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Application of Time Series Models to Predict Water Quality of Upstream and Downstream of Latian Dam in Iran

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Abstract:

Analyzing surface water quality parameters and prediction of variation in future is a principal step in water quality management. Various techniques can be applied to analysis and prediction; among which, time series model including exponential smoothing and Box- Jenkins is one of the suitable tools. In this study, water quality data of two inlet branches and an outlet branch of water in Latian dam, located in North West of Tehran is analyzed according to the above-mentioned model. The trend of parameters quality change can be predicted from the developed models. The predicted values and observation data of the last six months based on one month ahead predictions have a good consistency. Hence, the technique may be applicable for the regions which enough information are not available for basins, and the prediction data may be applied for water quality management in the latian dam.

Keywords: water quality parameter, Box-Jenkins model, exponential smoothing model

1. Introduction:

Considering the deficit of water in Iran, protection of water resources against pollution is vital. In this regard, water quality monitoring is a tool which produces up to date information. Having a great amount of raw data without interpretation is not sufficient , and it is necessary to analysis data and predict the variation of water quality in the future for any decision making on water quality management. Recently, more researchers have become interested in the application of time series models for the prediction of water quality. Time series approach for analyzing water resources were first applied by Thomann (1967) who studied variation of temperature by the time and dissolved oxygen level for the Delaware Estuary. The data were obtained by continuous recording by monitoring stations, operated jointly by the U.S. Geological Survey Department and the city of Philadelphia. Carlson et al. (1970) and McMichael and Hunter (1972) reported the successful use of the Box-Jenkins method for time series analysis.

The Box-Jenkins method for the time series analysis was applied to model the hourly water quality data recorded in the St. Clair River near Corunna, Ontario, for chloride and dissolved oxygen levels by Huck and Farquhar (1974), the models were physically reasonable and successful results were obtained. Autoregressive and first difference moving average models represented the chloride data well. Lohan and Wang (1987) also reported to have used this model to study the monthly water quality data in the Chung Kang River located at the northern part of Miao-Li County in the middle of Taiwan. Jayawardena and Lai (1991) applied an adaptive ARMA model approach for water quality forecasting. MacLeod and Whitfield (1996) analyzed water quality data using Box-Jenkins time series analysis of the Columbia River at Revelstoke. Caissie et al. (1998) studied water temperature in the Catamaran Brook stream. The short-term residual temperatures were modeled using different air to water relations, namely a multiple regression analysis, a second-order Mar for process, and a Box-Jenkins time series model. Asadollahfardi (2002) applied Box Jenkins and. Exponential smoothing models to monthly surface water quality data in Tehran for three years. Most of the models showed seasonality. Kurunc,etal (2004) applied ARIMA and Thomas- Fiering techniques for thirteen years to monthly data of the Duruacasu station at Yesilirmark River.

Hasmida (2009) applied ARIMA model (parametric method) and Mann-Kendall test (non-parametric method) to analyze the water quality (NH4, turbidity, color , SS pH, Al, Mn and Fe.) and rainfall-runoff data for Johor River recorded for a long period (2004 to 2007). He showed that all of the water quality parameters were generated by ARIMA processes ranges from ARIMA (1,1,1) to (2,1,2). He concluded that color, Turbidity, SS, NH4 and Mn follow a similar trend with rainfall-runoff pattern while pH, Al and Fe have the opposite trend compare to rainfall-runoff pattern. Pekarova et al. (2009) investigate the long-term trends in water quality parameters of the Danube River at Bratislava, Slovakia (Chl-a, Ca, EC, SO42-, Cl-, O2, BOD5, N-tot, PO4-P, NO3-N, NO2-N, etc.), for the period 1991–2005. They applied selected Box-Jenkins models (with two regressors – discharge and water temperature) to simulate the ex-treme monthly water quality parameters. They concluded that the impact of natural and man-made alters in a stream's hydrology on water quality can be readily well simulated by means of autoregressive models. Faruk (2010) applied a hybrid ARIMA and neural network , which consists of an ARIMA methodology and feed-forward, backpropagation network structure with an optimized conjugated training algorithm. The hybrid approach for time series prediction was examined applying 108-month actual of water quality data, including boron, water temperature and dissolved oxygen, during 1996–2004 at B¨uy ¨ uk Menderes river, Turkey. He concluded that the hybrid model provides much better accuracy over the ARIMA and neural network models for water quality predictions. Tabari et al (2011) studied water quality trends for four stations in the Maroon River basin using the Mann– Kendall test, the Sen's slope estimator and the linear regression for the period 1989–2008. The results showed that significant trends were found only in Ca, Mg, SAR, pH, and turbidity series.

