

Emotional ANN (EANN): A New Generation of Neural Networks for Hydrological Modeling in IoT



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1 Introduction

Referring to the water resources engineering literature, it is observed that artificial intelligence (AI) methods are applied as versatile decision support tools to solve wide range of associated problems. They were typically implemented to attain the cause-effect relationships between nonlinear hydro-environmental processes (i.e., system identification) and time series modeling hydro-meteorological variables that often cannot be modeled by classic statistical models such as autoregressive integrated moving average with exogenous input (ARIMAX). A few studies are also available using AI methods as system identifiers of hydrological processes (e.g., [3, 4, 10, 11, 36, 38, 57]).

Most of the hydrological processes are known as highly nonlinear process that cannot be expressed in simple or complex mathematical forms [48]. To address such difficulty, AI-based modeling can be more effective than the probabilistic or distributed (physically based) models mainly because of (i) complex underlying systems of the hydrological processes, (ii) unknown factors/parameters involved in the processes, (iii) and spatiotemporal variation of the processes and their forcing

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factors. Some of the AI methods applied in hydrological studies include (but not limited to) artificial neural networks (ANNs, e.g., [1, 34, 35]), fuzzy logic (FL, e.g., [36, 45]), support vector regression (SVR, e.g., [8, 12]), and genetic programming (GP, e.g., [11, 27]).

ANNs, known as the universal approximator, have been widely used for modeling nonlinear hydrological processes over the past decades [5]. In general, the advantages of ANN models in comparison with other statistical and conceptual methods can be categorized as [39]:

- Regarding to the black box feature of ANN models, the use of these models does not require prior knowledge of the process.
- Due to the application of a nonlinear filter, known as the activation function on neurons, ANN models can handle the nonlinear properties of the process.
- ANN models have the ability to apply multivariate inputs with different characteristics.

The ability of ANN for linking input and output variables in complex hydrological systems without the need of prior knowledge about the nature of the process has led to a huge leap in the use of ANN models in hydrological simulations [2, 5, 13, 14, 22, 23, 32, 42].

In spite of popularity and capability of nonlinear modeling, ANNs suffer from some deficiencies when the interested hydrological process includes inadequate observed samples or the associated time series comprises high rate of non-stationary and seasonal variations [39]. To achieve reliable models and increase the accuracy of results, a number of data preprocessing approaches such as wavelet transform, season algorithm, singular spectrum analysis, and others have been developed and used in the hydrological modeling issues [8, 12, 39, 49]. The effectiveness of wavelet-based de-noising and multi-resolution analysis in optimizing AI models has been recently introduced and widely employed by the hydrologists to simulate different components of the hydrologic cycle such as rainfall-runoff, river flow, groundwater, precipitation, and sedimentation [41]. For example, Kisi and Cimen [26] examined the efficiency of wavelet-SVR to one-day-ahead rainfall predicting in Turkey and demonstrated that the hybrid model can increase forecasting precision and performs superior than the stand-alone SVR and ANN models. Wavelet-based data preprocessing approach has also been employed to extract the seasonal features of the hydrological processes by decomposing the main time series into multi-scale sub-series, each representing a specific seasonal scale [3, 28]. Such studies showed that the data preprocessing by wavelet transform may improve the modeling efficiency over different time scales (both short and long terms). Corresponding improvement was found to be more sensible in large time scales such as seasonal or monthly, because in most of hydrological process, the seasonal (periodic) patterns in the large-scale time series are more dominant than that of the small-scale time series. In other words, the autoregressive property is more remarkable in small-scale hydrological time series (e.g., daily), whereas the seasonal specification is more highlighted in large-scale time series (e.g., monthly) (see [26, 49, 53]). However,

it should be noted that such wavelet-based data processing scheme should be conducted within an external unit apart from the ANN's framework.

