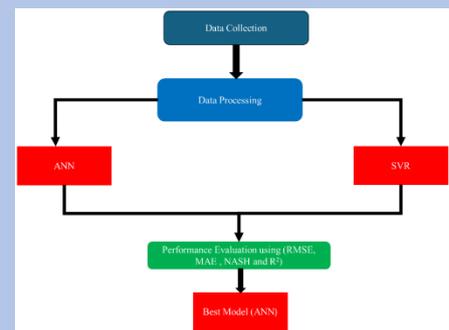# Estimation of Evaporation Rate Using Advanced Methods

Mohammed Falah Allawi[1,*], Uday Hatem Abdulhameed[1], Mohammed Freeh Sahab[1] &
Sadeq Oleiwi Sulaiman[1]

Abstract: One of the hydrological components of the cycle is evaporation, which has actual quantities that are challenging to quantify in the field. As a result, estimations of the evaporation rate's value are made using empirical relationships derived from data on climate components. Several applications of water resources, including hydrological, hydraulic, and an optimal agricultural irrigation system, depend heavily on accurate estimation of evaporation losses. Accurately estimating and forecasting hydrological phenomena is thought to be one of the most critical aspects of managing and developing water resources, as well as creating future water plans that consider various climate change scenarios. The Artificial Neural Network (ANN) and Support Vector Regression (SVR) methods are cutting-edge models that have been employed in several recent research to estimate various hydrological parameters. In the current study, the evaporation rate of Haditha Dam Lake on the Euphrates River in the Al-Anbar Governorate, Iraq, was predicted using ANN and SVR methods. It was designed to receive daily meteorological data, such as temperature, sunshine duration, wind speed, and humidity levels. Evaporation was chosen as the network's output. The present study presented several input scenarios with different input variables to examine the performance of the proposed models. Several statistical indicators have been used to evaluate the prediction results which are root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), mean absolute error (MAE), and correlation (R2) the prediction accuracy. The outcomes demonstrated that ANN could predict evaporation value with a high degree of accuracy better than the SVR method. The best prediction model achieved high correlation and mean error between actual and predicted data.

Keywords: Evaporation, Data-driven model, hydrology.

Introduction

Iraq and most other countries in arid or semi-arid regions struggle with a lack of water resources for diverse uses [1,2]. These nations' growing populations and the effects of climate change have increased the frequency of their droughts, which has reduced the amount of water available for use [3–6]. As a result, these nations must manage and utilize their water resources as best they can [7,8]. For sensible water resource management, the amount of water revenues has to be calculated and compared to the entire amount of water demand, together with the amount of losses, which include transpiration and evaporation [9–13]. The practical of evaporation is one of the essential elements of the natural hydrological cycle phenomenon. One of the key components that the decision-maker needs in order to estimate the agricultural, industrial, and environmental plans as well as the water budget is the depth of evaporation [14–18]. Evaporation from bodies of water, such as lakes, can be determined using several direct or indirect methods. One of the direct methods is the pan evaporation of several kinds. Numerous equations, including the Penman equation and Blaney-Criddle equations, have been produced by researchers from various parts of the world.

In fact, the Penman method is unsuitable for arid regions due to its reliance on intermittent large water usage, which poses a challenge in these areas. Additionally, The Blaney-Criddle method may not be suitable for large bodies of water, such as Haditha Lake which is a case study. This is because the Blaney-Criddle equation relies primarily on temperature and does not consider the impact of wind, humidity, or local weather conditions, all of which significantly affect evaporation rates.

Researchers have employed various alternative techniques to gauge the amount of evaporation from water bodies due to the advancement and speed of computers. In [19], an evaporation simulation was created and assessed, and the effectiveness of a hybrid model was utilized to estimate the mean daily evaporation in northern Iran at the Talesh meteorological station. Two plants in Iraq had their monthly evaporation loss estimated using sophisticated machine learning algorithms [20], where the monthly climate data were utilized as inputs to replicate the monthly depth of evaporation.

Objectives

The present study introduced a robust prediction method based on data-driven models. The proposal model is applied to predict daily evaporation rate parameters. The research tried to discover the effect of the two different meteorological parameters on the prediction results. Therefore, daily temperature and relative humidity were utilized to investigate reliable prediction results. A comprehensive comparison has been made between two different models.