2.0 Methodology

2.1 Study Area:

In this study, time series models were applied to some parameters of inlet and outlet water quality in Latian dam. There are five water quality monitoring stations downstream and upstream of the dam. Among which three of them are remarkably significant because of passing the greatest volume of water (Figure 1). These stations are Roudak on Jadjrood River, Aliabad on the Lavark River and Zir-e-pol on the outlet of the dam. Table 1 and Figure 1 shows the situation and characteristics of the dam and the stations. The study area is a 71000 hectare river basin in the Alborz Mountains. The rainfall regime is primarily derived from the Mediterranean region. According to pluviometry data of 14 stations in the region, annual rainfall variations in height with a 20- year statistical period follows the equation below:

$$P = -185.3 + 0.379Z$$

Where Z is height above sea level, and P is the annual rainfall (Kakavand 2001)

In this basin, average annual temperature is 10ºC. The hottest month of the year is Mordad (July 22-August 22) with a maximum temperature of 34ºC, and the coldest is the Day (Dec21-Jan 21) with the minimum temperature of -8ºC.The average rainfall of Latian basin is more than 500 mm a year. (Islamic Republic of Iran Meteorological Organization, 1983). Latian dam is located at 35^{o} 47′N, 51^{o} 40′E. In addition to producing 70,000 Mw/hours hydropower energy, it supplies drinking water for some parts of Tehran and also agricultural water in some parts of the Southeast of Tehran (Varamin Plain). Some characteristics of the dam are shown in Table 2 . The primary objective of the study was to develop suitable and confident time series models for water quality data in the two inlets and the outlet of the dam. A second objective was the acquisition of accurate prediction of variations of water quality for future from developed models, which will also validate the model.

.

Table 1: The situation and characteristics of stations upstream and downstream of Latian dam

River	Station	Longitude (Degree/ Min)	Latitude (Degree/ Min)	Altitude (m)	Area (km^2)
Jajrud	Rudak	51^{o} 33'	35^{o} 51'	1690	416
Lavark	Ali Abad	51^{o} 41'	35^{o} 48'	1600	103
Afjah	Narvan	51^{o} 40'	35^{o} 50'	1750	30
Galandovak	Najar Kola	51^{o} 38'	35^{o} 49'	1700	59
Jadjrud	Zir-e-pol	51^{o} 41'	35^{o} 47'	1560	710

Table 2: The characteristics of Latian dam

Type of dam	Concrete and weight
Height from foundation	107 m
Height from river-bed	80 m
Length of crest	450 m
Total capacity of reservoir	95×10^6 m^3
Useful capacity of reservoir	85×10^6 m^3
Capacity of evacuation of spillways	Uncovered 650 m^3
	Tunnel 1100 m^3

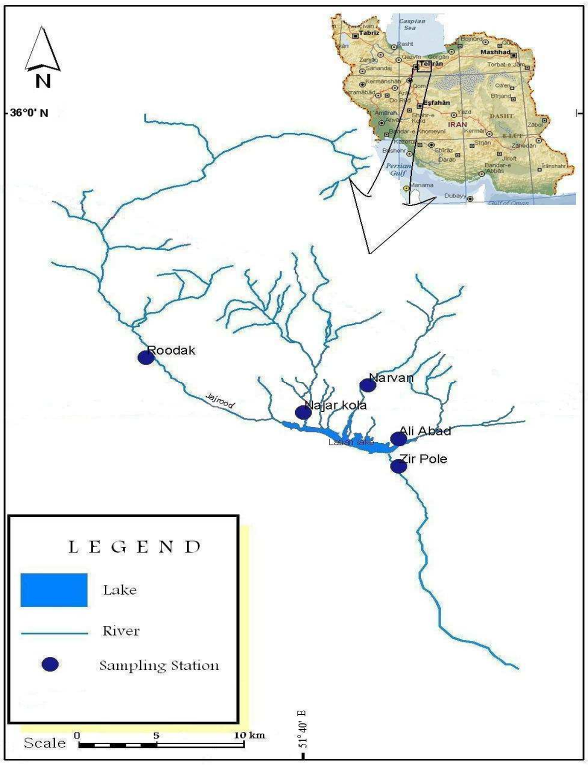

Figure 1: The location of water quality stations on Latian dam

2.2 Time Series:

The purpose of time series analysis is to describe the series behavior regarding short term and long term changes, to study the dependencies between series elements and the most important to predict future values. To analyze a series and predict the future values, it is necessary to get familiar with the series as a function of time and then to justify the series behavior suing the model. The time series is a sequel of observations that is recorded in determining times. Average of temperature, moisture, wind speed, which are recorded weekly or monthly are examples of time series.

