Monthly runoff forecasting by means of artificial neural networks (ANNs)

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Abstract

Over the last decade or so, artificial neural networks (ANNs) have become one of the most promising tools for modelling hydrological processes such as rainfall runoff processes. However, the employment of a single model does not seem to be an appropriate approach for modelling such a complex, nonlinear, and discontinuous process that varies in space and time. For this reason, this study aims at decomposing the process into different clusters based on self-organizing map (SOM) ANN approach, and thereafter modelling different clusters into outputs using separate feed-forward multilayer perceptron (MLP) and supervised self-organizing map (SSOM) ANN models. Specifically, three different SOM models have been employed in order to cluster the input patterns into two, three, and four clusters respectively so that each cluster in each model corresponds to certain physics of the process under investigation and thereafter modelling of the input patterns in each cluster into corresponding outputs using feed-forward MLP and SSOM ANN models. The employed models were developed on two different watersheds, Iranian and Canadian. It was found that although the idea of decomposition based on SOM is highly persuasive, our results indicate that there is a need for more principled procedure in order to decompose the process. Moreover, according to the modelling results the SSOM can be considered as an alternative approach to the feed-forward MLP.

Keywords: Artificial neural networks; Forecasting; Monthly; Rainfall-runoff; Runoff; Self-organizing map

1. Introduction

Modelling of a transformation of rainfall to runoff (or in broader sense, precipitation to runoff) is a prime focus of hydrological modelling. In particular, runoff forecasting for a watershed subjected to rainfall is central for efficient planning and management of water resources such as flood control and management. Usually, the hydrologists have used a variety of models, including deterministic (physical) models, conceptual models and systems theoretic/black-box models, in order to model this transformation. The deterministic (physical) models describe the transformation using physical laws of mass and

energy transfer (Dawson & Wilby, 2001). Alternatively, in conceptual models instead of using physical laws of mass and energy transfer, a simplified, but a plausible or reliable conceptual representation of the underlying physics is adopted (Jain & Srinivasulu, 2006). Another alternative approach in modelling of the rainfall-runoff process is black-box models, built upon the input and output observations without detailed understanding of the physics involved in the process under investigation. Artificial neural networks (ANNs) can be considered as black-box models. The ANN is a nonlinear mathematical structure capable of identifying complex nonlinear relationships between input and output data of a system (Hsu et al., 1995). Due to the superiority of their performance compared to the alternative counterparts inmost of the cases, ANN models have been widely used by hydrologists

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particularly in modelling of the rainfall-runoff process (e.g. Hsu et al., 1995; Lorrai & Sechi, 1995; Minns & Hall, 1996; Dawson & Wilby, 1998; Tokar & Johnson, 1999; Rajurkar et al., 2002; Wilby et al., 2003; Giustolisi & Laucelli, 2005; Jain & Srinivasulu, 2006). A comprehensive review of ANNs along with their applications in hydrology can be found in Maier & Dandy (2000), ASCE Task Committee (2000a; b), and Dawson & Wilby (2001).

Most of the papers published on rainfall-runoff process modelling by means of ANN employ a single ANN model in order to model this complex, nonlinear and discontinuous process. However, in the following part of the introduction section we briefly review some papers that regard the issue of decomposition of hydrological processes, particularly rainfall-runoff process, into various clusters, corresponding to the various physics involved in a watershed runoff generation, hence employing a separate model for each cluster or segment. Furundzic (1998) used a self-organizing map (SOM) to decompose the rainfall-runoff process input-output space into three classes and thereafter employed a separate feed-forward multilayer perceptron (MLP) model for each class. Abrahart & See (2000) used SOM to cluster the whole modelling domain into distinct individual event types (64 clusters) and found encouraging results for the examined watersheds. Hsu *et al.* (2002) developed a Self-Organizing Linear Output mapping network (SOLO) for hydrologic modelling and analysis. The SOLO consists of three layers: an input layer, an input classification layer which uses SOM and a mapping layer that maps the inputs to the outputs using piecewise linear regressions. In a related study, Hong *et al.* (2005) developed and used a self-organizing nonlinear output (SONO) ANN architecture for estimation of rainfall based on cloud patch. The SOLO and SONO models are similar except in the mapping layer where mapping input to the corresponding output is achieved by nonlinear regression in the SONO model. Parasuraman *et al.* (2006) developed a spiking modular neural network (SMNN). A SMNN consists of three layers: an input layer, a spiking layer, and an associator neural networks layer. Classification of input space in the spiking layer is achieved by means of (1) competitive learning and (2) SOMs; and mapping of inputs to outputs is achieved by feed-forward MLP models in the associator neural networks layer. On the basis of their study, they concluded that the SMNNs performed better than a single feed-forward MLP for the examined cases. Jain & Srinivasulu