2 Emotion in ANNs

Fellous is probably the first researcher who stressed on the need for emotions in AI systems describing that the emotions must be dynamically interacted with together [18]. Emotion tends to be used in medical terminology for what a person is feeling at a given moment. Examples for emotion include joy, sadness, anger, fear, disgust, surprise, pride, shame, regret, and elation. The first six emotions are typically considered as the basic emotions, and the last four are treated as elaborations or specializations of them [6]. More recent descriptions either emphasized the external stimuli that trigger emotion or the internal responses involved in the emotional state, when in fact emotion includes both of those things and much more [25]. Perlovsky [43] defines emotion as the exaggeratedly expressive communications related to feelings. Love, hate, courage, fear, joy, sadness, pleasure, and disgust can all be described in both mental and physical terms. Emotion is the realm where thought and physiology are inextricably entwined, and where the self is inseparable from individual perceptions of value and judgment toward others and ourselves [6]. Emotions are sometimes considered as the antithesis of reason. A distinctive and challenging fact about human beings is a potential for both opposition and entanglement between will, emotion, and reason [25]. According to Khashman [25] researchers and scientists studied the role of emotions in artificial intelligence (AI) from a variety of viewpoints: to develop agents and robots that interact more gracefully with humans, to develop systems that use the analog of emotions to aid their own reasoning, or to create agents or robots that more closely model human emotional interactions and learning [29]. Although computers do not have physiologies like humans, information signals and regulatory signals travel within them. According to Picard [44], "There will be functions in an intelligent complex adaptive system, that have to respond to unpredictable, complex information that play the role that emotions play in people. Therefore, for computers to respond to complex affective signals in a real-time way, they will need something like the systems we have, which we call emotions." Such computers will have the same emotional functionality, but not the same emotional mechanisms as human emotions [25, 44].

Recent studies have shown that scientists attempt to integrate the artificial emotion into the ANN in order to solve complex engineering problems via emotional ANN (EANN) models. From the biological standpoint, the mood and emotion of animal due to the activity of hormone glands can affect neurophysiological response of the animal, sometimes by providing different actions for a similar task at different moods [37]. Similarly for an EANN, there will be a feedback loop between the hormonal and neural systems; each is influenced by the other which in turn, the learning ability of the network is relatively enhanced. Over the past decades, a few

kinds of EANNs have been developed and suggested. They have their own merits and features. For instance, Moren [33] proposed brain emotional learning (BEL)-based ANN inspired by some biological evidences that an emotional stimulus (such as fear) can be processed more quickly than a regular stimulus through available shorter routes in the emotional brain to act fast when the logical mind does not have enough time for processing an external situation (such as danger).

BEL networks have been efficiently used by Rahman et al. [46] to control interior permanent magnet synchronous motor drive. Khashman [25] considered emotional anxiety and confidence factors to modify back propagation (BP) learning algorithm of the multilayer perceptron (MLP) networks. The author developed emotional back propagation (EmBP) neural network in which anxiety factor was initialized according to the pattern of input samples, and then it was modified through the process of iteration. In a contrary manner, confidence factor was related to the anxiety factor as well as the network output at the first iteration. In the beginning of the network training, the anxiety and confidence levels were found high and low, respectively, but they received optimal values after a few iterations. Within the training procedure of EmBP, assigning a high value to the anxiety factor forces the network to have less attention to the derivative of the errors (error gradient) in the network's output. However the rise of confidence factor (due to stress reduction) dictates the network to pay more heed to the alteration of the weights in the previous training step. In fact, the procedure was similar to the magnification of inertia term to moderate the alteration degree from a pattern to the other as the learning iteration is progressed [37]. In the studies by Lotfi and Akbarzadeh [30, 31], BEL, EmBP, and some other emotional concepts were conjugated in order to develop some EANNs for clustering, pattern recognition, and predication tasks. From the mathematical perspective and apart from the biological concepts, with regard to the conventional ANN, an EANN includes a few extra parameters which are dynamically interacted with inputs, outputs, and statistical weights of the network [37]. Returning to the hydro-environmental studies, Nourani [37] demonstrated the first application of EANN in which the author proposed the revised BP algorithm to train MLP networks by incorporating emotional anxiety concept. The new algorithm was used to solve streamflow forecasting problem when there is lack of long-observed training time series. Details of this pioneer study are described in the following section after a brief overview on the structure of EANN and its difference with classic ANN.

