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Application of wavelet neural network in estimation of average air-temperature

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Abstract
Standard weather station evaluates air-temperature which is a major descriptor of earth environmental condition. Estimation of average daily temperature is one of the main perquisites for agricultural programming and water resource management which is possible by empirical, quasi-empirical and intelligent methods. This study evaluates the application of wavelet neural network (WNN) to estimate the average daily air-temperature in Sari weather station and also compares its efficiency with artificial neural network (ANN). We used thermograph data of Sari weather station for modeling. Relative humidity, maximum temperature, minimum temperature, wind velocity and daily evaporation were considered as network input and air-temperature was considered as network output for the years 2010 to 2020 years. Criteria including correlation coefficient, root mean square error (RMSE), Nash-Sutcliffe (NS) coefficient were used to evaluate and comparison the models efficiency. Results showed that WNN model had better performance than ANN for modeling with the coefficient of determination 0.999, RMSE 0.001 and NS 0.998. In conclusion, results showed reliability of WNN model in estimation of air-temperature.

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Introduction

Forecasting average air-temperature is valuable in various fields including water resource management, agriculture, etc. Air-temperature is also one of the input components for evaluation models, ecological and hydrological models. On the other hand, many scientific centers try to investigate weather problems, since weather has major effect on social and individual life of humans. Weather forecasting is about how daily atmospheric situation changes. Temperature and rainfall are the most important climate elements which have major role in determination of role and dispersion of other climatic elements. Since temperature plays basic role in climate classification, hence, its fluctuation and changes are important. It is well known that temperature affects evapotranspiration, surface waters, diseases, forest fire and drought. Average daily air-temperature is the most important climate parameter which is calculated by exact and approximate methods in weather stations. Daily maximum and minimum temperatures are used to calculate daily average air-temperature. Thermograph data are used in exact methods and average air-temperature is calculated using integral and daily temperature change curve. Studies have shown that the first method has low precision, with usually a difference of 3 degrees centigrade. Conversely, the second method has high precision (Singh and Xu, 1997). Today, intelligent methods are used for forecasting non-linear phenomenon, of which wavelet neural network (WNN) and artificial neural network (ANN) methods are two examples. ANN is designed using human brain information processing system and its capability has increased its application. Ding et al. (2016) predicted air pollutant in Hong Kong based on back-propagation feed-forward neural networks in 2012 year and concluded that ANN method had higher precision in prediction of weather parameters. Pires et al. (2012) used average air-temperature, solar irradiance, relative humidity and wind velocity in a combined neural network and genetic algorithms for surface ozone concentration forecasting and concluded that combined model has better efficiency compared with ANN.

Wang and Ding (2003) investigated the capability WNN model and its application to the prediction of hydrology and stated that the model has high precision and it can be beneficial to prediction of hydrology. Okkan (2012) applied WNN to the prediction of reservoir inflow in Turkey and stated that the method is suitable for prediction of reservoir inflow. Venkata Ramana et al. (2013) applied WNN to the prediction of monthly rainfall and showed that WNN has better efficiency compared to the ANN. Sharifi et al. (2016) estimated daily global solar radiation using wavelet regression, ANN, gene expression programming in Tabriz and Urmia cities and showed that the method has high precision in estimation of daily global solar radiation. Karthika and Deka (2016) predicted average air-temperature using wind velocity, relative humidity, and rainfall using basin ANN and WNN models in Shimoga-India. Yang et al. (2020) predicted monthly rainfall in Darjeeling station in the foothills of the Himalayas, and showed that the wavelet neural network model has a better performance than the artificial neural network model. Yakut et al. (2020) predicted the maximum temperature in a city in Turkey, using the artificial neural network and showed that the artificial neural network has an acceptable performance in estimating the air temperature. Many researchers have validated the potential utility of AI techniques for modelling of temperature (Alexiadis et al., 1998; Imran et al., 2002; Soleimani-Moheseni et al.,2006; Kemajou et al., 2011; Pires et al., 2012; Khatibi et al.,2012; Khatibi et al., 2012; Dutta and Kumar.2013; Ghorbani et al., 2015; Kisi et al., 2016; Pammar and Deka, 2016; Wang et al., 2019; Astsatryan et al., 2021; Hou et al., 2022; Bellagarda et al., 2022).