2.3 Box-Jenkins Methodology for Time Series Modeling:

Decomposition of time series data into their components, however instructive and revealing, is a difficult job. Moreover, it causes greater errors by accumulation of component errors. To avoid these difficulties, Box and Jenkins (1976) developed a new methodology, which in essence, does the same job but unifies all the concepts discussed above. In this method, using some transformation such as simple and seasonal differences, the trends, seasonal and cyclical components present in the data are removed. Then, a family of models is entertained for the transformed data, which is expected to be as simple as possible. The Box- Jenkins approach is based on the notion of stationary time series briefly explained in the following section.

2.3.1 Classification of Non-seasonal Time Series Models:

The general non-seasonal autoregressive moving average model of order (p, q) is:

$$Z_t = \delta + \phi_1 Z_{t-1} + \ldots + \phi_P Z_{t-P} + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q} \quad (1)$$

Where $\phi_P(B)$ and $\theta_q(B)$ are the autoregressive and moving average operators, respectively, defined as:

$$\phi_P(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_P B^P \quad (2)$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 \beta^2 - \ldots - \theta_q B^q \quad (3)$$

Where B is the backward shift operator, so that $B^k Z_t = Z_{t-k}$.

When series of show nonstaionarity, i.e., the mean and variance of the series is changing with t, then it may still be related to the random deviates a_t by means of following a model.

$$\phi_P(B)\nabla^d Z_t = \theta_q(B) a_t \quad (4)$$

Where ∇^d equals the backward difference operator. Equation 4 represents the autoregressive integrated moving average ARIMA (p, d, q) model with integers p, d, q, defining the order of the model. Essentially, the Box-Jenkins procedure consists of four basic steps, which are shown in Table 3 and Fig. 2. For more detail readers refer to the Box-Jenkins (1976) and Bowerman, O'Connell, (1987).

2.3.2. Exponential Smoothing Models:

Exponential smoothing refers to a particular type of moving average technique applied to time series data, either to produce smoothed data for presentation, or to make forecasts. Exponential smoothing is commonly applied to financial market and economic data, but it can be used with any discrete set of repeated measurements. The raw data sequence is often represented by (x_t), and the output of the exponential smoothing algorithm is commonly written as (s_t). When the sequence of observations begins at time $t = 0$, the simplest form of exponential smoothing is given by the formulas (Asadollahfardi, 2000):

$$s_0 = x_0 \quad (5)$$

$$s_t = ax_t + (1-a)s_{t-1} \quad (6)$$

Where α is the *smoothing factor*, and $0 < \alpha < 1$ (Asadollahfardi, 2000).

Table 3: Stages of Box-Jenkins modeling

Step	Description
1	**Check the data for normality** a) No transformation
	b) Square root transformation
	c) Logarithmic Transformation
	d) Power transformation
2	**Identification** a) Plot of the transformed series
	b) Autocorrelation function (ACF)
	c) Partial autocorrelation function (PACF)
3	**Estimation** a) Maximum likelihood estimate (MLE) for model parameters (Ansley algorithm)
4	**Diagnostic checks** a) Over fitting
	b) Examination of residuals (modified Portmanteau test)
5	**Model Structure selection criteria** a) AIC criteria
	b) PP criteria
	c) BIC criteria

2.4 The Software:

Statistical Analysis System (SAS) version9/1 (2004) was applied for calculations and analysis of the models of this paper. This software needs to be programmed; however there are also some menus for simplicity. First, it is necessary to build a library in the software to save data and calculations of each stage. Figure 3 shows the procedures for building, confirming and, forecasting models with SAS software.