Case Study

With a storage capacity of 8.28 billion m3, Haditha Lake and Dam is situated 7 kilometers ahead of Haditha City on the

---

1 Dams and Water Resources Engineering Department, College of Engineering, University of Anbar, Ramadi, Iraq
* Corresponding author email: mohmmd.falah@gmail.com

65 | 70

An - Najah Univ. J. Res. (N. Sc.) Vol. 40 (1), 2026

Published: An-Najah National University, Nablus, Palestine

Euphrates River in the Anbar Governorate [1]. The dam measures 57 meters in height, 8933 meters in length at its peak, 386 meters in breadth at its base, 20 meters at its top, and 154 meters above sea level [21,22]. The dam lake spans 503 square kilometers and has an operational level of 147 meters.

With a reservoir size of 575 square kilometers and a storage volume of 10.0 billion m3, the emergency level of the flood is 150.2 m [23–25]. The Haditha Dam meteorological station has a Class A evaporation pan to record daily data on temperature minimums and maximums, relative humidity, wind speed, solar radiation, and evaporation depth.

Figure (1): Haditha Lake which is located on Euphrates River in Iraq.

Methodology

Artificial Neural Network (ANN)

An artificial neural network (ANN) is made up of several simple parts that function together [26,27]. Connections and communication channels between these components frequently convey numerical data or weight. The units only utilize internal data and inputs obtained through connections in order to function. The field of artificial neural networks (ANN) is primarily motivated by the goal of developing artificial systems that are able to do sophisticated computations, much like the human brain [28,29].

A structured learning rule that adjusts the connection weights according to input/output data should be a part of an ANN [30,31]. Or, to put it another way, an ANN exhibits strong representational capability outside of the training set and learns given instances (of well-known input/output sequences). ANN usually has great potential for parallelism because the component calculations are essentially independent of each other [32]. Because they can tolerate certain errors and have access to a wealth of training data, artificial neural networks (ANN) are especially useful in real-world applications for problems involving categorization and function interpolation methods [33,34]. The artificial neural network method's architecture is displayed in Figure 2.
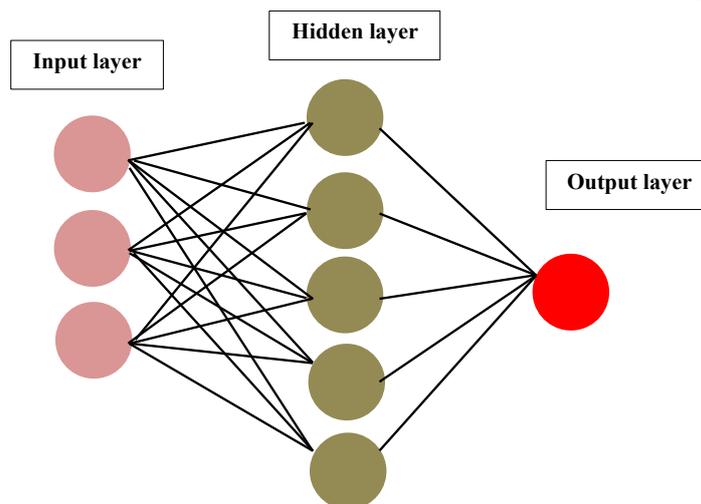

Figure (2): The structure of artificial neural network method.

Support vector regression:

Support vector regression (SVR), which was introduced by [35] based on the theory of statistical learning, is a set of supervised learning methods used for classification and regression tasks. SVR is a popular technique for prediction, pattern recognition, classification, regression, and function approximation [36,37]. [38] introduced SVMs for dividing a set of vectors into two classes. SVMs are based on a hyperplane in the form of w. X+b=0 that optimally separates a set of n-dimensional vectors ($X_i \in R_n$) into two categories. This optimal hyperplane has the farthest distance from support vectors and the nearest data points from each class. Finding w is equivalent to solving a quadratic programming problem. To solve this problem, a trade-off parameter (c > 0) needs to be determined. To categorize vectors that are not linearly separable, a kernel

Mohammed Falah Allawi, *et al*.   Estimation of Evaporation Rate Using Advanced Methods

function such as degreed polynomial, radial basis, or hyperbolic tangent is used to map the observed multidimensional vectors to a space with higher dimensions [39]. The following radial basis function was used:

$$k(X_i, X_j) = exp(-\gamma \,||X_i - X_j||^2) \qquad (1)$$

Where γ>0 is the parameter of the kernel and Xi, Xj represents feature vectors in some input space. The nonlinear regression version of SVMs is written as follows:

