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Research Article

Applicability of radial-based artificial neural networks (RBNN) on coliform calculation: A case of study

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ABSTRACT

Due to the increasing population, urbanization and economic reasons, it is inevitable to use deep-sea discharges. The fact that there is no alternative and less pollution of the environment is the reason for the preference of deep-sea discharges. In this study, it is aimed to estimate the coliform values of the Tekkekoy deep sea discharge system, which is chosen as an application area, by using a radial-based artificial neural network structure. Firstly, samples taken from the field were examined in a laboratory environment. Values obtained as a result of laboratory studies were used as input in Radial basis artificial neural network (RBNN) architecture. It has been determined that the models prepared by using various combinations have correlation values ranging from 91.5% to 97.2%. The best performing models were models prepared using 10 neurons. From these successful results, it was determined that RBNN structures are useful in coliform prediction.

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INTRODUCTION

Deep-sea discharge (DSD) is a method of disposal to take advantage of the sea's dilution capacity. The main purpose of DSD systems is to make the wastewater collected with the city wastewater network harmless with very high dilution rates by giving them to the marine environment after being treated at a level determined according to the need. In our country and the world, the discharge of domestic and industrial wastewaters to coastal waters constitute the main causes of pollution in seas and rivers. It is widely used because wastewater is a reliable and relatively inexpensive waste removal technology with DSD. Today, DSD systems will continue to be used until a better alternative is available [1]. Especially without primary treatment, widespread discharge of sewage is of great importance,

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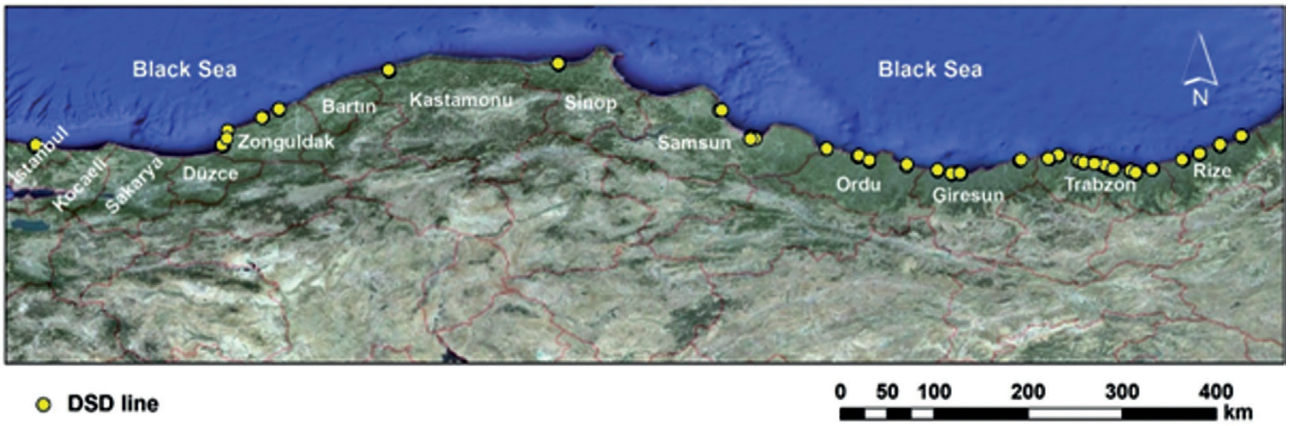

Figure 1. DSD Lines in the Black Sea Region (Google Earth) (Ardali, 2015).

because these wastes contain only high concentrations of suspended solids and nutrients, they also contain a significant amount of organic matter and coliform [2].

The Black Sea is located between 41.0° and 46.5° northern latitudes, 27.5° and 41.5° eastern longitudes in an area where the European and Asian continents converge. When analyzed based on hydrographic data, the Black Sea, which has a total area of 413490 km^2 and a water volume of 537000 km^3, can be defined as the largest anoxic basin in the world [1]. In Turkey, the Black Sea region should have greater geographical factors of population density in coastal areas due to both land distribution. There are a total of 36 deep-sea discharge points, 33 domestic and 3 industrial, which are used as wastewater discharge by the municipalities on the Black Sea coast in Figure 1.