(2006) presented a procedure for decomposing a flow hydrograph into different segments based on physical concepts in a watershed and thereafter modelling different segments using feed-forward MLP ANN and conceptual techniques. In addition, they developed one-dimensional SOM models for decomposing the effective rainfall runoff data into different segments (three and four segments) in order to test the proposed procedure. They concluded that dividing the rainfall runoff data into different segments based on the physical concepts is better than relying on the SOMs for classification. More recently, Kalteh & Berndtsson (2007) used a SOM both for regionalization and estimation of monthly precipitation in northern Iran. The authors used unsupervised SOM as a classifier for regionalization and thereafter supervised SOM for estimation. It was found that the extreme values are estimated somewhat better after regionalization. In their study, they also compared the performance of SOM and feed-forward MLP models and found that without regionalization feed-forward MLP is generally better than SOM but when regionalization is included SOM performed better. According to the above studies it seems that clustering of the modelling domain leads to improved modelling performance.

The objectives of the study presented in this paper can be summarized as follows:
(a) Decomposition of the input patterns into different number of clusters based on SOM in order to test the effect of number of clusters in modelling performance.
(b) To apply feed-forward MLP and SOM models for building functional relationships between input and output data.
(c) To evaluate the performance of employed models based on the modelling performance criteria.
(d) And finally, to evaluate the suitability of SOM for decomposition.

2. Materials and methods

2.1. Study area and data

In this study, the monthly precipitation totals and average runoff database derived from a watershed located in a semiarid region in northern Iran was used in order to develop ANN models. This watershed consists of 5 stations including 13001 (54°4′E, 36°38′N), 13004 (53°40′E, 36°37′N), 13005 (53°54′E, 36°35′N), 13007 (54°44′E, 36°36′N), and 13013 (53°19′E, 36°38′N). The station 13013 (1962km^2) is

located in the downstream end of the watershed under study. Two of the five stations, 13005 and 13013, record both precipitation and runoff data hence we have used P and R in parenthesis in front of each station's code in order for indication of this. Moreover, two time variables represented by a sine and cosine curves respectively were used as extra input variables to the ANN models for representing seasonality in the watershed. To summarize, 9 variables including precipitation, runoff and time information which is representing of the seasonality in the watershed, were employed as input variables in order to forecast one-month ahead runoff at the downstream station 13013. The time series spans from 1969-70 to 1998-99 (i.e. 30-years). It must be mentioned that the utilized time series contained missing values which were filled-in by means of SOM. The selection of this method was based on a study by Kalteh & Hjorth (2007) where five different methods, SOM, feed-forward MLP, multivariate nearest neighbor (MNN), regularized expectation-maximization algorithm (REGEM), and multiple imputation (MI), were compared. Out of this available database, the data from 1969-70 to 1988-89, 240 patterns, is used for training and the remaining data from 1989-90 to 1998-99, 120 patterns, is used for validation.

We also used monthly runoff values derived from a watershed located in a temperate humid region in Canada in order to develop ANN models. Parasuraman *et al.* (2006) used this database in their study for runoff estimation and found good estimation results. Moreover, two time variables represented by a sinus and cosine curves respectively were used as extra input variables to the ANN models for representing seasonality in the watershed. This watershed consists of 2 stations; Umfreville (91°27′W, 49°52′N) and Sioux Lookout (91°56′W, 50°4′N). The Sioux Lookout (13900 km^2) is located in the downstream end of the watershed under study. The time series spans from 1951 to 1980 (i.e. 30-years). Out of this available database, the data from 1951 to 1970, 240 patterns, is used for training and the remaining data from 1971 to 1980, 120 patterns, is used for validation. To summarize, 4 variables including runoff and time information which is representing of the seasonality in the watershed, were employed as input variables in order to forecast one-month ahead runoff at the downstream Sioux Lookout.

In both watersheds, prior to the analysis, input and output data variables were standardized in the range of 0 and 1 using a simple linear transformation. The reason behind

the selection of the Iranian and Canadian watersheds is that the Iranian watershed is located in a semiarid region which generally demanding more data while the latter is located in a temperate humid region and its database was successfully employed for runoff estimation by Parasuraman *et al.* (2006) hence it can be used for comparison and evaluation.

2.2. Artificial neural networks

The ANN is a massively parallel-distributed information processing system resembling biological neural networks of the human brain (ASCE Task Committee, 2000a) and capable of solving large-scale complex problems such as pattern recognition, nonlinear modelling, classification, and control (ASCE Task Committee, 2000a; b). The most commonly used ANN is the feed-forward multilayer perceptron (MLP) as shown in Fig. 1. The figure shows a three layer feed-forward MLP that consists of an input layer, a hidden layer, and an output layer, in which each neuron is represented by a circle and each connection weight by a line so that each neuron in a layer is connected to all the neurons of the next layer while the neurons in one layer are not connected among themselves. Each individual neuron multiplies every input by its connection weight, sums the product, and then passes the sum through a nonlinear function called the activation function in order to compute its output. The number of input and output layer neurons depends upon the problem at hand so that the number of neurons in the input layer is equal to the number of input variables (denoted with m) and the number of neurons in the output layer is equal to the number of output variables while the number of neurons in the hidden layer is usually selected via a trial and error procedure. Determination of connection weights is called training process. In this study, a back-propagation algorithm was used for training the feed-forward MLPs. In a feed-forward MLP, patterns from the inputs presented to the neurons in an input layer are propagated through the network from the input layer to the output layer, i.e. in a forward direction and the outputs from the network are compared with the target values in order to compute the error. Thereafter the calculated error is back-propagated through the network and the connection weights are updated (ASCE Task Committee, 2000a). The training process is repeated until an acceptable convergence is achieved. After training has been accomplished, the network is able to compute