The above studies reported better efficiency of WNN compared with the basic ANN model. Sari, a city in the north east of Iran has one of the most important weather stations in North-Iran and the area is a major center of agriculture dependent on air-temperature. Thus, exact modeling of air-temperature in Sari is essential for increasing the efficiency of agricultural practices and water management. The present study aimed to estimate the air-temperature using WNN which is divided to upper and lower frequencies. Low-pass and high-pass signals decomposed from wavelet have appropriate fitting sinusoidal equations, so that precision increases as the orders increase. Low-pass frequencies have more noise but as decomposition level increases the signal becomes softer (Wang et al., 2000).

Materials and Methods

Study area

Sari is a city between Caspian Sea, Alborz Mountain, Neka, Behshahr and Ghaem Shahr (Figure 1). Sari is placed in Alborz mountains with coordinates $36^0$33'48"N53^0 03'36"E. Its area is 3923 km.m^2. The city has mild and wet summers and dry and cold winters. South of Sari has long and very cold winters. Winds originating from west cause cold weather and sometimes brings snow to the area. The average annual rainfall is 789 mm most of it pouring in autumn and some small amount in spring. Some parameters including relative humidity (RH), maximum temperature (T.Max), minimum temperature (T.Min), wind velocity (WV) and evapotranspiration

(ET) as input and average air-temperature (T) as output were considered over the years 2010 to 2020 in Sari weather station.

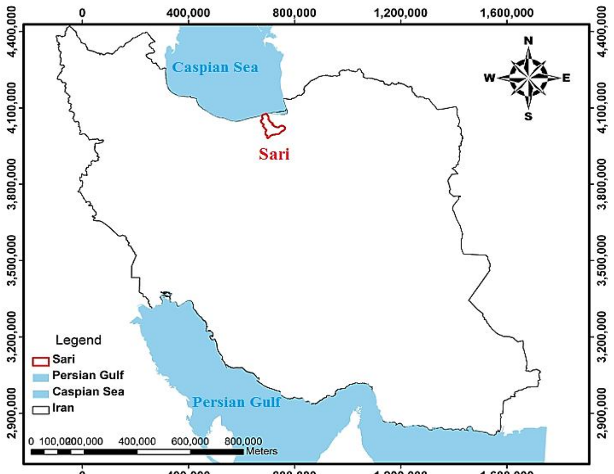

Figure 1. Geographical position of the study area

Wavelet neural network

Wavelet-based neural networks which are also called wave-net are developed from combination of wavelets and neural networks theory (Safavi and Romagnoli, 1997). These networks have advantages and disadvantages, attractiveness, flexibilities, rigorous mathematical principles and multi-scaling analysis facilities. Wavelet functions and scaling functions are used in wave-nets. Functions $\emptyset(x)$ is expressed as follows:

(1) $\emptyset_{m,k}(x) = 2^{-m/2}\emptyset(2^{-m}x - k) \quad m, k \in z$

where 2^{-m} and k correspond respectively to the dilation and translation factors of the scaling function. Scaling functions resolution m and $\emptyset_{m,k}(x)$ are orthogonal bases of vector space v_m in resolution m. In other words, vector space v_m contains all functions of f(x) with resolution m. Thus, vector space $[v_m]$ has all functions f(x) in different resolutions. If wm is to be hypothesized as orthogonal vector space in resolution m, then we can consider other class of orthogonal-based space which is called $\Psi(x)$ and expressed as follows (Safavi and Romagnoli, 1997):

(2) $\Psi_{m,k}(x) = 2^{-m/2}\Psi(2^{-m}x - k) \quad m, k \in z$

In general all physical functions are expressed as follows (Wang et al., 2000):

(3) $(x) = f_0(x) + \sum_{m=-\infty}^{0}\sum_{k=-\infty}^{\infty} d_{m,k}\Psi_{m,k}$

(4) $f_0(x) = \sum_k a_{0,k}\emptyset_{0,k}$

These relations state that each physical function can be approximated in zero resolution and followed by wavelet functions until different resolution. Wave-net neural network is created using equations 3 and 4 explained by Wang et al., (2000). In general, continuous wavelet class is expressed as follows:

(5) $\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \quad a, b \in R$

Wavelets transformation for continuous data is calculated as follows:

(6) $W_{a,b}(f) = \tilde{f}_{(a,b)} = <\Psi_{a,b}(t), f(t)> = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\Psi^{*}\left(\frac{t-b}{a}\right)dt$

where (a) is dilation parameter according to the frequency and (b) is transform parameter in line with time. Combined wavelet theory with neural network concepts caused WNN and it application to be an appropriate replacement in feed-forward neural networks for approximation of non-linear functions. Feed-forward neural networks have sigmoidal activation function in hidden layer. While, in WNN, wavelet functions are considered as hidden activation function of feed-forward neural networks, but the transform parameter and scale change is optimized using their weights. The main steps in training and accuracy of WNN are as follows:

a) Input data are used in two classes for training and accuracy assessment.

b) Mother wavelet is transformed to child wavelet after application of transformation coefficient.
c) Neuron activation functions in hidden layers are replaced with various child wavelet.
d) WNN is trained by the data related to network training.

