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Flow forecast by SWAT model and ANN in Pracana basin, Portugal

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ABSTRACT

This study provides a unique opportunity to analyze the issue of flow forecast based on the soil and water assessment tool (SWAT) and artificial neural network (ANN) models. In last two decades, the ANNs have been extensively applied to various water resources system problems. In this study, the ANNs were applied to the daily flow of the Pracana basin in Portugal. The comparison of ANN models and a process-based model SWAT was established based on their prediction accuracy. The ANN model was found to be more successful than the SWAT in relation to better forecast of peak flow. Nevertheless the SWAT model results revealed a better value of mean squared error. The results of this study, in general, showed that ANNs can be powerful tools in daily flow forecasts.

1. Introduction

Streamflow, which is known an integrated process of atmospheric and topographic processes, is of prime importance to water resources planning [19]. In a wide spectrum of engineering applications, it is critical to have reliable long-term or short-term flow forecasts. The lead time of day is often used for the flood warning systems. However, the tools for forecast are not free of error and usually expensive when they are set in a physical base. Stochastic and conceptual models have been always common in use [20]. It is possible to work on a sophisticated model considering both hydrologic and climatologic variables, such as precipitation, runoff, temperature and evaporation; however, it is economically preferable to use a model simulating flow variations on the basis of historical observations. For this reason, the historical observations will be used as input to artificial neural networks (ANNs) models to evaluate two different flow forecast models. Black-box models are not physically based models as they tackle with a system in the input–output manner. Unit hydrograph and autoregressive moving average models are the types of black-box models used in examining the rainfall–runoff relation [32]. Burlando et al. [9] applied ARMA models to hourly rainfall data for forecasting. They made comparison for the point and grid data (average rainfall over the basin) using autocovariance structure of certain low-order ARMA processes. They concluded that the event-based estimation approach yields better forecasts. The nonlinear approach of ANN can represent the rainfall–runoff precisely if the input variables are coherent with output of the system [3]. The ANNs have been extensively used in hydrology for simulating rainfall–runoff and other hydrological processes [27,23,26,25].

Maier and Dandy [27] presented an extensive literature review of the ANN model applications and outlined the steps that should be followed in the development of such models. They examined a total of 43 papers and 41 out of these papers included the use of feed forward networks. Majority of these neural networks were associated with the back propagation algorithm in training part. Kisi [23] compared two different feed forward neural network algorithms for the estimation of daily reference evapotranspiration from available climatic data. He showed that the Levenberg–Marquardt and conjugate gradient algorithms successfully employed in modeling evapotranspiration process. Lee et al. [26] carried out three tests to demonstrate the representative elementary watershed approach could be used for soil moisture predictions. Their approach was more successful than a distributed model called CATFLOW. Kisi [25] performed three different ANN techniques, namely, feed forward neural networks, generalized regression neural networks and radial basis in monthly flow forecasting. The generalized regression neural networks were found to be more successful in forecast of one-month advanced streamflow of the two stations from the Eastern Black Sea region of Turkey. Zealand

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et al. [41] carried out a short-term flow forecasting in a part of the Winnipeg River system in northwest Ontario (Canada) having a large catchment area of 20.000 km^2. They then compared the ANN methods to conventional approaches, indicating that the former methods resulted in more accurate forecasts. Moreover, a very good fit to observed flow value were achieved with respect to the root mean squared error (RMSE) in training and testing parts. Their results also showed that using specific network architecture for each forecast lead time was more appropriate in the multi-week forecasting. Chen and Adams [12] integrated the ANN with semi-distributed form of conceptual models. They achieved the runoff generation and water budget among different runoff components including surface runoff and groundwater by the spatially distributed model parameters and rainfall inputs for the each sub-catchment. Baratti et al. [8] used the ANN in the rainfall–runoff modeling process when different time step durations have to be considered in the reservoir management. They made numerical comparisons with observed data that are provided for runoff prediction in the Tirso basin at the S. Chiara section in Sardinia (Italy). Calvoa and Portelab [10] applied the ANN to forecast daily flow in the northern Portugal domain. They used Castanheiro and Cidadelhe stations in Douro watershed to compare the ANN and ARIMA models. Both models are defined as data-driven approaches which are based on historical records. Toth et al. [38] compared simple heuristic short term (1–6 h lead time) prediction results with the ANN model for the purpose of real time flood forecast. An excellent collection of studies concerning the ANN are collected in [6,7,16]. The SWAT model is a widely used process-based model that embeds most of the hydrologic processes by the principle of water balance. It can also be used in ungauged catchments [4]. Kaur et al. [21] used the SWAT model to predict runoff and sediment loss from Nagwan basin in India. They also developed a decision support tool to identify the priority areas for soil and water conservation measures.