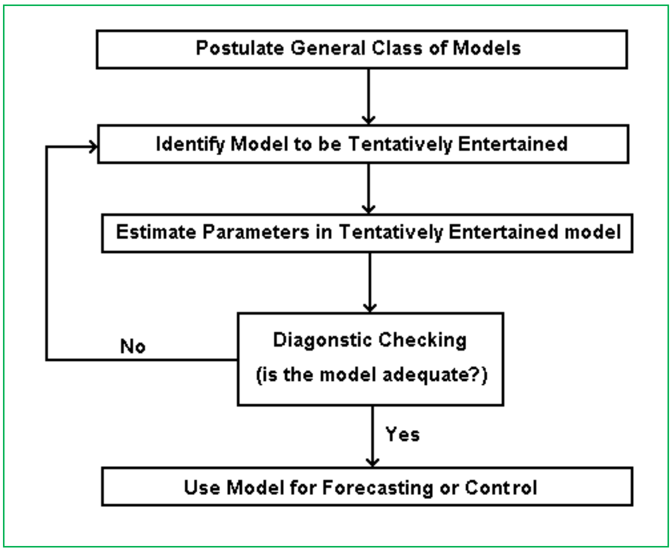

Fig. 2: Stages in the iterative approach to model building

3. Results and Discussion:

The primary objective of this study was to develop proper models for each of Ca^{++}, Mg^{++}, SO_4^{--}, PH, HCO_3^-, Na^+, CL^- and TDS parameters. Secondary data accumulated over 24 years (1981 – 2005) by the local water authority in Tehran was used for developing time series models. Also for confirming and comparing the models, the data from the year 2005 was used. Lastly, for each of the water quality parameters, an equation was developed individually for each of the monitoring stations. These are presented in Tables 3, 4 and 5. As shown in Tables 3 and 4, most of the models developed for water quality in Aliabad and Rodak stations are Auto Regressive Integrated Moving Average (ARIMA) but for Zer-e-pol station, there are two types of ARIMA models, among which some exhibit seasonality, while others are non seasonal. For Na^+, Mg^{++} and SO_4^{--} parameters, ARIMA models with autoregressive order 2 and seasonal autoregressive order 1 was obtained and for CL^-, pH and Ca^{++} non-seasonal ARIMA with autoregressive order 2 and for TDS and HCO_3^- parameters Non seasonal ARIMA with autoregressive order 1 and moving average order 1 was obtained. Some of the models in Tables 3, 4 and 5 are discussed in detail in the following section. On a similar note, If P-Value is more than 0.9, the model is considered excellent, good between 0.75 to 0.9 and average of 0.5 to 0.75.

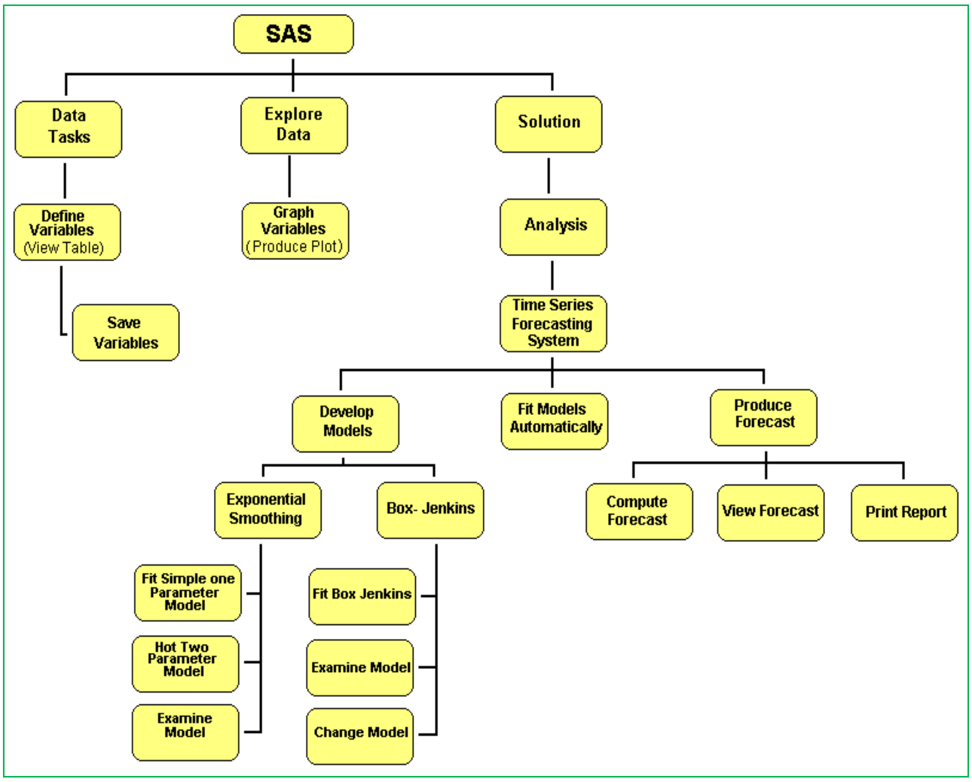

Fig 3: The stages for building models in SAS software

4. Selected models of few water quality parameters in Zer-e- pol station

4.1 Ca^{++}

As shown in Figure 4, the proper model for calcium (Ca^{++}) is an ARIMA (2,0,0) (0,0,0). The equation of the model is as follows:

$$Z_t = 2.186 + 1.02Z_{t-1} - 0.338Z_{t-2} + a_t$$

Where the Z_t is the amount of the calcium, a_t is an error. The standard error is 0.331. Akaike Information Criteria (AIC) and Schwartz Bayesian Information Criteria is less than of other model for calcium. Also, correlation coefficient, being 0.95, is proper.

