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Application of Neural Networks to Optimise the Coagulant Dosing Process in Industrial Wastewater Treatment

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Abstract: The purpose of this study is to develop a neural network model for optimising the coagulant dosing process. To achieve this goal, the study used methods of analysis, systematisation, modelling, and comparison. Industrial wastewater treatment methods designed to remove pollutants and improve water quality before being poured into reservoirs or water intakes were considered. Conventional methods include coagulation and flocculation, which involve adding a coagulant to agglomerate polluting particles and remove them from the water. The paper investigated the use of neural networks in the coagulant dosing system during wastewater treatment. In particular, a direct propagation network, also known as a multilayer perceptron, was considered. A neural network model has been created that allows determining the optimal dose of coagulant based on input parameters, such as water pH, turbidity, electrical conductivity. It is noted that the use of neural networks for coagulant dosing can improve the accuracy and efficiency of the wastewater treatment process, as well as reduce the cost of chemicals and ensure the stable operation of wastewater treatment plants.

Keywords: multi-layer perceptron; water purification automation; automated system; water parameters

1. Introduction

Increased production and intensive use (waste disposal) of water resources lead to the accumulation of large amounts of pollution in water bodies, which negatively affects the environment and threatens to ensure water quality for household and municipal needs. Optimal dosage of coagulant in the water treatment process is one of the key factors in achieving high cleaning efficiency and reducing negative environmental impacts.[1),2)] Accurate dosage of coagulant in the industrial water treatment process is critical for achieving high treatment efficiency and reducing the negative impact on the environment. Coagulants are used to form large flocculants that easily separate from water, helping to remove a variety of substances such as dissolved particles, colloids, and heavy metals. Incorrect dosing can lead to under- or over-dosing, which will increase chemical costs and can reduce cleaning quality. Optimized dosing of coagulant allows you to reduce costs while maintaining a high level of water purification, which is critical for ensuring sustainable water quality for domestic and communal needs, as well as for preserving the ecological safety of water resources. The problem of the study is that conventional methods of monitoring and regulating the dosage of coagulant may not be effective enough due to the complexity and dynamism of water parameters. The properties of wastewater can change due to various factors, such as the type of production, process cycle. Therefore, finding new approaches to optimising coagulant dosage is an urgent task, and the use of neural networks is a promising method that can help solve this problem.[3)]

The problem of coagulant dosage has been considered in a number of scientific papers. The study by A.P. Safonyk and M.V. Matviichuk[4)] discusses the use of neural networks to optimise the coagulant dosing process in industrial wastewater treatment. The researchers developed a model of an artificial neural network, in particular, a direct propagation network, which allows precise and dynamic adjustment of the coagulant dose depending on complex and variable water parameters. The results show that the use of this neural network allows for high efficiency of water purification and increases the productivity of the process due to rapid training of the model and precise adjustment of the coagulant dosage. Research conducted by O.I.V. Mora et al.,[5)] focuses on the use of neural networks in pH control and coagulant dosage systems in water treatment. They emphasise the importance of neural networks in achieving optimal pH levels, which is a key parameter in water treatment.

The study by S. Narges et al.[6] is devoted to the use of adaptive network-based fuzzy inference system (ANFIS) to predict the optimal dose of coagulant in water treatment. They demonstrate that ANFIS is able to determine coagulant doses, increasing model responsibility and intelligent model recognition. M. Kulisz and J. Kujawska[7] examine the application of neural network models to predict water quality in surface and underground sources. Their models use a variety of input variables to accurately predict water quality. This highlights the potential of neural networks for predicting and monitoring water quality. The study by L.R. Salvino et al.[8] proposes a control system project using artificial neural networks to optimise energy consumption in water distribution systems. The study shows that neural networks can improve the optimisation of energy consumption in water distribution systems. S. Zhang et al.[9] developed an energy consumption model for wastewater treatment plants based on machine learning techniques, including neural networks. The model predicts energy consumption and evaluates factors that affect energy use in full-scale wastewater treatment plants.

A general look at these studies allows drawing conclusions about the powerful potential of neural networks in water treatment. Research shows their usefulness in solving a variety of tasks, including regulating pH levels, coagulant dosing, predicting water quality, and optimising energy consumption in water distribution systems and wastewater treatment plants. However, to provide greater prospects for the application of neural networks in water treatment, more research is needed to better understand their functioning and impact on practical results. The purpose of this study is to develop a neural network model in order to optimise this process to further improve water treatment methods and water quality.