Few studies made accuracy comparisons between process-based models and ANNs [37,30,36]. Sivakumar et al. [34] tested two nonlinear black-box approaches (phase-space reconstruction and artificial neural networks) for forecasting river flow dynamics. They used multi-layer perceptron nets and the daily river flow rates from the Nakhon Sawan station at the Chao Phraya River basin in Thailand to achieve 1-day and 7-day in advance forecasts.

Finally, two inspiring works (i.e. [36,30]) provided the performance assessment of the SWAT and ANN models in simulating hydrologic responses for different watersheds. Srivastava et al. [36] reported that winter months and the models' inaccurate base flow simulation both affected the SWAT model performance on the agricultural watershed located in the south eastern Pennsylvania. However, the ANN models in their current form are not spatially distributed watershed modeling systems. Morid et al. [30] examined the ANN and SWAT models together and found that the ANN models performed better than the snow module of SWAT during low flow periods, namely summer, autumn and winter. Conversely the SWAT revealed better results during high flow period (spring), in particular for peak flow. In a nutshell, the following question still deserves more scientific attentions particularly in the regions under flood risk that the flow changes abruptly: what is the best model to use in flow forecast?

The main objective of this study is to compare the artificial neural network model with a process-based semi-distributed model for the accuracy of flow forecasting scheme. This task is aimed to be accomplished in the Pracana basin, Portugal. The accuracy of ANN and SWAT models will be investigated in daily temporal resolution. The flow forecast models will be described in detail in the following section.

2. Description of study area and data

Portugal is located between latitudes 37°N and 42°N and longitudes of 9.5°W and 6.5°W. The country lies in the transition zone stretching from the subtropical anticyclones (the Azor anticyclone) to the area of sub poles depressions. The factors that most affect the climatic conditions in the region are the latitude, the orography and the influence of the Atlantic Ocean [39].

The Pracana is a sub-basin of Tejo region with an area of 1433 km^2. It is located in the central east part of Portugal, close to the border of Spain (Fig. 1).

The climate in this region is, in general, characterized by a temperate climate that features warm and dry summers and winters with precipitation. Microclimatology varies dramatically with respect to elevation. The precipitation fluctuates from 900 to 1400 mm per year. The average annual temperature is between 9 °C and 20 °C. The primary counties are Castelo Branco and Proenca-A-Nova, occupying 80% of the basin. Castelo Branco hosts most of the industrial facilities that creates a big load of nutrients. Estimated nitrogen is 213 ton/year and phosphorus is 63 ton/year. The contamination from agricultural sources is low as the permanent pastures and trees constitute 57% of the utilized agricultural area. Hence the region cannot be defined as vulnerable [39]. The dam of Pracana is located between the county of Macau and Vila Velha de Rodao. It was built for hydroelectric and water regulation that feeds the Ocreza River. The hydrology of the basin is the main driving force for the transport of nutrients, sediment, or other properties, however, the retention of nutrients is not the objective of this study. The main information required by the SWAT is DEM (digital elevation model), land use, soil types, and hydrological and meteorological data. The data used to create the digital terrain model of the Pracana were obtained from SRTM (Shuttle Radar Topography Mission, www2.jpl.nasa.gov). The DEM determines the direction of flow as well as the physical characteristics of the basin. The hydrographic network can be determined automatically from the digital terrain model or can be provided via a map. The land use and soil types are important data which will significantly influence the water balance. The soil texture is a basic property of soil physics. The textures were obtained from the soil map developed by The Commission of the European Communities, Directorate General for Agriculture, Coordination of Agricultural Research in 1985. According to this map; 6.1% of the area is fine texture, 1.2% is coarse texture and 93.7% is medium texture. For other soil characteristics and vegetation information, readers are referred to Venancio and Chambel [39]. The SWAT model simulations were performed over a period of 52-year, 1953–2001. But the compari-

