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# River Water Salinity Impact on Drinking Water Treatment Plant Performance Using Artificial neural network

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#### ABSTRACT

**T**he river water salinity is a major concern in many countries, and salinity can be expressed as total dissolved solids. So, the water salinity impact of the river is one of the major factors effects of water quality. Tigris river water salinity increase with streamline and time due to the decrease in the river flow and dam construction from neighboring countries. The major objective of this research to developed salinity model to study the change of salinity and its impact on the Al-Karkh, Sharq Dijla, Al-Karama, Al-Wathba, Al-Dora, and Al-Wihda water treatment plant along Tigris River in Baghdad city using artificial neural network model (ANN). The parameter used in a model built is (Turbidity, Ec, T.s, S.s, and TDS in) to predict the salinity TDS<sub>out</sub>. Results showed that the effectiveness of the artificial neural network model to predicting the salinity is a good agreement between observed and the predicted value of the TDS, through the determination coefficient of the model is (0.998, 0.966, 0.997, 0.998, 0.996, and 0.996) for Al. Karkh, Sharq Dijla, Al-Karama, Al-Wathba, Al-Dora and Al-Wihda respectively. From this value can be shown that ANN is a successful tool for predicting the nonlinear equation of the salinity under different and complicated environmental case along the river.

Keywords: Salinity impact, Drinking water, Tigris River, ANN, TDS, WTP

تأثير ملوحة مياه النهر على أداء محطة معالجة مياه الشرب بإستخدام الشبكة العصبية الصناعية

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#### الخلاصة

تعتبر ملوحة مياه النهر مصدر قلق لكثير من البلدان ويمكن التعبير عن الملوحة بكمية المواد الصلبة الذائبة. تزداد ملوحه مياه نهر دجلة على طول مجرى النهر بالابتعاد عن مصبات النهرو مع الوقت، بسبب نقصان تدفق المياه والسدود التي يم انشاءها من قبل الدول المجاورة. الهدف الريئسي من هذا البحث هو لتطوير نموذج لدراسة تغيير الملوحة وتاثيره على محطات معالجة المياه ( الكرخ ،شرق دجلة ، الكرامه، الوثبة، الدورة و الوحدة ) لمعالجة المياه على طول نهر دجلة في مدينة بغداد باستخدام برنامج الشبكة العصبية الصناعية.

العوامل التي تم استخدامها لدر اسة النموذج هي العكارة ، التوصيلية الكهر بائية ، المواد الصلبة الكلية ، المواد الصلبة العالقة والمواد الصلبة العالقة والمواد الصلبة الذائبة ) الخارجة من المحطة خلال الفترة من 2013-2017 من 2017-2013

اظَهرت النتائج فعالية برنامج الشبكة العصبية الصناعية للتنبوء بالملوحة وهو مطابقة جيدة للمواد الصلبة الذابئة بين القيم المقاسة والقيم المتوقعة، من خلال معامل التحديد للنموذج هي(0.998 ، 0.966 ، 0.997 ، 0.998 ، 0.996 ، 0.996) للمحطات الكرخ ، شرق دجلة ، الكرامة ، الوثبة، الدورة و الوحدة بالتتابع. من خلال هذه القيم يمكن اثبات ان برنامج الشبكة العصبية الصناعية كان اداة ناجحة للتبوء بالمعادلات الغير خطية للملوحة تحت ظروف مختلفة ومعقدة بيئية على طول النهر في منطقة الدراسة.

**الكُلمات الْرنيسية:** الملوحة، مياه الشرب،نهر دجلة، الشبكة العصبية الصناعية، المواد الصلبة الذائبة، محطات معالجة المياه

## **1. INTRODUCTION**

Salinity can be defined as the weight of mineral salt found in the water and is expressed either in grams of salt per kilogram of water or in parts per thousand (ppt). The salinity of the water is variation due to the season of the year and along the length of the river. Therefore when the season is summer the salinity increase and increases along the year because of the accumulation of concentration along the year, **Rahi and Halihan**, **2018**. Many researchers have been studied the effects of salinity on the ecosystem in Australia, and the result showed that salinity increased with change the ecosystem and affected the biota and physical environmental, **Nielson, et al.**, **2003**. The salinity of drinking water and maternal health in Bangladesh, have been studied the influence of the environment change and the result appeared that salinity increased due to having been exacerbated of sea-level rise and climate change, **Khan**, et al., **2011**.