2. Methodology

Industrial wastewater treatment involves removing pollutants from wastewater produced by various industries before it is discharged or reused. The properties of industrial wastewater can vary widely depending on the industry, but often include parameters such as:

– pH levels
– Turbidity
– Electrical conductivity
– Chemical oxygen demand (COD)
– Biological oxygen demand (BOD)
– Total suspended solids (TSS)
– Heavy metals
– Organic compounds

Common industries producing wastewater requiring treatment include chemical manufacturing, food and beverage processing, pharmaceuticals, textiles, and metal finishing. Coagulation is a critical step in many industrial wastewater treatment processes. Common types of coagulants include:

- Metal salts (e.g. aluminum sulfate, ferric chloride)
- Polymeric coagulants (e.g. polyaluminum chloride)
- Natural coagulants (e.g. Moringa oleifera seeds)

Traditional coagulant dosing methods often rely on jar tests to determine optimal dosage, which can be time-consuming and may not adapt well to rapidly changing wastewater conditions. Typical dosing amounts can range from 10-200 mg/L depending on wastewater characteristics, with dosing frequency often being continuous or semi-continuous. This study aims to develop a neural network model to optimize the coagulant dosing process by considering multiple input parameters such as pH, turbidity, and conductivity. The model is designed to dynamically adjust coagulant dose in real-time based on changing wastewater conditions.

To develop and evaluate the neural network model, methods of analysis, systematization, modelling, and comparison were used. Historical data on wastewater parameters and corresponding optimal coagulant doses would be used to train and validate the model. The performance of the neural network model would then be compared to traditional dosing methods in terms of treatment efficiency and coagulant usage.

3. Results

3.1. Industrial wastewater treatment

Industrial wastewater treatment is an integral part of industrial processes and at the same time a challenge to ensure the safe disposal or reuse of this wastewater. To achieve this goal, various methods and technologies have been developed to effectively clean and remove pollutants. One important step in this process is the dosage of the coagulant, which plays a crucial role in facilitating the removal of pollutants and improving the efficiency of wastewater treatment. The coagulation process involves the addition of chemicals that contribute to the destabilisation and aggregation of suspended particles, colloids, and solutes in wastewater, forming larger particles known as flakes that can be easily separated from the water.[10]

Neural networks offer several specific advantages when applied to coagulant dosing in industrial wastewater treatment. Neural networks excel at handling nonlinear relationships between input parameters (such as pH, turbidity, pollutant concentrations) and the optimal dose of coagulant. They can learn from historical data and adapt to varying conditions, ensuring effective treatment even with changing wastewater characteristics. By automating the dosing process, neural networks minimize the reliance on human operators and reduce the potential for errors that can arise from subjective decision-making. This automation enhances reliability and consistency in coagulant dosing. Neural networks can swiftly adjust coagulant doses in response to immediate changes in wastewater conditions, such as variations in pH, turbidity, or flow rate. This real-time responsiveness ensures that treatment efficiency remains optimal despite fluctuations.

Various types of coagulants are used for industrial wastewater treatment, including chemical coagulants, natural coagulants, and hybrid coagulants. Chemical coagulants such as metal salts (e.g. aluminium sulphate, iron chloride) and polymer coagulants (e.g. polyaluminium chloride) are commonly used because of their effectiveness in destabilising particles and promoting flocculation.[11] These coagulants act by neutralising particle charges, allowing them to combine to form flakes.

The choice of a suitable coagulant depends on a variety of factors, including wastewater characteristics, target pollutants, and desired treatment targets. Factors such as pH, dosage, mixing intensity, and contact time should be optimised to achieve optimal coagulation and flocculation. Response surface methodology, factor design, and statistical methods are often used to optimise the coagulation process and determine optimal conditions.[12] Coagulants are usually added during the primary stage of industrial wastewater treatment, where they help remove suspended solids, organic matter, heavy metals, and other pollutants. The coagulation process is often accompanied by precipitation or filtration to separate the flakes from the purified water. Coagulation efficiency may be affected by factors such as pH, temperature, wastewater composition, and the presence of interfering substances.[13]

Coagulant dose determination systems are used in industrial wastewater treatment to optimise the dosage of coagulants for efficient removal of pollutants. These systems use various methods, such as empirical models, statistical analysis, and computational algorithms, to determine the optimal dose of coagulant based on specific treatment targets and wastewater characteristics. One approach to determining the dose of a coagulant is to use empirical models based on ANFIS. These models use historical data and input parameters such as wastewater composition, pH, turbidity, and target pollutant concentrations to predict the optimal coagulant dose.[6] ANFIS models can effectively capture complex relationships between input variables and coagulant dosage, providing accurate dose determination.

