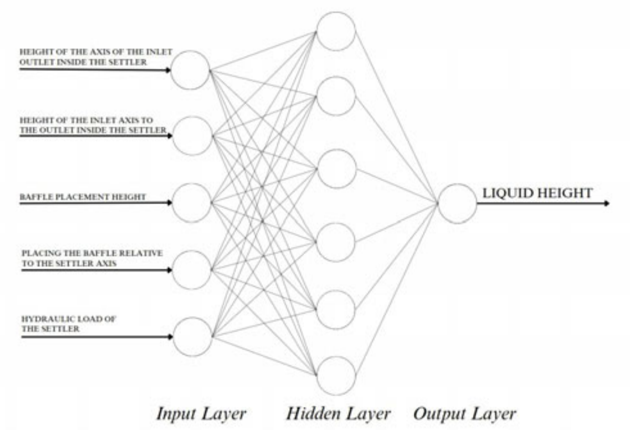

Figure 5. Structure of the neural network

Table 4. Statistical characteristics of input parameters used in the neural network modeling

Variable	Min	Max	Mean	Median	Standard deviation	CV
O_h	3.5288	70.5754	42.7176	42.3452	15.7827	36.9466
h_{1w}	80.0000	400.0000	183.4171	200.0000	77.0328	41.9987
h_2	0.0000	400.0000	331.6583	400.0000	142.3167	42.9106
h_b	0.0000	360.0000	173.5678	220.0000	147.9095	85.2171
l_b	0.0000	55.0000	9.6734	0.0000	20.9395	216.4651

Table 5. Linear regression analysis of input parameters

Variable	R^2	F-statistic	p-value (Slope)	Interpretation
h_{1w}	0.6467	360.6734	<0.0001	The relationship is not linear
h_2	0.0535	8.3309	0.0043	The relationship is not linear
h_b	0.0543	11.3138	0.0010	The relationship is not linear
l_b	0.0035	0.0025	0.9605	The relationship may be linear
O_h	0.2014	5.5629	0.0193	The relationship is not linear

The analyzes showed that the MLP 5-6-1 model had the best network quality and obtained the smallest errors. The model accuracy was approximately 97% for training, 98% for testing, and 96% for validation. The BFGS learning algorithm was used in the analysis. The activation function was a hyperbolic tangent function in both the hidden and output layers. Detailed information about the network is presented in Table 6.

Table 6. Summary of the results for the selected neural network

Network	MLP 5-6-1
The training quality	0.9725
The testing quality	0.9837
The validation quality	0.9621
The training error	<0.0001
The testing error	<0.0001
The validation error	<0.0001
The learning algorithm	BFGS 120
The error function	SOS
Activation (hidden)	Tahn
Activation (output)	Tahn

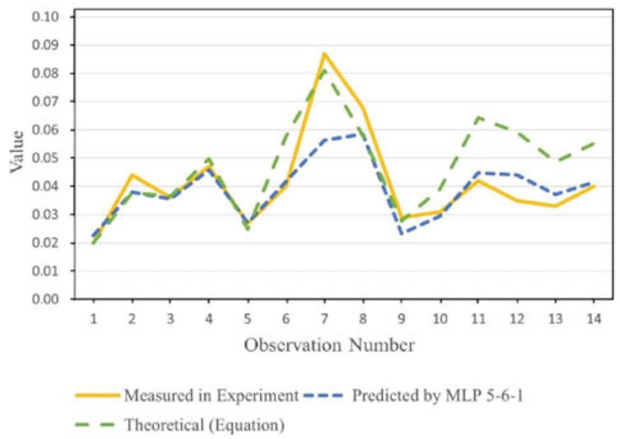

Figure 6. Comparison of measured, predicted, and theoretical values

As in the previous case, a control group was randomly selected for **verification** from the training set. A prediction sheet was prepared for these samples, which also included the values of liquid damming (Δh) calculated using the flow resistance equation presented in the Introduction. A comparison of the results obtained using different methods is presented in Table 7.

The comparison of the MLP network predictions and theoretical equation predictions with experimental values is presented in Figure 6. It can be observed that the MLP network predictions align closely with the experimental data, exhibiting minimal deviations. While the theoretical equation also demonstrated reasonable predictive accuracy, its deviations from the experimental values were more noticeable in specific cases. This suggests that the MLP network was better equipped to capture the underlying relationships in the dataset, potentially due to its ability to model complex and non-linear dependencies. The detailed comparison is further highlighted in Table 7, which includes calculated errors for both methods.

