Research Article

Forecasting Different Types of Droughts Simultaneously Using Multivariate Standardized Precipitation Index (MSPI), MLP Neural Network, and Imperialistic Competitive Algorithm (ICA)

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Precipitation deficit causes meteorological drought, and its continuation appears as other different types of droughts including hydrological, agricultural, economic, and social droughts. Multivariate Standardized Precipitation Index (MSPI) can show the drought status from the perspective of different drought types simultaneously. Forecasting multivariate droughts can provide good information about the future status of a region and will be applicable for the planners of different water divisions. In this study, the MLP model and its hybrid form with the Imperialistic Competitive Algorithm (MLP-ICA) have been investigated for the first time in multivariate drought studies. For this purpose, two semi-arid stations of western Iran were selected, and their precipitation data were provided from the Iranian Meteorological Organization (IRIMO), during the period of 1988–2017. MSPI was calculated in 5-time windows of the multivariate drought, including MSPI_{3–6} (drought in perspectives of soil moisture and surface hydrology simultaneously), MSPI_{6–12} (hydrological and agricultural droughts simultaneously), MSPI_{3–12} (soil moisture, surface hydrology, and agricultural droughts simultaneously), MSPI_{12–24} (drought in perspectives of agriculture and groundwater simultaneously), and MSPI_{24–48} (socio-economical droughts). The results showed acceptable performances in forecasting multivariate droughts. In both stations, the larger time windows (MSPI_{12–24} and MSPI_{24–48}) had better predictions than the smaller ones (MSPI_{3–6}, MSPI_{6–12}, and MSPI_{3–12}). Generally, it can be reported that, by decreasing the size of the time window, the gradual changes of the index give way to sudden jumps. This causes weaker autocorrelation and consequently weaker predictions, e.g., forecasting droughts from the perspective of soil moisture and surface hydrology simultaneously (MSPI_{3–6}). The hybrid MLP-ICA shows stronger prediction results than the simple MLP model in all comparisons. The ICA optimizer could averagely improve MLP's accuracy by 28.5%, which is a significant improvement. According to the evaluations (RMSE = 0.20; MAE = 0.15; $R = 0.95$), the results are hopeful for simultaneous forecasting of different drought types and can be tested for other similar areas.

1. Introduction

Drought, one of the most complex environmental catastrophes, continuously has an effect on the rest of the world [1]. It occurs naturally in all climatic areas, such as pluvial and arid areas, and causes many economic, environmental, and social costs around the world [1–4]. In recent decades, drought has been one of the costliest natural disasters that has created major challenges in Iranian water resource management. The arid and semiarid climate of Iran has

made it highly vulnerable to droughts [5]. During 1998–2000, Iran experienced one of the worst and most damaging drought periods in the last 50 years [6]. During this 3-year period, water shortage in more than 270 cities fell down to below the critical point, and as a result, thousands of villages lost their drinking water, surface water flow decreased to 55%, and Iran's dams and tanks were forced to act with minimal capacity for water transfer because of low input flow and high temperature [6, 7]. So, during this period, the country faced different types of droughts, such as

meteorological, hydrological, agricultural, social, and economic droughts simultaneously.

Drought prediction is a major concern for water managers, farmers, and other final users because it limits their decisions. Since droughts have slowly begun, it is possible to present temporal forecasts in order to take measures and develop policies to reduce the effects of droughts [8–10]. A wide range of artificial intelligence (AI) models and modified standalone and hybrid versions have been used for the forecasting of different drought indices. The studies revealed the higher performance of AI models in forecasting drought indices [11–17]. In fact, the AI models can predict the drought events that do not have a good and straightforward mathematical solution and were proven to have the ability to capture the white noise, nonstationary, and nonlinearity in the time series [18]. Multilayer Perceptron (MLP) neural network is the most famous type of AIs which has been widely used in hydrological and meteorological modeling studies [19–30]. Malik and Kumar [31] used the MLP model for meteorological drought prediction based on Effective Drought Index (EDI) in the Uttarakhand state of India and reported the acceptable performance of this model. MLP is also used for predicting the Standardized Precipitation Index (SPI) in Iran as a meteorological drought indicator and was superior compared to the other models such as Adaptive Neuro-Fuzzy Inference System (ANFIS), Radial Basis Function Neural Network (RBFNN), and Support Vector Machine (SVM) [32]. In forecasting agricultural drought based on the Standardized Precipitation-Evapotranspiration Index (SPEI), the MLP model was reported as an acceptable predictor model in Pakistan [33]. This model has been well evaluated for predicting SPI as a meteorological drought index in Awash river basin in Ethiopia [34], Selangor river basin in Malaysia [35], and Santa Ysabel Creek and Leaf rivers in America [36]. The study of Borji et al. [37] based on the Streamflow Drought Index (SDI) confirms the ability of the MLP model for drought forecasting from the perspective of surface hydrology too.