P-Value is 0.99 which shows that the model is excellent (Table 5).

4.2 SO_4^{--}

Figure 4 shows the variation of sulfate parameter and the best model for $SO_4^{-}$is ARIMA (2, 0, 0) (1, 0, 0) S with seasonal components (Table 5). The equation of the model is as follows:

Z_t=0. 88+ ($0.997Z_{t-1}$-$0.381Z_{t-2}$ +a_t) ($0.207Z_{t-12}$+ϵ_t)

Where the part ($0.997Z_{t-1}$-$0.381Z_{t-2}$+a_t) is the non seasonality component of autoregressive model, while ($0.2076Z_{t-12}$+ϵ_t) is the seasonality component of the autoregressive model. The standard error of the model is 0.202. Akaike Information Criteria (AIC) and Schwartz Bayesian Information Criteria (SBC) of the model less than other suggested models. Also, the correlation coefficient is 0.53 (Table 5). The amount of risk is less than 0.0001 and confident level P-Value is 0.99 which shows affirms the model.

4.3 pH

The best developed model for pH parameter is ARMA (2,0,0) (0,0,0) (Figure4). The equation of the pH is as follows:

Z_t= 7.775+$0.842Z_{t-1}$-$0.142Z_{t-2}$+a_t

According to comparison methods, standard error of the model is 0.267. The AIC and the SBC of the model are less than the other developed models. The correlation coefficient of 0.83 is also good (Table 5). According to the considered assumptions, the amount of risk is less than 0.0297 and confident level of P-Value equals 0.97.

4.4 Total Dissolved Solid (TDS)

In Figure 4, variations in TDS are presented. The best model developed for TDS is an ARIMA (1, 0, 1) (0, 0, 0) which has the autoregressive order 1 and moving average order 1. The equation of the model is as follows:

Z_t=228. 8+$0.8Z_{t-1}$+a_t+$0.591a_{t-1}$

The standard error of the model is 29.36 and AIC and SBC are less than the other developed model, also correlation coefficient is 0.91 (Table 5). The amount of the risk is equal to 0.0001 and P-Value is 0.99 which reaffirms the model. Adsollahfardi (2002) ; Pekarova et al. (2009) and Hasmida (2009) worked with the same type of models as we did in this study , and they concluded the Box- Jenkins model is suitable for application in water quality. The characteristic of all models is shown in Tables 3, 4 and 5. It is noted that there are no negative values in practice and 95% confident level in calculation caused the lower limit to be negative. Hence, negative values should be omitted or replaced with zero.