General performance of WNN is evaluated using accuracy analysis and the step ends when satisfaction is achieved. Otherwise the previous steps are evaluated to achieve better results (Wang et al., 2000). Examples of three-layer structures including input layer, hidden layer and output layer are shown in Figure 2.

Artificial neural network

ANN is extensively used in hydrology studies and water resource management (Hornik, 1988). Neural network structure is composed of input layer, hidden layer and output layer. The input layer is the tool for preparing the data. The output layer includes the predicted values by the network and the hidden layer or middle layer is composed of processing nodes for data processing. The first application of ANN was implemented using multi-layer perceptron. From the learning algorithms, back propagation (BP) and feed-forward neural network with three-layer architecture are mostly applied to resolving the complex engineering problems and predicting hydrological time series (Nourani et al., 2009; Hornik 1988). One of the functions in BP is sigmoidal activation function and hyperbolic tangent (Nourani et al., 2011). Examples of three-layer architecture including input, output and hidden layers are presented in Figure 3.

Evaluation criteria

To evaluate the precision and efficiency of the models, coefficient of determination (R^2), root mean square error (RMSE), and Nash-Sutcliffe (NS) coefficient were calculated as follows. The optimum values are between zero and 1 for each.

$$(7) \quad R=\frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2 \sum_{i=1}^{N}(y_i-\bar{y})^2}} \qquad -1\leq R \leq 1$$

$$(8) \quad RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i-y_i\right)^2}$$

$$(9) \quad NS=1-\frac{\sum_{i=1}^{N}(x_i-y_i)^2}{\sum_{i=1}^{N}(x_i-\bar{y})^2} \qquad -\infty\leq NS \leq 1$$

In the above equations, x_i and y_i are respectively observations and calculations in step i, N is number of time steps, and $\bar{x}$ and $\bar{y}$ are mean observed and calculated values, respectively. In addition to the above criteria, dispersion curves and observed-calculated series are used to compare the results and assess the accuracy.

Results and Discussion

In the present study, WNN and ANN were used to model the average air-temperature. Parameters including RH, T.Max, T.Min, WV and ET were used as input and T was the output during the years 2010 to 2020 in Sari weather station. The general purpose of intelligent models is showing the complex relationships among the input and output variables. The average air-temperature was the main weather parameter with high importance in management of the area. The mentioned method was used to decrease the error and also estimate the air-temperature with high precision which will present better performance rather than approximate methods. The purpose of the study was development of a model for relating the input variables to air-temperature and its prediction in future. Since air-temperature has high importance, thus it was selected as the target variable. Table 1 presents the parameters and their statistical characteristics used in the modeling. It is essential to mention that 80% of data was used for training and the rest 20% for test (Kisi et al., 2006: Nagy et al., 2002). It is important to normalize data before neural networks training, especially when changes are high (Xhu et al., 2007). Below equation is used for data normalization.

$$(10) \qquad X_n=0.1+0.8\frac{X_i-X_{min}}{X_{max}-X_{min}}$$

where Xn is the normalized data, and X_{min} and X_{max} are minimum and maximum desirable input, respectively. One of the most important steps in modeling is selection of appropriate combination of input variables. In intelligent models selection of the initial inputs may improve performance, and this was what we did in our modeling for Sari. Thus, different combinations of input parameters were selected to achieve the optimum model for average daily air-temperature which is shown in Table 2.