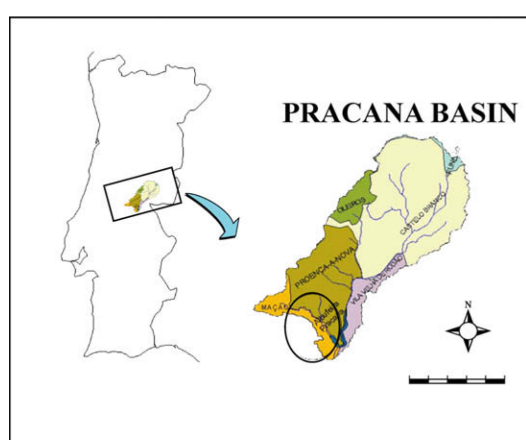

Fig. 1. The location of Pracana basin.

Table 1
Geographic information of the gauging station used in this study.

Parameter	Gauge identification PRACANA
Latitude (°N)	39.568
Longitude (°W)	7.816
Altitude (m)	140
River	Rio Ocreza
Precipitation station	Castelo Branco
Streamflow station	Almourao

son of the ANN–SWAT was done for the interval 1953–1965 years in which there is a continuous daily flow and precipitation data span. The updated data is available at Sistema Nacional de Informacao de Recursos Hidricos (SNIRH). Table 1 provides descriptive information of the gauging station used in this study.

3. Methodology

Increasing interests and appreciation of the practical manner and potential efficiency associated with data-driven technologies (i.e., ANN) and their flow forecasting applications stimulated us to investigate their effectiveness as a prediction tool using data in the Pracana basin. In this respect, the principal direction for this hydrological neural network study is to benchmark neural networks and a process-based model (SWAT) for flow forecast by considering two general cases: single input/single output and multiple input/single outputs. The SWAT model simulations for the Pracana basin were detailed in [39] and its outputs were included into the contents of this comparative study.

3.1. Artificial neural networks

The neural networks is a powerful soft computational technique for linear and nonlinear approximations in many disciplines, inspired by biological cerebral activity called neuroscience [17,28,11,22,23,1]. The idea of ANN is based on the estimation of an output by a function of the input as in the process of biological neuron cell in the brain. This cell network has the ability in which it can be trained and learned by previous examples (experience) so that it can recognize the patterns, such as sounds and faces. The estimation of the model parameters is called training in ANN terminology. The neural network has three main layers; input, hidden and output. Each layer may have multiple units interconnected completely with the adjacent layer and an adjusted weight is attached to each link in the system (Fig. 2). The nodes (dendrites) in input layer receive the data then the nodes in hidden layer (cell body) process and send them to output layer (axon). The human brain has more than a billion neurons with many working interconnections; hence, it is able to learn and then distinguish different human voices. It can also differentiate background noises such as car traffic, ocean wave and mechanical noise of refrigerators which are very difficult task for most of the supercomputers today [33]. Wu et al. [40] proposed a practical solution that the optimal number of units in the hidden layer could be estimated as two thirds of the sum of the number of input and output neurons. While fewer neurons could be insufficient to capture intricate relations between predictors and calculated output, the larger number of hidden nodes may perform better, but the training time must be increased and probably the accuracy will then be deficiently affected or the problem "over fitted network" will occur [33,40]. Over fitting is simply the inconsistent behavior of the network. While the network memorizes the data in training part, it fails to work with new input data in validation part.