In the abovementioned studies, the referred indices can monitor the different drought types separately, for example, SPI individually for meteorological droughts, SDI individually for hydrological droughts [38], and SPEI for agricultural droughts. Among the drought indices, SPI is a different index that can indicate different types of droughts in its different time windows [39]. For example, the 1-month SPI (SPI1) shows the meteorological drought condition. Also, 3-month, 6-month, 12-month, or 24-month SPI (SPI3, SPI6, SPI12, or SPI24) talk about droughts in perspectives of soil moisture, surface hydrology, agriculture, and groundwater, respectively [12, 40]. According to the literature, no model has been evaluated in forecasting different drought types simultaneously. Multivariate drought indices can theoretically monitor different types of droughts simultaneously. So, forecasting a multivariate drought index can theoretically present a perspective about the status of different drought types in the future. Multivariate Standardized Precipitation

Index (MSPI) is one of the newest introduced multivariate drought indices. This index was developed by Bazrafshan et al. [1] based on SPI by merging SPI's different time windows. Also, MSPI was superior in comparison with the Joint Deficit Index (JDI) [41] to monitor multivariate drought in all of the Iranian climates [6]. Up to now, MSPI was used in agricultural drought studies. Bateni et al. [42] used MSPI to develop an agrometeorological drought index. Aghelpour et al. [12] evaluated MSPI in monitoring and forecasting agricultural drought for Iranian climates and found the index acceptable for the issue.

According to the literature, no investigation was carried out on MSPI for different types of droughts simultaneously (multivariate drought forecasting). Due to MLP's high capability in drought forecasting and, generally, hydrological modeling studies, this model is used in the current study for forecasting MSPI for multivariate drought forecasting. Two semiarid climate stations located in western Iran have been selected for this issue. Also, in numerical modeling issues of hydrology, the optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Firefly Algorithm (FA) have been well used recently to optimize the prediction/estimation accuracies of the MLP model. The imperialistic Competitive Algorithm (ICA) is another powerful optimization algorithm developed by Atashpaz-Gargari and Lucas [43], which has been used less in hydrological modeling cases, especially in drought forecasting cases. Therefore, as another innovation in drought studies, in this study, the ICA is merged with MLP to improve its forecasting accuracy.

2. Materials and Methods

2.1. Study Area. According to the extended De-Martonne climatic classification, about 22.91% of the total area of Iran located in a semiarid climatic condition is equal to 377533.4 km² [44]. These semiarid regions receiving appropriate solar radiation are important areas for agricultural production, but they are highly dependent on available water and affected by incoming rainfall and consequent drought events, which directly and indirectly affect various aspects of human life. In fact, precipitation deficit and consequent drought events can be more effective in semiarid regions than humid areas. Therefore, the current study aims to investigate and predict the multivariate drought condition for two ground station about Iran's semiarid climate. Hamedan and Kermanshah are located in western Iran. Hamedan and Kermanshah having urban area of 19368 and 24998 square kilometers are elevated with 1820 meters and 1400 meters, respectively (Figure 1).

Calculating MSPI needs total monthly precipitation data. The precipitation data was provided from the Iranian Meteorological Organization (IRIMO) for these synoptic stations and were used for MSPI calculation. The stations' geographical coordinates and statistical characteristics of their monthly precipitation data are shown in Table 1.

FIGURE 1: The geographical location of Hamedan and Kermanshah provinces.

TABLE 1: Coordinates of the stations; descriptive statistics of the monthly precipitation time series; climate type based on the extended De-Martonne classification method [44].