outputs given inputs that have not been seen by the network before.

The feed-forward MLP described above employs a supervised training algorithm which involves a target to oversee the training process.

The self-organizing map (SOM) employs unsupervised or self-organizing training method so that it does not involve a target to oversee the training   process.
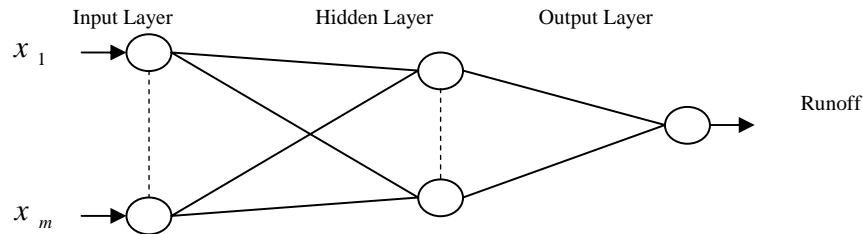

Fig. 1. Three-layer feed-forward multilayer perceptron (MLP)

The SOM, originally proposed by Kohonen (1982a; b), is typically used for clustering input patterns from high dimensional input space to a low dimensional lattice space, usually one or two dimensional, while preserving the topological structure of the data which means that input patterns that are similar or close together will fire the same or nearby neurons in the output layer. Since it was developed in the early 1980s, the SOM has been used in various hydrological problems. A SOM generally consists of two layers, an input layer and a Kohonen or output layer (Fig. 2). The input layer contains a neuron for each input variable in the data set. The Kohonen layer neurons are connected to every neuron in the input layer through adjustable weights or network parameters (w_{ij}). As stated previously, the SOM employs an unsupervised training process of connection weights. At the outset of training, the weights for each SOM connection weight are randomly initialized. Then, an input pattern $X(t)$ from the data set is introduced to the SOM so that each neuron of the Kohonen layer competes to respond to the given input pattern. The similarity of a given input pattern to each neuron is calculated based on Euclidean distances (d) as given in equation (1):

$$d_j = \left[\sum_{i=1}^{m} (x_i(t) - w_{ij})^2 \right]^{0.5}, \quad i = 1,...,m; \; j = 1,...,n. \quad (1)$$

where m denotes the number of input variables, n denotes the number of neurons in the Kohonen layer, and w_{ij} represents the connection weight linking i th input variable and j th neuron of Kohonen layer. The neuron with the lowest value of d_j is the best matching unit (BMU) for the given input pattern. Thereafter the weights of the BMU and its neighbors are updated to be even closer, whilst neurons in the Kohonen layer that fall outside of this neighborhood are left intact. After the weights have been updated,

the next input pattern from the data is presented to the network and the process continues till convergence. Once the training of SOM has been accompolished, each neuron in the Kohonen layer will be fired by similar input patterns i.e. clustering or grouping of input patterns. Thereafter separate models can be developed for each group of input patterns, corresponding to different physics of the process in the watershed. Although the SOM is usually used in applications for above objective i.e. clustering or grouping of similar input patterns, we also used SOM in a supervised manner or so-called supervised self-organizing map (SSOM) in order to build functional relationships between input and output data. However the SSOM is similar to SOM and the difference lies in a minor modification needed during training of the network so that finding the BMU is based on the input portion of data presented to the SOM while updating applies to all input-output data.

2.2.1. Model development

As stated in the introduction, the transformation of rainfall to runoff is a complex, dynamic, discontinuous, and nonlinear process. Consequently, the development of a single model in order to model this process by the modeller does not seem to be an appropriate approach such that the studies by Jain & Srinivasulu (2006) and Parasuraman *et al.* (2006) among others indicate that the modelling of the process through decomposition outperforms the case when only a single model is devoted to model the process. In this study, we use SOM in order to group the input data and thereafter we devote a separate feed-forward MLP or SSOM model to each group in order to map the inputs to the corresponding outputs.
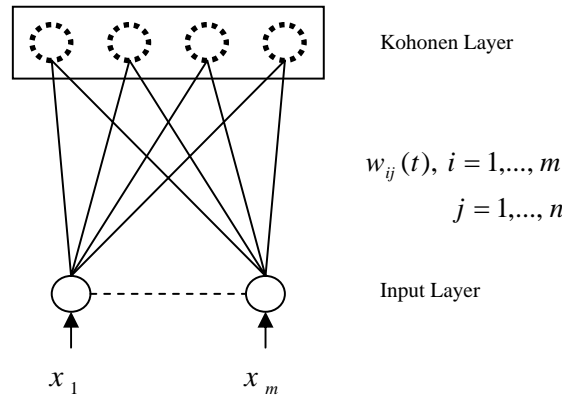
Fig. 2. A one-dimensional self-organizing map (SOM) with 4 neurons in the Kohonen layer