The number of nodes in the first layer designated by M in Eq. (1) equals to the number of input parameters.When the input values pass to the next layer, they are multiplied by the weight of the connection. Each node j receives incoming signals from every node i in the previous layer. Incoming signal (x_i) is associated with a weight (w_{ji}). The effective signal (E_j) to node j is the weighted sum of all incoming signals (Eq. (1)). In the first phase of training, the weights (i.e., w_{ji}) are set to random values:

$$E_j = \sum_{i=1}^{M} x_i w_{ji}. \tag{1}$$

At the next phase, the effective signal (E_j) passes through a transfer function (i.e., Eq. (2)) to produce the outgoing signal (y_j) of node j. There are transfer functions different than sigmoidal-types (logistic and hyperbolic tangent function): hard limit transfer function (bounded to 0 or 1), linear, polynomial, rational function (ratios of polynomials) and Fourier series (sums of cosines). In the literature, the most commonly used transfer functions are sigmoidal-type transfer functions in the hidden layers and linear transfer functions ($y_j = E_j$) in the output layer due to its advantage in extrapolation beyond the range of the training data [17,27,41,10]:

$$y_j = f(E_j) = \frac{1}{1+\exp(-E_j)}. \tag{2}$$

The connection weights manifest the importance of input to the overall estimation process. The fitting error (Eq. (3)) between the desired and estimated output is used as feedback to enhance the performance of the network by altering the connection weights:

$$Error = \sum_{j=1}^{N} (y_j - d_j)^2, \tag{3}$$

where N = number of output nodes, y_j = calculated output, and d_j = desired data value. This process is repeated until establishing a successive layer [33]. Therefore, these kinds of networks are called *feed forward back propagation* (FF-BP) networks, which are the most popular supervised algorithm for training networks in prediction, pattern recognition, and nonlinear function fitting [13,41,40,25,2]. When using a FF-BP network, the sigmoid activation function is often preferred [34,24,17]. Training (calibrating) is a crucial process, in which the network is tested by a set of data pairs (input–output) and changing the initial conditions in each iteration step to achieve an accurate forecasting. Minimization is performed by calculating the gradient for each node at the output layer

$$\delta_k = d\sigma_k \cdot (y_k - d_k), \tag{4}$$

$d\sigma_k$ = the derivative of the sigmoid function applied at y_k which is defined for each kth output node. For hidden layer (one layer back), the gradient function becomes

$$\delta_j = d\sigma_j \cdot \sum_{i=1}^{N} \delta_i w_{jk}, \tag{5}$$

where $d\sigma_j$ is the derivative of the sigmoid function and w_{jk} = weight value from hidden node j to output node k. When the input data are chosen, then the network runs; the weights for each connection are updated by the procedure in Eq. (6) until the error is minimized to a predefined error target or the desired number of training periods is reached:

$$\Delta w_{jk} = w_{jk} - \eta \delta_k y_j, \tag{6}$$

where the notation η is the learning rate of each layer back to the network. Each passes through the training data is called *epoch*. In the Matlab routines, the user can define the number of epochs prior to analysis and manually adjusts until the plausible performance is achieved in the trial and error period [13]. In this study, we used

