The Performance of The Wavelet De-Noising-Based Combined Model (WDCM) In Forecasting The Groundwater Level

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***Abstract*—**Groundwater level (GWL) time series are highly non-stationary, noisy, multi-scale, and complexity due to varieties of natural and anthropogenic factors which are closely related to the GWL fluctuation. The direct forecasting of GWL with noisy and multi-scale data is usually subject to large errors. This paper, for first time, was applied wavelet de-noising in a combined model (WDCM) forecasting of GWL. The seasonal autoregressive integrated moving average model (SARIMA) and neural networks (ANNs) were used as combined model in WDCM. Firstly, the original data of GWL were decomposed into an approximate part associated with seasonal component (linear pattern) and some detailed part associated with random component (nonlinear pattern) via a wavelet transform. The SARIMA established by the seasonal signal and the multilayer perceptron neural network (MLP) using the random signal to forecast. Finally, the GWL was forecasted by combining the prediction values of SARIMA and MLP. To evaluate the performance of the proposed approach, a comparison was done with the SARIMA, MLP, and W-SARIMA and W-MLP combined model, which were established using the de-noising data. The results were shown that the proposed model can effectively improve the forecasting accuracy**.**

***Keywords*—**Groundwater level; Wavelet Transform; Hybrid Model; MLP; SARIMA

I. INTRODUCTION

Groundwater level (GWL) forecasting is an essential subject in water resources management. The GWL data is essentially dynamic, complex, nonparametric, and chaotic in nature. In fact, many natural and anthropogenic factors affect the GWL data, such as the precipitation, temperature, evaporation, groundwater exploitation and river flow. This influence implies that accurate GWL forecasting is difficult.in fact, the groundwater time series consists of three principal components (autoregressive, seasonality and stochastic) and the performance of the time series models are related to these components. GWL can be predicted using data driven and knowledge- driven models. The performance of data driven models is based on identifying relations between input and output variables of a system without the need for experimental apparatus and complex hydro-physical models based on physical principles and mathematical equations [20]. Required inputs of data driven models in groundwater are the hydrological and meteorological variables which are closely related to the GWL fluctuation. Generally, data driven methods can be divided into two categories contain statistical models and artificial intelligence (AI) models.

Based on factors influence the groundwater, time series models such as the Holt-winters (HW) model, the autoregressive moving average (ARMA) model, the Autoregressive integrated moving average model (ARIMA), and the seasonal autoregressive integrated moving average (SARIMA) model have been applied[9]. For instance, [3] predicted the chloride content for short-term in the mineral waters of the Ustron Health Resort using SARIMA and HW models. The results of analyses indicated that the good performance of the HW model highlights its utility compared with complicated physically based numerical models. [25] used three time series analysis methods, HW, integrated time series (ITS), and SSARIMA to simulate the groundwater level in a coastal aquifer in China. The comparisons of three models show revealed that the HW model is more accurate in predicting the GWL than SARIMA and ITS models.

It should be notice that the chaotic and stochastic characteristics of GWL time series need more complex functions for capturing the nonlinear relations, but most of these models are based on the assumption that a linear correlation structure exists among time series values. However, the statistical models generally are not perfect in forecasting. To overcome this limitation, many AI approaches have been proposed to address this problem. These AI approaches, which primarily include neural networks[4], fuzzy logic-based approaches [6], and genetic algorithms [14], have yielded impressive results in dealing with GWL prediction.

