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Ground Water Quality Management Using Time Series Prediction Model

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ABSTRACT

This paper addresses the critical importance of assessing the quality of raw water before treatment as a determinant for predicting the subsequent quality and natural attributes of mineral water intended for public consumption. The study introduces a comprehensive model for managing raw water quality within a water treatment plant. Specifically, the investigation focuses on the temporal trends of pH and Total Dissolved Substances (TDS) in the raw water entering the treatment facility. A time series model is developed to monitor the pH and TDS of the raw water, aiming to evaluate whether the treatment plant can sustain water quality without the need for additional additives. The research employs R-console and Eviews software for data analysis. Results reveal discernible upward and downward trends in the pH and TDS series over time. In response, an ARIMA (3,0,4) model is proposed for both the pH and TDS series, serving as a predictive tool to generate forecasts. The findings suggest that the pH and TDS values of the raw water indicate the treatment plant's capability to consistently produce quality water over time without the reliance on external additives. This research contributes to advancing the understanding and management of raw water quality in water treatment processes, offering insights that can enhance the sustainability of water treatment practices.

***Keywords*:** Water Quality Management, Time Series Modeling, Sustainability

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1. INTRODUCTION

Increase in population, urbanization and multipurpose use of water have resulted in water becoming scarce and at times low in quality. Water quality is one of the most significant challenges in applied hydrology. Because the primary functions of hydrology are to provide water for drinking, agriculture, or industry, each of which has certain quality requirements, and because if such a water supply is not attainable, these functions are essentially ineffective (Eslamian et al. 2018a; Eslamian et al. 2018b; Talebmorad et al. 2020; Fan 2020). Studies on water quality are more common and now cover concerns including surface and groundwater pollution (Cheng 2021). About 20% of the fresh water supply in the globe comes from groundwater (Alsalme et al., 2021). For human health, socioeconomic growth, and ecosystem function, groundwater is regarded as a vital natural resource (Dhayachandhran and Jothilakshmi, 2020). Due to overuse of fertilizers and pesticides, increased anthropogenic activities, and quickly expanding enterprises, the groundwater is vulnerable to pollution (Karthika et al., 2018; Verla et al., 2017; Ihenetu, et al., 2021).

Geological structure, salinity, excessive groundwater extraction, discharge of residential and municipal sewage into surface waters, crop drainage, and a wide range of chemical compounds can all harm very good water. Golian et al. 2020; Derakhannia et al. 2020; Fatahi Nafchi et al. 2021; Ostad-Ali-Askari et al. 2017a; Ostad-Ali-Askari et al. 2018b). Threats to human health and severe environmental impacts are caused by groundwater contamination (Kumar and Sangeetha, 2020). Studying water quality aids in the development of methods for reducing surface and groundwater pollution (Kumar and Sangeetha, 2020). Affum et al. (2015) also believe that, toxic elements, salinity pollution, and hardness are the main factors affecting the quality of ground water. This has resulted in water treatment companies adding many purification chemicals to the raw water to improve quality standards. In-as-much as the quality of water ingested into the human body is important, the methods employed in treating natural water should be of prime concern. What is quality and how natural is the water we consume? Water treatments plants pride themselves on producing high quality natural mineral water in Ghana with no additives as a result of the raw water meeting certain requirements. Such requirement includes meeting the pH in the range of 6.5-8.5 and the TDS (Total Dissolved Solids) of at most 1000 mg/l. In measuring the quality and naturalness of water, it is important to predict the state of quality of the raw water prior to treatment.

This paper investigates raw water quality management for ground water using a time series prediction model in a water treatment plant. Time-series models are widely employed for a variety of air pollution applications (Taneja et al; 2017; Liu et al; 2019; Mirsangari et al; 2020). One of the practical methods for modeling and forecasting water satisfaction is time series (Abdollahi et al. 2021; Nafchi et al. 2021, 2022; Fattahi Nafchi et al. 2022; Ostad-Ali-Askari et al. 2021a).

It is also helpful in generating future observations, which mostly depend on past memories, projecting future values (Madani 2021). In hydrology, time series serve the following crucial purposes: Understanding and transcribing a hydrological system's random tools, and estimating the system's fate standards (Pirnazar et al. 2018; Salehi Hafshejani et al. 2019; Talebmorad et al. 2021; Javadinejad et al. 2018, 2019a, b, 2021; Ostad-Ali-Askar et al. 2018a, 2019, 2020a; Kumar 2021, Ibrachim et.al, 2017). Models are made up of equations, relationships, and observational evaluation data that are used to explain how natural systems behave under various conditions.