3 Difference Between EANN and Simple ANN

Feed-forward neural networks (FFNN) are of the most popular ANN structures extensively applied to model different components of the hydrologic cycle [4, 13]. A FFNN with three layers of input, output, and hidden, trained by BP algorithm, has shown appropriate efficiency in nonlinear hydrological modeling tasks [5, 20].

Figure 1 shows a schematic of a three-layered FFNN, and the explicit equation to calculate the target of such FFNN can be written as [40]:

$$\hat{y}_j = f_j \left[\sum_{h=1}^m w_{jh} \times f_h \left(\sum_{i=1}^n w_{hi} x_i + w_{hb} \right) + w_{jb} \right] \tag{1}$$

where i, h, j, b , and w indicate, respectively, neurons of the input, hidden, and output layers and bias and applied weight (or bias) by the neuron; f_h and f_j show activation functions of hidden layer and output layer, respectively; x_i, n , and m represent, respectively, input value, input, and hidden neuron numbers; and y and \hat{y}_j denote the observed and calculated target values, respectively. In the calibration phase of the model, the values of hidden and output layers and corresponding weights could be varied and calibrated.

On the other hand, an EANN model is the improved version of a conventional ANN including an emotional system which emits artificial hormones to modulate the operation of each neuron, and in a feedback loop, the hormonal parameters are also adjusted by inputs and output of the neuron. The schematic of an inner neuron from FFNN and EANN has been depicted in Figs. 1 and 2, respectively.

By comparing these two neurons, it is deduced that in contrast to the FFNN in which the information flows only in the forward direction, a neuron of EANN can reversibly get and give information from inputs and outputs and also can provide hormones (e.g., H_a, H_b , and H_c). These hormones as dynamic coefficients are initialized according to the pattern of input (and target) samples and then are modified through the training iterations. Through training phase they can impact on all components of the neuron (i.e., weights, I ; net function, $F(I)$; and activation

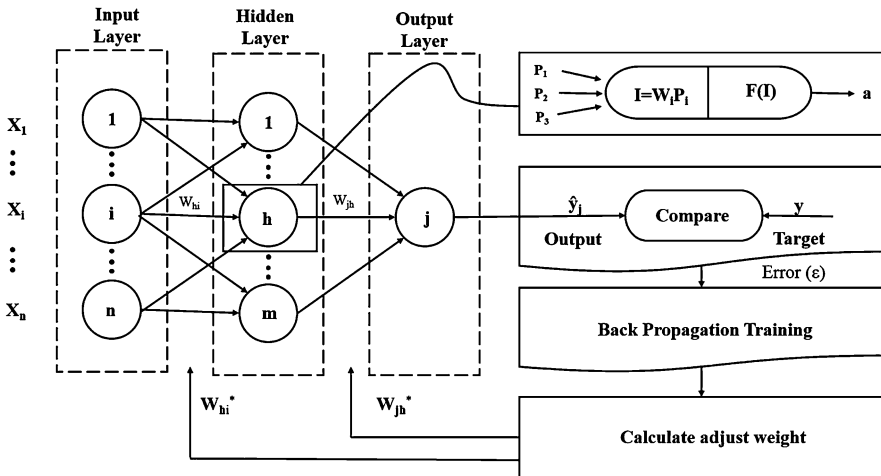
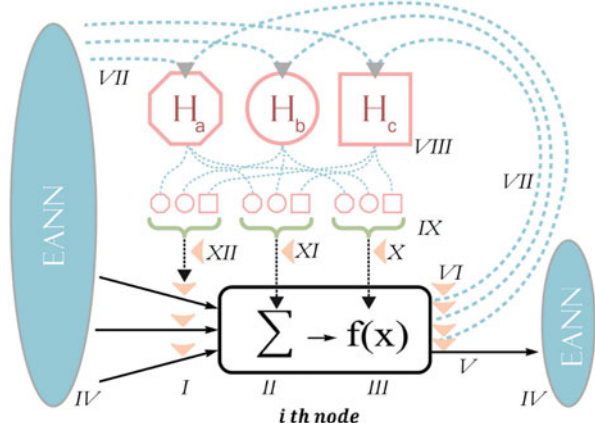