Iraq was relied upon the Tigris River for drinking, agriculture and municipal water supply, **Al Murib**, **2018**. Tigris river salinity increase due to the many factor climate change, dam's construction of the neighboring countries, and a decrease of stream flow. The water salinity evaluation along Tigris River, have been Studied the relationship between the salinity and the discharge, and the resulted have been recommending for salinity management is excluding Lake Tharthar from storage water, administer salinity flows of tributaries and utilize the minimum of the flow from the river. Some of the researchers have been studied the salinity based on TDS along the Euphrates river, the result appeared the salinity increase due to the flow decrease from neighboring countries and internal factor and the direct disposal waste sewage to the river, **Rahi and Halihan, 2010**.

Artificial neural network modeled was used for prediction of TDS in Shatt Al. Arab, the result showed the model is successful, more effect and significance for prediction of TDS, **Hamdan and Dawood, 2016**. ANN has been used to predict the value of chlorine concentration the water distribution system, **Cordobaa, et al., 2014**. Also, ANN has been used to predict the concentration of dissolved oxygen (DO) for water quality indicator, **Sarkara and Pandeyb, 2014**.



The objective of this research for a prediction salinity model and study the change of it and the effect for the drinking water along the Tigris River along with Baghdad city. This prediction model can use for future salinity predict and estimation if have any manage and planning of the water treatment plant

## 2. MATERIAL AND METHOD

### 2.1 Description of the Case Study

Tigris River is one of the major rivers in Iraq that used into feeding water for drinking and irrigation. In the recent year the morphology of Tigris River in Baghdad city change due to huge sediment of reservoirs construction and climate change. So, this river exposed to suffering water and salinity increase over the years. Deterioration of the water due to the dam's construction and some climatic change. The study area description is between logntidnal 33° 24` 33<sup>°</sup>-33° 17` 14<sup>°</sup>N and longitudes 44° 21` 06<sup>°</sup>-44° 26` 23<sup>°</sup>E as shown in **Fig. 1**.

In Baghdad, there is a need for a dramatic increase in demand for fresh water due to rapid population growth and accelerated industrialization. In addition to the increase in pollution along the river due to the discharge of effluent by various sources uncensored such as local industries and agriculture along the course of the river. Therefore, the river's water quality control is necessary to assess the quality of water for different purposes, **khudair**, **2013**.

Several research and studies have been carried out to assess the water quality of the Tigris River, which amounts to the influence of contaminants within the city of Baghdad, **Shami**, et al., 2006.



Figure 1. Tigris River along with Baghdad city from Google map.



#### 2.2 Data Collection and analysis

In the current study, the data were taken from the municipality of Baghdad for Al-Karkh, Sharq dijla, Al-Wathba, Al-Karama, Al-Dora, and Al-Wihda water treatment plant along the Tigris River in Baghdad city during the period 2013-2017. The parameter that chooses in this study is (Turbidity, Ec, TS, TSS, and TDS in) for raw water and TDS supply for the W.T.P. The samples of water examine according to the Standard Methods for the Examination of Water and Wastewater. The data were analyzed by using SPSS program version 23, to achieving the purpose of the study that describes above.

#### 3. ARTIFICIAL NEURAL NETWORK SALINITY MODEL (ANNSM)

Neural networks are the preferred tool for many applications looking for predictive data because of their flexibility, strength, and ease of use (**SPSS user guide**). In the last years, ANN used for prediction the relationships of complex hydrological. ANN has been used for the production of the target data from the independent data, so the internal operation manner of the program is similar to the nervous human system, model is different from any statistical model, did not have any assumption for the model structure due to its learned from the data and specify the model who is suitable for the data. ANN model is a nonlinear relationship between the target salinity and in the depended variable. On a case of the salinity impact model, the relationships are between the target variable (salinity) and independent variable (Turbidity, Ec, T.s, S.s, TDS in), the program learns from the previous data entry to it for giving a model for future prediction salinity, therefore. Knowledge obtained from past data is popularized and stored on ANN for prediction the salinity impact, **Hamdan and Dawood**, **2016**.