$$y = \sum_{\{i=1\}}^{m} (g_i - g_i^*)\, k(X_i, X_j) + b \qquad (2)$$

Where m indicates the total number of input data; g_i and g_i^* are the Lagrange multipliers for upper and lower constraints, respectively, and k denotes the kernel function employed to map the n-dimensional input vectors. There are some fundamental kernel functions provided by support vector machines such as linear, polynomial, sigmoid, and radial basis functions. Among these functions, the radial basis function (RBF) was used by some researchers [39], and the RBF kernel was selected for this study. Figure 3 shows the structure of the SVR model.
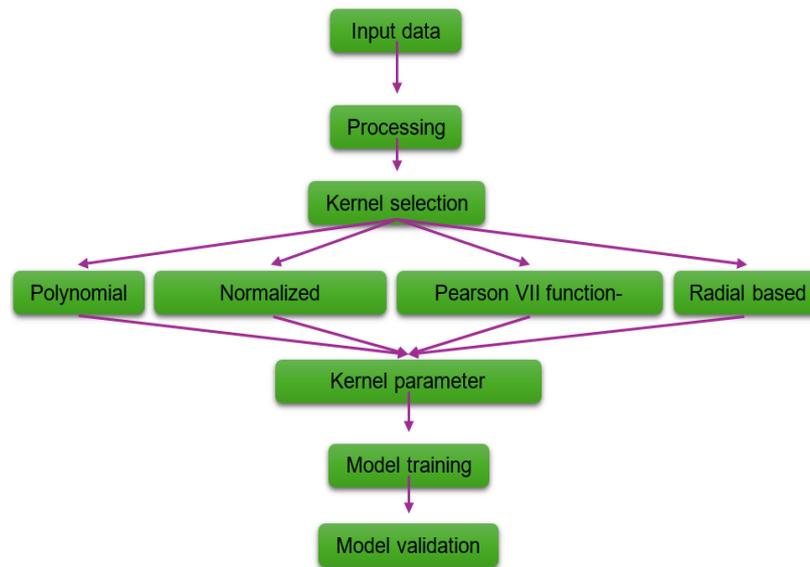

Figure (3): The structure of the support vector regression method.

Results and Discussion

Predicting the evaporation rate has been done using the Artificial Neural Network (ANN) approach. Four distinct architecture models were created to investigate the predictive model's effectiveness with various input variables. The architecture of the evaporation prediction models with ANN and SVR methods are expressed as the following:

$$Model\ 1 : (E_f = E_a(t-1)) \qquad (3)$$
$$Model\ 2 : (E_f = E_a, T_a) \qquad (4)$$
$$Model\ 3 : (E_f = H_a, T_a) \qquad (5)$$
$$Model\ 4 : (E_f = E_a, H_a, T_a) \qquad (6)$$

Where Ef = the predicted evaporation value, Ea = actual evaporation, Ha = actual humidity, and Ta = actual temperature.

The accuracy of the evaporation prediction is displayed in the table. The (M4) model was the least accurate model, obtaining the highest values of RMSE (0.86) and MAE (0.69),

also the lowest value of NASH = 0.81. Nonetheless, the ANN approach produced very good prediction results when the second model's structure was considered.

Table (1): lists the ANN model's evaluation performance metrics.

Model No.	RMSE	MAE	NASH
M 1	0.44	0.34	0.86
M 2	0.41	0.29	0.94
M 3	0.86	0.62	0.83
M4	0.86	0.69	0.81