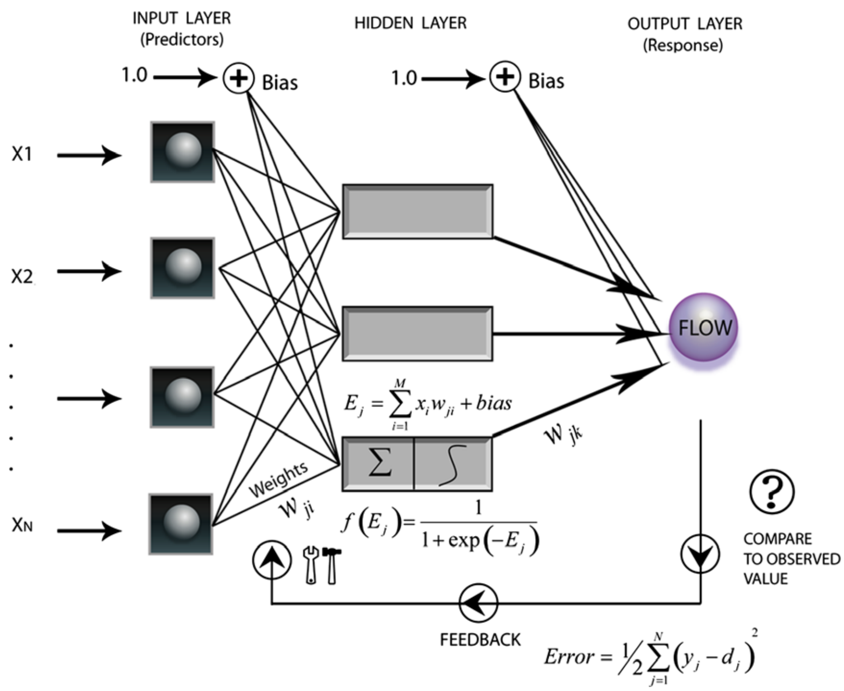

Fig. 2. Conceptual diagram of three-layer neural network model.

MSE (Eq. (7)), RMSE for the highly extreme flow and run time for the performance assessment. Only the run time depends on computer resources:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}(Q_{\mathrm{obs.}} - Q_{\mathrm{est.}})^2}{N}, \tag{7}$$

where $Q_{\mathrm{obs.}}$ is the observed flow, $Q_{\mathrm{est.}}$ is the estimated flow, and N is the total number of observations of the validation set. In ANN modeling, unlike the SWAT model, a prior knowledge of the underlying physical processes concerned is not required. Moreover, there is no need to satisfy preliminary conditions (i.e., normal distribution) as required in typical statistical models and optimization models. However, there are few disadvantages of ANNs, such as an exponential increase in training time with increased data size owing to the complex relationships used by the network to produce output [33].

3.2. A process-based model: SWAT

Process-based models attempt to formulate the entire physical process from precipitation to flow in the hydrologic cycle by balancing the amount of water. These models can provide accurate estimation of flow on daily, monthly and seasonal time scales. However, these models require a large number of parameters. For instance, the Water Balance (Watbal) model has 50 adjustable parameters as the simple conceptual rainfall–runoff (SCRR) model consists of seven fitting coefficients [37]. Hence, the success of the model prediction is dependent on the user's knowledge about the region and ability to manipulate the model components. The input data are usually temperature, humidity, soil moisture, soil texture, precipitation, evapotranspiration, lateral flow and percolation rate. The well-calibrated conceptual model presents a reasonable accuracy in forecasting flow. However, the number of inputs that are required to run the model and the difficulties which were discussed above are limiting the use of the physical based models to a very small number of river basins [37]. One of the most popular process-based models is SWAT. It is a mathematical model developed for the US Department of Agriculture, Agricultural Research Service. The SWAT is used to analyze the impacts of land use changes on the runoff and groundwater, production of sediment and water quality; for example, flow in the tributaries or agricultural issues (e.g., nutrient/pesticide loads) Eq. (8) [37]. The model simulates the water balance in a watershed and can be formulated as

$$SW_{\mathrm{final}} = SW_{\mathrm{init.}} + \sum_{i=1}^{t}(P_p(i) - Q_s(i) - E_e(i) - P_{\mathrm{per.}}(i) - Q_r(i)). \tag{8}$$

In this equation, SW_{final} = the final soil water content (mm), $SW_{\mathrm{init.}}$ = the soil water content available for plant uptake (initial water content – permanent wilting point water content), t = the time in days, $P_p(i)$ = the amount of precipitation on day i (mm), $Q_s(i)$ = the amount of surface runoff (mm), $E_e(i)$ = the amount of evapotranspiration (mm), $P_{\mathrm{per}}(i)$ = the amount of percolation (mm), and $Q_r(i)$ = the amount of return flow (mm). The SWAT model uses two phases of hydrologic cycle; one for the land processes and the other for the channel processes. The following phases of hydrologic cycle should be recalled in its realization. Precipitation may be intercepted and kept in the vegetation canopy or fall over the soil surface where it will infiltrate into the soil profile or flow overland as runoff. Runoff arrives relatively quickly to a stream channel and creates a short-term flow response. Infiltrated water may be kept in the soil and then evapotranspired to the atmosphere or it may slowly make its way to the stream water system via underground paths. The SWAT model has been extensively used and tested since 1993 by mainly hydrologists for soft engineering related issues [4,35,18,29,14,15]. The digital elevation model (DEM), a crucial tool for delineating the sub-watersheds using Arcview GIS software, is integrated to the SWAT model. The last versions of SWAT (e.g., SWAT 2000) enable users to input solar radiation, wind speed, relative humidity and evaporation data from more than one gauge station into the model simulation structure. Readers are referred to Tokar and Markus [37] and Arnold and Fohrer [5] for further information. Venancio and Chambel [39] presented adaptation of the parameters and all required procedures needed by the SWAT model in the Pracana basin as a case study.