Sea discharge studies in Turkey, Water Pollution Control Regulations and Regulation of Urban Wastewater Treatment are carried out within the framework of this regulation [1]. Quality standards are defined to protect the beneficial use of the sea and its product. Setting water standards is very complicated and following these standards is strongly linked to water use [3]. Therefore, pathogens are a serious concern for water resource managers. Because it is known that an excessive amount of fecal bacteria in sewage and urban flow indicates an increased risk of pathogenic illness in humans [4]. A small amount of coliform is known to indicate the presence of other harmful bacteria or viruses in the stomachs. Coliforms are among the bacterial indicators to be monitored [3]. Total coliform (TC) is chosen as target marker organisms as it is present in the feces of human / warm-blooded animals and high concentrations in wastewater [1].

Tay and Zhang (1999) modeled the complex process of anaerobic biological treatment of wastewater using neural-fuzzy techniques. Scarlatos made coliform calculations using an artificial neural network (ANN) model using samples of river mouth systems. He stated that the graphical results of coliform prediction make it difficult to express model performances [5]. In a study, the peak coliform values of the Delaware River were estimated using feed forward artificial neural network (FFNN) models. It is stated in the study that artificial neural network models can be successfully applied in coliform prediction [6,7,8]. In another study, using the FFNN model, a coliform estimation was made using 7 point values from the Southwest Scottish coast. At the end of the study, they stated that the correlation values of the models they prepared approached to 0.50 [9]. In another study, FFNN and regression models were used in coliform prediction. They made the performance evaluation of using the models and as a result of the evaluation, it was stated that although the artificial neural models were more successful, they performed poorly in predicting the peak values [10,11]. Another study investigated the use of regression models to estimate fecal coliform levels in the Charles River basin in Massachusetts [12]. In another study, they tried to estimate the amount of free chlorine using FFNN based on a statistical model such as flow, pH and temperature of a sample drinking water network. They stated that flow and temperature variables are effective in the amount of chlorine [13]. In another study, they estimated the daily coliform amount using 6 different models in which neural network-based sedimentation and sedimentation-based artificial variables were preferred, and they stated that the models containing precipitation parameters gave successful results in coliform estimation [14]. Another work from the Iznik lake basin from turkey has been to develop fecal pollution model structures with FFNN for cost-effective lake water quality management studies. The study was indicated that multilayer FFNN models could be used to predict microbial pollution in deep lakes [15].

In this study, the parameters affecting the total coliform were evaluated using Radial Based Artificial Neural Networks, which is a different artificial neural network model than those used in studies in the literature. Samsun

Figure 2. The location of Tekkekoy DSD (Google Earth).

Tekkekoy DSD system was chosen as the study area, taking into account the high population density in the Black Sea region.

MATERIAL AND METHODS

Study Area

This study was carried out in Tekkekoy DSD of Samsun in Turkey's northern coast. The location of tekkeköy DSD satellite image, which is a domestic discharge system, is given in Figure 2. Field studies were carried out between July 2015 and 2016 under the contractor of the Ministry of Environment and Urbanization and the direction of Ondokuz Mayıs University Environmental Engineering Department.

Sampling from various points, dissolved oxygen, pH values were determined at the time of sampling by conductivity-temperature-depth (CTD) experiments. Using 5 L Niskin water sampler, seawater samples were collected at three different water depths (surface, middle, and bottom) at each point. Laboratory studies were performed according to standard methods and then tested for three parameters (total suspended solids (TSS, APHA 2540D), BOD_5 (APHA, 5210B), total coliform (TS EN ISO 9308-1). Detailed information about the sampling points and their geographical locations are presented in Table 1. Satellite image of the deep sea discharge sampling points is given in Figure 3.

MODELING STUDY

Radial based artificial neural networks

Radial Based Artificial Neural Networks (RBNN) was developed in 1988 inspired by the effect response behaviors seen in biological nerve cells and entered the history of ANN by applying it to the filtering problem [16].

It is possible to view the training of RBNN models as a curve-fitting approach in multidimensional space [17]. For this reason, the training performance of the RBNN model turns into an interpolation problem, finding the most suitable surface for the data in the output vector space. RBNN models are defined in three layers as the input layer, hidden layer and output layer, similar to general ANN architecture

Figure 3. Sampling points of Tekkekoy DSD (Google Earth).