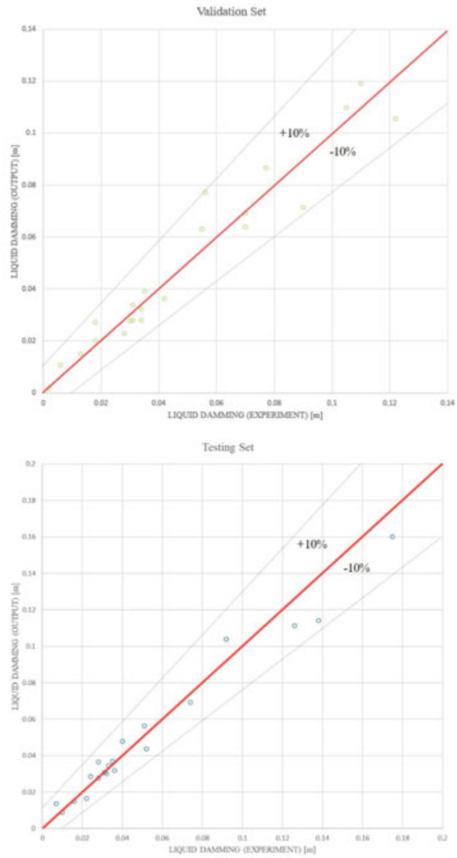

Figure 7. Distribution of the neural network model's predictions

Table 7. Comparison of the results obtained using different methods

Measured in Experiments [1]	Predicted by MLP 5-6-1	Theoretical (Equation)	Absolute Error (Neural Network)	Relative Error (Neural Network)	Absolute Error (Equation)	Relative Error (Equation)
0.0200	0.0227	0.0200	0.0027	13.2617	0.0000	0.2227
0.0440	0.0380	0.0378	0.0060	13.7105	0.0062	14.1774
0.0360	0.0355	0.0365	0.0005	1.2619	0.0005	1.3893
0.0470	0.0458	0.0497	0.0012	2.5467	0.0027	5.7728
0.0270	0.0271	0.0249	0.0001	0.3240	0.0021	7.7797
0.0400	0.0418	0.0577	0.0018	4.5573	0.0177	44.2174
0.0870	0.0563	0.0810	0.0307	35.3351	0.0060	6.8428
0.0680	0.0585	0.0580	0.0095	13.9653	0.0100	14.6409
0.0290	0.0232	0.0277	0.0058	19.8305	0.0013	4.5134
0.0310	0.0295	0.0390	0.0015	4.8368	0.0080	25.7923
0.0420	0.0447	0.0643	0.0027	6.5156	0.0223	53.0573
0.0350	0.0441	0.0592	0.0091	25.9114	0.0242	69.0272
0.0330	0.0372	0.0487	0.0042	12.8015	0.0157	47.6311
0.0400	0.0415	0.0552	0.0015	3.7973	0.0152	37.9886

Figure 7 shows the distribution of the dependent variable of the neural network for the test and validation sample. The spread of the actual and predicted values is within 10%. The neural network model predicts the peak values well, especially in the lower and middle range of values.

The histogram of model residuals (Fig. 8) shows the differences between the actual values and those predicted by the neural network model. The majority of residuals are concentrated in a narrow range close to zero, primarily between –0.01 m and 0.01 m, indicating the high predictive accuracy of the model. The symmetrical nature of the distribution suggests that the model does not exhibit systematic bias, such as consistently overestimating or underestimating the predictions. The concentration of residuals near zero and the lack of significant asymmetry highlight the model's robustness and its ability to generalize well across the test and validation datasets.

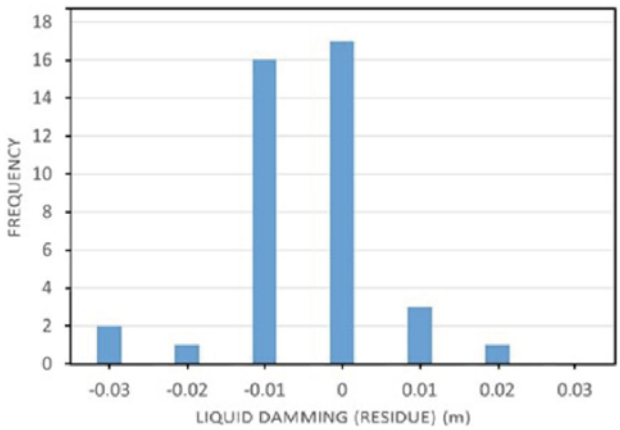

Figure 8. Histogram of the residuals of the neural network model's predictions

CONCLUSIONS

The paper presents the results of an analysis of the influence of design parameters, such as the geometry of outlet nozzles, suspension height, and the position of longitudinal partitions, on the efficiency of the sedimentation process and the height of liquid dammings in a centrifugal settling tank. The results of previous experimental research were used for the learning process of artificial neural networks[1, 19].