Fig. 1 Schematic of a three layer FFNN model

Fig. 2 A node of EANN and emotional unit [37]



function, III, in Fig. 2). In Fig. 2 the solid and dotted lines, respectively, show neural and hormonal routes of information. The output of i th neuron in an EANN with three hormonal glands of H_a , H_b , and H_c can be computed as [37]:

$$\begin{aligned}
 Y_i = & \underbrace{\left(\gamma_i + \sum_h \partial_{i,h} H_h \right)}_1 \times f \left(\sum_j \left[\underbrace{\left(\beta_i + \sum_h \chi_{i,h} H_h \right)}_2 \right. \right. \\
 & \times \underbrace{\left(\alpha_{i,j} + \sum_h \Phi_{i,j,k} H_h \right)}_3 X_{i,j} + \underbrace{\left(\mu_i + \sum_h \psi_{i,h} H_h \right)}_4 \left. \right) \quad (2)
 \end{aligned}$$

where the artificial hormones are computed as [37]:

$$H_h = \sum_i H_{i,h} \quad (h = a, b, c) \quad (3)$$

In Eq. 2, term (1) shows the imposed weight to the activation function (f). It includes the statistic (constant) neural weight of γ_i as well as dynamic hormonal weight of $\sum_h \partial_{i,h} H_h$. Term (2) stands for the imposed weight to the summation (net) function. Term (3) shows imposed weight to the $X_{i,j}$ (an input from j th node of former layer), and term (4) shows the bias of the summation function, including both neural and hormonal weights of μ_i and $\sum_h \psi_{i,h} H_h$, respectively.

The contribution of overall hormonal level of EANN (i.e., H_h) among the hormones should be controlled by $\partial_{i,h}$, $\chi_{i,h}$, $\Phi_{i,j,k}$ and $\psi_{i,h}$ factors which in turn, the i th node output (Y_i) will provide hormonal feedback of $H_{i,h}$ to the network as [37]:

$$H_{i,h} = glandity_{i,h} \times Y_i \quad (4)$$

where the *glandity* factor should be calibrated in the training phase of EANN to provide appropriate level of hormone to the glands. Different schemes may be used to initialize the hormonal values of H_h according to the input samples, e.g., mean of input vector of learning samples. Thereafter considering the network output (Y_i) and Eqs. 2 and 3, the hormonal values are updated through the learning process to get appropriate match between observed and computed time series of the target.

4 Application of EANN for Hydrological Modeling

As previously mentioned, Nourani [37] proposed EANN model to simulate rainfall-runoff process in two watersheds, namely, Lobbs Hole Creek in Australia and Moselle River in France. The study incorporated emotional anxiety into a FFBP structure and investigated its efficiency using different efficiency measures including root-mean-square error (RMSE), determination coefficient (DC), and determination coefficient for peak values (DC_{peak}). To assess the capability of modeling with limited observed time series, the author developed three different scenarios (i.e., strategy1, strategy2, and strategy3) in which the EANN was trained and validated by different size of training and validation samples.

The first case study was demonstrated using observe data from Lobbs Hole Creek, a sub-basin of Murrumbidgee in Australia, and the second was shown using data from Moselle River catchment, a sub-basin of river Rhine in France. The selected watersheds had two distinct climatic conditions showing quite different hydrological behavior and response to the rainfall. The Lobbs Hole Creek is upstream of the main river including mountainous and hilly regions and experiencing irregular precipitation pattern over a year with higher coefficient of variation (because of higher fluctuations of the observed data). However, Moselle watershed experiences a well-dominated seasonal weather with a larger area.

Different data division strategies were assumed to evaluate the overall performance and also efficiency of models to estimate peak discharge values. To this end, the first 75%, 50%, and 40% of data samples were considered as training data sets at the strategies1, strategies2, and strategies13, respectively. By decreasing the number of training samples, the generalization of the resultant network to predict the unseen data sets was found as a challenging task. Furthermore, due to importance of multi-step-ahead forecasts of the hydro-environmental processes, already pointed out by some studies (e.g., [7]), 2-, 4-, and 7-day-ahead predictions of the process were performed and compared as well as single-step-ahead forecasting scenario.