Statistical analysis methods such as the Box-Wilson methodology, Response Surface Methodology (RSM), and factor design are also used to optimize coagulant dosage. These methods involve conducting a series of experiments with different coagulant doses and other process parameters to determine the optimal dose that achieves the desired treatment goals, such as maximising pollutant removal or reducing turbidity.[11],[14] RSM and factor design determines the optimal dose of coagulant within a certain parameter space.

Computational models and algorithms are increasingly used in coagulant dose determination systems. These models use mathematical algorithms and simulations to predict the optimal coagulant dose based on input parameters and targets. For example, computational models based on Computational fluid dynamics (CFD) can model the coagulation process and predict the optimal dosage of coagulant for effective pollutant removal.[15] These models consider factors such as flow dynamics, mixing intensity, and coagulant dispersion to determine the optimal dosage.

Coagulant dose determination systems may also include real-time monitoring and control technologies. Online sensors and analysers can continuously measure key parameters such as turbidity, pH, and concentrations of pollutants in wastewater. This real-time data is then transmitted to the coagulant dose determination system, which adjusts the dose accordingly to maintain optimal efficacy.[16] The development of coagulant dose determination systems is conditioned by the need for efficient and cost-effective wastewater treatment. By accurately determining the optimal coagulant dose, these systems can minimise the use of chemicals, reduce cleaning costs, and improve efficiency. In addition, they allow operators to adapt the dosage of coagulant according to changes in wastewater characteristics, ensuring stable and efficient treatment operation.

3.2. Use of neural networks for coagulant dosing

The use of neural networks in the coagulant dosing process represents a significant step in improving industrial wastewater treatment processes. Neural networks based on the ideas of artificial intelligence and machine learning allow automating and optimising the dosage of coagulant based on various parameters and input data. One of the key applications of neural networks is their ability to adapt to changing conditions and a large number of input parameters. Neural networks can analyse complex relationships between wastewater parameters that affect coagulation efficiency. This means that they can factor different characteristics of wastewater, such as pH, turbidity, pollutant concentrations, and even changes in these parameters over time.[17] In addition, neural networks can use historical data and the results of previous studies to predict the optimal dose of coagulant. They can assess the effect of different doses of coagulant on purification results and find the optimal dose that meets the desired treatment goals.

Industrial water treatment systems often use outdoor pools located in the open air. It is important to keep in mind that conditions in these basins may change, in particular, due to precipitation. During rain, the pool water level may rise, which may affect the amount of coagulant required. In such situations, the amount of coagulant previously calculated based on the volume of water in the pool before precipitation begins may not be sufficient to achieve the desired cleaning results. The use of neural networks in coagulant dosing systems allows considering such changes in conditions, for example, an increase in the volume of water in the pool during rain, and automatically adjusting the dose of coagulant to ensure optimal cleaning efficiency. This makes the dosing process more flexible and adaptive to changing conditions, which can be important for achieving stable and efficient industrial wastewater treatment.

The use of neural networks in coagulant dosing also allows adjusting the variety of types of coagulants that can be used in the wastewater treatment process. Different coagulants can have different effects depending on the characteristics of wastewater, and neural networks can help choose the best coagulant for a particular case.

3.3. Direct propagation neural network

Feedforward neural networks, also known as multilayer perceptrons or Rosenblatt perceptrons, are an important architecture in the field of artificial neural networks and deep learning. Their significance is determined by their ability to solve various problems of classification, regression, pattern recognition, and many other tasks in the field of artificial intelligence. Direct propagation neural networks consist of neurons that are located in different layers and connected by weights. Each neuron receives input signals, calculates their linear combination with weights, and applies a nonlinear activation function to generate the output signal. This sequential transmission of signals from one layer to another forms a mathematical model that can learn to adapt to input data and solve problems with high accuracy. This network contains several types of layers, including input, hidden, and output layers (Fig. 1).