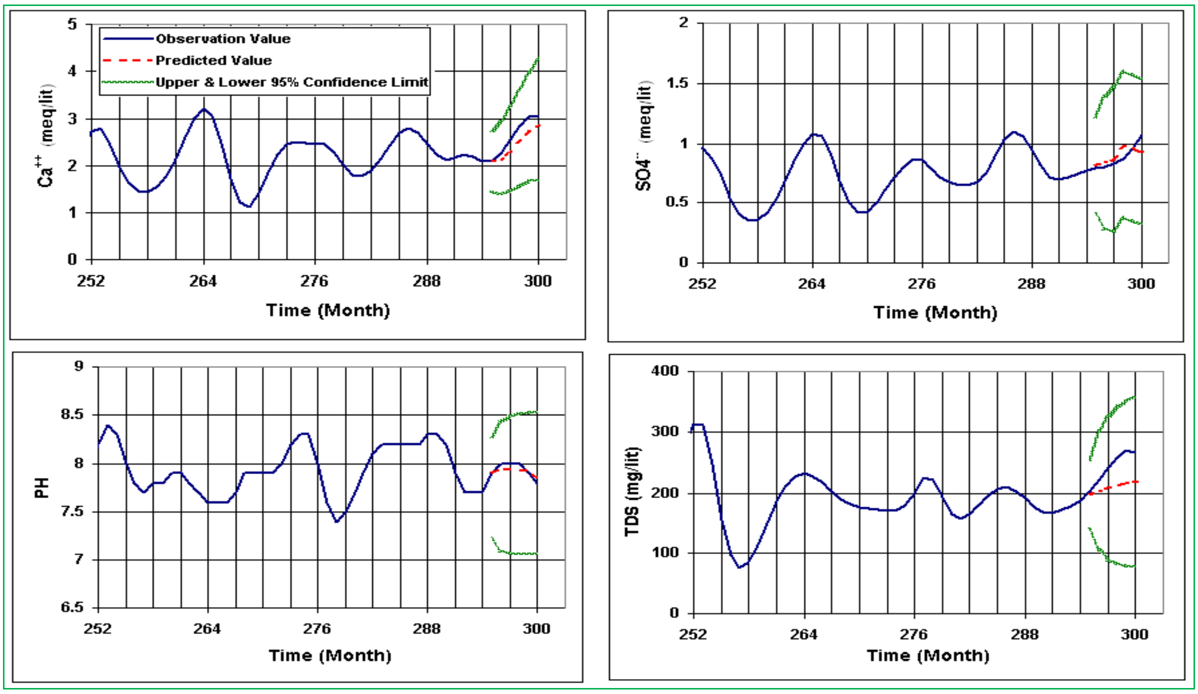

Figure 4: diagrams of time series for each of water quality parameters and their predictions. (The predictions are based on one-month ahead projections)

Table 4: Characteristics of developed models for Rudak Station at Jadjarood River

Rudak Station							
Parameter	**Suggested Model Equation**	**AIC**	**Intercept**	**AR Lag1**	**AR Lag2**	**SAR Lag12**	**P-Value**
		SBC	**T**	**T**	**T**	**T**	**RV**
		R-Square	**Prob>ITI**	**Prob>ITI**	**Prob>ITI**	**Prob>I TI**	**ME**
		Std. Error					
Na^+	ARIMA (1,0,0) (0,0,0)	-355.33	0.4367	0.6858	.	.	0.99
		-347.92	17.964	16.328	.	.	0.0177
	$Z_t=0.44+0.686(Z_{t-1})+a_t$	0.79	<.0001	<.0001	.	.	E
		0.1332					
Ca^{++}	ARIMA (1,0,0) (0,0,0)	320.57	2.2394	0.5859	.	.	0.99

	$Z_t=2.24+0.586(Z_{t-1})+a_t$	327.98	12.481	39.183	.	.	0.1692
		0.97	<.0001	<.0001	.	.	E
		0.411					
Mg^{++}	ARIMA (2,0,0) (0,0,0)	73.23	0.912	0.6346	-0.1883	.	0.99
		84.34	32.223	11.1097	-3.296	.	0.0738
	$Z_t=0.912+0.635(Z_{t-1})-0.188(Z_{t-2})+a_t$	0.59	<.0001	<.0001	0.001	.	E
		0.2718		.	.	.	
Cl^-	ARIMA (2,0,0) (0,0,0)	-425.29	0.295	0.6619	-0.1632	.	0.99
		-410.47	14.335	11.539	-2.854	.	0.0139
	$Z_t=0.295+0.662(Z_{t-1})-0.163(Z_{t-2})+a_t$	0.69	<.0001	<.0001	0.004	.	E
		0.1182					
HCO_3^-		296.29	2.561	0.6084	.	0.145	0.99
	ARIMA (1,0,0) (1,0,0)	307.4	38.1248	13.311	.	2.5098	0.1552
	$Z_t=2.561+(0.608(Z_{t-1})+a_t)$ x$(0.145(Z_{t-12})+\varepsilon_t)$	0.89	<.0001	<.0001	.	0.012	E
		0.394					
SO_4^{--}	ARIMA (1,0,0) (0,0,0)	45.336	0.759	0.453	.	.	0.99
		52.743	27.718	8.793	.	.	0.0675
	$Z_t=0.759+0.453(Z_{t-1})+a_t$	0.79	<.0001	<.0001	.	.	E
		0.259					
pH	ARIMA (1,0,0) (0,0,0)	136.52	7.793	0.676	.	.	0.99
		143.92	145.29	15.924	.	.	0.0915
	$Z_t=7.793+0.676(Z_{t-1})+a_t$	0.86	<.0001	<.0001	.	.	E
		0.302					
TDS		3034.66	213.05	0.675	-0.1125	.	0.95
	ARIMA (2,0,0) (0,0,0)	3045.77	42.818	11.711	-1.953	.	1430.88
	$Z_t=213.05+0.675(Z_{t-1})-0.113(Z_{t-2})+a_t$	0.95	<.0001	<.0001	0.05	.	E
		37.826					