The rainfall value at time t (R_t) and current and antecedent runoff values (Q_t , Q_{t-1} , ..., Q_{t-p}) were imposed to the FFBP and EANN to predict runoff value one-d-ahead (Q_{t+1}) as the network output. Since the effect of antecedent rainfall values is implicitly considered by antecedent runoff values, only R_t was entered to the

networks as a potential input. Therefore the general mathematical formulation of the networks could be expressed as:

$$Q_{t+k} = f_n(Q_t, Q_{t-1}, Q_{t-2}, \dots, Q_{t-p}, R_t) \quad (5)$$

in which f_n denotes the FFBP or EANN and $k = 1$ for single-step-ahead forecasting and $k = 2, 4,$ and 7 for multi-step-ahead forecasts.

Selection of appropriate architecture of the network, i.e., appropriate lag No. of p (No. of neurons in input layer will be $p + 1$), hidden layer No., and optimal iteration epoch No., is a key issue in any training task which can prevent the network from the overtraining problem. Considering tangent sigmoid and pure line as activation functions of hidden and output layers, respectively, the FFBPs were trained using Levenberg-Marquardt scheme of BP algorithm [19], and the best structure and epoch number of each network were determined through trial-error procedure. Also for EANN model, hormones as dynamic coefficients are initialized according to the pattern of input (and target) samples and then are modified through the training iterations. Through training phase, they can impact on all components of the neuron (i.e., weights, net function, and activation function).

Overall comparison of the results denotes superiority of the EANN over FFBP in rainfall-runoff modeling of both watersheds. According to higher coefficient of variation (because of higher fluctuations of the observed data) for the observed rainfall and runoff time series of the Lobbs Hole Creek watershed due to the hydro-geomorphologic condition, this watershed has a wild hydro-climatic regime with regard to the Moselle watershed. Therefore for Lobbs Hole Creek watershed, the performance of both models is lower as compared to the Moselle watershed. However this difference between modeling performances of two watersheds using EANN is relatively lower than the FFBP modeling. The results are listed below:

1. Computed values of DC_{peak} (see Table 1) indicate the ability of EANN to catch the peak values of hydrographs better than FFBP in both watersheds. Since autoregressive models, according to the Markovian property of a process, consider states of the process at some previous time steps to predict the state of system at the next time step, they usually underestimate the peak values which occurred due to instantaneous imposition of an external force (intensive rainfall) to the system. In this condition, the system is experiencing an emotional situation which is different from normal conditions of the system. Therefore in the training phase, a hormone of the emotional unit of EANN acts as a dynamic weight to recurrently gives the feedback to other components of the network and regulates the model for the emotional situation. In the mathematical point of view, such dynamical weights are activated in extraordinary situations (e.g., intensive rainfall) and affect and magnify the weights of network, all done within the EANN framework without any need to external data processing approach.
2. The obtained results by data division strategies of 2 and 3 presented in Table 1 showed that EANN can be trained efficiently even in the presence of the sparse training data sets. In the Lobbs Hole River, the strategies 2 and 3 resulted in 1.4%

Table 1 Results of FFBP and EANN models for both watersheds via three data division strategies