Given particular time constraints and economic circumstances, models can be used to suggest the best management strategy (Shayannejad et al. 2022; Ostad-Ali-Askari et al. 2017b, 2020b, 2021b, c; Ostad-Ali-Askari 2022a, b; Raeisi Vanani et al. 2017; Pregun 2022).

This paper investigates the ongoing viability of utilizing raw water in a water treatment plant without the addition of chemicals, ensuring continuous adherence to quality standards. The study specifically examines the pH and Total Dissolved Substances (TDS) values of the raw water.

1. 1. Objectives of the Study

1) *Examine Trends:* Investigate the temporal trends of pH and TDS in the raw water utilized by a water treatment plant.
2) *Develop Time Series Model:* Create a time series model to monitor the pH and TDS values of the water from the treatment plant.

2. MATERIALS AND METHODS

This work adopts a quantitative descriptive survey approach as its methodology. The descriptive survey, as outlined by Gay (1992), involves collecting data from participants within a population to assess the present status of that population with respect to one or more variables. Data regarding the daily pH and TDS of water were collected from a water treatment plant over the period spanning November 2018 to October 2019. The equipment employed for parameter measurement included a pH Meter (Lovibond Senso Direct 150, manufactured in Germany), a TDS Meter (Lovibond Senso Direct 150), and a 500 ml beaker. The pH accuracy is ± (0.02 pH + 2 digits), while the TDS accuracy is ± (2% F.S. + 1 stelle), where FS denotes Full Scale.

To analyze the data, the researchers actively employed the Econometric Views (EViews) and R-Console software programs. Conducting a dynamic time series analysis, we explored descriptive statistics for both the pH and TDS series. We generated Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to assess the stationarity of the series. We confirmed stationarity through rigorous testing, employing the Augmented Dickey Fuller (ADF) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) unit root tests. For modeling the series, we adopted the proactive Box-Jenkins ARIMA process, selecting models based on the Akaike Information Criterion (AIC). Moving forward, we actively calculated model parameters at the next level (Estimation) to minimize the number of square residuals. Conducting a thorough model diagnostic, we utilized projections of the parameters for the forecast, determining new series values and standard errors for the expected values. The estimation process unfolded on transformed (differentiated) data, guaranteeing that the forecasts resonated with the input data values. This approach ensured not only analytical precision but also a vibrant and dynamic exploration of the dataset.

3. RESULTS AND DISCUSSION

3. 1. Descriptive Statistics of pH and TDS of water

Table 1 presents the statistics of the two series. The highest and lowest recordings for pH of water were 7.34 and 6.64; and for TDS they are 810.75 and 418.22. The means and standard deviations for the variables showed that there were less deviations. The variables had low kurtosis values that tend to have light tails, signifying a lack of outliers with values 3.04 and 3.47 for pH and TDS respectively. Therefore, a uniform distribution would be the extreme case. The Jarque-Bera normality test, tests the null hypothesis that a variable is normally distributed against its alternative. A p-value of less than 5% indicates the existence of great variations between the variables, including they are not normally distributed.

Table 1. Descriptive Statistics of pH and TDS of water

Statistics/Series	pH	TDS
Mean	6.92	621.04
Maximum	7.34	810.75
Minimum	6.64	418.22
Standard Dev.	0.11	59.67
Skewness	0.13	0.34
Kurtosis	3.04	3.47
Jarque-Bera	1.03	10.45
P-Value	0.60	0.01
No. of Observations	364.00	364.00