Station	Latitude (°)	Longitude (°)	Elevation (m)	Mean (mm)	St. Dev (mm)	Min (mm)	Max (mm)	Skew.	Period	Climate
Hamedan	+30.87	+48.53	+1741.5	25.07	26.62	0.00	186.10	1.43	1988–2017	Semiarid very cold
Kermanshah	+34.35	+47.15	+1318.6	34.21	40.05	0.00	295.40	1.63	1988–2017	Semiarid cold

2.2. Multivariate Standardized Precipitation Index. Multivariate standardized precipitation index (MSPI) is derived by applying Principal Components Analysis (PCA) on the K time series of SPI (where K is corresponding to the time window K). The first major component (PC_1) of the PCA analysis is used to describe the percentage changeability

in K of the initial variable. Due to the PC_1 character, unlike the SPI, which has a mean 0 and standard deviation 1, its values are not comparable between months. Therefore, it is necessary to standardize the PC_1 time series using the average and standard deviation of the different months of the year using [1]

$$Z_{1ym} = \frac{PC_{1ym} - \overline{PC_{1m}}}{SD_{1m}} \approx \frac{PC_{1ym}}{SD_{1m}}, \quad (1)$$

where Z_{1ym} is the standardized value of PC1 in year (y) and month (m), PC_{1ym} is the value of PC1 in year (y) and month (m), $\overline{PC_{1m}}$ is the average PC1 in the month (m), SD_{1m} is the standard deviation of PC1 in month (m), and Z_{1ym} is taken as the multivariate Standard Precipitation index (MSPI). The value of PC_{1m} is statistically very small and close to zero; hence, in the case of the fraction of the above equation, it can be neglected [1, 45]. In order to determine the drought severity classes of the MSPI, the time series is arranged in ascending order, and its probability distribution is plotted on a diagram (for example, Figure 2).

Then, the values corresponding to the probability thresholds of different classes of SPI (Table 2) are extracted from the above diagram. The extracted values are taken as the MSPI thresholds, which can be used in the MSPI time series classification for drought severity [1].

According to the main literature of MSPI [1], MSPI can simultaneously monitor different droughts by its five time windows; so, these time windows are getting calculated in the current study. The time windows included are 3–6 months ($MSPI_{3-6}$), 6–12 months ($MSPI_{6-12}$), 3–12 months ($MSPI_{3-12}$), 12–24 months ($MSPI_{12-24}$), and 24–48 months ($MSPI_{24-48}$). The mentioned time windows of MSPI are its multivariate drought time windows and theoretically related to more than one type of droughts. SPI's time windows show the different drought types' severity and weakness. Extensionally, the time windows SPI_3 , SPI_6 , SPI_{12} , and SPI_{24} relate to droughts in perspectives of soil moisture, surface hydrology, agriculture, and groundwater level, respectively, and the larger time windows can be related to the economic and social effects of drought [1, 12, 40]. Therefore, the merged form of these time windows of MSPI can theoretically monitor the different perspectives of droughts simultaneously. For example, the $MSPI_{3-6}$ time window can theoretically monitor drought in perspectives of soil moisture and surface hydrology or $MSPI_{6-12}$ can monitor both hydrological and agricultural droughts, simultaneously. $MSPI_{3-12}$ relates to 3 perspectives of droughts simultaneously, including soil moisture, hydrological, and agricultural droughts. Among the larger time windows, $MSPI_{12-24}$ can simultaneously indicate drought in perspectives of agriculture and groundwater, and $MSPI_{24-48}$ is theoretically related to the socio-economic effects of droughts [1, 6, 12, 39, 47].

2.3. Artificial Neural Networks. An artificial neural network is a parallel information processing system that has a distinct function inspired by the biological structure of the human brain [48]. These systems are able to determine the complexity and nonlinear relationship between the inputs and outputs of a physical system by a network of nodes that are interconnected. In these systems, the activity of each of these connections is set by historical information (learning process).

FIGURE 2: Percentiles of 6 to 12 months' time window of MSPI for Hamedan synoptic station.

TABLE 2: Classification of the SPI's values and corresponding probability limits [1, 46].

SPI classes	Probability limits	Description
$SPI \geq 2$	$\geq 97\%$	Extremely wet
$2 > SPI \geq 1.5$	93.3–97.7%	Severely wet
$1.5 > SPI \geq 1$	84.1–93.3%	Moderately wet
$1 > SPI > -1$	15.9–84.1%	Normal
$-1 \geq SPI > -1.5$	6.7–15.9%	Moderately dry
$-1.5 \geq SPI > -2$	2.3–6.7%	Severely dry
$-2 \geq SPI$	$2.3\% \geq$	Extremely dry

2.3.1. MLP Neural Network. MLP network is one of the most important structures of artificial neural networks. These networks consist of the layers of sensory units (neurons), the input layer made of one or more hidden layers, and the output layer. The input signal is transmitted through the network in the forward direction to the hidden layer and then to the output layer [48]. The output of each neuron is multiplied by weight coefficients and given as input to a nonlinear excitation function. In the training phase, the training data is given to the perceptron, and then, the grid weights are adjusted to minimize the error between the target and output of the model or to reach the number of training times to the default value. Then, like all modeling processes, different inputs (not present in the training phase) are used for model validation. The training of neural networks is generally very complex and can be stated to be an optimization problem with a large number of variables [49].