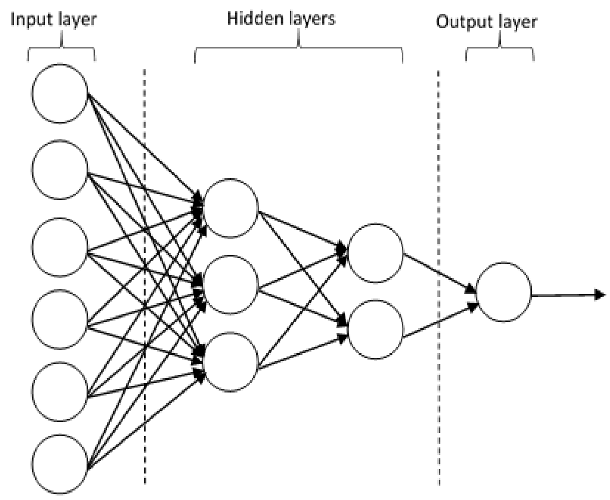

Fig. 1: Multi-layer perceptron.

The input layer is the first component of a neural network and is used to receive and transmit input data to the system. Input data can be numeric values, metrics, or any other form of information that is transmitted to the network for processing. The number of input neurons in the input layer usually corresponds to the number of input variables or features used to solve a particular problem. Each input neuron receives input information and transmits it further for processing and analysis by the network. The role of the input layer is to start the process of transmitting data through a neural network. Each input neuron can represent a specific feature or parameter that is important for the problem being solved. In networks designed for image processing, input neurons can correspond to image pixels, in audio recognition audio signal fragments. The input layer plays a key role in transmitting this input data to the network for further analysis and processing.

Hidden layers are the middle layers of the network located between the input and output layers. Neurons in hidden layers are not inputs or outputs, and they perform calculations that allow the network to learn complex relationships between input data and output results. Each neuron in the hidden layer calculates a linear combination of input data and transmits it via a nonlinear activation function, such as sigmoidal or ReLU. The output layer is the last layer of the network that contains output neurons. The number of output neurons usually corresponds to the number of classes or variants for classification or regression.[18),19)] Each neuron in the network calculates a weighted sum of input data, adds bias (bias), and feeds the result through a nonlinear activation function. This allows the network to model complex nonlinear data dependencies. An important characteristic of neural networks is the absence of loops in the transmission of information. Information moves in one direction, from the input layer to the output layer, without going back. Designing hidden layers is a complex task, and there are many recommendations for determining their number and configuration depending on the specific task.

For effective treatment of industrial wastewater and determination of the required dose of coagulant, it is important to consider a number of parameters that can affect the coagulation process in various ways. The presented scheme (Fig. 2) is based on the use of a neural network to automatically determine the optimal dose of coagulant depending on the input parameters.

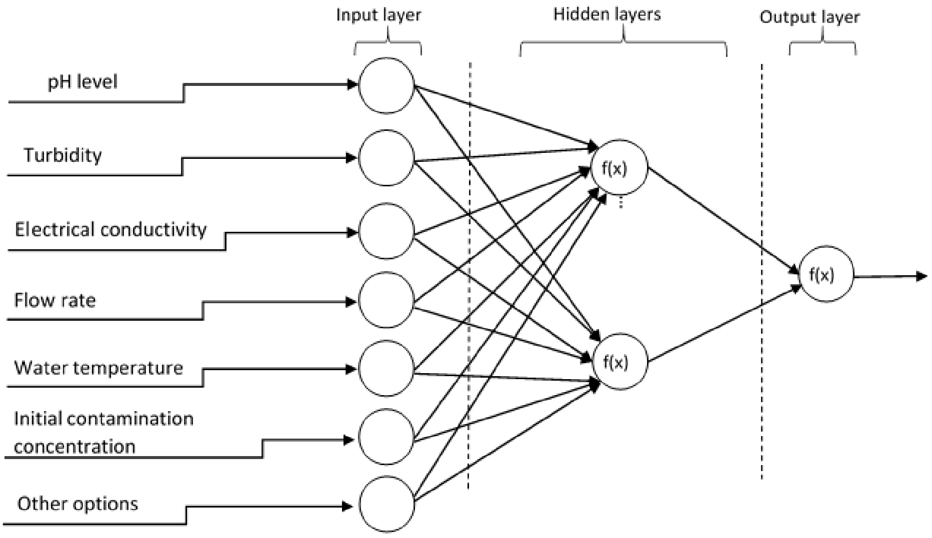

Fig. 2: Neural network model for coagulant dosing.