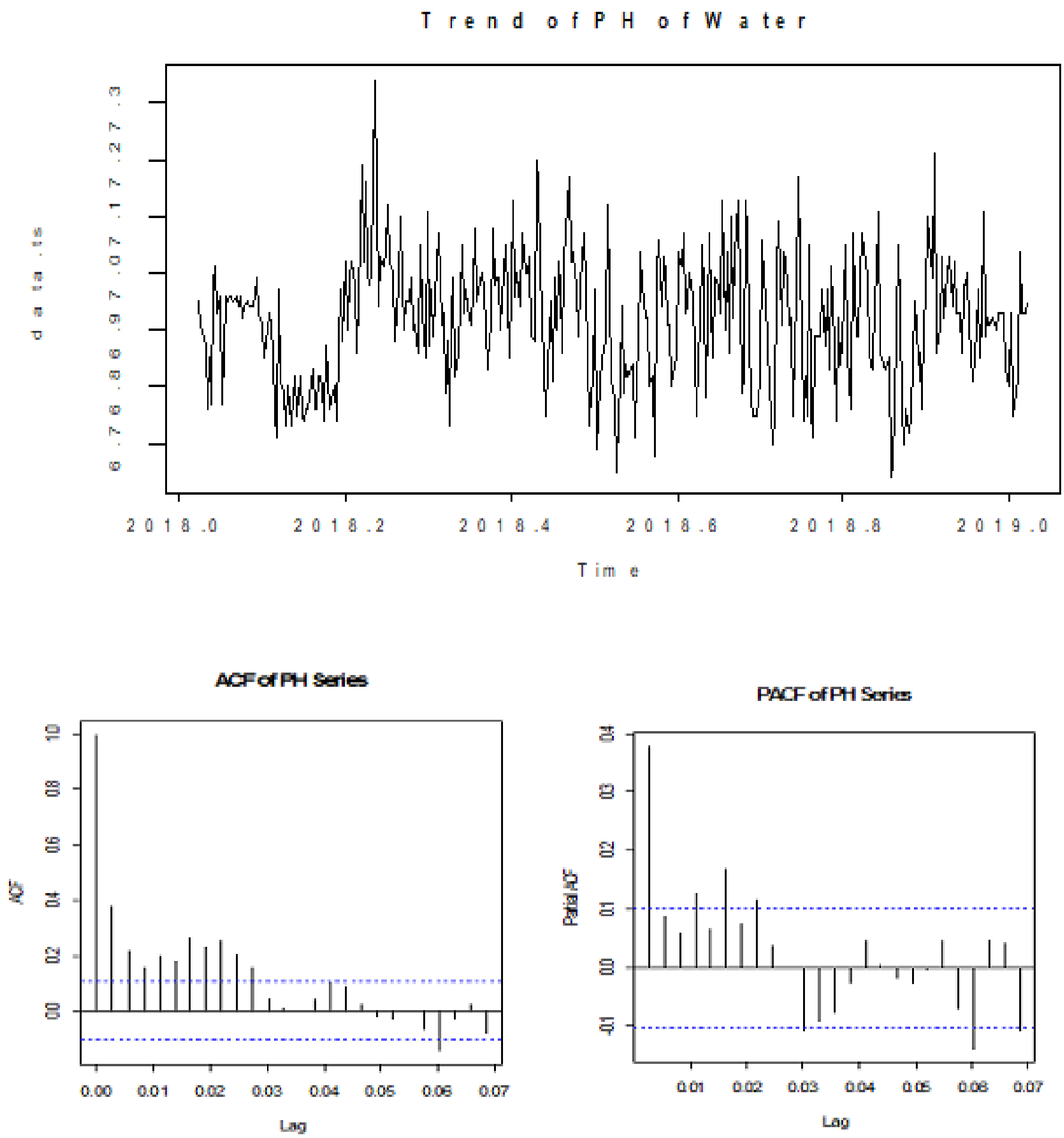
Source: Researchers' Estimation (2020)

3. 2. Analysis of pH series

Figure 1 presents the time series, ACF and PACF plots of the behaviour of the original series of the pH of water. The Fig. basically illustrates how the data behaved within equally spaced time intervals. It was observed that the series does not follow a specific systematic global trend.

However, it is clear from the Fig. that there are local upward and downward moving trends in the series over the time. That is, the data exhibits an irregular swinging pattern; the series seems to have a uniform pattern (upward or downward) over the entire period, seeming to wander up and down slowly. This is an indication that the series may be stationary.

From the ACF and the PACF, it was observed that the sample autocorrelations of the original series die out at higher lags, confirming the stationarity behaviour of the series. This therefore suggests that a transformation may not be required. However, a unit root test was carried out to confirm the stationarity or otherwise of this series. The results of the unit root and stationary tests for the original series are shown in Table 2 and the null hypothesis that the time series includes a unit root was evaluated against the alternative hypothesis that the series is stationary. The variable does not have unit roots since the null hypothesis was rejected using p-values at 0.05. Hence, the original series was stationary.