| Watershed | Model | Data division strategy | Input ^a | No. hidden neuron | Epoch | DC | | RMSE (normalized) | | DC Peak | |
|------------------|-------|------------------------|----------------------------|-------------------|-------|-------|--------|-------------------|--------|---------|--------|
| | | | | | | Train | Verify | Train | Verify | Verify | Verify |
| Lobbs Hole Creek | FFBP | 75-25 | Q(t), Q(t-1), R(t) | 6 | 80 | 0.701 | 0.648 | 0.122 | 0.203 | 0.46 | 0.46 |
| | | 50-50 | | | 40 | 0.682 | 0.6 | 0.141 | 0.23 | 0.43 | 0.43 |
| | | 40-60 | | | 60 | 0.741 | 0.454 | 0.11 | 0.314 | 0.41 | 0.41 |
| Moselle | EANN | 75-25 | Q(t), Q(t-1), R(t) | 5 | 20 | 0.791 | 0.74 | 0.091 | 0.184 | 0.67 | 0.67 |
| | | 50-50 | | | 70 | 0.764 | 0.74 | 0.103 | 0.182 | 0.63 | 0.63 |
| | | 40-60 | | | 60 | 0.778 | 0.7 | 0.107 | 0.212 | 0.61 | 0.61 |
| Moselle | FFBP | 75-25 | Q(t), Q(t-1), Q(t-2), R(t) | 11 | 90 | 0.872 | 0.85 | 0.0037 | 0.0038 | 0.81 | 0.81 |
| | | 50-50 | | | 40 | 0.851 | 0.823 | 0.004 | 0.0041 | 0.79 | 0.79 |
| | | 40-60 | | | 70 | 0.89 | 0.8 | 0.0032 | 0.0042 | 0.79 | 0.79 |
| Moselle | EANN | 75-25 | Q(t), Q(t-1), Q(t-2), R(t) | 3 | 20 | 0.931 | 0.92 | 0.002 | 0.0024 | 0.9 | 0.9 |
| | | 50-50 | | | 10 | 0.93 | 0.91 | 0.0022 | 0.0024 | 0.82 | 0.82 |
| | | 40-60 | | | 50 | 0.952 | 0.901 | 0.0018 | 0.0026 | 0.84 | 0.84 |

^aOutput is $Q_{(t+1)}$

and 5.7% reduction in the performance of the EANN. Regarding the results of the same strategies in the Moselle Rivere, 1% and 2.2% performance reduction were obtained. Based on the FFBP modelling results, the performance reduction values were 8.5% and 32% for the Lobbs Hole River and 3.5% and 6.3% for the Moselle River. The FFBP even shows overtraining alert for Lobbs Hole Creek watershed in strategy 3. However during FFBP training, the network does not consider the difference between the system's situations, and therefore when the statistical weights of network start to be trained using the ordinary situation data of system (e.g., base flow data of river, observed at the outlet of watershed), sudden appearance of severe rainfall values in the input layer can alter the trained weights, and then again this confusion continues by returning the system to the ordinary state. This is the main reason that usually FFBP models need long data set to be trained appropriately. The aforementioned obtained results approve the efficiency of EANN with regard to conventional FFBP model when it is trained using relatively fewer data samples.

3. Although both FFBP and EANN models are interpolators and must experience critical and extreme conditions in the training phase, the results indicated that EANN is capable of producing more reliable predictions for the unseen data samples. In other words, EANN can generate better estimations using less observed extreme values.
4. Since the ability of a forecasting model to provide a useful horizon of forecasts is a crucial task in hydrological modeling, several lead times of runoff time series (i.e., 2, 4, and 7 d of lead time) were also considered as the networks' outputs to evaluate and compare the performance of FFBP and EANN models in multi-step-ahead runoff forecasts. The results of multi-step-ahead forecasting obtained via FFBP and EANN models with data division strategies of 1 and 3 have been presented in Table 2 for both watersheds. It should be noticed that the outputs of multi-step-ahead models were Q_{t+2} , Q_{t+4} and Q_{t+7} , and only the results of the best networks have been presented in the table. As the results show, by increasing the forecast horizon, the performance of both FFBP and EANN models is decreased mostly due to the magnification of the forecast noise at each forecasting time step. However again, it is clear that the performance of EANN in multi-step-ahead forecasting is relatively better than FFBP model about 10% in average. According to the presented results in Table 2, although by decreasing the number of training samples the training efficiency is increased, the verification performance for unseen data is remarkably decreased, and the difference between calibration and verification DCs is increased.

At the first glance, it brings to mind that EANN is structurally more complicated than FFBP, but actually the EANN with only a few hormonal parameters could lead to better outcomes without the need for any external data processing operation. Even though, in some cases the best structure of trained EANN contains fewer input neurons than FFBP which makes the EANN more comparable with the FFBP model from structural simplicity point of view (see Table 1).