Figure 4 presents a comparison of model performance based on the correlation coefficient indication. The outcomes showed adequate prediction accuracy offered by models 1 and 4. In contrast, model 2 was able to attain a high degree of correlation between the actual and anticipated evaporation data. Compared to the other models, the Artificial Neural Network (ANN) approach using the (M2) model is a more trustworthy forecasting procedure.
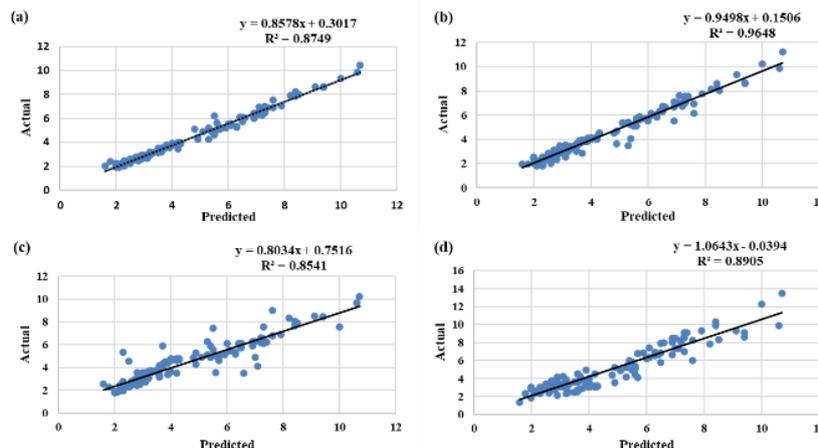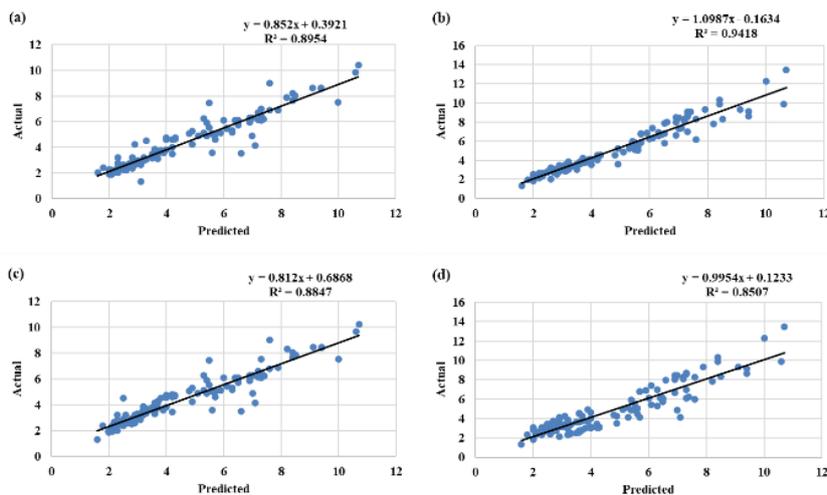

Figure (4): The correlation coefficient indicator for each proposed model based on the ANN method.

67 | 70

An - Najah Univ. J. Res. (N. Sc.) Vol. 40 (1), 2026

Published: An-Najah National University, Nablus, Palestine

Support Vector Regression has also been employed to predict the monthly evaporation rate. The performance of the proposed model was examined with different input variables. The prediction results based on several indicators are presented in Table 2. The evaluation indicators showed that Model-2 achieved a minimum RMSE value between actual and predicted data. The higher RMSE value was obtained by Model-4 as shown in the Table. The prediction results indicated that Model-4 can provide high level accuracy compared to other models.

Table (2): lists the SVR model's evaluation performance metrics.

Model No.	RMSE	MAE	NASH
M 1	0.62	0.44	0.82
M 2	0.57	0.35	0.90
M 3	0.92	0.66	0.78
M4	0.93	0.72	0.77

Correlation between actual and predicted data during the testing period using SVR method is presented in Figure 5. The correlation magnitude was calculated for each proposed model (i.e, Model-1 to Model-2). The lowest correlation has been attained using Model-4. It can be seen that the results of Model-1 and Model-3 are relatively close. The prediction results indicated that high prediction accuracy can be obtained with Model-2.

Figure (5): The correlation coefficient indicator for each proposed model based on the SVR method.

Conclusion

Based on data inputs from meteorological stations, this study discovered that the (ANN) model created had good accuracy and prediction of the daily evaporation from Haditha Lake's values. In order to create an efficient model that can be used to estimate the daily evaporation rate in the Governorate of Anbar with a high degree of accuracy, the study suggests testing the (ANN) model developed using climatic data gathered from all Al-Anbar governorate meteorological stations. The research suggests that decision-makers and water resource managers should utilize artificial neural network models to predict evaporation and manage water scarcity. Moreover, the proposed model can enhance irrigation scheduling, oversee water resources, and assess water quality.

Disclosure Statements

– **Ethical Approval:** The manuscript is conducted within the ethical manner advised by the targeted journal.

– **Consent for publication:** Not applicable.

– **Availability of data and materials:** The raw data required to reproduce these findings are available in the body and illustrations of this manuscript.

– **Author's contribution:** First author: Write the original manuscript, Second and third author: Formal analysis and investigation and Fourth author: Review and editing.

– **Funding:** Not applicable.

– **Conflicts of interest:** The authors declare that there is no conflict of interest regarding the publication of this article.

Open Access

References

1] Sulaiman SO, Kamel AH, Sayl KN, Alfadhel MY. Water resources management and sustainability over the Western desert of Iraq. Environ Earth Sci. 2019 Aug;78(16):495.