Source: Researchers' Estimation (2020)

Figure 1. Time Series Plot, ACF and PACF of the PH of Water

Table 2. Stationarity Test of the pH Series

Unit Root Tests	Test statistic	Critical Value	P-Value
ADF	30.94	-3.42	2.2×10^{-16}
KPSS	0.0836	0.146	0.46

Source: Researcher's Estimation (2020)

Since the pH of water series was stationary, the parameters of the proposed Autoregressive Integrated Moving Average (ARIMA) model were then estimated. A model selection was, however, first performed (Table 3). The selection criterion for a model was based on the Akaike Information Criteria (AICs) generated by the selected models. The AIC was used because of its wide applications in the field of modeling.

3. 2. 1. Model Selection

After transforming the variable under projection into a stationary series, ARIMA models were then be estimated. Table 3 shows the selection of the proposed model for pH of water. The auto-arima function in the forecast package of the R-software was used. The ARIMA model (3, 0, 4) produced the least AIC value of (-626.50) and hence the best model that fits the data set and was used for forecasting. The parameters of the selected model were then estimated as presented in Table 4.

3. 2. 2. Parameters of the Selected Model for pH of Water

Estimates of the model parameters were obtained from the pH values of water for the appropriate autocorrelation of the level series (Table 4).

Table 3. Selection of the Proposed Model for pH of Water.

ARIMA Model	AR(1)	AR(2)	AR(3)	MA(1)	MA(2)	MA(3)	MA(4)	AIC	-2 Log-likelihood
(3,0,4)*	0.44	0.47	-0.86	-1.18	-0.21	1.16	-0.55	-626.5	321.3
(2,0,4)	-0.39	0.37	-	-0.27	-0.82	0.14	0.16	-618.6	316.3
(1,0,4)	-0.82	-	-	0.16	-0.72	-0.18	0.06	-619.1	315.6
(0,0,4)	-	-	-	-0.67	-0.18	-0.05	0.11	-620.5	315.3
(3,0,2)	-0.62	0.07	-0.12	-0.04	-0.65	-	-	-619.7	315.8
(0,0,2)	-	-	-	-0.67	-0.16	-	-	-620.9	313.5
(3,0,1)	0.12	-0.08	-0.12	-0.79	-	-	-	-620.8	315.4
(3,0,0)	-0.53	-0.38	-0.26	-	-	-	-	-583.5	295.7
(1,0,1)	0.20	-	-	-0.87	-	-	-	-620.6	313.3
(2,0,2)	0.24	0.08	-	-0.43	-0.38	-	-	-	-

Source: Researchers' Estimation (2020); *Selected ARIMA model*

Table 4. Parameters of the Selected Model for pH of Water

	Parameters	Estimates	S.E
Coefficients	AR(1)	0.4359	0.0991
	AR(2)	0.4658	0.0805
	AR(3)	-0.8575	0.1022
	Difference	0	-
	MA(1)	-1.1756	0.1347
	MA(2)	-0.2118	0.1616
	MA(3)	1.1618	0.1737
	MA(4)	-0.5452	0.1322

Source: Researchers' Estimation (2020)

After identifying a suitable model, the least square estimates of the parameters of the model were obtained. The coefficients of the ARIMA (3, 0, 4) process was not significantly different from zero, hence the model equation:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \alpha_3 X_{t-3} + \beta_1 Z_{t-1} + \beta_2 Z_{t-2} + \beta_3 Z_{t-3} + \beta_4 Z_{t-4} + Z_t . \tag{1}$$

Replacing the equation with one in which the estimated parameters are substituted, we get:

$$X_t = 0.43 X_{t-1} + 0.47 X_{t-2} - 0.86 X_{t-3} - 1.18 Z_{t-1} - 0.21 Z_{t-2} + 1.16 Z_{t-3} - 0.55 Z_{t-4} + Z_t$$

As the appropriate model for forecasting future pH of water. The significance of the estimated model was then verified before proceeding to forecast (Table 5).

3. 2. 3. Model Diagnostics

Table 5. Model diagnostics

Residual Tests	Chi-Square	DF	P-Value
Ljung-Box	34.339	30.000	0.268
Jarque Bera	5.202	2.000	0.074

Source: Researchers' Estimation (2020)

After modeling, some forecasts are normally generated. However, before the estimated model can be used to generate any forecast, it is imperative to undertake residual analysis or model diagnostics. The diagnostic test results in this study include Ljung-Box test to detect the existence of serial correlation, Jarque Bera Test and the Normal QQ-Plot to investigate normality. Table 5 provides information on the analysis of the residuals of the selected model.