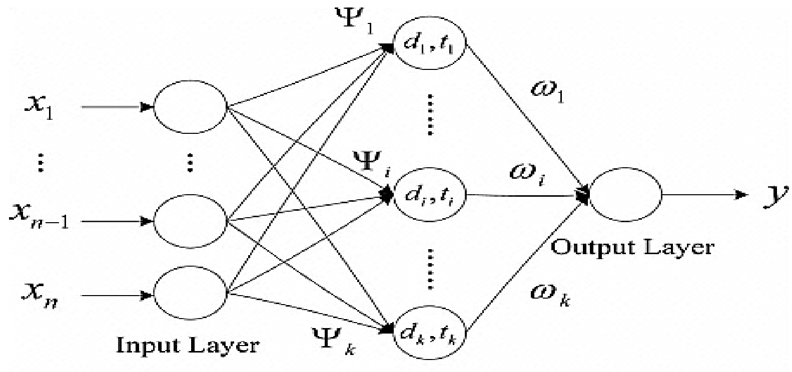

Figure 2. General view of three-layer WNN

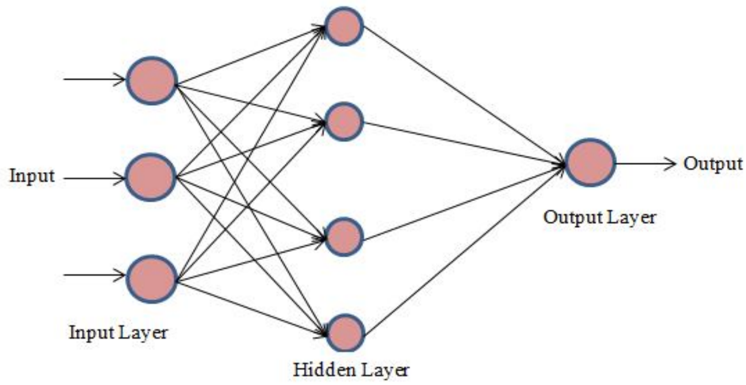

Figure 3. General view of three-layer ANN

Table 1. The range of parameters used for training and data accuracy

Data set	Parameters	Training			Testing		
		Minimum	Mean	Maximum	Minimum	Mean	Maximum
Input	RH(%)	25.333	76.178	100	27.666	75.921	100
	T_{max}(^{0}C)	-5	21.276	40	1	24.351	38
	T_{min}(^{0}C)	-17	10.473	28	-15	7.747	17
	WV(km/h)	0.400	2.780	7.600	0.500	2.842	5.800
	ET(mm)	0	2.870	15	0	2.805	11.400
Output	T_{mean}(^{0}C)	-6	15.875	33	-4	16.549	26

Table 2. The selected combinations of input parameters of ANN and WNN.

Number	Structure Input	Output
1	RH(t)	T(t)
2	RH(t), T_{min}(t)	T(t)
3	RH(t), T_{min}(t),T_{max}(t)	T(t)
4	RH(t),T_{min}(t),T_{max}(t),WV(t)	T(t)
5	RH(t),T_{min}(t),T_{max}(t),WV(t),ET(t)	T(t)

Results of WNN

The WNN with different neuron numbers were used to estimate the average air-temperature in Sari. Suitable wavelet was initially selected in WNN and then we extracted approximate coefficients using data transformation. The data were transformed by Mexican HAT Function as activation function which is a Gaussian function. The gradient descent was used for network gradient which is applied in neural network learning, parameter setting and error minimizing. Considering Table 3, No.5 was the best architecture with 7 nodes in the first hidden layer and the highest correlation coefficient (R=0.999), RMSE (0.001 ^{0}C) and NS coefficient (0.998) in the accuracy stage. Similar to ANN, WNN aimed to minimize error. Increasing and decreasing number of neurons in the hidden layer was completed with regard to minimizing error. As shown in Table 3, WNN provides very good results and distribution (Wang et al., 2000). Considering Table 3, it is observed that WNN has better performance in estimation of the air-temperature, even when used with one parameter; showing that WNN can be used in regions with poor statistic. As shown in Figure 4b, WNN provides good similarity between the observed and calculated air-temperature values. With regard to Figure 4 and parallel to other studies (Sharifi et al., 2016; Karthika and Deka 2016) high capability of WNN is evidenced in estimation of the most values. It can be stated that separating upper and lower frequency in wavelet transformation and its multi-scaling characteristics has increased model precision. Low pass and high pass signals derived from wavelet have appropriate fitting with sinusoidal equations, so that precision increases as equation orders increase. Low pass frequencies have more noise but as decomposition level increases signals become softer.