(Figure 4). However, unlike conventional ANN structures, RBNN s use radial-based activation functions in the transition from the input layer to the hidden layer. The structure between the hidden layer and the output layer continues to function as in other ANN types, and the actual training is carried out here.

Radial-based artificial neural networks (RBNN) are networks that have radial-based activation functions in the transition to the hidden layer, unlike other networks [19]. There are three components for the radially symmetrical middle layer processor element. The first is a center vector in the input space. This vector is stored as the weight vector between the input and hidden layers. The second is the distance measure to determine how far an input vector is from the center. Typically this criterion is taken as the standard Euclidean distance. The last one is an activation function structure that determines the output value of the processor element, which is one variable and takes the distance function output as input. The processor elements in the first layer do not use the weighted shape of the inputs. The outputs of the processor elements in the first layer are determined according to the distance between the ANN inputs and the center of the basic function. The last layer of the RBNN structures is linear and the total output weighted from the outputs of the first layer is produced [20].

The output (y) produced by the network in RBNN models can be calculated with the help of equation 1.

$$y_i = \sum_{k=1}^{N} w_{ik}\phi_k(x,c_k) = \sum_{k=1}^{N} w_{ik}\phi_k\|x - c_k\|_2,\ i = 1,2,\dots,m \quad (1)$$

In this equation, $x \in R^{n\times 1}$ is the input vector of the network; $\phi_k \in R^{+}$ radial based activation function; $c_k \in R^{n\times 1}$

Table 1. Geographical locations of sampling points (Ardali, 2015).

Station	Latitude	Longitude	Depth (m)	Station	Latitude	Longitude	Depth (m)
N1-Surface	41°15’57”	36°26’09”	0.68	**N6- Surface**	41°15’42”	36°26’02”	0.47
N1-Middle	41°15’57”	36°26’09”	11.86	**N6- Middle**	41°15’42”	36°26’02”	10.43
N1-Bottom	41°15’57”	36°26’09”	22.89	**N6- Bottom**	41°15’42”	36°26’02”	21.85
N2- Surface	41°15’58”	36°26’05”	0.86	**N7- Surface**	41°16’03”	36°25’49”	0.36
N2- Middle	41°15’58”	36°26’05”	11.72	**N7- Middle**	41°16’03”	36°25’49”	8.35
N2- Bottom	41°15’58”	36°26’05”	23.19	**N7- Bottom**	41°16’03”	36°25’49”	16.41
N3- Surface	41°16’01”	36°26’11”	0.47	**N8- Surface**	41°16’12”	36°26’17”	0.46
N3- Middle	41°16’01”	36°26’11”	13.98	**N8- Middle**	41°16’12”	36°26’17”	12.52
N3- Bottom	41°16’01”	36°26’11”	23.95	**N8- Bottom**	41°16’12”	36°26’17”	22.84
N4- Surface	41°15’56”	36°26’13”	0.48	**N9- Surface**	41°16’25”	36°25’48”	0.34
N4- Middle	41°15’56”	36°26’13”	10.33	**N9- Middle**	41°16’25”	36°25’48”	12.53
N4- Bottom	41°15’56”	36°26’13”	21.07	**N9- Bottom**	41°16’25”	36°25’48”	23.83
N5- Surface	41°15’52”	36°26’29”	0.75	**N10- Surface**	41°14’58”	36°25’26”	0.47
N5- Middle	41°15’52”	36°26’29”	13.05	**N10- Middle**	41°14’58”	36°25’26”	3.52
N5- Bottom	41°15’52”	36°26’29”	25.02	**N10- Bottom**	41°14’58”	36°25’26”	4.69