$$w_{ij}(t), \ i = 1,...,m$$
$$j = 1,...,n$$

2.2.1.1. The SOM models

In this study, a one-dimensional SOM model that employs an unsupervised training method similar to the one explained in the artificial neural networks section in order to decompose input patterns into different clusters, was used. Three different SOM models were developed for the watershed in northern Iran, each of which explores the possibility of decomposition of the input patterns into different number of clusters as follows : the first model, with two neurons in the Kohonen layer or SOM(2), was developed in order to study the possibility of decomposition of the input patterns s, the second model, with three neurons in the Kohonen layer or SOM(3), was developed in order to study the possibility of decomposition of the input patterns into three clusters, and finally the third model, with four neurons in the Kohonen layer or SOM(4), was developed in order to study the possibility of decomposition of the input patterns into four clusters. The plots of each SOM model are shown in Fig. 3(a) so that the horizontal axis in each subfigure represents the input variables and vertical axis in each subfigure represents the value in each dimension which is the mean value represented by the coefficient of the SOM neurons for each input variable.

The result of this clustering is that the SOM (2) clusters the training input patterns (240 patterns) s each consisting of 119 and 121 patterns, respectively. As seen from the figure, the first cluster corresponds to lower mean values compared to the second cluster hence the former will probably be associated with low runoff values while the latter with high runoff values. To examine, the mean and standard deviation of the corresponding output patterns for the first and second cluster were calculated and 4.41, 5.76; and 6.44, 3.62; were obtained, respectively. It is found that the first and second

cluster correspond to low and high runoff values, respectively. The SOM (3) clusters the training input patterns into three cluster each consisting of 99, 41, and 100 patterns, respectively. As seen from the figure, the first cluster corresponds to lower mean values and the third cluster to higher mean values while the second lies in between. To examine, the mean and standard deviation of the corresponding output patterns for the first, second, and third cluster were calculated and 2.90, 4.70; 7.74, 5.55; and 7.00, 3.54; were obtained, respectively. In terms of these statistics the first, second and third cluster correspond to low, high and medium runoff values, respectively. As seen these results are physically unusual as the third cluster with higher mean values exhibit medium runoff magnitude while the second cluster which lay between the other two clusters exhibit high runoff magnitude. Finally, the SOM (4) clusters the training input patterns into four cluster each consisting of 79, 41, 40, and 80 patterns, respectively. As seen from the figure, the first cluster corresponds to lower mean values and the fourth cluster corresponds to higher mean values while the second and third clusters lie in between. To examine, the mean and standard deviation of the corresponding output patterns for the first, second, third, and fourth cluster were calculated and 3.05, 5.20; 3.08, 2.33; 5.41, 2.74 and 9.02, 4.23; were obtained, respectively. The first, second, third and fourth cluster correspond to low, medium, medium and high runoff values, respectively which is physically plausible. It may be mentioned that the SOM clusters correspond to different runoff magnitudes based on mean. In order to make a comparison with the descriptive statistics (the mean and standard deviation) above, it must be mentioned that these statistics for the training output patterns when such a clustering or decomposition are not applied are 5.44, and 4.90, respectively.