2.3.2. Imperialistic Competitive Algorithm (ICA). The imperialistic competitive algorithm was first proposed by Atashpaz-Gargari and Lucas in 2007 [43]. This algorithm, in the first place, with a completely new perspective on optimization, establishes a new link between the humanities and social sciences on the one hand and the technical and mathematical sciences on the other. In particular, this algorithm views the process of colonization as a stage of human socio-political evolution and uses mathematical

modeling as the source of inspiration for a powerful optimization algorithm. With the formation of the early empires, the imperialist rivalry between them began. Any empire that fails to compete for colonial power and increase its power (or at least prevent it from losing its influence) will be removed from the arena of imperialistic competition. Thus, the survival of an empire will depend on its power to attract and control the colonies of rival empires. As a result, during the imperialists' competitions, the power of the larger empires gradually increased, and the weaker empires were eliminated. To increase their power, empires will have to develop their colonies as well. Over time, the colonies will become closer to the empires in terms of power, and we will see a kind of convergence. The final limit of imperialistic competition is when there is a single empire in the world with colonies that are very close to the imperialist country in terms of position. In the following sections, different parts of the algorithm are presented [43].

Like other evolutionary algorithms, this algorithm starts with several random primary populations, in which each of them is called a "country." A number of the best elements of the population (equivalent to elitism in genetic algorithm or particle in particle swarm optimization) are selected as imperialists. The rest of the population is also considered a colony. Depending on their power, the colonizers will specially colonize these colonies; they pull towards themselves. The total power of an empire depends on both its constituent parts and the imperialist country (as the central nucleus) and its colonies. In mathematical terms, this dependence is modeled by defining the power of the empire as the total power of the imperial state, plus a percentage of the average power of its colonies. For supplementary information about this algorithm and its mathematical equations, the references are suggested [43, 50, 51]. The learning processes of the ICA algorithm is presented step by step in the form of a flowchart (Figure 3).

2.3.3. Combining MLP with Imperialist Competitive Algorithm (MLP-ICA). As a metainnovative neural network, the ICA can be merged with MLP to improve MLP's modeling accuracy. This approach gets done by optimizing the parameters of MLP by ICA. The makeup of MLP depends on the hidden layers, neurons, and transfer functions, which are found by the trial and error method. The optimizable parameters are the weights and biases of the MLP neural network that these two subjects are optimized by ICA optimization. The schematic form of merging MLP with ICA (MLP-ICA) is shown in Figure 4.

2.4. Evaluation Measures. To ensure the accuracy of modeling and predicting, the outputs of the model should be compared with their actual values. For this purpose, the model performance evaluation criteria are used. The criteria used in this study are the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Pearson correlation coefficient (R), whose equations (2)–(4) have been described below:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - f_i)^2}, \quad (2)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |(y_i - f_i)|, \quad (3)$$

$$R = \frac{\sum_{i=1}^N (y_i - \bar{y})(f_i - \bar{f})}{\sqrt{\sum_{i=1}^N (y_i - \bar{y})^2} * \sqrt{\sum_{i=1}^N (f_i - \bar{f})^2}}. \quad (4)$$

In the above equations, y_i and $\bar{y}$ are the observational data and their mean and f_i and $\bar{f}$ are the models' predictions and their mean, respectively, and n is the number of data, respectively. The values closer to zero for RMSE and MSE criteria and the values close to 1 for the Pearson correlation coefficient represent the optimal performance of the model. In this research, coding in MATLAB software has been used to run the MLP and MLP-ICA models.

3. Results

3.1. Input Selection. According to the main reference [1], the MSPI was calculated in five time windows including MSPI_{3–6}, MSPI_{6–12}, MSPI_{3–12}, MSPI_{12–24}, and MSPI_{24–48}, which resulted 5 time series for each station. For predicting the index, the model's input must be the previous amounts of the index (time lags of MSPI). For this, the Autocorrelation Function (ACF) plot was used to determine the correlation signification of the time lags (Figure 5).