2] Ramal MM, Jalal AD, Sahab MF, Yaseen ZM. River water turbidity removal using new natural coagulant aids: case study of Euphrates River, Iraq. Water Supply. 2022;22(3).

3] Sahab MF, Abdullah MH, Hammadi GA, Hamad NS, Ayad Abdulazez A, Fayyadh AH, et al. Ground Water Quality Evaluation for Irrigation Purpose: Case Study Al-Wafaa Area, Western Iraq. Available from: http://creativecommons.org/licenses/by/4.0/

4] AL-Somaydaii JA, Abdaljader A. Earned Value Management Application in Construction Projects of Anbar Governorate. In: AIP Conference Proceedings. 2024.

5] Al-Somaydaii JA, Albadri AT, Al-Zwainy FMS. Hybrid approach for cost estimation of sustainable building projects using artificial neural networks. Open Eng. 2024;14(1).

6] Zayan HS, Farhan JA, Mahmoud AS, AL-Somaydaii JA. A parametric study and design equation of reinforced concrete deep beams subjected to elevated temperature. In: Lecture Notes in Civil Engineering. 2019.

7] Noon AM, Ahmed HGI, Sulaiman SO. Assessment of Water Demand in Al-Anbar Province- Iraq. Environ Ecol Res. 2021 Apr;9(2):64–75.

8] Sulaiman SO, Najm ABA, Kamel AH, Al-Ansari N. Evaluate the optimal future demand of water consumption in al-anbar province in the west of Iraq. Int J Sustain Dev Plan. 2021;16(3).

9] Oleiwi S. Cost-Benefit Analysis of suggested Ramadi Barrage Hydroelectric Plant on the Euphrates River. Int J Comput Aided Eng Technol. 2022;17(1):1.

10] Sayl KN, Sulaiman SO, Kamel AH, Muhammad NS, Abdullah J, Al-Ansari N. Minimizing the Impacts of Desertification in an Arid Region: A Case Study of the West Desert of Iraq. Adv Civ Eng. 2021;2021.

11] Eryiğit M, Sulaiman SO. Specifying optimum water resources based on cost-benefit relationship for settlements by artificial immune systems: Case study of Rutba City, Iraq. Water Supply. 2022 Jun;22(6):5873–81.

12] Allawi MF, Hussain IR, Salman MI, El-Shafie A. Monthly inflow forecasting utilizing advanced artificial intelligence methods: a case study of Haditha Dam in Iraq. Stoch Environ Res Risk Assess 2021. 2021 Jun 24;1–20.

13] Abaza O. Effect of Wind Speed and Air Temperature on the Durability of PCC Surfaces. An-Najah Univ J Res - A (Natural Sci. 2006;20(1).

14] Abdulhameed IM, Sulaiman SO, Najm ABA. Reuse Wastewater by Using Water Evaluation and Planning (WEAP) (Ramadi City–Case Study). IOP Conf Ser Earth Environ Sci. 2021 Jun;779(1):12104.

15] Aude SA, Mahmood NS, Sulaiman SO, Abdullah HH, Ansari N Al. Slope Stability and Soil Liquefaction Analysis of Earth Dams with A Proposed Method of Geotextile Reinforcement. Int J GEOMATE. 2022 Jun;22(94):102–12.

16] Sulaiman SO, Abdullah HH, Al-Ansari N, Laue J, Yaseen ZM. Simulation Model for Optimal Operation of Dokan Dam Reservoir Northern of Iraq. Int J Des Nat Ecodynamics. 2021 Jun;16(3):301–6.

17] Allawi MF, Othman FB, Afan HA, Ahmed AN, Hossain MS, Fai CM, et al. Reservoir evaporation prediction modeling based on artificial intelligence methods. Water (Switzerland). 2019;

18] Samara M. Effect of Feeding Natural Zeolite on Performance of Laying Hens Drinking Saline Water. An-Najah Univ J Res - A (Natural Sci. 2003;17(2).

19] Ali Ghorbani M, Kazempour R, Chau K-W, Shamshirband S, Taherei Ghazvinei P. Forecasting pan evaporation with an integrated artificial neural network quantum-behaved particle swarm optimization model: a case study in Talesh, Northern Iran. Eng Appl Comput Fluid Mech. 2018 Jan;12(1):724–37.

20] Al Sudani ZA, Salem GSA. Evaporation Rate Prediction Using Advanced Machine Learning Models: A Comparative Study. Rathnayake U, editor. Adv Meteorol. 2022 Feb;2022:1–13.