LSW	**Level Smoothing weight**	**AIC**	**Akaike Information Criteria**
SL	**Smoothed Level**	**Cl^-**	**Cholride Ion**
AR	**Autoregressive**	**HCO_3^-**	**Bicarbonate Ion**
SAR	**Seasonal Autoregressive**	**SO_4^{--}**	**Sulfate Ion**
MA	**Moving Average**	**Ca^{++}**	**Calcium Ion**
RV	**Residual Variance (Sigma Squared)**	**Mg^{++}**	**Magnesium Ion**
ME	**Model Evaluation**	**Na^+**	**Sodium Ion**
E	**Excellent**	**TDS**	**Total Dissolved solids**
SBC	**Schwartz Bayesian Information Criteria**	**Std. Error**	**Standard Deviation**

Table 5: The characteristics of developed models for Ali Abad station at Lavark River

Ali Abad Station									
Parameter	Suggested Model Equation	AIC	LSW	Intercept	AR Lag1	AR Lag2	MA1	SAR Lag12	P-Value
		SBC	T	T	T	T	T	T	RV
		R-Square	Prob>lTl	Prob>lTl	Prob>lTl	Prob>lTl	Prob>lTl	Prob>lTl	ME
		Std. Error	SL						
Na^{+}	ARIMA (2,0,0) (0,0,0)	634.93	.	1.13018	0.82969	-0.18931	.	.	0.99
	$Z_t=1.13+0.829(Z_{t-1})-0.189(Z_{t-2})+a_t$	649.66	.	7.7518	14.1942	-3.2364	.	.	0.4994
		0.86	.	<.0001	<.0001	0.00135	.	.	E
		0.7066	.						
Ca^{++}	ARIMA(1,0,0)(0,0,0)	712.51	.	2.6573	0.64663	.	.	.	0.99
	$Z_t=2.66+0.647(Z_{t-1})+a_t$	723.56	.	15.799	14.4323	.	.	.	0.6528
		0.88	.	<.0001	<.0001	.	.	.	E
		0.8079	.						
Mg^{++}	Simple Exponential Smoothing	-232.591	0.999	.	.	.	.	.	0.99
	$S_t=0.999Y_{t-1}+(1-0.999)S_{t-1}$	-228.88	24.4298	.	.	.	.	.	0.45903
	in above equation:	0.72	<.0001	.	.	.	.	.	E
	S; Prediction & Y;Observation	0.0409	0.69	.	.	.		.	
CL^{-}	ARIMA(2,0,0)(0,0,0)	328.59	.	0.86873	0.91671	-0.15305	.	.	0.99
	$Z_t=0.869+0.917(Z_{t-1})-0.153(Z_{t-2})+a_t$	343.33	.	7.555	15.807	-2.6354	.	.	0.1759
		0.95	.	<.0001	<.0001	0.0088	.	.	E
		0.4195	.						
HCO_3^{-}	ARIMA(2,0,0)(0,0,0)	455.02	.	2.447	0.9873	-0.2285	.	.	0.99
	$Z_t=2.45+0.987(Z_{t-1})-0.228(Z_{t-2})+a_t$	469.76	.	17.4681	17.4556	-4.0145	.	.	0.2704
		0.97	.	<.0001	<.0001	<.0001	.	.	E
		0.52	.						
SO_4^{--}	ARIMA(1,0,0)(0,0,0)	914.61	.	1.703	0.70071	.	.	.	0.99
	$Z_t=1.703+0.7(Z_{t-1})+a_t$	925.66	.	6.4669	16.7293	.	.	.	1.297
		0.83	.	<.0001	<.0001	.	.	.	E
		1.139	.						
pH	ARIMA(2,0,0)(0,0,0)	101.15	.	7.775	0.84247	-0.1425	.	.	0.99
	$Z_t=7.775+0.842(Z_{t-1})-0.142(Z_{t-2})+a_t$	115.88	.	118.086	14.524	-2.455	.	.	0.081
		0.77	.	<.0001	<.0001	0.014	.	.	E
		0.285	.						
TDS	ARIMA(2,1,1)(1,0,0)	3549.35	.	-0.615	0.955	-0.2356	0.9954	0.1499	0.95
	$Z_t=-0.615+(0.955(Z_{t-1})-0.236(Z_{t-2})$	3571.43	.	-2.0069	16.483	-4.0563	23.236	2.53	10353
	$.+a_t-0.995(a_{t-1}))$	0.91	.	0.0457	<.0001	<.0001	<.0001	0.0117	E
	$x(0.1499Z_{t-12}+\varepsilon_t)$	101.74	.	.	.	.			