However, GWL time series contain both linear and nonlinear patterns. Many research efforts have indicated that prediction methods depend on the data patterns and there is no single best prediction method that can be applied to any data patterns. Therefore, combining different models can increase the chance of capturing different patterns in the data and improve the forecasting performance. This approach has led to the rapid development of hybrid models based on popular methods. Wavelet transforms (WT), as a pre-processing effective tool, can be combined with data driven models to constitute a hybrid model. Wavelet transform (WT) is a useful tool which splits up the time series into subseries containing different frequencies. The obtained subseries are very beneficial for increasing the prediction ability of a model by extracting effective information at various levels [2]. Recently, there has been an increasing interest in combination wavelet transform with artificial intelligence and time series models in groundwater modeling [1,8,10,12,18,17,22,21,]. [1] studied the prediction of fluctuation groundwater by a combination of wavelet transform and ANN models. They decomposed GWL and rainfall data by wavelet transform. Then, all efficient subseries of groundwater levels and rainfall were considered as inputs of the ANN model. The relative performance of the proposed coupled wavelet–neural network models (WA–ANN) was compared to regular artificial neural network (ANN) models and autoregressive integrated moving average (SARIMA) models for monthly groundwater level forecasting. The results indicated the potential of WA–ANN models in forecasting groundwater levels. [22] compared WA-SVR with ANN, SVR and autoregressive integrated moving average model (SARIMA) to show that the WA-SVR yielded better accuracy. [21] applied Wavelet-Support Vector Regression (W-SVR) forecasting monthly groundwater level fluctuations observed in three shallow unconfined coastal aquifers in the southwestern part of Karnataka adjoining the Arabian Sea. To assess the accuracy efficiency of the model, The Sequential Minimal Optimization Algorithm-based SVR model was also used in the same data sets. The comparison was made with different statistical indices. Results demonstrated that WP–SVR model outperforms the classic SVR model in predicting GWL at all the three well locations. [12] predicted GWL for lead times of 1, 2 and 3 months for 3 observation wells in the Ejina Basin using the wavelet-artificial neural network (WA-ANN) and wavelet-support vector regression (WA-SVR). Results showed that WA-ANN and WA-SVR have better performance than ANN and SVR models. WA-SVR yielded better results than WA-ANN model for 1, 2 and 3-month lead times.

It is obvious from the related literature that in the hybrid models were a single data driven that directly were constructed from the de-noising data of GWL. As wavelet analysis was applied to decompose the historical data of GWL into different sub series and each component was predicted by using the statistical models or artificial intelligence (AI) models and predicted components were summed to predict GWL. To date, no work has reported the capability of combination three methods include wavelet transform, SARIMA, and MLP for GWL forecasting. This provided an impetus for the current research. However, for the first time, this research is applied a new technique to predict groundwater level by wavelet transform as an effective tool to remove the useless information in a time series, the SARIMA model to forecast linear relationships, and the Multilayer Perceptron model (MLP) to handle nonlinear patterns. In this model, the historical data are first decomposed the original data into an approximate part associated with seasonal component (low frequency) and some detailed part associated with random component (high frequencies) via a wavelet transform. The SARIMA model is established by the seasonal signal and the MLP model using the low-frequency signal to forecast. Finally, the GWL is forecasted by combining the prediction values of SARIMA and MLP. Finally, the performance of WDCM model is compared with the SARIMA, MLP, and W-SARIMA and W-MLP combined model, which were established using the de-noising data.

II. METHODOLOGY

A. Case study

The Urmeih plain is a coastal aquifer located at the east of Urmeih Lake, Iran which lies between the eastern longitude of 44°, 20′ and 45°, 20′ and northern latitude of 37°, 05′ and 38°, 05′ (Fig. 1). Urmeih Lake is a large natural reservoir, which provides water requirements for different uses such as agricultural, industrial, and domestic. The total length of coastline is around 3000 m. It is influenced under the sub-tropical marine monsoon climate. This plain covers an area of about 248.34 km2 and mean annual temperature and precipitation in the area are 16 °C and 304 mm, respectively. In this aquifer, groundwater flows from areas of a high hydraulic head in the west to the areas of a low hydraulic head in the east. To monitor the GWL, 55 observation wells were installed in the Urmeih aquifer. In this study, for providing the wavelet de-noising- based combined model (WDCM) to predict groundwater level at observation well was used (Well 1, in Fig. 1). Groundwater level data used in the current study cover 16 years data (192 monthly levels) between 2000 and 2016. The data set from 2000–2011 is used for model establishment, and the data set from 2012–2016 is used for predicting the dynamic change. Descriptive statistics for groundwater level at the observation well is shown in Table 1.