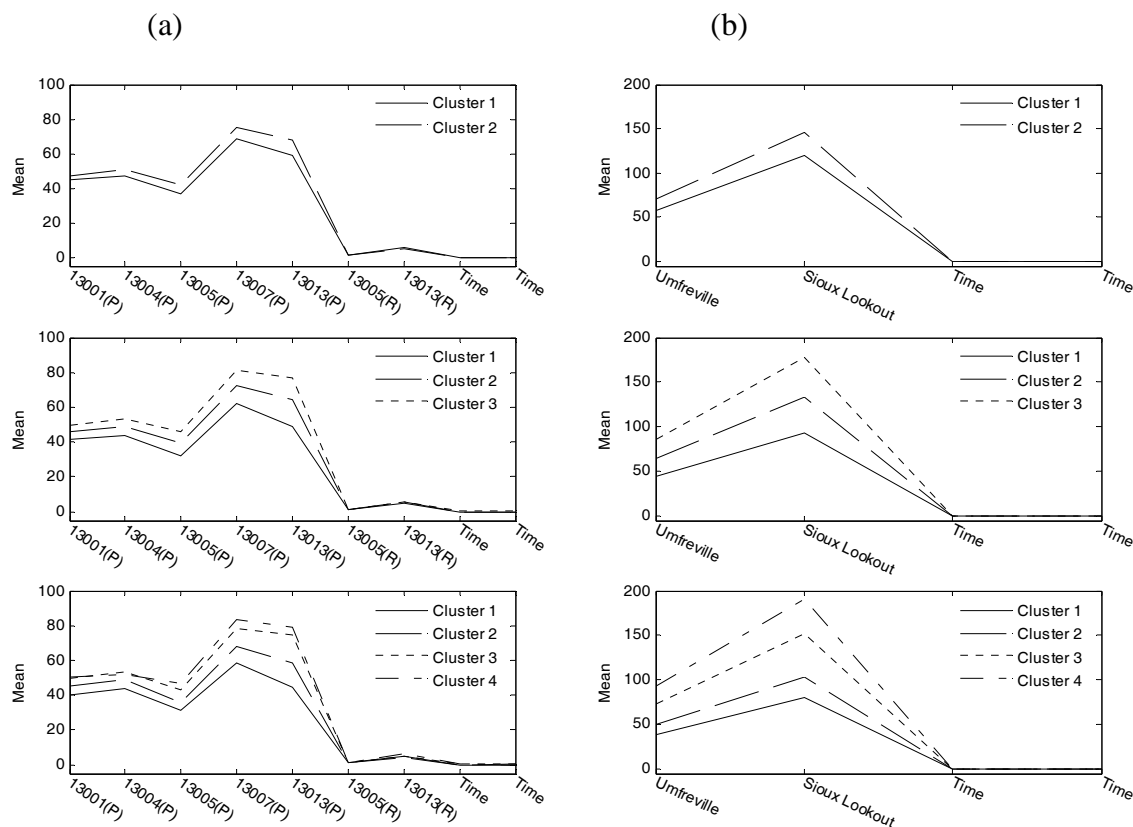(a)   (b)

fig. 3. The plots of 2, 3, and 4 clusters based on SOM or SOM (2), SOM (3), and SOM (4) in which the horizontal axis represent the input variables and vertical axis represent the value in each dimension which is the mean value represented by the coefficient of the SOM neurons for each input variable for: (a) Iranian watershed, and (b) Canadian watershed

We also developed the same number of SOM models for the Canadian watershed, in order to explore the possibility of decomposition of the input patterns into different number of clusters from two to four segments or clusters and compare the obtained results with the Iranian watershed. The plots of each SOM model are shown in Fig. 3(b) so that the horizontal axis in each subfigure represents the input variables and vertical axis in each subfigure represents the value in each dimension which is the mean value represented by the coefficient of the SOM neurons for each input variable. The result of this clustering can be summarized as follows: the SOM (2) clusters the training input patterns (240 patterns) each consisting of 119 and 121 patterns, respectively. As seen from the figure, the first cluster correspond to lower mean values compared to the second cluster hence the former will probably be associated with low runoff values while the latter with high runoff values. To check, the mean and standard deviation of the corresponding output patterns for the first and second cluster were calculated and 93.82, 55.40; and 177.10, 98.56; were obtained, respectively. It is seen that the first and second cluster correspond to low and high runoff values, respectively. The SOM (3) clusters the training input patterns into three clusters each

consisting of 112, 26, and 102 patterns, respectively. As seen from the figure, the first cluster corresponds to lower mean values and the third cluster to higher mean values while the second lies in between. To validate, the mean and standard deviation of the corresponding output patterns for the first, second, and third cluster were calculated and 91.11, 55.89; 117.82, 55.85; and 189.47, 99.17; were obtained, respectively. The first, second and third cluster correspond to low, medium and high runoff values, respectively which is physically plausible. Finally, the SOM (4) clusters the training input patterns into four clusters each consisting of 80, 39, 40, and 81 patterns, respectively. According to the figure, the first cluster corresponds to lower mean values and the fourth cluster corresponds to higher mean values while the second and third clusters lie in between. To check, the mean and standard deviation of the corresponding output patterns for the first, second, third, and fourth cluster were calculated and 96.98, 63.59; 87.32, 32.56; 116.17, 61.25; and 207.19, 99.84; were obtained, respectively. The first, second, third and fourth cluster correspond to medium, low, medium and high runoff values, respectively. The results for the third and fourth cluster are physically plausible but the remaining are not. It

may also be mentioned that the SOM clusters correspond to different runoff magnitudes based on mean. However, it must be mentioned that these statistics for the training output patterns when such a clustering or decomposition are not applied are 135.81, and 90.19, respectively. It is worthy to mention that although it was possible to characterize the SOM results somehow, according to the fact that the SOM clusters the input patterns based on their similarity it is not always easy to interpret the results due to the fact that ANNs including SOM are black-box models.