For the Ljung-Box test (detection of the presence of serial correlation), the null hypothesis is that there is no serial correlation. The residual passes the test since an insignificant p-value of 0.268 is recorded. Same conclusions for the case of the Jarque-Bera test which also checks normality of the residuals.

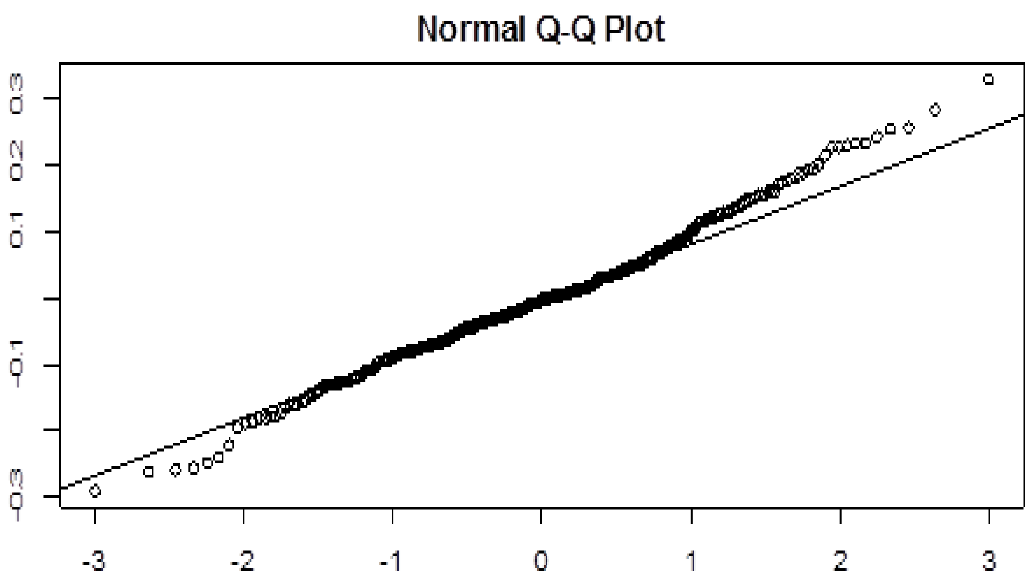


Figure 2. Normal QQ-Plot of pH Model
Source: Researchers' Estimation (2020)

Figure 2's Normal QQ-Plot provides additional insights into the normality of the residuals. The residual normality plot suggests a potentially symmetric distribution, with most residuals exhibiting minimal deviation from the best-fit line and displaying an approximately linear distribution. Following model diagnostics, the pH series was projected for the upcoming 14 days, as detailed in Table 6

Table 6. Forecasts of the PH Series

Days	Series	S.E
1	6.88	0.10
2	6.87	0.10
3	6.90	0.10

4	6.92	0.11
5	6.94	0.11
6	6.94	0.11
7	6.94	0.11
8	6.91	0.12
9	6.90	0.12
10	6.89	0.12
11	6.90	0.13
12	6.91	0.13
13	6.93	0.13
14	6.93	0.13

Source: Researchers' Estimation (2020)

It was observed that the forecasts for the series appears to slowly wander up and down as the days went by same as in the case of the original series. In summary, the pH values of raw water used by a water treatment plant will continue to maintain the requirement at which it can be treated without adding chemicals with respect to time.

3. 3. Analysis of TDS series

Figure 3 presents the time series, ACF and PACF plots of the behaviour of the original series of the TDS of water series. The Fig. basically illustrates how the data behaved within equally spaced time intervals. It is observed that the series do not follow a specific systematic trend. It is also clear from the Fig. that there are upward and downward moving trends in the series over the time.

That is, the data exhibits an irregular swinging pattern. That is, the series seems to have a uniform pattern (upward or downward) over the entire time period. The series, therefore, seems to wander up and down slowly, an indication that it may be stationary. The Fig. also provides more information on the stationarity of the series.