Table 6: Characteristics of developed models for Zir-e-pol station in outlet of the dam

Latian Station								
Parameter	Suggested Model Equation	AIC SBC R-Square Std. Error	Intercept T Prob>lTl	AR Lag1 T Prob>lTl	AR Lag2 T Prob>lTl	MA1 T Prob>lTl	SAR Lag12 T Prob>lTl	P-Value RV ME
Na^+	ARIMA(2,0,0)(1,0,0)	-178.19	0.5663	0.7281	-0.1513	.	0.14079	0.98
	$Z_t=0.566+(0.728(Z_{t-1})-0.151(Z_{t-2}).+a_t)x(0.1407(Z_{t-12})+\varepsilon_t)$	-163.46	20.12	12.484	-2.605	.	2.399	0.0314
		0.6	<.0001	<.0001	0.009	.	0.017	E
		0.1772						
Ca^{++}	ARIMA(2,0,0)(0,0,0)	193.26	2.1862	1.02	-0.3385	.	.	0.99
	$Z_t=2.186+1.02(Z_{t-1})-0.338(Z_{t-2})+a_t$	204.38	36.474	18.697	-6.1837	.	.	0.1099
		0.95	<.0001	<.0001	<.0001	.	.	E
		0.3316						
Mg^{++}	ARIMA(2,0,0)(1,0,0)	139.59	1.035	0.9301	-0.3091	.	0.1251	0.97
	$Z_t=1.035+(0.9301(Z_{t-1})-0.309(Z_{t-2}).+a_t)x(0.1251(Z_{t-12})+\varepsilon_t)$	154.32	19.52	16.682	-5.543	.	2.1409	0.0925
		0.72	<.0001	<.0001	<.0001	.	0.03	E
		0.3042						
Cl^-	ARIMA(2,0,0)(0,0,0)	-247.83	0.4909	1.105	-0.3931	.	.	0.99
	$Z_t=0.491+1.1(Z_{t-1})-0.3931(Z_{t-2})+a_t$	-236.78	15.534	20.558	-7.317	.	.	0.0248
		0.9	<.0001	<.0001	<.0001	.	.	E
		0.1575						
HCO_3^-	ARIMA(1,0,1)(0,0,0)	141.02	2.455	0.6279	.	-0.584	.	0.99
	$Z_t=2.45+0.628(Z_{t-1})+a_t+0.584(a_{t-1})$	152.07	32.611	12.273	.	-10.904	.	0.0931
		0.94	<.0001	<.0001	.	<.0001	.	E
		0.305						
SO_4^{--}	ARIMA(2,0,0)(1,0,0)	-98.25	0.8803	0.9967	-0.3812	.	0.2076	0.99
	$Z_t=0.88+(0.997(Z_{t-1})-0.381(Z_{t-2}).+a_t)x(0.2076(Z_{t-12})+\varepsilon_t)$	-83.51	22.965	18.302	-6.935	.	3.57	0.0411
		0.53	<.0001	<.0001	<.0001	.	<.0001	E
		0.2028						
pH	ARIMA(2,0,0)(0,0,0)	63.13	7.799	0.7692	-0.1255	.	.	0.97
	$Z_t=7.775+0.842(Z_{t-1})-0.142(Z_{t-2})+a_t$	74.24	181.058	13.371	-2.183	.	.	0.0713
		0.83	<.0001	<.0001	0.0297	.	.	E
		0.267						
TDS	ARIMA(1,0,1)(0,0,0)	2826.91	228.79	0.801	.	-0.591	.	0.99
	$Z_t=228.8+0.8(Z_{t-1})+a_t+0.591(a_{t-1})$	2837.96	16.904	21.822	.	-11.847	.	862.4
		0.91	<.0001	<.0001	.	<.0001	.	E
		29.366						

4. Conclusions:

The developed models for Mg^+ , Na, $^+$ SO_4^-2 parameters in Zir-e-pol station (only outlet), a TDS model in Lavark station and HCO_3^- model in Rudak station show seasonality behaviors and the rest of the models are non seasonal. Approximation of the trend of observations shows that the amounts of TDS, Mg $^+$, Na^+, and SO_4^-2 parameters are maximum in April and minimum in September. This may be due to a maximum amount of rainfall in early spring and diminishing rainfall in summer in the catchment area.

All the developed models have P-Values above 0.9 which implies they are excellent according to the definition. Comparison of predicted and observation data for the last six months shows good conformity. Hence, the developed models are proper and confidential and may be useful tools for water quality management in inlets and outlet water in the dam.

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