#### 4. RESULTS AND DISCUSSION

#### 4.1 River Water Salinity Assessment (RWSA)

**Table 1** showed the raw water quality along the Tigris River in Baghdad city, as the average value of turbidity is (60 NTU), electric conductivity is (867  $\mu$ s/cm), total solids is (579 mg/L), total suspended solids is (74 mg/L), and total dissolved solids is (506 mg/L). Where the value of the correlation coefficient between the TDS and EC is between (0.56-0.61). Either for drinking water salinity the value between (394-554) mg/L and the average value is (507 mg/L) during the period of the study between (2013 – 2017). From the above data notice that no removal of the TDS in the WTP, that's due to the coagulant added and that may increase the TDS.

The TDS concentration for raw water and drinking water was increased with time during (2013-2017) as shown in **Fig.2**, and **Fig.3** showed the value of TDS for raw water versus the location of WTP. From this figure, the value of TDS increases from upstream to the downstream in Tigris River along with Baghdad city. So, from **Fig** 2 and 3 can show the value of TDS increase with time and distance. The drinking water TDS from these WTP is compared with Iraqi specification is suitable for drinking were assumed that the other parameter agrees with specification and according to the, **WHO**, **2011** specification of drinking water, the water is unsuitable for drinking. While final according to the Australian Drinking Water Guidelines that showed in **Table 2**, the water can be classified in the range (0-600) mg/L so it's in a good class.

		Drinking				
WTP	Turbidity	EC	TS	TSS	TDS	water TDS
	(NTU)	(µs/cm)	(mg\L)	(mg\L)	(mg\L)	(mg/L)
Al-Karkh	61	701	452	62	390	394
Sharq Dijla	59	840	563	89	474	475
Al-Karama	51	907	632	88	544	545
Al-Wathba	59	907	609	59	551	554
Al-Dora	46	924	600	51	550	542
Al-Wihda	81	925	620	95	525	531
Average	60	867	579	74	506	507

Table 1. Average of Annual parameter for W.T.P.



Figure 2. Average TDS Supply from W.T.P variation versus Time.



Figure 3. Average TDS variation versus WTP location



Salinity (mg/L)	Quality
0 - 600	good
600 - 900	fair
900 - 1,200	poor
> 1,200	unacceptable (unpalatable)

**Table 2.** The range of salinity according to (Australian Drinking Water Guidelines).

### 4.2 Artificial neural network model (ANNM)

ANN model was used for predicting the value of salinity for Al-Karkh, Sharq Dijla, Al-Karama, Al-Wathba, Al-Dora, and Al-Wihda water treatment plant along Tigris River in Baghdad city. The model was made after many trails of testing, training, and holdout. The available data was 60 and it's divided 49 for training, 6 for testing and 5 for a holdout. The input data (Turbidity, Ec, T.s, S.s, TDS in), for prediction salinity (TDS <sub>out</sub>). A standardized method is the rescaling method of input data, the number of the hidden layer can show according to the **Fig.4**, three hidden layers for Al-Karkh and Al-Dora, two hidden layers for Al-Karama and Al-Wihda and one hidden layer for Sharq dijla and Al-Wathba. The activation function for covariates is the hyperbolic tangent.

The outputs layer is salinity as the target of the model, also standardized is the rescaling method for output, the activation function is identified as shown in **Fig.4**. While in **Table 3** show the parameter estimation prediction of input layer bias and a hidden layer of covariates and the output layer.

**Fig.5 and Table 4,** show the coefficient of determination and the equation between the predictors and observed value, the best and highest value coefficient of determination is (0.998) in Al-Karkh the high value of it's because of the location in the upstream in Baghdad and (0.998) in Al-Karama due to the highest distance of the polluted point. The overall WTP determination coefficient is (0.997) and the equation along the Tigris River in Baghdad city was shown in eq.1.

y = 1.25 + 1 \* x(1)

Where; y represents the target value and x: the observed value

**Table 5** shows the most important factor that effect of salinity is totally solid in the Al-Karkh, Al-Karama, Al-Wathba, Al-Dora, and Al-Wihda because total dissolved solids it is a part of the total solids. For Sharq Dijla total dissolved solids input to WTP. The least effect of salinity in Al-Karkh, Sharq Dijla, Al-Karama, Al-Dora, and Al-Wihda is electric conductivity but it is total dissolved solids for Al-Wathba WTP. The overall of all water treatment plant high importance effect of TDS supply is TDS of raw water, and the least importance is Ec.