TABLE I. THE DESCRIPTIVE STATISTICS FOR OBSERVATION WELL.

Number of Data	Table Column Head			
	Mean	***Max***	***Min***	***StD***
192	1281.92	1284.24	1279.3	1.16

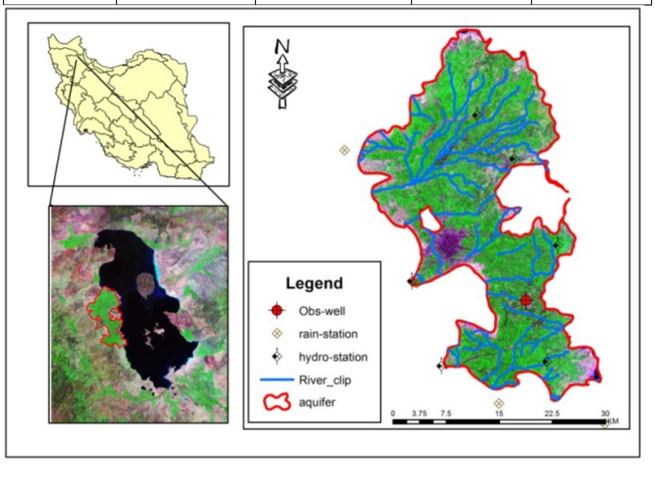

Fig. 1. The location of the study area and the spatial distributions of observation well

B. Dicrete Wavelet Transform (DWT)

The wavelet transform is the popular tool of the Fourier Transform because of its multi resolution in time and frequency domain. The function ψt presents a mother wavelet, which has shock characteristics and diminishes to zero quickly [5,23,13]. Wavelet functions decompose the time series into subseries with various frequency domains, and then considers each subseries with a resolution corresponding to its frequencies thus dominating the deficiencies of Fourier transform. In employing Discrete Wavelet Transform (DWT), a finite number of shifts and scale levels are considered. The wavelet coefficients are calculated using DWT and the simplest and most impressive approach, where scales (a) and shift (τ) are chosen on basis of the powers of 2, called dyadic scales and shifts 5,13]. DWT functions are usually presented by

$$a = a_0^j \quad \tau = ka_0^j\tau_0 \qquad a_0 > 0$$

$$\tau_0 \in R,\ \forall j,k = 0,1,2,3,\dots,m \in Z \tag{1}$$

$$\varphi_{j,k}(t) = a_0^{-j/2}\varphi\left(\frac{t-ka_0^j\tau_0}{a_0^j}\right) = a_0^{-j/2}\varphi(ta_0^{-j} - k\tau_0) \tag{2}$$

The most common selection is $a_0 = 2, \tau_0 = 1$, and then the DWT becomes binary. For a discrete GWL time series LL(t), in which LL(t) happens at a discrete integer time step t, the dyadic discrete wavelet transformation can be defined as:

$$\mathrm{W_f(j,k)} = \sum_{\mathrm{j,k\in z}} \mathrm{LL(t)} 2^{-j/2} \varphi\,(2^{-j}t - k) \tag{3}$$

Here, $W_f(j,k)$ shows the specifications of the lake level time series in scale (a or j) and time domain (τ or k). When either a or j is small, the frequency resolution diminishes, but the time domain increases. When either a or j is large, the frequency resolution increases, but the time domain diminishes (Wang and Ding 2003). The input signal can be built using the equation:

$$\mathrm{LL(t)} = \sum_{\mathrm{j,k\in z}} \mathrm{W_f(j,k)}\varphi_{\mathrm{j,k}}(t) \tag{4}$$

