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The Effect of Nanomaterial Type on Water Disinfection Using Data Mining

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ABSTRACT
Multiple linear regression and artificial neural network (ANN) models were utilized in this study to assess the type influence of nanomaterials on polluted water disinfection. This was accomplished by estimating *E. coli* (E.C) and the total coliform (TC) concentrations in contaminated water while nanoparticles were added at various concentrations as input variables, together with water temperature, PH, and turbidity. To achieve this objective, two approaches were implemented: data mining with two types of artificial neural networks (MLP and RBF), and multiple linear regression models (MLR). The simulation was conducted using SPSS software. Data mining was revealed after the estimated findings were checked against the measured data. It was found that MLP was the most promising model in the prediction of the TC and E.C concentration, s followed by the RBF and MLR models, respectively.

Keywords: water disinfection; artificial neural networks; nanotechnology; data mining.

INTRODUCTION

Conserving water sources and improving drinking water quality are becoming increasingly vital, particularly in isolated and rural locations. Multiple water disinfection techniques, such as chlorination and water boiling, have been used for this purpose; additionally, Solar Water Disinfection (SODIS) method has been utilized, as it is regarded as a simple, cheap, and may be considered a practical solution for household water purification [Burhan, 2015]. It is based on the fact that ultraviolet (UV) rays in the solar spectrum destroy and kill bacteria and viruses in wastewater [Boyle et al., 2008; Castro-Alférez et al., 2017]. If the water has low turbidity and appropriate ambient temperatures, having exposed this contaminated water to over 500 W/m² of solar radiation for several hours, pathogens will be destroyed.

SODIS has been studied previously, with numerous changes based on the experimental settings and the type of wastewater. The findings were all in agreement that the concentrations of bacteria and viruses were generally reduced significantly after the contaminated water was exposed to solar radiation for 5 to 6 hours [Aboushi et al., 2021; Islam et al., 2015; Lawrie et al., 2015; Polo et al., 2015]. Furthermore, the effect of adding iron oxide to wastewater, using polymer bags, water temperature, turbidity, and pH levels in water on the speed of the disinfection process was investigated [Gutiérrez-Alfaro et al., 2016; Keogh et al, 2017; Dawney and Pearce, 2012; Giannakis et al., 2015].

Recently, research was carried out on using silver nanoparticles to enhance water purification. Silver nanoparticles have antibacterial activity against bacteria, according to Agnihotri et al. [2013]. Koslowski et al. [2018] discovered that adding 0.05% silver nanoparticles to a sample impregnated with polyamide-66 resulted in a 97.89% reduction in bacteria after one day at 25 °C.

The first report on TiO_2 photocatalyst inactivation of bacteria and viruses was in the eighties of the last century; this was followed by a certain amount of research work in this field, which were reviled that the most effective common nano photocatalysts in water disinfection were ZnO and TiO_2 [Keane et al., 2014; Kumar et al., 2014]. TiO_2 has proven to be the best catalyst for the degradation of organisms within the UV region of the solar spectrum. Its properties include being recyclable, simple to prepare, tolerating both alkaline and acidic solutions, being radiation stable, and not requiring a significant oxidizing agent.

Experimental work was conducted on water disinfection under different variable parameters such as nanoparticles type and their concentrations, time, and pH by Lydakis-Simantiris et al. [2010]. It was discovered that TiO_2 performs better than other nanoparticles. Duarte and Amorim [2017], proved that the antibiotic removal efficiency of TiO_2 ranged from 96 to 98 percent.

Hamdan and Darabee [2017] investigated the effects of TiO_2 and Al_2O_3 nanoparticles on wastewater disinfection. They concluded that 0.06 % Al_2O_3 worked best for minimizing the concentration of *E. Coli* (E.C) and total coliform (TC), while 0.06% TiO_2 worked best for minimizing total counts of *E. Coli*. Furthermore, they concluded that TiO_2 was found to be a high potential to speed up the disinfection process.

Because of their mechanical strength and thermal stability, TiO_2 catalysts have enormous promise in water purification from other nanoparticles, according to Utami et al. [2019]. TiO_2 enhanced the photocatalytic activity of nanomaterials, while the combination of ZnO/rectorite was responsible for photoreduction and adsorption [Wang et al., 2018]. It is recommended to use this mixture in conjunction with other water treatment methods, such as biological processes, photocatalysis, and adsorption, to ensure the purity of the water.