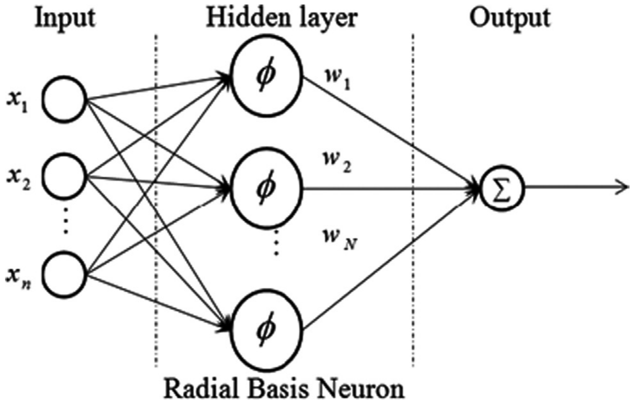

Figure 4. RBNN structure (He et al., 2019).

radial-based centers selected from a subset of the input vector space; $||.||_2$ is the Euclidean norm which is a measure of how far the input vector is from the center; w_{ik} weights in the output layer; N indicates the number of cells in the hidden layer.

Many types of functions can be used as activation functions in RBNN models. Linear, Cubic, Gauss, Multi-Quadratic, Inverse Multi-Quadratic functions are some of them and the Gauss function was preferred in this study. The mathematical structure of the Gauss function is shown in equation 2.

$$\phi_k(x) = exp^{\left(-\|x - c_k\|_2^2 / 2\sigma^2\right)} \quad (2)$$

In this equation, x represents the input vector, CK centers. σ symbolizes the standard deviation value. In ANN terminology, it is also referred to as the scatter parameter that significantly affects the performance of the RBNN model [17]. The scattering parameter is usually taken as a constant for all cells. Although there are approximate equivalents for the dispersion parameter in RBNN models, this parameter can also be determined by the trial-and-error method (Ham & Kostanic 2001). In this study, 10 different parameters have been tried with the values of the dispersion parameter between 0.1-1 and step size of 0.1.

RESULTS AND DISCUSSION

Various combinations were used as input to make coliform calculations using a radial-based artificial neural network. The 17 elements that make up these combinations are, pH, suspended solids, dissolved oxygen, crude oil, and its derivatives, organic pollutants, chlorophyll, phenols, ammonia, Cu, Cd, Cr, Pb, Ni, Zn, Hg, As and light transmittance values. The Models which have five to ten neurons were prepared to apply with the RBNN model were given in Table 2.

Table 2. Model structures

Model	Model Structure	Parameters Used
M1	17-10-1	
M2	17-9-1	
M3	17-8-1	All Parameters
M4	17-7-1	(Scenario 1)
M5	17-6-1	
M6	17-5-1	
M7	7-10-1	
M8	7-9-1	Parameters except
M9	7-8-1	
M10	7-7-1	Ammonia and Heavy Metals
M11	7-6-1	(Scenario 2)
M12	7-5-1	

Table 3a. Model results of scenario 1

	Dispersion Parameter	RMSE	R	R^2
M1	**0.1**	**22.42301**	**0.9782**	**0.956875**
M2	0.3	23.81412	0.9758	0.952186
M3	0.6	24.85174	0.9736	0.947897
M4	0.6	25.87693	0.9714	0.943618
M5	0.4	27.53301	0.9676	0.93625
M6	0.4	27.90228	0.9667	0.934509

Table 3b. Model results of scenario 2

	Dispersion Parameter	RMSE	R	R^2
M7	**0.1**	**22.58343**	**0.9783**	**0.957071**
M8	0.1	23.77356	0.9759	0.952381
M9	0.1	25.4391	0.9724	0.945562
M10	0.1	27.549	0.9675	0.936056
M11	0.1	33.96029046	0.9502	0.90288004
M12	0.1	35.49612	0.9455	0.89397

In the prepared models, all parameters are divided into their maximums and normalized to values between 0-1 and size homogeneity is provided. The normalized data were inserted into the RBNN structure with dispersion parameters ranging from 0.1-1, and the results were denormalized and evaluated according to the selected error evaluation criteria. In the prepared models randomly selected 70% of