In Eq. (4), $W_f(j,k)$ applies down-sampling to calculate an approximation coefficient (a_I) at decomposition level I with a low pass filter $L(\varphi_{j,k}(t))$, and detail coefficients$(d_1, d_2, d_3, \dots, d_I)$ at various levels 1, 2, . . ., I with a high pass filter$H(\varphi_{j,k}(t))$. a_I presents identity of the time series and $d_1, d_2, d_3, \dots, d_I$ show the detailed information of the time series such as jump, period, break and so on. However, the coefficient (a_I) and (d_I) cannot be directly summed to generate the time series as they are produced by down-sampling and are only half the length of the time series. So, it is indispensable to reconstruct the approximations (a_I) and details (d_I) before summing them [23]. Then the time series can be explained as:

$$\mathrm{LL(t)} = \mathrm{a_I} \mathrm{L}\left(\varphi_{\mathrm{j,k}}(\mathrm{t})\right) + \sum_{\mathrm{I=1}} \mathrm{d_I} \mathrm{H}(\varphi_{\mathrm{j,k}}(\mathrm{t})) \tag{5}$$

$$\mathrm{LL(t)} = \mathrm{a_I} + \sum_{\mathrm{I=1}} \mathrm{d_I} \tag{6}$$

C. SARIMA Model

An SARIMA model can be explained as ARIMA (p, d, q) (P, D, Q)s, where (p, d, q) is the nonseasonal part of the model and (P, D, Q)s is the seasonal part of the model in which p is the order of non-seasonal auto-regression, d is the number of regular differencing, q is the order of non-seasonal MA, P is the order of seasonal auto-regression, D is the number of seasonal differencing, Q is the order of seasonal MA, and s is the length of season [19].

D. Multilayer perceptron (MLP)

ANN models are powerful non-linear modeling approaches that work by imitating how the human brain functions. ANN is able to create a complex network mapping between input and output variables that has the ability to estimate non-linear functions. Multilayer Perceptron (MLP) one of the most widely used ANNs [15]. The MLP is composed of one input layer, one output layer and at least one hidden layer[16]. The MLP can be expressed as follows:

$$\mathrm{y_i} = \mathrm{f}\left(\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{w_{ji}} \mathrm{x_i} + \mathrm{b_j}\right) \tag{7}$$

where x_i and N denote the ith nodal value and the number of nodes, respectively, in the previous layer; f and y_j, b_j are the jth nodal value, the bias of the jth node and the activation function, respectively, in the current layer; and w_{ji} is a weight connecting x_i and y_j. A number of studies have found that one hidden layer is sufficient for the ANN model to estimate complex non-linear functions for hydrological data[4]. Initial results of our study also indicated that one hidden layer was adequate to approximate the relationship between groundwater level and the different components of the hydrologic cycle. Determining the size of the hidden nodes is an important part of the MLP and it is often done using a trial and error approach although guidelines on how to best determine the size of the hidden nodes have also been proposed. number of hidden nodes was proved to learn N^i samples with a negligibly small error is identified as follows[11]:

$$N^H = 2\sqrt{(N^o + 2)N^i} \tag{8}$$

N^H denotes the maximum size of hidden nodes and N^i and N^o are the size of input and output nodes, respectively. In this study, the optimal size of hidden nodes was specified based on a trial and error approach, where the size of the hidden nodes was modified from one to N^H. The Levenberg–Marquardt (LM) algorithm, one of the most efficient and fast algorithms in MLP, was used for training [11].