4. Results and discussion

Following to Rumelhart et al. [31] Govindaraju and Ramachandra Rao [16] and ASCE [7], we selected the FF-BP ANN model to employ to daily flow records in the Pracana basin. Three layers including input, hidden and output nodes were selected as a basis for our network. The observed historical data (i.e., daily flow values) is introduced to the model as an input layer. We used one hidden layer and carefully tested many hidden node options, but showed here only the results of 6, 22 and 28 node options in Table 2. The number of units in the output layer is the number of values to be estimated. In our flow forecast network, we have only one output node for the flow which will be predicted (see output column in Table 2). We used a network training function that updates weight and bias values according to gradient descent with adaptive learning rate. Moreover, the weights were adjusted by nonlinear sigmoid function (Eq. (2)) for the hidden layer besides linear function utilized for the output layer. We tried various scenarios for the model parameters such as transfer function and the number of epochs to achieve a better performance; thus, several numerical experiments were conducted to the model architecture. Selected model structures and results were given in Tables 2 and 3.

In the first stage the following model was investigated for the flow simulation. Model 1: $S(t) = f(P(t-1), S(t-1))$, where P_{t-1} and S_{t-1} are the precipitation and flow recorded in the previous day, respectively. It should be noted that model 1 is labeled as Exp-I in Table 2 and evaluated by different criteria in Table 3. Unfortunately, this model (shown in Fig. 3) failed to generate acceptable estimations; hence, we decided to incorporate precipitation and flow as an individual input into the model formation. The modifications that we adapted for a better performance are as follows:

(i) The data were normalized within a range of 0.1–0.9 as we used log sigmoid transfer function (Logsig) which only takes on a value in the interval 0 to +1.
(ii) Since the number of neurons in the hidden layer plays an important role in the model performance, we tested 6–28 neurons. We noticed that there was no noticeable difference; hence, we preferred 6 neurons.
(iii) Epochs (iteration) size was adjusted to 100 as a result of the trail and errors application to the different higher magnitudes.

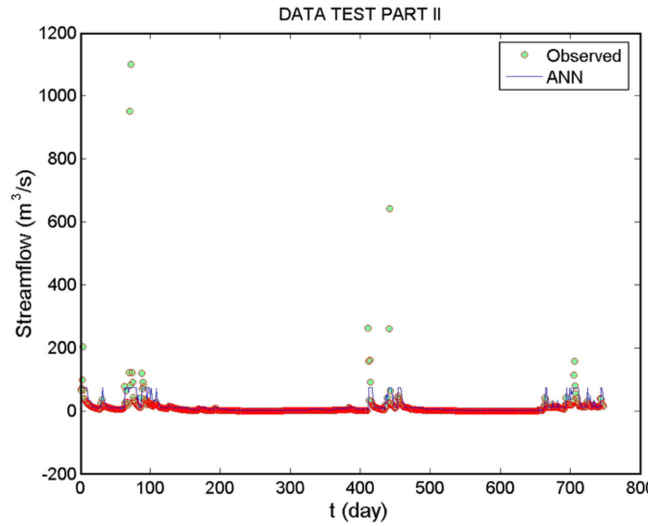

Fig. 3. Experiment I: One day in advance flow forecast for Pracana basin.