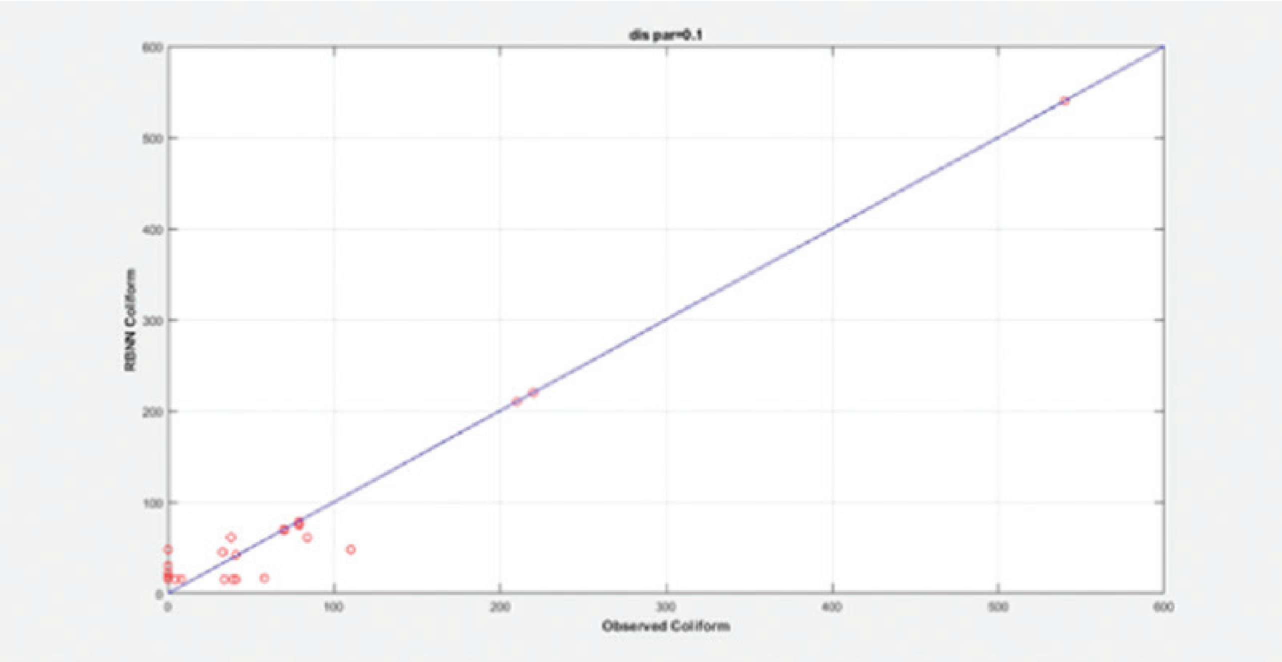

Figure 5. Best Result Scatter Diagram for Scenario 1 (M1).