2.2.1.2. The MLP models

Once clustering of the input patterns is achieved using SOM, the next step is mapping of inputs in each cluster to the corresponding outputs, corresponding to different physics in the watershed, using MLP models. In other words, we employed a separate MLP model in order to map input patterns of each cluster to the corresponding outputs. All the MLP models employed in this study consisted of an input layer, a hidden layer, and an output layer (i.e. three layers). The number of neurons in the input and output layer are defined based on the number of input and output variables for the system under investigation, respectively. In this study, the utilized input and output variables for both watersheds under investigation were explained in the study area and data section. However, the number of neurons in the hidden layer was determined via trial and error procedure based on performance criteria discussed in the model performance section. By doing so, the selected number of neurons in the hidden layer for the Iranian watershed for various employed MLP models can be summarized as follows:

Single MLP model: containing 14 neurons.
Two MLP models (or "SOM (2)"): first and second cluster containing 8, and 9 neurons, respectively.
Three MLP models (or "SOM (3)"): first, second, and third cluster containing 4, 3, and 5 neurons, respectively.
Four MLP models (or "SOM (4)"): first, second, third, and fourth cluster containing 6, 3, 4, and 5 neurons, respectively.
The selected number of neurons in the hidden layer for the Canadian watershed for various employed MLP models can also be summarized as follows:
Single MLP model: containing 10 neurons.

Two MLP models (or "SOM (2)"): first and second cluster containing 4, and 9 neurons, respectively.
Three MLP models (or "SOM (3)"): first, second, and third cluster containing 6, 3, and 6 neurons, respectively.
Four MLP models (or "SOM (4)"): first, second, third, and fourth cluster containing 4, 3, 3, and 5 neurons, respectively.

2.2.1.3. The SSOM models

In the previous subsection we employed MLP models in order to map input patterns of each cluster, corresponding to different physics in the watershed, to the corresponding outputs. However, in this study we also employed SSOM models (described before) to carry out this objective and as well as comparison of its performance with MLP model. As stated previously, this network consisted of an input layer and an output layer so that the number of neurons in the input layer is defined based on input and output variables with regard to the study purpose while the number of neurons in the output layer is defined via trial and error procedure, which is in this study, was based on the performance criteria described in the model evaluation section. The selected number of neurons for the various SSOM models in the output layer for the Iranian watershed can be summarized as follows:
Single SSOM model: containing 14×14 neurons.
Two SSOM models (or "SOM (2)"): first and second cluster containing 9×9 and 8×8 neurons, respectively.
Three SSOM models (or "SOM (3)"): first, second, and third cluster containing 7×7, 5×5, and 7×7 neurons, respectively.
Four SSOM models (or "SOM (4)"): first, second, third, and fourth cluster containing 6×6, 4×4, 6×6, and 7×7 neurons, respectively.
The selected number of neurons in the output layer for the Canadian watershed for various employed SSOM models can also be summarized as follows:
Single SSOM model: containing 14×14 neurons.
Two SSOM models (or "SOM (2)"): first and second cluster containing 9×9 and 10×10 neurons, respectively.
Three SSOM models (or "SOM (3)"): first, second, and third cluster containing 10×10, 4×4, and 10×10 neurons, respectively.

Four SSOM models (or "SOM (4)"): first, second, third, and fourth cluster containing 9×9, 6×6, 5×5, and 9×9 neurons, respectively.

2.2.1.4. Model performance

In this study, the correlation coefficient (*r*), coefficient of determination (R^2), and root mean square error (RMSE) performance criteria were used to evaluate the employed ANN models. These criteria were calculated using equations (2), (3), and (4), respectively as follows:

$$r = \frac{\sum_{k=1}^{p}(Q(k)-\overline{Q})(\hat{Q}(k)-\tilde{Q})}{\sqrt{\sum_{k=1}^{p}(Q(k)-\overline{Q})^2 \sum_{k=1}^{p}(\hat{Q}(k)-\tilde{Q})^2}} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{k=1}^{p}(Q(k)-\hat{Q}(k))^2}{\sum_{k=1}^{p}(Q(k)-\overline{Q})^2} \quad (3)$$

$$RMSE = \left[\frac{\sum_{k=1}^{p}(Q(k)-\hat{Q}(k))^2}{p}\right]^{0.5} \quad (4)$$

Where $\hat{Q}(k)$ are the *P* forecasted runoff values, $Q(k)$ are the *P* observed runoff values, $\overline{Q}$ is the mean of the observed runoff values, and $\tilde{Q}$ is the mean of the forecasted runoff values.