From the Fig., it is observed that the sample autocorrelations of the original series die out at higher lags, confining the stationarity behaviour of the series. This therefore suggests that transformation may not be required. However, a unit root test was carried out to confirm the stationarity or otherwise of this series. The results of the unit root and stationary tests for the original series are shown in Table 7 and the null hypothesis that the time series includes a unit root is evaluated against the alternative hypothesis that the series is stationary. The variable does not have unit roots since the null hypotheses was rejected using p-values at 0.05. Hence, the original series was stationary. Since the TDS of water series was stationary, the parameters of the proposed Autoregressive Integrated Moving Average (ARIMA) model were then estimated. A model selection was, however, first performed (Table 8). The selection criterion for a model was based on the Akaike Information Criteria (AICs) (1974) generated by the selected models.

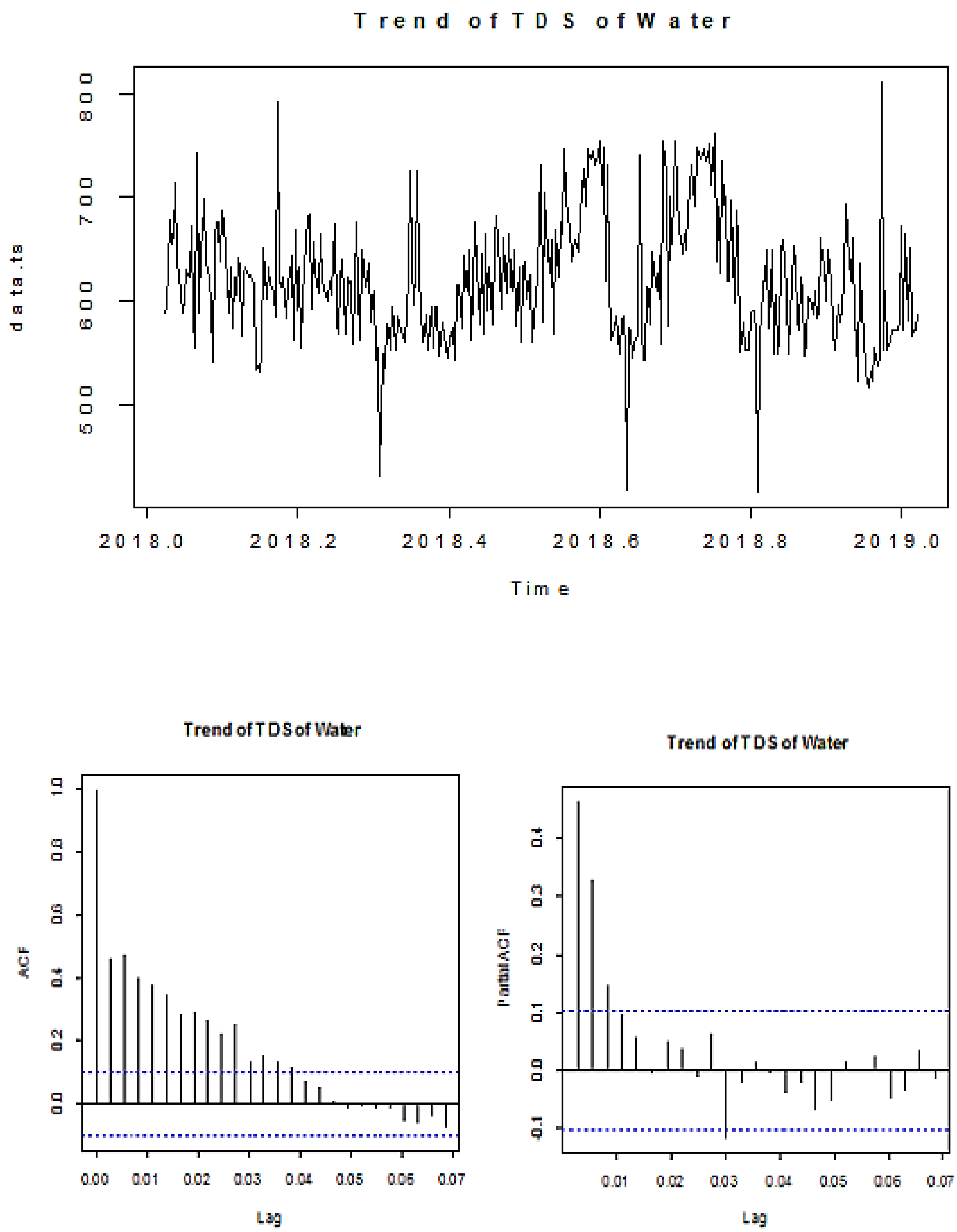


Figure 3. Time Series Plot, ACF and PACF of the TDS Series
Source: Researchers' Estimation (2020)