However, there has been little investigation into assessing residual microorganisms in SODIS-treated water. This approach has been used previously to predict the concentration of TC and E.C on tomato plants and romaine lettuce after sterilization, rather than in water [Keeratipibul et al., 2011]. ANN and Multiple regression approaches were employed in this article to estimate EC and TC concentrations in SODIS-treated effluent. The findings will help optimize the SODIS water treatment technique by identifying the factors and variables that influence the effectiveness of the solar treatment process, whether positively or negatively.

Xu et al. [2015] used two modeling methods, ANN and Genetic Programming (GP), to simulate the U.V. wastewater plant. The simulation inputs for the model training were acquired using Computational Fluid Dynamics (CFD) software. Modeling error and generalization ability for fresh inputs were used to compare the accuracy of these two modeling methods. Using multi-objective optimization, the ANN and GP models were employed to estimate the optimal design and operational factors of the UV disinfection process.

Multiple Regression (MR) and ANN approaches were employed in this work to estimate the E.C and TC concentrations in contaminated water treated with SODIS and nanotechnology. The results of this study will help optimize the disinfection strategy by identifying the factors and variables that influence the effectiveness of the solar disinfection process, whether positively or negatively.

MATERIALS AND METHODS

The multiple regression approach was simulated using the Statistical Package for the Social Sciences (SPSS). Input variables included time, water temperature, pH, types of nanoparticles, concentration of nanoparticles, and turbidity, as per previous studies [Aboushi et al., 2021; Hamdan and Darabee, 2017; Hamdan et al.; 2022]. The output variables used were E.C and TC concentrations in the water being disinfected.

The experiments began by obtaining contaminated water from the water treatment plant at Al Zaytoonah University. The sample was collected before it was treated with chlorine and after it had gone through filtration, to ensure that there were no impurities and that the water was as clear as possible. The water was then tested to determine the levels of TC and E.C using the IDEXX system. This method of using the IDEXX system to detect water contamination has been described in many previous studies [Aboushi et al., 2021; Hamdan and Darabee, 2017].

The 500 ml contaminated water samples were introduced into sterilized laboratory glass containers. Each container was weighed on a digital scale, and various types and concentrations of nanoparticles were added. These containers were placed next to one another, and measurements of turbidity, pH, and water temperature were taken. In addition to testing for quality and quantity, TC and E.C were also analyzed using the IDEXX system, which is certified and known for its rapid, easy, and accurate results. It is worth noting that the samples were also placed in beaker holders and exposed to direct sunlight for 2.5 and 3.5 hours to ensure exposure to UV rays from all angles. A total of 33 samples were prepared during the summer season and were exposed to sunlight between 11:00 AM and 02:30 PM at ambient temperatures.

DISCUSSION OF THE RESULTS

Multiple Linear Regression

Statistical Package for the Social Sciences (SPSS) was utilized to simulate the multiple regression approach. As stated above, time, water temperature, pH, kind of nanoparticles, the concentration of nanoparticles, and turbidity as input variables. While the E.C and TC concentrations in the water to be disinfected were employed as the output variables. The following linear equations were obtained using 33 samples:

Table 1 summarizes the outcomes achieved using this model. For fixed values of time, water temperature, pH, type of nanoparticles, the concentration of nanoparticles, and turbidity, the value of the coefficient of determination (R) varies substantially on the dependent variable for prediction the concentration of TC and EC. Table 2 shows the relationship between time, water temperature, pH, and turbidity as predictor variables (input) and TC and EC as dependent variables.

Artificial Neural Network Model

An Artificial Neural Network (ANN) is a machine-learning model inspired by the human brain's structure and function. It is a collection of interconnected nodes, or "neurons," that process and transmits information. ANNs can be used for a variety of tasks, such as image recognition, natural language processing, and prediction. They are particularly useful for tasks that involve large and complex datasets, as they are able to learn and make predictions based on patterns in the data. ANNs have been used to achieve state-of-the-art performance in many fields, and continue to be an active area of research.

Table 1. Statistical Package for the Social Sciences model output variables

Model	R	R square	Adjusted R square	Std. error of the estimate
Total coliform	0.930[a]	0.865	0.732	464.0519
E. Coli	0.921[a]	0.848	0.657	508.2810
a. Predictors (constant): turbidity, pH, time, type of nano, temperature, concentration.				