3. Results and discussion

The results of the various MLP and SSOM models in terms of the correlation coefficient *(r)*, coefficient of determination (R^2), and root mean square error (*RMSE*) in forecasting monthly runoff for the Iranian and Canadian watersheds are presented in Tables 1 and 2, respectively. It can be noticed from the Table 1

that in the case of MLP models the best performance was achieved by the two and four cluster MLP models with the two cluster models doing somewhat better. It is worthy to mention that although the four cluster MLP models performed better during training compared to the two clusters MLP models, the four cluster MLP models were not able to generalize better during validation which may indicate the importance of principled procedures for determination of the number of neurons for decomposition. However, all of the modular MLP models outperform the single MLP model during validation which indicates that the process under investigation is not continuous hence the importance of decomposition of the process. In the case of SSOM models for the Iranian watershed, Table 1, the best performance was achieved by the four cluster SSOM models. It is worthy to mention that although the single SSOM model performed slightly better than the four cluster SSOM models during training the four cluster SSOM models outperformed it during validation hence again indicating the importance of decomposition of the process. As seen from the Table 1, the performance of the SSOM models during training was better than that for the MLP models both before decomposition and after decomposition while after decomposition during validation period the MLP models outperform the SSOM models. However, it can also be noticed from the Table 1 that the performance of single SSOM model is better than single MLP model for both training and validation period. Considering these results, in the selection of best model between the single MLP and single SSOM model the latter was selected while in terms of decomposition results the two cluster MLP models is considered to be the best model for forecasting monthly runoff for the Iranian watershed. The performance of these selected models during validation period is shown in Fig. 4(a) and (b), respectively.

Table 1. The performance of models in forecasting monthly runoff for the Iranian watershed

|	Training			Validation		
Model	r	R^2	RMSE	r	R^2	RMSE
MLP models						
Single MLP	0.652	0.426	3.706	0.383	0.132	6.469
Two MLPs	0.630	0.395	3.803	0.441	0.193	6.237
Three MLPs	0.642	0.412	3.748	0.401	0.160	6.362
Four MLPs	0.671	0.450	3.627	0.447	0.192	6.241
SSOM models						
Single SSOM	0.733	0.534	3.337	0.403	0.159	6.366
Two SSOMs	0.723	0.516	3.402	0.378	0.138	6.448
Three SSOMs	0.709	0.499	3.460	0.394	0.152	6.395
Four SSOMs	0.722	0.520	3.387	0.406	0.163	6.353
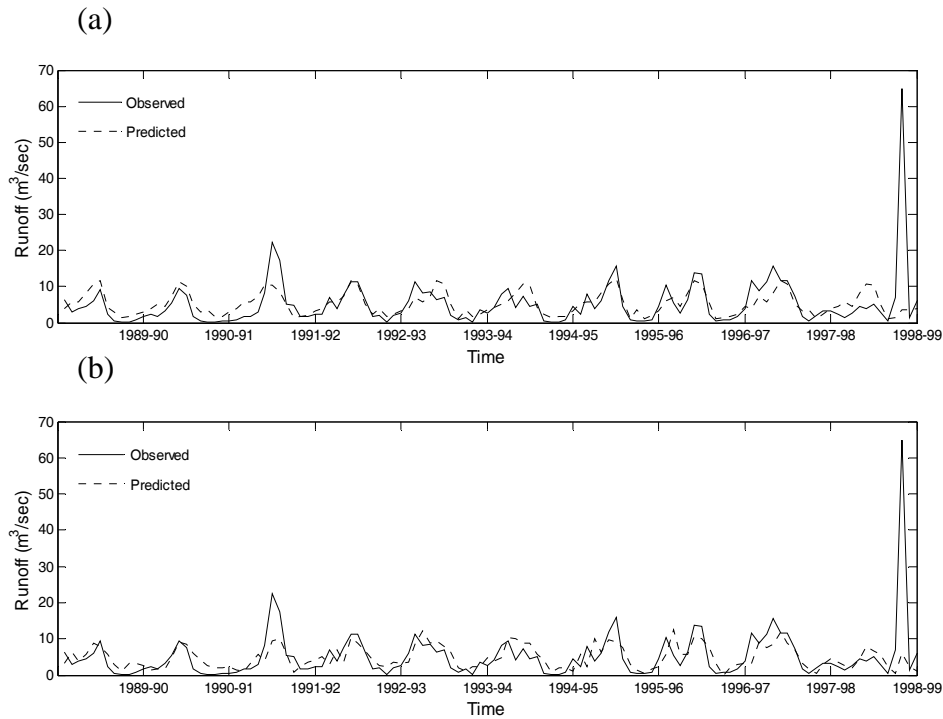
Fig. 4. Observed and predicted runoff for the Iranian watershed from: (a) single SSOM model, and (b) two MLP model

In the case of the Canadian watershed (Table 2) the models for forecasting monthly runoff performed differently compared to the Iranian watershed results. For instance, although the decomposition procedure improved the modelling performance during training for MLP models, it could not improve the generalization ability of the models as the performance of the single MLP model is slightly better than that of the two cluster MLP model and substantially better than the three and four cluster MLP models. However, in the case of the SSOM models, the decomposition procedure improved the performance of the models so that there are improvements in forecasting performance by using the two, three, and four cluster SSOM models compared to the single SSOM model. As seen from the Table 2, the performance of the SSOM models is mostly better than for MLP models after decomposition for both training and validation. However, the performance of the single MLP and single SSOM models is almost similar with a small advantage for the single MLP. By considering these results, the single MLP and four cluster SSOM models are considered to be the best models for forecasting monthly runoff in the Canadian watershed. The performance of these models during validation is shown in Fig. 5(a) and (b), respectively.