21] Mhmood HH, Yilmaz M, Sulaiman SO. Simulation of the flood wave caused by hypothetical failure of the Haditha Dam. J Appl Water Eng Res. 2022 Mar;1–11.

22] Sulaiman SO, Al-Ansari N, Shahadha A, Ismaeel R, Mohammad S. Evaluation of sediment transport empirical equations: case study of the Euphrates River West Iraq. Arab J Geosci. 2021;14(10).

23] Mustafa AS, Sulaiman SO, Al_Alwani KM. Application of HEC-RAS Model to Predict Sediment Transport for Euphrates River from Haditha to Heet 2016. J Eng Sci. 2017;20(3):570–7.

24] Mustafa AS, Sulaiman SO, Hussein OM. Application of SWAT Model for Sediment Loads from Valleys Transmitted to Haditha Reservoir. J Eng. 2016;22(1):184–97.

25] Sulaiman SO, Mahmood NS, Kamel AH, Al-Ansari N. The Evaluation of the SWAT Model Performance to Predict the Runoff Values in the Iraqi Western Desert. Environ Ecol Res. 2021 Dec;9(6):330–9.

26] Allawi MF, Jaafar O, Ehteram M, Mohamad Hamzah F, El-Shafie A. Synchronizing Artificial Intelligence Models for Operating the Dam and Reservoir System. Water Resour Manag. 2018 May 3;1–17.

27] Allawi MF, El-Shafie A. Utilizing RBF-NN and ANFIS Methods for Multi-Lead ahead Prediction Model of Evaporation from Reservoir. Water Resour Manag. 2016 Oct 28;30(13):4773–88.

28] Souza PR, Dotto GL, Salau NPG. Artificial neural network (ANN) and adaptive neuro-fuzzy interference system (ANFIS) modelling for nickel adsorption onto agro-wastes and commercial activated carbon. J Environ Chem Eng. 2018 Dec 1;6(6):7152–60.

29] Bozorg-Haddad O, Zarezadeh-Mehrizi M, Abdi-Dehkordi M, Loáiciga HA, Mariño MA. A self-tuning ANN model for simulation and forecasting of surface flows. Water Resour Manag. 2016 Jul 19;30(9):2907–29.

30] Allawi MF, Aidan IA, El-Shafie A. Enhancing the performance of data-driven models for monthly reservoir evaporation prediction. Environ Sci Pollut Res [Internet]. 2020 Feb 1 [cited 2021 Feb 9];28(7):8281–95. Available from: https://link.springer.com/article/10.1007/s11356-020-11062-x

31] Osman A, Afan HA, Allawi MF, Jaafar O, Noureldin A, Hamzah FM, et al. Adaptive Fast Orthogonal Search (FOS) algorithm for forecasting streamflow. J Hydrol. 2020 Jul 1;586:124896.

32] Yafouz A, AlDahoul N, Birima AH, Ahmed AN, Sherif M, Sefelnasr A, et al. Comprehensive comparison of various machine learning algorithms for short-term ozone concentration prediction. Alexandria Eng J. 2022;61(6).

33] Kakaei Lafdani E, Moghaddam Nia A, Ahmadi A. Daily suspended sediment load prediction using artificial neural networks and support vector machines. J Hydrol. 2013;478.

34] Arslan CA. Artificial Neural Network Models Investigation for Euphrates River Forecasting & Back Casting. J Asian Sci Res. 2013;3(11):1090–104.

35] Vapnik VN, N. V. The nature of statistical learning theory. Springer; 1995. 188 p.

36] Moazenzadeh R, Mohammadi B, Shamshirband S, Chau KW. Coupling a firefly algorithm with support vector regression to predict evaporation in northern iran. Eng Appl Comput Fluid Mech. 2018;12(1).

69 | 70

An - Najah Univ. J. Res. (N. Sc.) Vol. 40 (1), 2026

Published: An-Najah National University, Nablus, Palestine

37] Aghelpour P, Mohammadi B, Biazar SM. Long-term monthly average temperature forecasting in some climate types of Iran, using the models SARIMA, SVR, and SVR-FA. Theor Appl Climatol. 2019;138(3–4).

38] Vapnik V, Golowich SE, Smola A. Support vector method for function approximation, regression estimation, and signal processing. In: Advances in Neural Information Processing Systems. 1997.

39] Mohammadi B, Mehdizadeh S. Modeling daily reference evapotranspiration via a novel approach based on support vector regression coupled with whale optimization algorithm. Agric Water Manag. 2020;237.

Mohammed Falah Allawi, *et al*.