Table 2 Results of multi-step ahead modeling via data division strategies 1 and 3

| Watershed | Model | Output | Input | DC strategy 1 | | DC strategy 3 | |
|------------------|-------|----------|----------------------------|---------------|--------|---------------|--------|
| | | | | Train | Verify | Train | Verify |
| Lobbs Hole Creek | FFBP | Q(t + 2) | Q(t), Q(t-1), R(t) | 0.7 | 0.617 | 0.72 | 0.608 |
| | | Q(t + 4) | | 0.678 | 0.611 | 0.705 | 0.603 |
| | | Q(t + 7) | | 0.65 | 0.554 | 0.672 | 0.525 |
| | EANN | Q(t + 2) | Q(t), Q(t-1), R(t) | 0.775 | 0.724 | 0.784 | 0.708 |
| | | Q(t + 4) | | 0.742 | 0.712 | 0.763 | 0.681 |
| | | Q(t + 7) | | 0.701 | 0.68 | 0.717 | 0.601 |
| | | | | | | | |
| Moselle | FFBP | Q(t + 2) | Q(t), Q(t-1), Q(t-2), R(t) | 0.828 | 0.802 | 0.835 | 0.778 |
| | | Q(t + 4) | | 0.77 | 0.751 | 0.791 | 0.7 |
| | | Q(t + 7) | | 0.715 | 0.702 | 0.723 | 0.645 |
| | EANN | Q(t + 2) | Q(t), Q(t-1), Q(t-2), R(t) | 0.918 | 0.9 | 0.921 | 0.845 |
| | | Q(t + 4) | | 0.87 | 0.849 | 0.88 | 0.822 |
| | | Q(t + 7) | | 0.821 | 0.788 | 0.823 | 0.74 |
| | | | | | | | |

Briefly, through the comparison of the proposed EANN and conventional FFBP models, two main objectives were targeted. Firstly to address the deficiency of network training in the lack of long training time series, three data division strategies with different sizes of training points were considered for the training purpose. The outcomes showed the ability of EANN to cope with the lack of long observed data used for network training. Secondly in the multi-step-ahead forecasting task, the obtained results indicated better performance of EANN than FFBP so that for 2, 4, and 7 d forecasts via EANN model, the reductions of forecasting performance of test data with regard to single-step-ahead forecasting were 2%, 4%, and 8.2% and 2.1%, 7.6%, and 14%, respectively, for the Lobbs Hole and Moselle watersheds. These reductions were 5%, 6.2%, and 15.4% and 5.9%, 11.8%, and 18% for the FFBP model. Overall, the comparison of experimental results shows the merits of EANN in the mentioned tasks of rainfall-runoff modeling with regard to the FFBP model. In contrast to the statistical weights of network, emotional parameters of an EANN dynamically get/give information from/to inputs and outputs of the network at each time step to distinguish the dry (e.g., rainless d) and wet (e.g., stormy d) situations of the system. Both watersheds studied in this research are almost free from remarkable anthropogenic influences. Clearly just like any other data-driven time series forecasting method, the performance of the EANN can be affected in presence of anthropogenic and/or climatic influences and shifts of the observed time series. In the presence of such shifts or strong non-stationary of time series, reliable data preprocessing approaches may be employed prior to performing the forecasts.

Such a reliable implementation of EANN in rainfall-runoff modeling offers its application to model other hydrological processes (e.g., sediment load, groundwater, precipitation, etc.) at different time scales (e.g., daily, monthly, and annual). According to the importance of accurate predictions of hydro-climatologic events (stressed by [55]), the proposed EANN model may be used to create ensemble extreme predictions at multiple lead times. The employed model in this study was a typical form of EANN among broad classes of EANNs trained by BP algorithm; future studies may focus on evaluating other types of EANNs and other training algorithms (e.g., metaheuristic approaches) in hydrological modeling.

More recently Sharghi et al. [51] implemented EANN to model Markovian and seasonal rainfall-runoff process in West Nishnabotna and Trinity Rivers in the USA (sub-basin in California, USA). The authors compared the prediction accuracy of EANN with those of FFNN and wavelet-ANN in terms of different statistical measures and demonstrated that for daily modeling, EANN outperforms the counterparts, especially for the Trinity River. By contrast, the results showed that wavelet-ANN is superior for monthly rainfall-runoff modeling.