ANN results

Hyperbolic tangent function is the most common form of activation functions which was used for output layer of ANN. The so called Levenberg-Marquardt algorithm, was used to train the multi-layer perceptron since it is faster. The different combinations of activation functions were used in hidden layer. The number of required repetitions in learning was 1000 and network results was evaluated by mean square error. The number of nodes in the input layer was assigned with regard to nature of the problem, while number of nodes in the hidden layer were assigned for reducing error. This action was initiated with small number of nodes gradually adding nodes until no increase in the accuracy was achieved. As seen in Table 4, architecture 5 has 8 neurons with correlation coefficient (0.975), RMSE (0.014 ^{0}C) and NS coefficient (0.837) as the best to evaluate the average air-temperature in the accuracy step. In Figure 5 a, the best model is shown for. As shown in Figure 5, WNN has had acceptable performance in estimation of the values. As shown n Figure 5 b, most of the observed and estimated values fall along the basis line (y=x). These findings are in agreement with those reported by others (Abhishek et al., 2012: Deo and Şahin. 2015). It can be stated that ANN has high speed, pattern learning capability, pattern generalization after learning, and flexibility against undesirable errors.

Table 3. Architecture and functions of the optimum function in WNN modeling in training and accuracy stages.

Number	Architecture	Stimulator Function		Training			Testing		
		Hidden Layer	Output Layer	R	RMSE (^{0}C)	NS	R	RMSE (^{0}C)	NS
1	1-5-1	Mexican hat	Linear	0.988	0.012	0.968	0.997	0.005	0.996
2	2-8-1	Mexican hat	Linear	0.987	0.014	0.965	0.996	0.004	0.995
3	3-6-1	Mexican hat	Linear	0.985	0.020	0.960	0.994	0.008	0.990
4	4-4-1	Mexican hat	Linear	0.986	0.015	0.966	0.995	0.007	0.993
5	5-7-1	Mexican hat	Linear	0.990	0.010	0.970	0.999	0.001	0.998

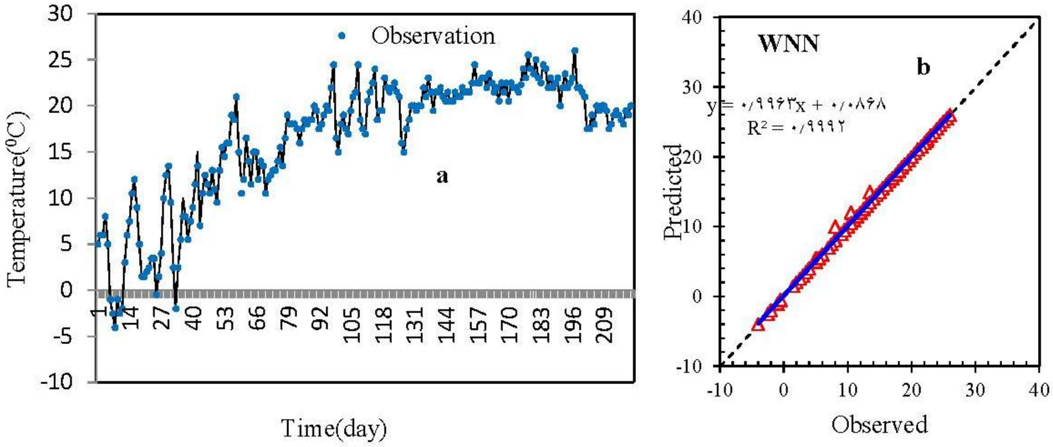

Figure 4. The optimum WNN model for data accuracy, a) observed and estimated values and b) duration of time studied

Table 4. Architecture and optimum functions in ANN modeling in training and accuracy steps.

Number	Architecture	Stimulator Function		Training			Testing		
		Hidden Layer	Output Layer	R	RMSE (^{0}C)	NS	R	RMSE (^{0}C)	NS
1	1-3-1	Hyperbolic tangent	Linear	0.885	0.045	0.801	0.918	0.02	0.826
2	2-5-1	Hyperbolic tangent	Linear	0.822	0.041	0.805	0.904	0.036	0.827
3	3-9-1	Hyperbolic tangent	Linear	0.826	0.041	0.801	0.907	0.032	0.830
4	4-6-1	Hyperbolic tangent	Linear	0.870	0.037	0.789	0.914	0.025	0.832
5	5-8-1	Hyperbolic tangent	Linear	0.963	0.021	0.820	0.975	0.014	0.837