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Figure 4. The architecture of the ANN model.



		1					ion of ma	aon ana	ourpurp	aranneter				-		
			Prec	licted					Pred	icted					Predicted	1
					Output			H	Hidden	Output	t					
		Hie	dden Laye	er 1	Layer				layer 1	Layer				Hiddon	Lovon 1	Output
					TDS	Predicto	r		H(1:1)	TDS or				Hidden	Layer I	Layer TDS
Predicto	or	H(1:1)	H(1:2)	H(1:3)	out	Input	(Bias)		-0.175	105 00		Predicto	r	H(1:1)	H(1:2)	out
Input	(Bias)	0.391	-0.087	-0.273		Layer	Turbid	:+	-0.175			Input	(Bias)	0.343	0.049	
Layer	Turbidity	-0.069	0.029	0.078		Layer	-	Ity				Layer	Turbidity	-0.176	0.124	
	Ec	0.006	0.041	0.032			Ec		-0.052				Ec	0.016	-0.021	
	T.s	-0.439	0.089	-0.148			T.s		-0.073				T.s	0.246	0.187	
	S.s	0.056	-0.100	0.208			S.s		0.208				S.s TDSin	-0.229	0.310	
	TDS in	0.013	0.179	-0.182			TDS in	1	-0.413			Hidden	(Bias)	-0.125	0.510	-0.524
Hidden	(Bias)				0.086	Hidden	(Bias)			-0.25	2	Layer	H(1:1)			1.472
Layer	H(1:1)				-0.768	Layer 1	H(1:1)			-2.03	8	1	H(1:2)			1.649
1	H(1:2)				1.178	2. S	2. Sharq Dijla WTP				3. Al.Karama WTP					
	H(1:3)				-1.121		1 5									
1. A	. ,	ГР			1.121											
1. A	Al.Karkh W		icted		1.121				Pre	licted					Predicted	1
1. A	. ,	Pred	icted Output	-	1.121				Pre	licted	Output				Predicted	
1. A	. ,	Pred Hidden	Output		1.121				dden Laye	er 1	Layer			Hiddon		Output
	Al.Karkh W	Pred Hidden Layer 1	Output Layer		1.121	Predictor		H(1:1)	dden Laye H(1:2)	er 1 H(1:3)		Predicto	r	Hidden H(1:1)	Layer 1	Output Layer
1. A Predicto	Al.Karkh W	Pred Hidden Layer 1 H(1:1)	Output		1.121	Input	(Bias)	H(1:1) -0.534	dden Laye H(1:2) 0.099	er 1 H(1:3) -0.050	Layer	Predicto	r (Bias)	H(1:1)		Output
Predicto	or (Bias)	Pred Hidden Layer 1 H(1:1) 0.087	Output Layer		1.121		Turbidity	H(1:1) -0.534 -0.026	dden Laye H(1:2) 0.099 0.037	er 1 H(1:3) -0.050 -0.151	Layer	Predicto Input Layer			Layer 1 H(1:2)	Output Layer
Predicto	or (Bias) Turbidity	Pred Hidden Layer 1 H(1:1) 0.087 0.050	Output Layer		1.121	Input		H(1:1) -0.534	dden Laye H(1:2) 0.099	er 1 H(1:3) -0.050	Layer	Input	(Bias) Turbidity Ec	H(1:1) 0.116 0.097 -0.140	Layer 1 H(1:2) -0.400 -0.240 0.358	Output Layer
Predicto	or (Bias) Turbidity Ec	Pred Hidden Layer 1 H(1:1) 0.087 0.050 -0.251	Output Layer		1.121	Input	Turbidity Ec	H(1:1) -0.534 -0.026 -0.257	dden Laye H(1:2) 0.099 0.037 0.108	er 1 H(1:3) -0.050 -0.151 0.235	Layer	Input	(Bias) Turbidity Ec T.s	H(1:1) 0.116 0.097 -0.140 0.304	Layer 1 H(1:2) -0.400 -0.240 0.358 0.274	Output Layer
Predicto	or (Bias) Turbidity Ec T.s	Pred Hidden Layer 1 H(1:1) 0.087 0.050 -0.251 0.483	Output Layer		1.121	Input Layer	Turbidity Ec T.s S.s TDSin	H(1:1) -0.534 -0.026 -0.257 -0.242	dden Laye H(1:2) 0.099 0.037 0.108 -0.287	er 1 H(1:3) -0.050 -0.151 0.235 -0.306	Layer TDSout	Input	(Bias) Turbidity Ec T.s S.s	H(1:1) 0.116 0.097 -0.140 0.304 -0.314	Layer 1 H(1:2) -0.400 -0.240 0.358 0.274 0.360	Output Layer