Table 7. Stationarity Test of the TDS Series

Unit Root Tests	Test statistic	Critical Value	P-Value
ADF	16.0637	3.42	2.2×10^{-16}
KPSS	0.1354	0.146	0.46

Source: Researchers' Estimation (2020)

3. 3. 1. Model Selection

After transforming the variable under projection into a stationary series, ARIMA models can then be estimated. A stationary series is one in whose values changes over time only around a constant mean and variance. Table 8 presents the selection of the proposed model for TDS of water.

The R-software's forecast package was employed, utilizing the Auto-Arima function. Among the considered ARIMA models, the one with parameters (3, 0, 4) yielded the lowest AIC value (3876.7), signifying its superiority as the optimal model for fitting the dataset and subsequent forecasting. The estimated parameters for this selected model are detailed in Table 9 below.

3. 3. 2. Parameters of the Selected Model for TDS of Water

Estimates of the model parameters were obtained from the TDS of water values of the appropriate autocorrelation of the level series. The results are presented in the Table 9.

Table 8. Selection of the Proposed Model for TDS of Water

ARIMA Model	AR(1)	AR(2)	AR(3)	MA(1)	MA(2)	MA(3)	MA(4)	AIC	-2 Log-likelihood
(3,0,4)*	-0.35	0.21	0.88	-0.37	-0.44	-0.83	0.64	3876.7	-1930.4
(2,0,4)	-	-	-	-	-	-	-	3881.3	-1933.6
(1,0,4)	-0.03	0.86	-	-0.73	-0.82	0.60	-0.05	3889.3	-1938.6
(0,0,4)	-0.30	-	-	-0.43	-0.15	-0.04	-0.02	3887.2	-1938.6
(3,0,2)	-	-	-	-0.73	0.07	-0.05	-0.01	3888.9	-1938.5
(0,0,2)	-0.26	0.15	0.06	-0.46	-0.27	-	-	3884.9	-1939.4
(3,0,1)	-	-	-	-0.72	0.03	-	-	3883.2	-1936.6
(3,0,0)	0.26	0.29	0.15	-1.00	-	-	-	3896.6	-1944.3

(1,0,1)	-0.68	-0.36	-0.17	-	-	-	-	3884.8	-1939.4
(2,0,2)	-0.05	-	-	-0.68	-	-	-	3877.8	1933.9

Source: Researcher's Estimation (2020) *Selected ARIMA model*

Table 9. TDS Model Parameters.

	Parameters	Estimates	S.E
Coefficients	AR(1)	-0.3450	0.0409
	AR(2)	0.2123	0.0417
	AR(3)	0.8778	0.0330
	Difference	0	-
	MA(1)	-0.3708	0.0601
	MA(2)	-0.4385	0.0234
	MA(3)	-0.8292	0.0296
	MA(4)	0.6384	0.0577

Source: Researchers' Estimation (2020)

After identifying a suitable model, the least square estimates of the parameters of the model were obtained. The coefficients of the ARIMA (3, 0, 4) process was not significantly different from zero. The model equation was hence written as:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \alpha_3 X_{t-3} + \beta_1 Z_{t-1} + \beta_2 Z_{t-2} + \beta_3 Z_{t-3} + \beta_4 Z_{t-4} + Z_t$$

Replacing with the estimated parameters gave:

$$X_t = -0.35 X_{t-1} + 0.21 X_{t-2} + 0.88 X_{t-3} - 0.37 Z_{t-1} - 0.44 Z_{t-2} - 0.83 Z_{t-3} + 0.64 Z_{t-4} + Z_t$$

as the appropriate model for forecasting future TDS of water. The significance of the estimated model was verified before proceeding to forecast.

3. 3. 3. Model Diagnostics

After modeling, some forecasts are normally generated. However, before the estimated model can be used to generate any forecast, it is imperative to undertake residual analysis or model diagnostics. The diagnostic test results in this study include Ljung-Box test to detect the existence of serial correlation, Jarque Bera Test and the Normal QQ-Plot to investigate normality. Table 10 provides information on the analysis of the residuals of the selected model.