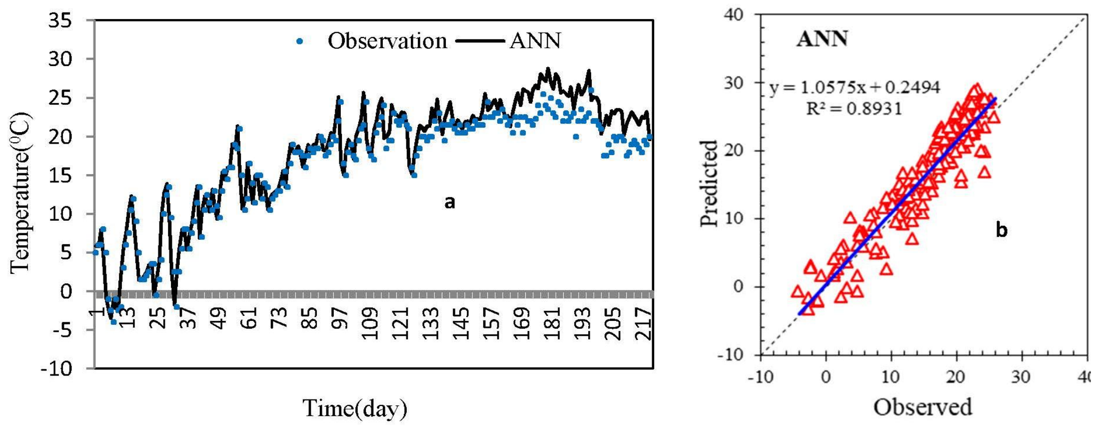

Figure 5. The optimum ANN model in terms of a) observed and estimated values, and b) duration of time studied

Comparison of models efficiency

We found that both models can simulate air-temperature for the study area. As shown in Figure 6, both models have performed well with regard to the observed values. In agreement with Ding et al., (2016), ANN model could not appropriately estimate maximum and minimum points. It can be stated that initial weights were selected in algorithm after BP error and the speed of network training and also the generalization capability of the network (Abhishek et al., 2012). On the other hand, WNN showed acceptable values, so that the estimated values were very close to the observed ones (Wang et al., 2000). On the other hand, the wavelet neural network model showed acceptable performance in estimating most of the values, such that all the values are estimated close to the real ones with well generalization capability.

Table 5. Comparison of training results and accuracy of ANN and WNN

Model	Training			Testing		
	R	RMSE (^{0}C)	NS	R	RMSE (^{0}C)	NS
Wavelet Neural Network	0.990	0.010	0.970	0.999	0.001	0.998
Artificial Neural Network	0.963	0.021	0.820	0.975	0.014	0.837

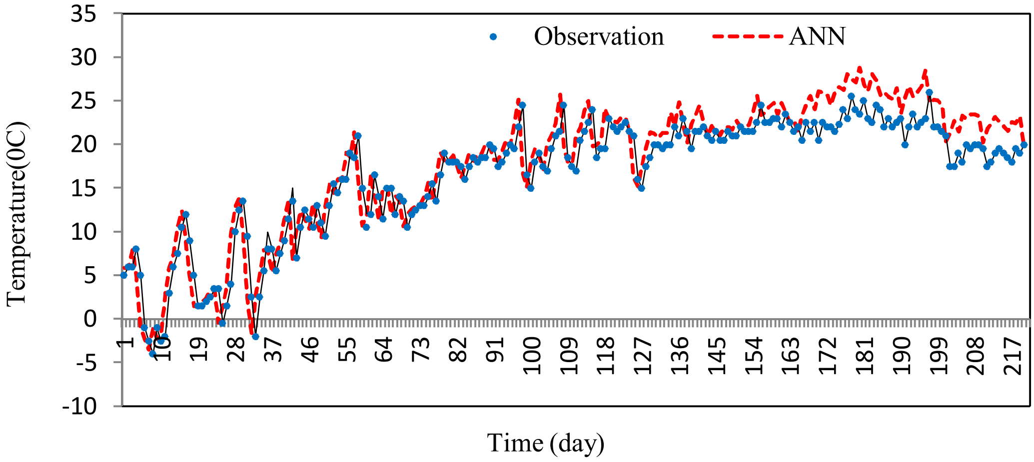

Figure 6. Comparison of predicted values by ANN and WNN with daily air-temperature for data in accuracy step.

Conclusion

This study tried to evaluate the efficiency of network models for simulating air-temperature in Sari using daily data of weather station during the years 2010 to 2020. The applied models included ANN and WNN. The observed air-temperature values were compared with the estimated air-temperature values using ANN and WNN based on error criteria. Results showed that increased parameter causes better efficiency in estimation of air-temperature. It was observed that WNN with the least input parameters is capable to predict the average air-temperature. Considering the evaluation criteria, both models can appropriately predict air-temperature. WNN provided better results through signal decomposition and discontinuous function compared to ANN. In conclusion, WNN very well estimated the air-temperature during 10 statistical years in this study and its results can help improve water resource and agriculture.

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