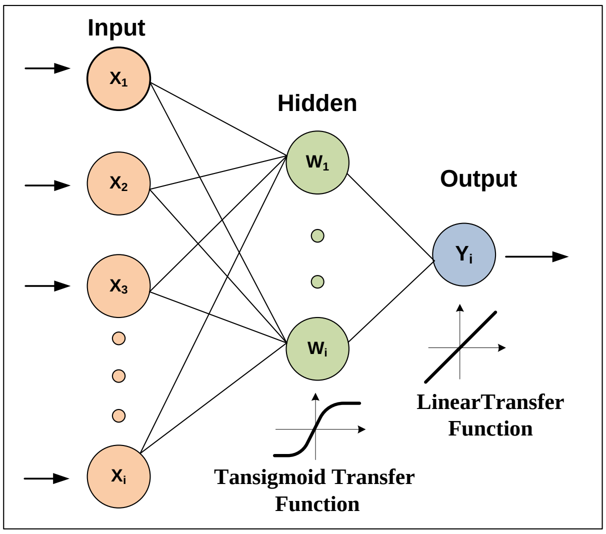

Fig. 2. A configuration of the Multilayer Perceptron (MLP) neural network model

E. The wavelet de-noising- based combined model (WDCM)

The WDCM model utilizes a wavelet transform to a hybrid model. This hybrid model consists of SARIMA and MLP. Firstly, the original GWL time series is decomposed into a low-frequency component (A) and a high frequency component (D) by the wavelet decomposition. Then, the SARIMA is used to capture the linear pattern and seasonal pattern of the GWL time series. After that, the MLP is primarily used to capture the non-linear pattern of the GWL time series. Finally, the forecasting values of the original GWL time series are calculated by combining the results of the SARIMA model and the MLP model. For establishing DWT and MLP modeling, MATLAB software was applied and for SARIMA modeling, MINITAB software was used.

III. Result

In this paper, the new WDCM hybrid model was applied for the first time to forecast monthly GWL. The WDCM model utilizes a wavelet transform to a hybrid model. This hybrid model consists of SARIMA and MLP. The performance of WDCM model was compared with the SARIMA, MLP, and WSARIMA and WMLP combined model, which were established using the de-noising data. Groundwater level data used in the current study cover 16 years data (192 monthly levels) between 2000 and 2016 in Urmieh aquifer, Iran. The observation values of GWL data set from 2000–2011 were used to establish and the GWL data set from 2012–2016 is used for validation. In the first step, the original GWL time series was decomposed into a low-frequency component (A) and a high frequency component (D) by the wavelet decomposition. The component of D represents the main features of the chaotic and stochastic components, and the component of A is often called the periodic and seasonal components. The idea of this step is to separate the random disturbance (nonlinear pattern) from the seasonal characteristics (linear pattern). The monthly groundwater level data were decomposed using Daubechies (db4) mother wavelet. DWT breaks up original time series into two subseries containing a detail component and one approximation component. The decomposition process of db4 is shown in Fig. 3 which includes the original groundwater signals (GWL), the approximation coefficients at level 1 (A1), and the detail coefficients at level 1 (Dl). The A1 is a smoothed version of the original series. Each component plays a particular role in time series and follows a special pattern about the original time series. For this reason, each two components (A_1 and D_1) were applied as inputs to the SSARIMA and MLP models, respectively. It is important in model development that the full data split to training and test data as a requirement to avoid incorporating future information[12]. Hence, the wavelet decomposition process was applied on each partition (i.e., training and testing) independently. It should be emphasized that if the full dataset (i.e., training and testing) is decomposed, then future data (that is not available to the modeler) could be used in the calculation of wavelet coefficients and lead to introduce bias into the forecasts [5]. In the second step, the SARIMA was primarily used to capture the linear pattern and seasonal pattern of the GWL time series. Then, the MLP was primarily used to capture the non-linear pattern of the GWL time series. Finally, the forecasting values of the original GWL time series were calculated by combining the predicted values of the SARIMA model with the predicted values of the MLP model. In SARIMA model, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the groundwater data were extracted. Then, parameters (p,d,q, P, D, Q) was defined considering the cutout and continuity features in the plot of ACF and PACF. In the MLP model, the weights were adapted using LM learning algorithm, the tansigmoid transfer function was used for the hidden nodes and the size of the hidden nodes was identified using a trial and error approach. The best structure and the R, RMSE, MAE, and NSE statistics of the optimal WDCM model in training and testing were given in Table 2. The comparison of calculated values of A1, D1, and GWL using the WDCM model with the actual values is shown in Fig. 4.