Table 10. Model Diagnostics

Residual Tests	Chi-Square	DF	P-Value
Ljung-Box	12.564	30.00	0.99
Jarque Bera	140.66	2.00	2.2×10^{-16}

Source: Researcher's Estimation (2020)

For the Ljung-Box test (detection of the presence of serial correlation), the null hypothesis is that there is no serial correlation. The residual passes the test since an insignificant p-value of 0.99 is recorded. The same conclusions can be drawn for the case of the Jarque-Bera test which also checks normally of the residuals.

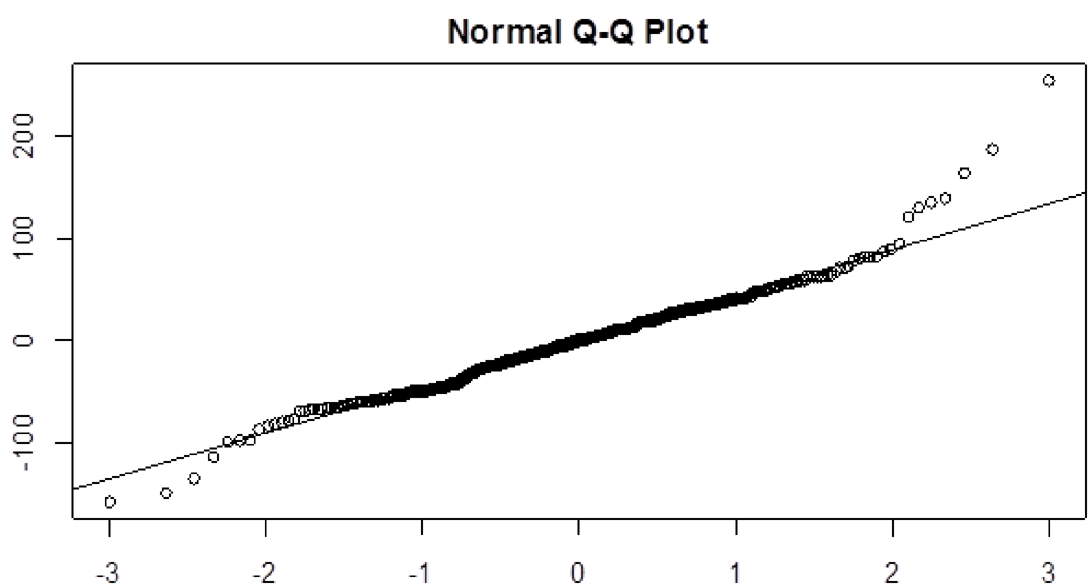


Figure 4. Normal Plot
Source: Researchers' Estimation (2020)

The Normal QQ-Plot in Fig. 4 sheds more light on the normality of the residuals. The normality plot for the residuals indicates a plausible symmetric distribution as most of its residuals do not deviate that much from the line of best fit and its distribution appears approximately linear. After model diagnostics, the series for TDS of water was forecasted for the next 14 days as shown in Table 11.

Table 11. Forecasts of the TDS Series

Days	Series	S.E
1	596.7	48.3
2	579.6	50.2
3	612.6	52.3
4	593.5	53.2
5	592.1	54.6
6	617.5	55.7
7	604.7	56.2
8	617.1	57.1
9	592.9	57.7
10	615.3	58.0
11	613.3	58.7
12	597.6	58.9
13	622.2	59.2
14	608.6	59.6

Source: Researchers' Estimation (2020)

It was observed that the forecasts for the series appears to slowly wander up and down as the days went by, same as in the case of the original series.

In summary, the TDS values of the raw water used by a water treatment plant will continue to maintain the requirement at which it can be treated without adding chemicals with respect to time.

4. CONCLUSION

Regarding the pH of the raw water series, it is evident that the series does not adhere to a specific systematic trend.

Fluctuating between upward and downward movements, the series displays dynamic behavior over time. In response to this, the proposed ARIMA (3, 0, 4) model for the pH effectively facilitated the generation of forecasts post-model diagnostics. Similarly, the TDS series was observed to lack a specific systematic trend, displaying both upward and downward movements over time.

The application of the ARIMA (3, 0, 4) model for the TDS series successfully contributed to the generation of forecasts following thorough model diagnostics.

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