Although sometimes arbitrary changes or over fitting may occur in the large epoch sizes the performance function becomes more stable after 100 epochs. For example, in the case of the Exp-IV model, when the epoch size is increased to 300, it was spoiled and over fitted. An overall evaluation of the applied experiments leads us to stress that the Exp-IV is the superior structure in terms of estimating high flow values (Table 3).

There are various criteria to be used in the comparison business like MSE. In addition we brought forward practical and specific criteria such as "adequate/poor peak magnitude estimation" and "run time". As concerning a success criteria we set one percentile as threshold indicating extremely high flow occurrences. In our calcu-

Table 2
ANN model architecture and test scheme.

ID	Model	Input	Output	Training	Test	Network structure	Epochs
Exp-I	ANN-dS	$P^p_{t-1}; S_{t-1}$	S_t	4×10^3	748	2-28-1	1×10^3
Exp-II	ANN-dS	$P^p_t - 1$	S_t	4×10^3	748	1-22-1	1×10^3
Exp-III	ANN-dS	P^p_{t-1}	S_t	3×10^3	1748	1-22-1	4×10^3
Exp-IV	ANN-dS	S_{t-1}	S_t	4×10^3	748	1-6-1	100
Exp-V	ANN-dS	S_{t-1}; S_{t-2}	S_t	4×10^3	746	2-6-1	100
Exp-VI	ANN-dS	S_{t-1}; S_{t-2}; S_{t-3}	S_t	4×10^3	744	3-6-1	300
Exp-VII	ANN-dS	S_{t-1}; S_{t-2}; S_{t-3}, S_{t-4}	S_t	4×10^3	742	4-6-1	300

Notations: Exp = experiment, ANN = artificial neural network; S = streamflow; P = precipitation, d = daily mean and p = Pracana station.

Table 3
Model performances.

ID	MSE	Run time (s)	1% Peak magnitude RMSE	Overall evaluation
Exp-I	2576.4	58.187	669, 2952	NP, PPME
Exp-II	2978.3	45.641	705, 3706	NP, PPME
Exp-III	2997.4	133	983, 4421	NP, PPME
Exp-IV	2611.6	5.141	650, 5933	NP, APME
Exp-V	2837.4	4.609	491, 2456	NP, APME
Exp-VI	2861.7	7.203	556, 3769	NP, APME
Exp-VII	2728.5	7.25	515, 2181	NP, APME
SWAT model	2098.30	814.83	711, 5250	NP, PPME

Notations: Exp = experiment, MSE = mean squared error, NP = not precise, PPME = poor peak magnitude estimation and APME = adequate peak magnitude estimation.

lations this value correspondence to a specific value of 238 m^3/s. According to this threshold value we computed a root mean square error (RMSE) value in the test part for each model and showed the results in Table 3. Once again derivatives of Exp-IV model (i.e., Exp-V, Exp-VI and Exp-VII) appear to be superior to the other models.

We computed significant autocorrelation coefficients in our flow series from lag-1 to lag-4. Significant correlations were equal and higher than 0.6 and taken into consideration in the ANN models. This comparative analysis shows us that it is possible to construct a successful simple and faster model structure based on the ANN to forecast daily flow in the Pracana basin (Fig. 4).

The SWAT model results were used to make a comparison with those of the ANN model. The SWAT model appears to have the best performance against the other ANN models with respect to having the smallest MSE value (Table 3). On the other hand, Fig. 5 displays a striking feature that the SWAT model did not perform as good as the ANN (Exp-IV and it's derivatives) model in estimating peak flow values.

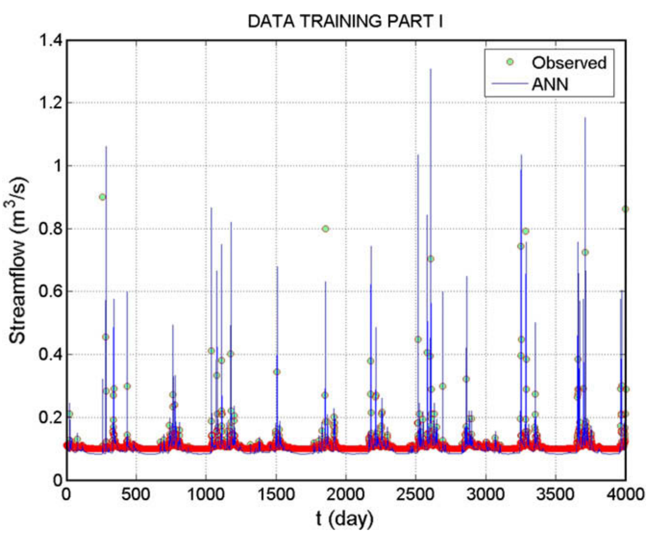

Fig. 4. Experiment IV: Lag-1 ANN model training part.