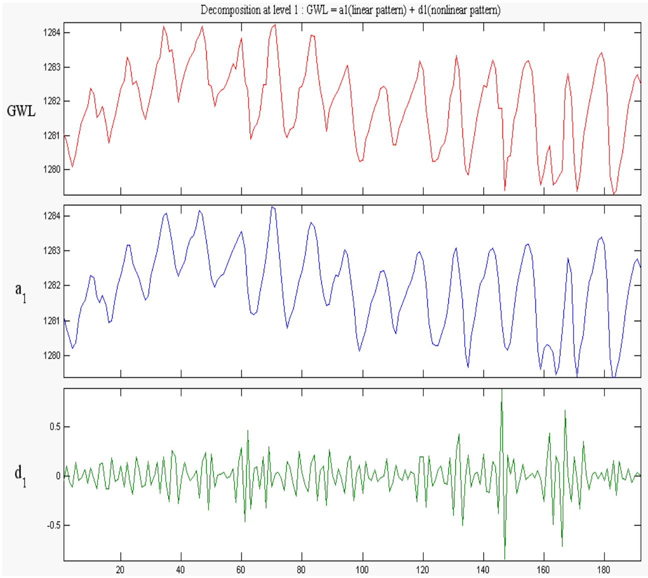

Fig. 3. The de-composition process of the original GWL data

TABLE II. THE BEST STRUCTURE AND PERFORMANCE OF MODELS FOR GWL FORECASTING

Method	De-noise	Model	Structure	Training Step R	Training Step RMSE	Training Step MAE	Training Step NSE	Testing Step R	Testing Step RMSE	Testing Step MAE	Testing Step NSE
DWT	A1	SARIMA	(2,1,1)(1,1,1)12	0.99	0.14	0.10	0.98	0.98	0.24	0.18	0.96
	D1	MLP	(1,3,1)	0.51	0.15	0.11	0.25	0.63	0.22	0.15	0.36
	WDCM		(SARIMA+MLP)	0.91	0.45	0.38	0.81	0.85	0.71	0.54	0.71

The results of Table 2 and Fig. 4 clearly show that the WDCM model can capture the nonstationary and highly noisy features of the GWL data very well. The R, RMSE, MAE and NSE values indicate that the WDCM model yields a satisfactory performance and a high forecasting accuracy.

verify the WDCM method, the performance of this model was compared with the SARIMA, MLP, and combined model which were established using the de-noising data (W-SARIMA and W-MLP). The comparisons of GWL values forecast using SARIMA, MLP, W-SARIMA, and W-MLP with the WDCM model are shown in Table 3.

With respect to R, RMSE and NSE criteria, it was concluded that the WDCM model has better performance than others models and can more accurately describe the GWL time series. It can be observed from the statistical results in Table 3 that the MLP model was found to outperform SARIMA. MLP model has higher R and smaller RMSE than SARIMA model. Comparison of the MLP and W-MLP indicated that DWT has had a high impact on improving the MLP model performance, so that the RMSE and NSE criteria in the W-MLP in compare with MLP model improve 28% and 57%, respectively. While, in SARIMA the RMSE and NSE criteria improve 4% and 5%, respectively. It is observed a worth note that there are more stochastic and nonlinear pattern in GWL data, so the SARIMA and W-SARIMA models were not able properly to predict this time series.