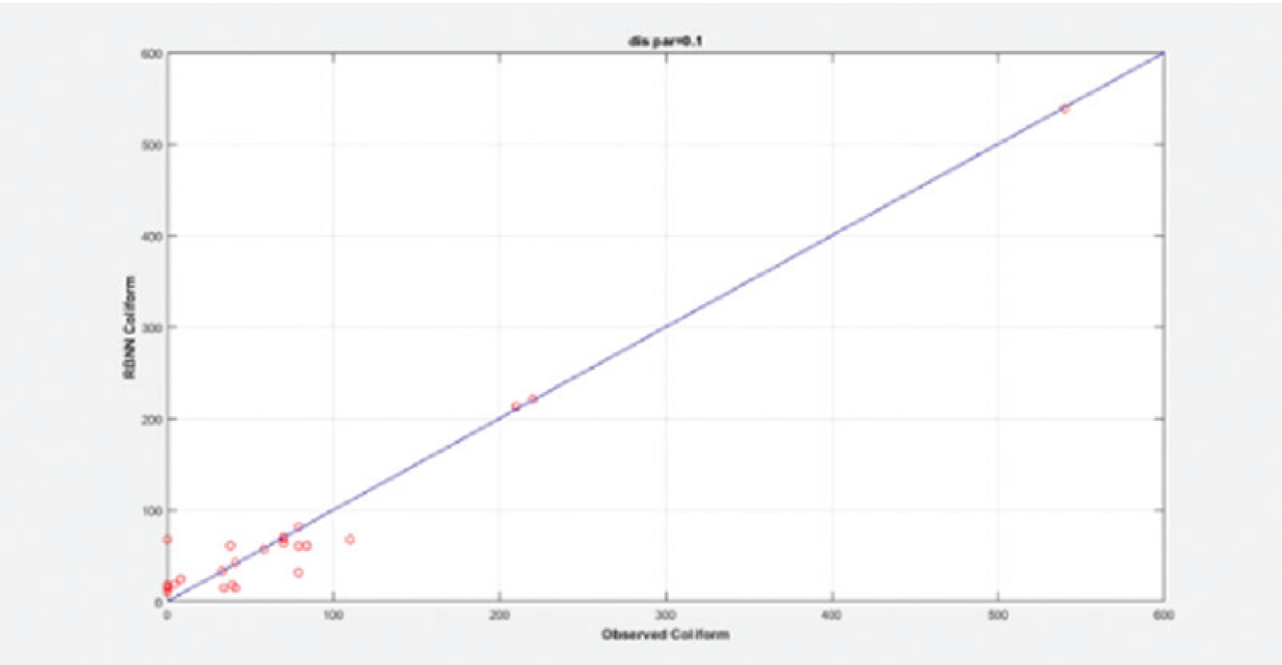

Figure 6. Best Result Scatter Diagram for Scenario 2 (M7).

data are used for training, 15% for validating and 15% for testing [21]. Root mean square error (RMSE), correlation (R) and determination (R^2) coefficients were used as error evaluation criteria. All data sets by using RBNN models have been also estimated.

Coliform estimation was made for all 30 samples via prepared models and statistical results of the models are given in Table 3a. and Table 3b, the scatter diagrams of the best results of the best models of two secenarios are presented in Figure 5 and Figure 6. In the scatter diagrams, the

Table 4. Comparison of RBNN results and FFNN (Ayeri et al., 2018) results

Model	Ayeri vd.		This article	
	RMSE	R^2	RMSE	R^2
M1	46.0858	0.5929	**22.42301**	**0.956875**
M6	44.9435	0.6561	27.90228	0.934509
M7	49.3001	0.6084	**22.58343**	**0.957071**
M12	28.0800	0.81	35.49612	0.89397

x-axis formed measured coliform values determined as a result of laboratory studies, and the y-axis formed the predicted coliform values as a result of RBNN.

The best results determined in the prepared models were obtained when the dispersion parameter was chosen as 0.1 the ten-neurons M1 model is determined to be the model that gives the best results. The models prepared by Ayeri et al. (2018) using the FFNN structures and the same models results of this study using the RBNN structures were compared. Values for comparing studies are presented in Table 4.

It has been determined that the models using the RBNN structures give better results than the models used in FFNN.

CONCLUSION

It is a fact that sea discharges, which have a very important place in reducing environmental pollution, are used extensively in the Black Sea region. Coliforms with indicator parameters can be determined in the laboratory environment or can be estimated using artificial intelligence methods in the light of laboratory measurements. In this study, the coliform values of Tekkekoy deep sea discharge were made to determine using a radial-based artificial neural network. Samples taken from the study area were analyzed in a laboratory environment and presented as input to RBNN architecture. The best model was determined by comparing the amount of coliform estimated using RBNN with the amount of coliform determined as a result of laboratory studies.

In the study where the dispersion parameter, which is one of the parameters of the RBNN structure, varies between 0.1–1.12 different model structures were prepared. Although heavy metals and ammonia were added as parameters in 6 of the 12 models prepared, these parameters were not used in the other models.

The correlation value in RBNN structures where the dispersion parameter of the best results was determined as 0.1 was 95.7%–98.67%. It has been determined that the model with 10 neurons expressed as M3 and all parameters except heavy metal and ammonia has a superior performance compared to other models.

In coliform estimation, it was determined that RBNN structures are more successful than FFNN structures and Artificial Neural Network structures can be used successfully in coliform prediction. More successful models can be developed by using various model structures and artificial neural network architectures in large work areas. In coliform estimation, it was determined that RBNN structures are more successful than FFNN structures and Artificial Neural Network structures can be used successfully in coliform prediction. More successful models can be developed by using various model structures and artificial neural network architectures in large work areas.

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AUTHORSHIP CONTRIBUTIONS

Aydın Er conducted experimental and statistical studies.

Sisman supported the map drawings and writing.

Ardali supported writing, experimental studies and statistical studies.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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