Table 2. Coefficients of variables

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
Total coliform	Constant	1345.573	5409.758		.249	.806
	Time	-816.989	198.223	-.881	-4.122	.000
	Concentration	241.962	76887.319	.001	.003	.998
	Type of nano	360.675	281.504	.320	1.281	.211
	Temperature	-26.073	46.724	-.132	-.558	.582
	pH	187.177	595.774	.076	.314	.756
	Turbidity	-3.485	2.505	-.312	-1.392	.176
E. Coli	Constant	1345.573	5409.758		.249	.806
	Time	-816.989	198.223	-.881	-4.122	.000
	Concentration	241.962	76887.319	.001	.003	.998
	Type of nano	360.675	281.504	.320	1.281	.211
	Temperature	-26.073	46.724	-.132	-.558	.582
	pH	187.177	595.774	.076	.314	.756
	Turbidity	-3.485	2.505	-.312	-1.392	.176

Multilayer perceptron and radial basis function models were employed in the present work to find the contents of E.C and TC in water to be disinfected. The variables (time, water temperature, pH, type of nanoparticles, nanoparticle concentration, and turbidity) were utilized for training the ANN models. This study used the concentration of TC and E.C in contaminated water as the outcome measures. The results were validated using multiple regression techniques.

The Statistical Package for the Social Sciences software was used to create and test two ANN models. The ANN model was fed experimental data from 33 previously collected samples.

Table 3. Case processing summary

		N	Percent
Sample	Training	21	63.6%
	Testing	12	36.4%
Valid		33	100.0%
Excluded		0	
Total		33	

Multilayer Perceptron Model

A Multilayer Perceptron (MLP) is a type of ANN that consists of multiple layers of interconnected nodes, or "neurons." It is a feedforward network, meaning that information flows through the network in one direction, from the input layer to the output layer. The input layer receives the input data and passes it through the hidden layers, where complex computations are performed before it reaches the output layer where the final predictions are made. MLPs are commonly used for a variety of tasks such as image classification, natural language processing,

Table 4. Network information

Input layer	Covariates	1	Time
		2	Concentration
		3	Type of Nano
		4	Temperature
		5	pH
		6	Turbidity
	Number of units[a]		6
	Rescaling method for covariates		Standardized
Hidden layer(s)	Number of hidden layers		1
	Number of units in hidden layer 1[a]		1
	Activation function		Hyperbolic tangent
Output layer	Dependent variables	1	Total coliform
		2	E. Coli
	Number of units		2
	Rescaling method for scale dependents		Standardized
	Activation function		Identity
	Error function		Sum of squares

Table 5. Multilayer perceptron model summary

Training	Sum of squares error		2.566
	Average overall relative error		.128
	Relative error for scale dependents	Total coliform	.094
		E. Coli	.162
	Stopping rule used		1 consecutive step(s) with no decrease in error[a]
	Training time		0:00:00.01
Testing	Sum of squares error		.817
	Average overall relative error		.070
	Relative error for scale dependents	Total coliform	.115
		E. Coli	.033

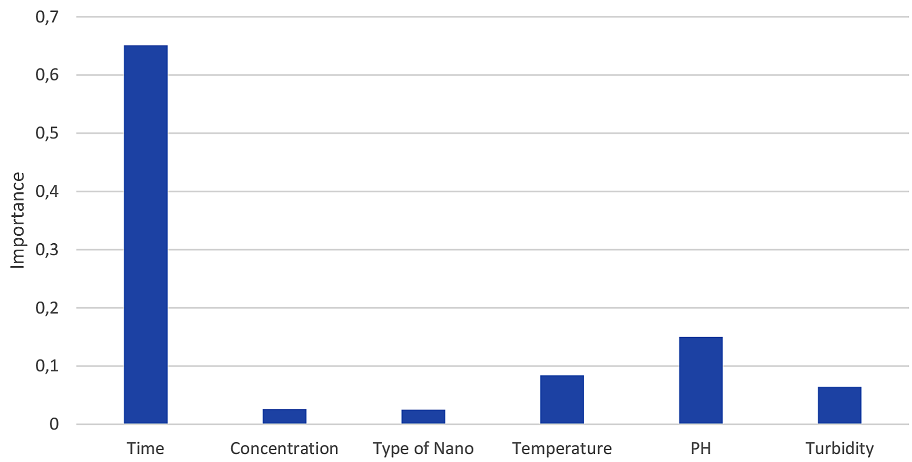

Figure 1. Independent variable importance for TC and E.C contents by using MLP

and prediction, it can also be used to approximate any function. The number of layers, and the number of neurons in each layer, can be adjusted to suit the complexity of the task at hand. MLP is a powerful tool for handling non-linear problems and has been used to achieve state-of-the-art performance in many fields.