5 The Internet of Things (IoT) in Hydro-Environmental Studies

The IoT is a concept in which the virtual world of information technology integrates seamlessly with the real world of things. Many of the initial developments toward the IoTs have focused on the combination of Auto-ID and networked infrastructures in business-to-business logistics and product life cycle applications [54]. Regarding the application of IoT in hydro-environmental studies, our review showed that only a few researches considered the IoT in their studies although web services as an online repository of historical and real-time hydrological data such as runoff, rainfall, streamflow, and groundwater level are available for more than a decade. However, it must be mentioned that geographical information systems (GIS), remote sensing (RS), and data storage systems were applied frequently in the hydro-environmental studies such as flood forecasting, flood hazard mapping, as well as climate change studies (e.g., [9, 50]).

One of the earlier studies in the application of the IoT in the wide range of hydro-environmental studies was carried out by Xiaoying and Huanyan [56]. The authors developed a wetland monitoring system on the basis of real-time, remote, and automatically monitored data in which wireless sensor networks and communication systems were used. The study showed that the new system may provide accurate sampling data that is important for conservation of wetlands. In the preliminary study of possible applications of IoT, Khan et al. [24] reported some applications in hydro-environment such as prediction of natural disasters and water scarcity detection at different places. The combination of sensors and their autonomous coordination and with the relevant modeling tools, one may predict the occurrence of natural disasters and take appropriate actions in advance. In addition, such network may be used to alert the users of a stream or water supply pipelines, for instance, when an upstream event such as the accidental release of sewage into the stream might have dangerous issues for downstream users. In a similar study, Dlodlo and Kalezhi [15] studied the potential applications of the IoT in environmental management in South Africa. The authors categorized IoT applications into four broad classes of environmental quality and protection management, oceans and coasts management, climate change adaptation, biodiversity, and conservation and environmental awareness. The results indicated that integrating IoT into environmental management in South Africa has likely more enhanced impact. Environmental IoT together with 1-year meteorological measurements was employed by Du et al. [16] to investigate the characterization of atmospheric visibility and its relationship with the variables comprising precipitation, relative humidity, wind speed, and wind direction at Xiamen, China. The study demonstrated that an optimal regression model can moderately simulate atmosphere visibility which provides new insights to its characteristics and forcing meteorological factors. Fang et al. [17] focused on the integration of RS data, GIS, and global positioning system with IoT and cloud services to develop snowmelt flood early-warning system for a case study catchment in Xinjiang, China. The results revealed that the process of snowmelt

flood simulation and early warning are greatly benefited by such an integrated system. Rathore et al. [47] proposed a hybrid IoT-based system for smart city development and urban planning using Big Data analytics that consists of various types of sensors deployment including smart home sensors, vehicular networking, weather and water sensors, smart parking sensors, surveillance objects, etc. The authors reported that weather and water information may increase the efficiency of the smart city by providing the associated data such as temperature, rain, humidity, pressure, wind speed and water levels at rivers, lakes, dams, and other reservoirs. All the information is gathered by placing the sensors in the reservoirs and other open places. Using rain-measuring sensors and snow-melting parameters, they were able to predict floods and water demands to the residents of the city. More recently, Shenan et al. [52] developed software and hardware in IoT environment to manage light, temperature, and soil water content in a greenhouse system. The authors used FL to monitor and manage the entire process in the system and showed that the single -code fuzzy controllers reside in single microcontroller chip may keep the practicality of the system. Most recently, González-Briones et al. [21] developed an innovative multicomponent system that uses information from wireless sensor networks for knowledge discovery (from weather and terrain conditions) and decision-making in both micro- and macroscale irrigation projects. The use of IoT was improved the efficiency of water use and optimized irrigation system in comparison to a traditional automatic systems.

With respect to the aforementioned review, the present study shows the lack of studies toward the integration of rapidly developing IoT technologies with hydrological modeling techniques, particularly artificial intelligence methods. To increase the efficiency of rainfall-runoff models for many applications in practice, one way may be the integration of IoT with the state-of-the-art EANN that has not been explored so far.

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