The presented system based on a neural network for determining the dose of coagulant has a number of advantages. First of all, it automates the coagulant dosing process, reducing the role of the human factor and eliminating possible errors that may occur due to the subjective decision of operators. In addition, this system demonstrates high adaptability to changing water conditions. It is able to quickly respond to fluctuations in wastewater parameters, such as pH level, turbidity, flow rate, thereby ensuring a constant optimal dosage of coagulant. Neural networks can be trained on historical data and determine the optimal dose of coagulant, taking into account all important parameters of wastewater. They are able to consider complex relationships between these parameters, which provides the best results in the water purification process.

However, a neural network-based system also has some drawbacks. First, it requires access to a large amount of data and a long training period to function effectively. The first stages of implementation can be time-consuming and resource-intensive, as the system needs to learn from the available data. In addition, the system is limited to those variables and parameters that are considered in the neural network during training. It may be less effective in environments where unpredictable factors or parameters are encountered that are not present in the training data. In addition, the system may require continuous monitoring and maintenance to maintain optimal efficiency. Hardware failures or insufficient data for training can lead to erroneous system decisions.

4. Discussion

The results of the study highlight the importance of industrial wastewater treatment and efficient coagulation. Choosing the right coagulant and optimising factors such as pH and dosage play a key role in achieving optimal results. Accurate determination of the coagulant dose helps reduce costs and improve cleaning efficiency, and consideration of factors such as pH and other contaminants is important for successful coagulation. The use of neural networks for coagulant dosing is important in the industrial wastewater treatment process. They allow automating and optimising dosing based on many parameters and changing conditions. Neural networks can analyse complex relationships between wastewater parameters and predict the optimal dose of coagulant. They can also adjust the dose during weather changes, such as rain, to ensure effective cleaning. The use of neural networks increases the efficiency and adaptability of the industrial wastewater treatment process.

Direct propagation neural networks are a key architecture in deep learning and artificial neural networks. They effectively solve classification, regression, pattern recognition, and other artificial intelligence tasks. Networks consist of neurons arranged in layers and connected by weights. Each neuron receives input data, calculates its linear combination with weights, and applies a nonlinear activation function to generate the output signal. This sequence of signal transmission from one layer to another allows the network to solve problems with high accuracy. The network has three types of layers: incoming, hidden, and outgoing. The input layer accepts input data, and the number of input neurons corresponds to the number of input parameters. Hidden layers perform calculations to study dependencies in the data, and the output layer generates output results. To use neural networks in industrial wastewater treatment, it is important to consider many parameters that affect the coagulation process. A neural network-based system automatically determines the optimal dose of coagulant based on these parameters, ensuring automation and adaptability of the process. It helps to avoid errors associated with subjective decisions of operators, and responds to changes in wastewater conditions. However, to work effectively, it requires access to a large amount of data and long-term training, and may be limited to parameters that were not considered during training. It also requires constant monitoring and maintenance to ensure optimal efficiency.

A study conducted by M. Yateh et al.[20] was aimed at investigating the effectiveness of the coagulation process for urban drinking water treatment. They used polyaluminium chloride (PAC) as a coagulant and investigated its effect on the removal of pollutants such as total organic carbon (TOC), total nitrogen (TN), and total distributed solids (TDS) from drinking water collected from the Yangtze River, Baoshan District, Shanghai, China. Their research highlights the need to optimise the water coagulation process, and the use of neural networks can be an important step towards achieving this goal, providing better control and removal of pollutants from water depending on specific conditions and parameters.

The study by K. Wang et al.[21] examines the optimisation of the industrial wastewater treatment process, which is an important issue for water supply companies. The coagulation-flocculation method for wastewater treatment was used. However, determining the optimal dose of coagulant is difficult due to the complex characteristics of wastewater. The researchers used a technique that combines genetic optimisation and particle swarm optimisation with regression model analysis to determine the optimal coagulant dose. This has helped improve the quality of outgoing water and waste levels at the wastewater treatment plant, reducing costs by 10%. The results of the study showed that the proposed method can effectively optimise the wastewater treatment process and provides improved efficiency in copper removal. This approach can be useful for engineering applications in industrial wastewater treatment.

N. Singh et al.[22] focused on wastewater treatment created by pharmaceutical companies. The researchers highlighted the serious negative impact of toxic emissions from pharmaceutical wastewater on the environment and public health. To solve this problem, they used artificial neural network (ANN) techniques. The study emphasises the advantages of using neural networks over traditional mathematical models for wastewater treatment. This is conditioned by complex cleaning mechanisms, dynamic changes in parameters, and the need to adapt to different conditions. The authors use artificial neural networks to predict the concentration of chemical oxygen demand (COD) in wastewater at different stages of treatment. They developed three types of back-propagation neural networks for predicting COD, particles in suspension, and total solids in wastewater.