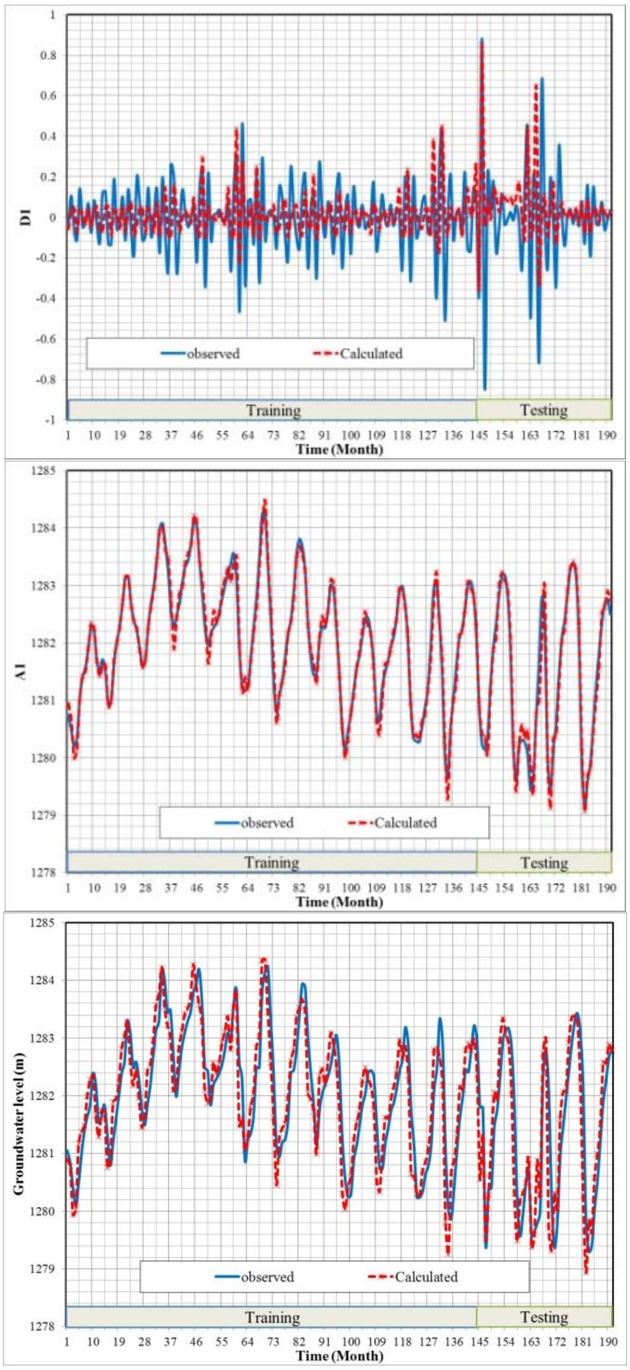

Fig. 4. The comparison of training and testing steps for the WDCM model

TABLE III. THE RESULTS OF SARIMA, MLP, W-SARIMA, W-MLP , AND WDCM MODELS

Model	Training Step				Testing Step			
	R	RMSE	MAE	NSE	R	RMSE	MAE	NSE
SARIMA	0.54	0.89	1.10	0.46	0.54	1.04	1.26	0.26
MLP	0.64	0.65	0.77	0.49	0.51	0.97	1.02	0.40
W-SARIMA	0.63	0.77	0.94	0.40	0.52	0.99	1.11	0.27
W-MLP	0.86	0.52	0.41	0.74	0.80	0.78	0.68	0.63
WDCM	0.91	0.45	0.38	0.81	0.85	0.71	0.54	0.71

IV. CONCLUSIONS

The moving average methods, such as SARIMA model, are capable to predict the time series containing the trend and seasonal variation and are a sophisticated method in time series that have linear characteristic. AI methods, such as MLP, are as an effective method in time series with nonlinear characteristic. In the other hand, in GWL time series contain both linear and nonlinear patterns, combining different models can increase the chance of capturing different patterns and improve the forecasting performance. In previous studies, combined models have been established with the de-composition data for GWL prediction. In this paper, for the first time, the wavelet de-noising- based combined model (WDCM) was applied for GWL forecasting. The WDCM model utilizes a wavelet transform to a hybrid model that DWT separate the original data into an approximate part (A1) associated with linear pattern and a detailed part (D1) associated with high frequencies, the SARIMA model to forecast linear relationships, and the Multilayer Perceptron model (MLP) to handle nonlinear patterns. Then, the GWL was forecasted by combining the prediction values of SARIMA and MLP. Finally, the performance of WDCM model was compared with the SARIMA, MLP, and W-SARIMA and W-MLP combined model, which were established using the de-noising data. Results showed that the WDCM could lead to a considerably increased accuracy of GWL modeling.

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