The modeling results showed that ANNs are an effective tool for predicting the key parameters of the operation of centrifugal settling tanks, such as efficiency and liquid damming. The study confirms that ANN is particularly effective in predicting the performance of centrifugal settling tanks. Unlike regression methods, ANN can incorporate multiple variables and their interactions without requiring assumptions about the form of dependencies. The MLP 6-19-1 and MLP 5-6-1 neural network models map the experimental results well, which is confirmed in the tables, charts and histograms. Moreover, for dammings, the use of a neural network often provides values closer to real results than those obtained using the equation. This reinforces the potential of ANNs to model and predict system performance more effectively than traditional methods, particularly in cases involving nonlinear dependencies. The verification process showed that the neural network is capable of generalization. This is evidenced by the fact that the testing and validation results were similar, but not identical. Validation and testing errors were not significantly larger than the training error, which proves the network's good generalization ability. In addition to errors, the quality indicators of the training, testing and validation processes are also important. In both cases, a very high quality was achieved in all these areas. Linear regression analysis was conducted prior to ANN modeling to evaluate the linear dependencies between input and output variables. The results highlighted weak linear dependencies for most parameters, justifying the choice of ANN to capture the nonlinear and complex relationships. Unlike linear regression, which examines individual input-output relationships in isolation, ANNs analyze all variables simultaneously, capturing both individual effects and intricate interactions between them. This comprehensive approach enables ANNs to model multifaceted dependencies more effectively, providing a more realistic representation of the system's behavior.

Analysis of the obtained graphs and histograms showed that there is high agreement between the model's predictions and the real values. The points are close to the regression line, which indicates high prediction precision. The distributions of the residuals in the histograms are concentrated around zero. However, the neural network model achieved better accuracy in predicting damming than it did in predicting efficiency. The predictions for the dammings are more similar to the real values, which is visible in the smaller dispersion of points around the regression line and the more concentrated distribution of residuals around zero. In the case of efficiency, despite good agreement, there is a greater dispersion of results, which suggests that the model could be even more precise. Future research should focus on expanding the dataset and exploring alternative ANN architectures to further improve model performance. The performance of the model can be improved by increasing the number of input data. More data allows the network to better capture patterns and relationships, in turn leading to more precise predictions and more satisfactory results across the entire range of measurement data. However, the experimental nature of sedimentation studies inherently limits the data volume due to the time-intensive process of obtaining precise measurements. This constraint emphasizes the importance of developing advanced computational techniques capable of optimizing predictions even with limited datasets.

Thanks to the use of the ANN, it was possible to accurately predict the results based on the input parameters, which in turn may allow for determining the most optimal design of settling tanks and hydraulic load without the need to conduct time-consuming experiments. However, further research with more data is needed to improve the model's accuracy and to ensure its effectiveness under a variety of operational conditions. Future studies could explore the integration of additional variables, such as dynamic fluid characteristics or the presence of chemical additives, to further refine predictions and broaden the applicability of the ANN models.

In chemical engineering, the assessment of the operation of sedimentation tanks is very important from the point of view of the proper functioning of the entire treatment process. Through careful evaluation, it is possible to ensure that settling tanks are effective in removing suspended solids and contaminants from liquids, and to also ensure that they meet the requirements of a given process. Traditional methods of assessing the operation of settling tanks, such as analyzing the content of suspended solids before and after the sedimentation process, are based on simple physical measurements. The choice of the appropriate method for assessing the work of settlers depends on the available resources and the specificity of the problem. Traditional methods of assessing the work of settlers remain a valuable tool in simpler analyses, while ANNs offer more advanced possibilities. Integration of both methods, using their advantages, can lead to a more precise and effective assessment of the work of settling tanks. This hybrid approach could potentially overcome the limitations of each individual method, providing enhanced reliability and adaptability for varied industrial conditions.

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