Predicto	or (Bias) Turbidity Ec T.s S.s	Pred Hidden Layer 1 H(1:1) 0.087 0.050 -0.251 0.483 -0.187	Output Layer		1.121	Input Layer Hidden	Turbidity Ec T.s S.s TDSin (Bias)	H(1:1) -0.534 -0.026 -0.257 -0.242 0.477	dden Laya H(1:2) 0.099 0.037 0.108 -0.287 -0.011	er 1 H(1:3) -0.050 -0.151 0.235 -0.306 0.216	Layer TDSout	Input Layer	(Bias) Turbidity Ec T.s S.s TDSin	H(1:1) 0.116 0.097 -0.140 0.304	Layer 1 H(1:2) -0.400 -0.240 0.358 0.274	Output Layer TDSout
Predicto Input Layer	or (Bias) Turbidity Ec T.s S.s TDSin	Pred Hidden Layer 1 H(1:1) 0.087 0.050 -0.251 0.483	Output Layer TDSout	-	1.121	Input Layer	Turbidity Ec T.s S.s TDSin (Bias) H(1:1)	H(1:1) -0.534 -0.026 -0.257 -0.242 0.477	dden Laya H(1:2) 0.099 0.037 0.108 -0.287 -0.011	er 1 H(1:3) -0.050 -0.151 0.235 -0.306 0.216	Layer TDSout -0.512 -1.258	Input Layer Hidden	(Bias) Turbidity Ec T.s S.s TDSin (Bias)	H(1:1) 0.116 0.097 -0.140 0.304 -0.314	Layer 1 H(1:2) -0.400 -0.240 0.358 0.274 0.360	Output Layer TDSout
Predicto	or (Bias) Turbidity Ec T.s S.s TDSin (Bias)	Pred Hidden Layer 1 H(1:1) 0.087 0.050 -0.251 0.483 -0.187	Output Layer TDSout -0.279	-	1.121	Input Layer Hidden	Turbidity           Ec           T.s           S.s           TDSin           (Bias)           H(1:1)           H(1:2)	H(1:1) -0.534 -0.026 -0.257 -0.242 0.477	dden Laya H(1:2) 0.099 0.037 0.108 -0.287 -0.011	er 1 H(1:3) -0.050 -0.151 0.235 -0.306 0.216	Layer TDSout -0.512 -1.258 -1.371	Input Layer	(Bias) Turbidity Ec T.s S.s TDSin	H(1:1) 0.116 0.097 -0.140 0.304 -0.314	Layer 1 H(1:2) -0.400 -0.240 0.358 0.274 0.360	Output Layer TDSout
Predicto Input Layer Hidden Layer 1	or (Bias) Turbidity Ec T.s S.s TDSin (Bias) H(1:1)	Pred Hidden Layer 1 H(1:1) 0.087 0.050 -0.251 0.483 -0.187 0.032	Output Layer TDSout	-	1.121	Input Layer Hidden Layer 1	Turbidity           Ec           T.s           S.s           TDSin           (Bias)           H(1:1)           H(1:2)           H(1:3)	H(1:1) -0.534 -0.026 -0.257 -0.242 0.477 0.448	dden Laya H(1:2) 0.099 0.037 0.108 -0.287 -0.011	er 1 H(1:3) -0.050 -0.151 0.235 -0.306 0.216	Layer TDSout -0.512 -1.258	Input Layer Hidden Layer 1	(Bias) Turbidity Ec T.s S.s TDSin (Bias) H(1:1)	H(1:1) 0.116 0.097 -0.140 0.304 -0.314 0.160	Layer 1 H(1:2) -0.400 -0.240 0.358 0.274 0.360	Output Layer TDSout -0.072 2.139
Predicto Input Layer Hidden Layer 1	or (Bias) Turbidity Ec T.s S.s TDSin (Bias)	Pred Hidden Layer 1 H(1:1) 0.087 0.050 -0.251 0.483 -0.187 0.032	Output Layer TDSout -0.279	-	1.121	Input Layer Hidden Layer 1	Turbidity           Ec           T.s           S.s           TDSin           (Bias)           H(1:1)           H(1:2)	H(1:1) -0.534 -0.026 -0.257 -0.242 0.477 0.448	dden Laya H(1:2) 0.099 0.037 0.108 -0.287 -0.011	er 1 H(1:3) -0.050 -0.151 0.235 -0.306 0.216	Layer TDSout -0.512 -1.258 -1.371	Input Layer Hidden Layer 1	(Bias) Turbidity Ec T.s S.s TDSin (Bias) H(1:1) H(1:2)	H(1:1) 0.116 0.097 -0.140 0.304 -0.314 0.160	Layer 1 H(1:2) -0.400 -0.240 0.358 0.274 0.360	Output Layer TDSout -0.072 2.139