Table 2. The performance of models in forecasting monthly runoff for the Canadian watershed

	Training			Validation		
Model	r	R^2	RMSE	r	R^2	RMSE
MLP models						
Single MLP	0.850	0.718	47.773	0.800	0.615	47.658
Two MLPs	0.864	0.743	45.553	0.805	0.612	47.886
Three MLPs	0.867	0.752	44.776	0.797	0.583	49.639
Four MLPs	0.873	0.758	44.208	0.772	0.559	51.033
SSOM models						
Single SSOM	0.909	0.794	37.696	0.824	0.604	48.363
Two SSOMs	0.904	0.815	38.693	0.799	0.605	48.298
Three SSOMs	0.914	0.833	36.678	0.808	0.631	46.654
Four SSOMs	0.919	0.842	35.748	0.815	0.635	46.445

4. Conclusions

In this study, we have investigated whether the modelling performance concerning forecasting monthly runoff can be improved by means of modularization of ANN models, where the modularization or decomposition of the process under investigation is achieved by means of SOM.
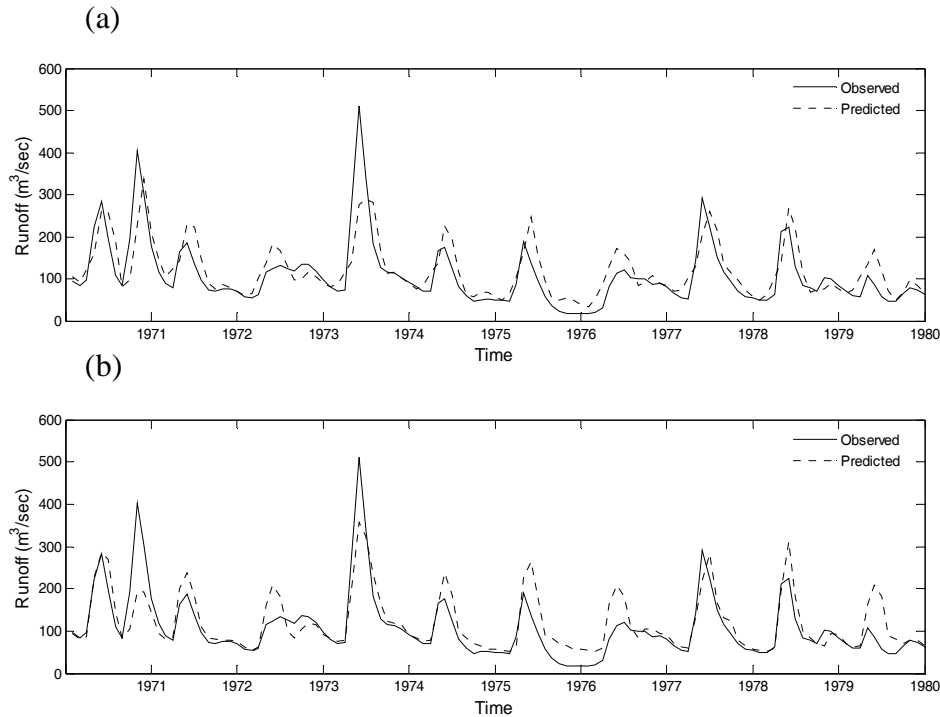
(a)

(b)

Fig. 5. Observed and predicted runoff for the Canadian watershed from: (a) single MLP model, and (b) four SSOM model

Where we found improvements, they were rather small. Thus, it is not possible to draw any general conclusions concerning the performance of models with one, two, three, or four modules, respectively. The idea that a modular model would be better at responding to the different physical processes at different stages of the hydrograph is highly persuasive. However, our results indicate that there is a need for a more informed and principled procedure for the modularization of the models, a conclusion that is also supported by the findings of Jain & Srinivasulu (2006). We also compared the performance of feed-forward MLP and SSOM models in mapping cluster data into corresponding outputs. Our results indicate that the SSOMs consistently perform better during training. However, during validation, there were very small differences in performance which may indicate the application of the SSOM model as an alternative to the well-known feed-forward MLP model. As expected, the forecasting performance was much worse for the Iranian watershed than for the Canadian. The Iranian watershed is located in a semiarid region, which in itself demands longer data series, and suffered from a significant amount of missing data. Furthermore, there was an extremely severe flooding event within the validation period. Obviously, there is a need for a principled pre-processing of the data to improve the reliability of the forecasting results for this watershed.

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