5. Conclusion

One of main focuses in this study was to develop the ANN models for flow forecasting and determine a more accurate architecture (i.e., number of hidden layers) in the design phase. Comparisons were made between the ANN model and one of the conventional forecasting approaches (e.g., SWAT). In order to find the best ANN architecture for extremely high flows, we tested seven major alternatives (Table 2) and decided to use the Exp-IV and its derivatives for the further steps.

We found that the process-based model SWAT simulations in the Pracana basin were not good enough in forecasting peak flow values. The peak flow inefficiency could be caused by the formulation used in the model. Data preprocessing might be necessary to get a better performance in SWAT as normalization of the data yielded a finest accuracy in the ANN for capturing peak magnitudes. The lag time of 1 day may not allow simulating phenomena of high-frequency occurrences. The deficiency of not capturing peak values becomes an important issue particularly in the studies of extreme hydrologic events (e.g., floods). However, according to the criteria of MSE, the SWAT model and first ANN model (i.e., Exp-I) which included precipitation and flow into the process, produced more accurate results than those of the used ANN model. One of known advantages of the SWAT model is to make reliable flow simulation when there are available climate and soil data at ungauged site [30]. The outcomes of this study were in a good agreement and relation with earlier studies conducted for, in general, the SWAT and ANN comparison in daily simulations, specifically peak flow prediction performance [36]. In Portugal, it is relatively easier to obtain flow and precipitation records through the governmental online resources compared to physical characteristics of river basins such as soil moisture, infiltration, soil classes, groundwater level and evaporation. Hence the black-box models might emerge as a faster tool to implement on flow forecasting business.

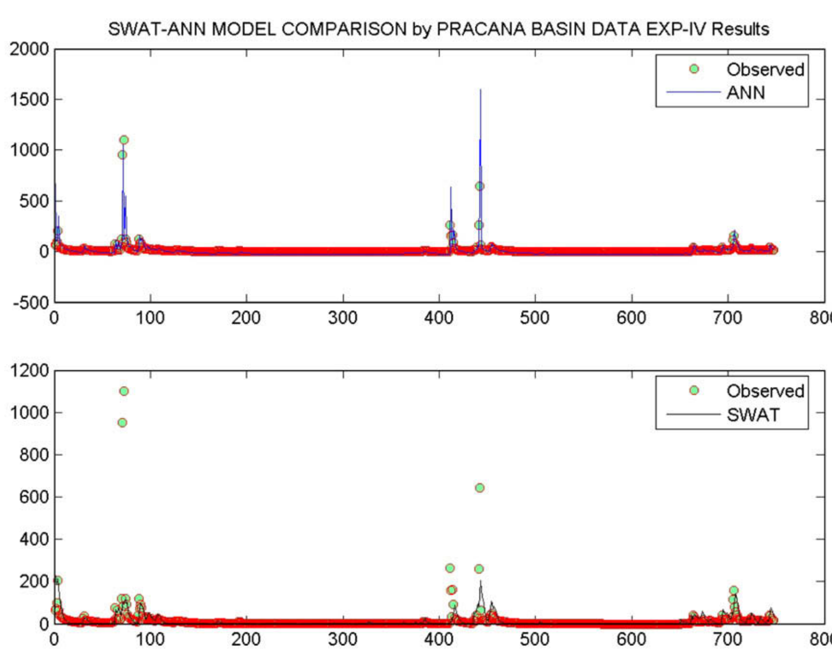

Fig. 5. ANN–SWAT comparison based on Exp-IV forecast.

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