A. Bressane et al.[23] emphasise the importance of coagulation in the drinking water treatment process. It is noted that the dosage of coagulant should be accurate, since insufficient or excessive use can lead to problems. Typically, the dosage is set based on experiments conducted manually, but this method is not reliable and accurate. The researchers decided to use artificial learning techniques to optimise the dosage of the coagulant. After comparing different methods, they concluded that the best alternative is a new system based on fuzzy interference systems (FIS), since it allows accounting for uncertainties in the coagulation process. It is shown that this method can be promising for real-time and accurate coagulant dosing in the drinking water treatment process.[24-27]

The results of this study are consistent with the aforementioned papers, which highlight the importance of optimising the water treatment process, especially in today's world where water pollution is becoming a serious problem.[24] One of the key components of optimisation is the dosage of coagulant to effectively remove dirt from the water. It is important to consider many parameters and conditions, such as pH, pollution concentrations, and weather changes. Recent studies show that the use of neural networks to optimise the coagulant dosing process in industrial wastewater treatment has significant potential to improve the efficiency of this process. The results of such studies indicate the possibility of reducing costs and improving the quality of water treatment, which are key tasks in the field of water treatment.[25] The joint result of this and the research under consideration is the confirmation that optimisation of water treatment processes and the use of the latest technologies, such as neural networks and optimisation using other methods, can significantly improve the quality of treated water and reduce the impact of pollution on the environment, which are extremely important tasks in the modern world.[28-30]

To achieve better results and improve water quality, an accurate and adaptive dosage of the coagulant is necessary, considering many parameters and conditions, such as pH, pollution concentration, and weather changes. Research shows that the use of advanced technologies, such as artificial neural networks and data-driven optimisation, can significantly improve water treatment processes.[31,32] These methods allow automating and optimising the dosage of coagulant, providing better control and removal of pollutants from the water, depending on specific conditions and parameters. In addition, research also points to the need to reduce the negative impact on the environment and reduce the costs of water supply companies and industrial enterprises. Accurate coagulant dosing and the use of advanced optimisation techniques can help improve the state of water resources and ensure a more sustainable and efficient water treatment process.[33]

While neural networks offer significant advantages in coagulant dosing for industrial wastewater treatment, they also come with several potential limitations and drawbacks. Data Dependency and Training Requirements: Neural networks require a substantial amount of historical data to train effectively. This data must accurately represent the range of conditions and variables encountered in wastewater treatment. Gathering and preparing this data can be time-consuming and resource-intensive. Neural networks are trained on specific datasets, which means they may not generalize well to conditions or parameters that differ significantly from those in the training data. If wastewater conditions change unpredictably or new contaminants appear that were not present in the training data, the network's performance may degrade. Neural networks are complex black-box models, meaning their decision-making process can be difficult to interpret or explain. Operators may find it challenging to understand why a particular dose recommendation is made, which can hinder trust and acceptance of the system.

5. Conclusions

As a result of the study, it was found that the use of direct propagation neural networks in the coagulant dosing process is an effective and promising approach for improving industrial wastewater treatment processes. Neural networks allow automating and optimising the dose of coagulant, considering various parameters and inputs that affect the coagulation process. An important advantage of this approach is the ability of neural networks to adapt to changing conditions and a large number of input parameters. Neural networks can analyse complex relationships between wastewater parameters, such as PH, turbidity, pollutant concentrations, and even changes in these parameters over time. This makes them effective when conditions in reservoirs may change, for example, due to precipitation. Neural networks are able to automatically adjust the dose of coagulant to ensure optimal cleaning efficiency, which makes the process more flexible and adaptive.

The use of neural networks in coagulant dosing is proving to be an effective solution for achieving stable and efficient industrial wastewater treatment. This approach simplifies the process, reduces possible errors, and provides adaptability to changing conditions, making it attractive for industrial wastewater treatment companies.

The practical significance of the study lies in the possibility of automating and optimising industrial wastewater treatment processes using neural networks, which increases the efficiency and stability of these processes in various conditions. Possible areas of future research include further improvements in training algorithms to improve the speed of adaptation to variable conditions and expand the range of wastewater parameters taken into account. In addition, an important area may be the study of the impact of using neural networks on improving efficiency and reducing costs in the process of water treatment in various industrial sectors.

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