The MLP approach is suitable for a versatile type of neural network known as a multilayer perceptron. It has a feed-forward design and may have several hidden levels. It is a commonly used neural network architecture. Furthermore, 63.6% of this data is used for training, and 36.4% is used for testing and the number of hidden layers is 50. The case processing summary is shown in Table 3, the network information in Table 4, and the model summary in Table 5. Figure 1 shows independent variable importance for TC and E.C contents. As indicated in this figure, time is the most influential variable on the TC and E.C.

Radial Basis Function Model

The Radial Basis Function (RBF) model is a type of artificial neural network that is based on the concept of radial basis functions. These functions have the property of being non-zero only in

Table 6. Case processing summary

Specification		N	Percent
Sample	Training	23	69.7%
	Testing	10	30.3%
Valid		33	100.0%
Excluded		0	
Total		33	

Table 7. Network information

Input layer	Covariates	1	Time
		2	Concentration
		3	Type of nano
		4	Temperature
		5	pH
		6	Turbidity
	Number of units		6
	Rescaling method for covariates		Standardized
Hidden layer	Number of units		6[a]
	Activation function		Softmax
Output layer	Dependent variables	1	Total coliform
		2	E. Coli
	Number of units		2
	Rescaling method for scale dependents		Standardized
	Activation function		Identity
	Error function		Sum of squares

a certain region around the center, and their value decreases as the distance from the center increases. In RBF networks, each neuron in the hidden layer represents a radial basis function, and the output of the neuron depends on the distance between the input and the center of the function. RBF networks are often used for function approximation and classification tasks, as they can accurately model complex non-linear decision boundaries. The number of neurons in the hidden layer, and the choice of radial basis functions, can be adjusted to suit the complexity of the task at hand. They are particularly useful for solving problems with a large number of inputs, as well as for problems with a small number of training examples.

RBF network is a type of training data system with a single invisible layer known as the radial basis layer. The RBF network can predict and classify data like the multilayer perceptron network. The MLP model is slower than the RBF

Table 8. Radial Basis Function model summary

Training	Sum of squares error		3.875
	Average overall relative error		.076
	Relative error for scale dependents	Total coliform	.194
		E. Coli	.033
	Training time		0:00:00.06
Testing	Sum of squares error		.456[a]
	Average overall relative error		.048
	Relative error for scale dependents	Total coliform	.018
		E. Coli	.060