## Table 3. Estimation of hidden and output parameters.



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Figure 5. Predicted values versus dependent variable for WTP.

W.T.P	Equation	Correlation Coefficient
Al.Karkh	y = 2.31 + 0.99 * x	0.998
Sharq Dijla	y = 22.6 + 0.95 * x	0.966
Al.Wathba	y = 8.11 + 0.98 * x	0.997
Al.Karama	y = 6.16 + 0.99 * x	0.998
Al.Dora	y = 8.37 + 0.99 * x	0.996
Al.Wihda	y = 5.31 + 0.99 * x	0.996
Overall	y = 1.25 + 1 * x	0.997

**Table 4.** Show the equation and correlation coefficient.

**Table 5.** Show the importance of the parameter for WTP.

	Al.Karkh	Sharq Dijla	Al.Karama	Al.Wathba	Al.Dora	Al.Wihda	Over all
Paramete r	Normalized Importance	Normalize d Importanc e	Normalized Importance	Normalized Importance	Normalized Importance	Normalized Importance	Normalized Importance
Turbidity	3.6%	37.0%	9.9%	19.8%	12.0%	17.4%	11.6%
Ec	2.6%	11.4%	1.9%	50.2%	7.4%	14.8%	8.6%
T.s	100.0%	16.0%	100.0%	100.0%	100.0%	100.0%	19.5%
S.s	80.7%	58.4%	49.1%	69.9%	89.0%	74.4%	11.9%
TDSin	71.8%	100.0%	55.1%	8.9%	32.0%	59.8%	100.0%

# 5. CONCLUSIONS

From the current study can conclude the following

1. The salinity along Tigris River increased during the study period and this can effect of drinking water quality.

2. According to the Iraqi specification, the water is suitable for drinking but according to the (**WHO**, 2011) specification the water in Al-Karkh and Sharq Dijla is suitable for drinking but in Al-Wathba, Al-Karama, Al-Dora, and Al-Wihda the water is unsuitable for drinking.

3. According to the Australia specification, the salinity in Tigris River is changing a good and when the year increase the direction of salinity go to be fair.

4. ANN model can be used for prediction future Salinity (TDS out) along the Tigris River in Baghdad city with a high coefficient of correlation.

5. ANN model the high importance factor effect of salinity is totally solid in the Al. Karkh, Al.Karama, Al.Wathba, Al.Dora, and Al.Wihda. For Sharq, Dijla is total dissolved solids for raw water to WTP and all WTP that found the TDS of raw water.



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