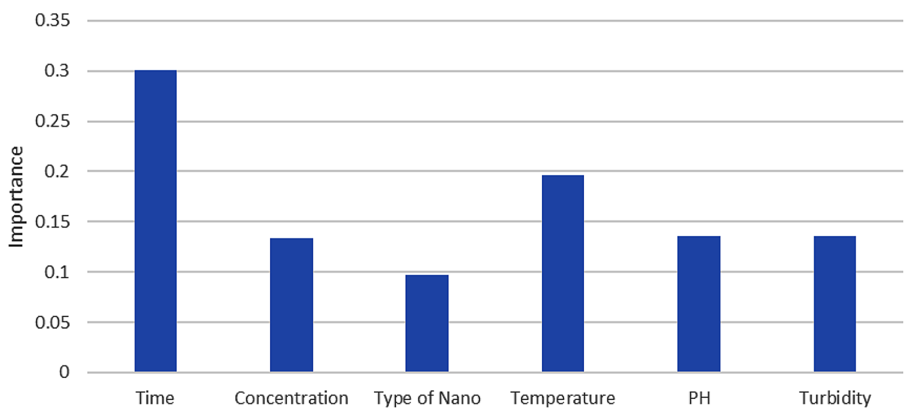

Figure 2. Independent Variable Importance for TC and E.C contents by using RBF

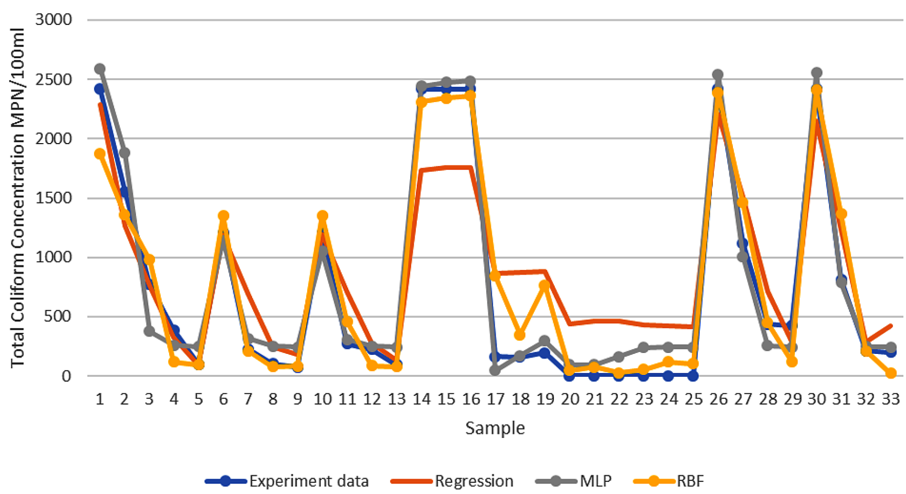

Figure 3. Verification of present results against experimental one of TC

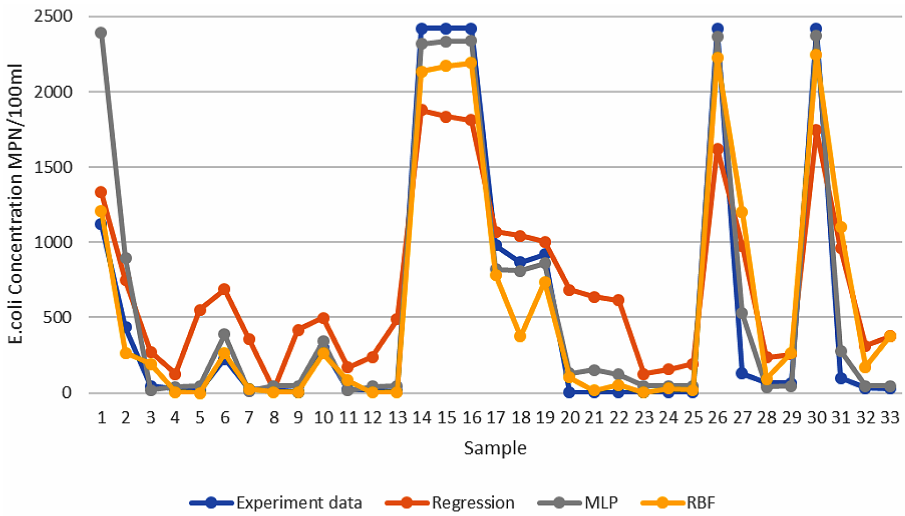

Figure 4. Verification of present results against experimental one of *E. Coli*

Table 9. Models performance using statistical analysis

	Regression			MLP			RBF		
	R	RMSE	MBE	R	RMSE	MBE	R	RMSE	MBE
Total coliform	0.930	393.570	127.061	0.986	155.915	44.961	0.962	244.384	47.636
E. Coli	0.921	444.491	178.334	0.959	257.173	32.442	0.937	301.385	76.585

model, but it is less versatile in terms of the types of models it can fit. Furthermore, 69.7% of this data is used for training, and 30.3% is used for testing and the number of hidden layers is 50. Table 6 presents a summary of the case processing, Table 7 displays the network data, and Table 8 presents a summary of the model. Figure 2 shows independent variable importance for TC and E.C contents. As indicated in this figure, time is the most influential variable on the TC and E.C.

Figures 3 and 4 compare the collected experimental results and the previously mentioned estimated power. Table 9 presents the statistically based performance comparison of the models tested. Lower Mean Bias Error (MBE) values suggest higher model accuracy, while larger Root Mean Square Error (RMSE) values indicate higher model accuracy.

According to the above table and numbers, data mining utilizing the MLP model, which is a form of ANN, produces more reliable results than the other models. As a result, this model can estimate data with excellent accuracy.

CONCLUSIONS

This study utilized ANN models and MLR approaches to predict the relationship between the amounts of *E. coli* and total coliform in disinfected water and the input parameters. This was accomplished by using two methods: a traditional method that involved the use of the MLR model and a data mining method that involved the use of two types of artificial neural networks, specifically the MLP and RBF models. Data mining that uses the MLP model can recognize the link across output and input variables according to comparisons between estimated and experimental data. Furthermore, the sampling error analysis demonstrated the MLP model's precision in data mining. According to the results, the RBF and MLR models were the least effective at determining the concentration of TC and E.C in wastewater, respectively.

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