ACF plots (Figure 5) can show the significance of the variable's correlation with its time lags, and due to this, the significantly correlated time lags can be used as the models' inputs for prediction. Figure 5 shows the ACF plots of Hamedan station, drawn for the 5 mentioned time windows of MSPI. As it is observable in the ACF plot of MSPI_{3–6}, the time lags of 1, 2, and 3 have significant correlations, and so, they are selected as the predictor inputs. In both MSPI_{6–12} and MSPI_{3–12} time windows, the 1, 2, 3, 4, and 5 time lags are significantly correlated. For MSPI_{12–24}, the significant time lags are 1, 2, ..., 12, and for MSPI_{24–48} time window, the significant correlations belong to the 1, 2, ..., 17 time lags. This method was similarly implemented for Kermanshah station, and the total results are shown in Table 3.

3.2. Predicting Multivariate Drought and Assessment. After selecting the input variables for each of the time windows, the input-target samples were divided into two phases: 75% for the training phase and 25% for the testing phase. Data with specified inputs were entered into the two artificial intelligence models for modeling and evaluation. The parameters of the MLP neural network model includes the number of hidden layers, number of neurons in hidden layers, and type of transfer functions within the neurons, which were selected by the trial and error method. Consequently, the best suitable number of hidden layers was up to 3 hidden layers (1, 2, and 3 hidden layers), best number of neurons was from 6 neurons to 18 neurons in each hidden

FIGURE 3: Flowchart of the ICA optimization.

layer, and best-fitted transfer function was the saturating linear transfer function (satlin). In the MLP-ICA model, the weights and biases of MLP (with similar makeup) were optimized by the ICA algorithm. The evaluation is carried

out by the evaluation criteria of RMSE, MAE, and R , and the results are shown in Table 4.

In Table 4, the models are evaluated separately for stations and time windows. The predictive section is actually

FIGURE 4: The interaction of the MLP model with Imperialist Competitive Algorithm in a schematic structure.

FIGURE 5: ACF plots of the five time windows of MSPI for Hamedan station.

TABLE 3: Time lags of MSPI as inputs selected by ACF.

Time window	Station	Time significant correlated time lags (month)
MSPI ₃₋₆	Hamedan	1, 2, 3
	Kermanshah	1, 2, 3
MSPI ₆₋₁₂	Hamedan	1, 2, 3, 4, 5
	Kermanshah	1, 2, 3, 4, 5
MSPI ₃₋₁₂	Hamedan	1, 2, 3, 4, 5
	Kermanshah	1, 2, 3, 4, 5
MSPI ₁₂₋₂₄	Hamedan	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
	Kermanshah	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
MSPI ₂₄₋₄₈	Hamedan	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17
	Kermanshah	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20

TABLE 4: Evaluating the predictions of the models MLP and MLP-ICA.

Station	Time window	Model	RMSE		MAE		R	
			Train	Test	Train	Test	Train	Test
Hamedan	MSPI ₃₋₆	MLP	0.42	0.63	0.31	0.46	0.91	0.78
		MLP-ICA	0.40	0.60	0.29	0.46	0.92	0.81
	MSPI ₆₋₁₂	MLP	0.31	0.50	0.22	0.38	0.95	0.87
		MLP-ICA	0.29	0.40	0.21	0.28	0.95	0.92
	MSPI ₃₋₁₂	MLP	0.30	0.54	0.21	0.38	0.95	0.84
		MLP-ICA	0.30	0.53	0.22	0.38	0.95	0.86
	MSPI ₁₂₋₂₄	MLP	0.23	0.36	0.17	0.26	0.98	0.89
		MLP-ICA	0.20	0.27	0.14	0.20	0.98	0.94
	MSPI ₂₄₋₄₈	MLP	0.19	0.32	0.15	0.26	0.98	0.91
		MLP-ICA	0.14	0.20	0.10	0.15	0.99	0.95
Kermanshah	MSPI ₃₋₆	MLP	0.42	0.73	0.29	0.57	0.91	0.73
		MLP-ICA	0.42	0.64	0.31	0.47	0.90	0.80
	MSPI ₆₋₁₂	MLP	0.42	0.71	0.29	0.53	0.92	0.67
		MLP-ICA	0.32	0.59	0.23	0.41	0.95	0.79
	MSPI ₃₋₁₂	MLP	0.40	0.80	0.30	0.60	0.92	0.60
		MLP-ICA	0.40	0.63	0.28	0.44	0.92	0.79
	MSPI ₁₂₋₂₄	MLP	0.24	0.47	0.18	0.37	0.98	0.79
		MLP-ICA	0.16	0.31	0.12	0.24	0.99	0.92
	MSPI ₂₄₋₄₈	MLP	0.18	0.30	0.14	0.25	0.99	0.78
		MLP-ICA	0.12	0.20	0.09	0.15	0.99	0.92

The bold numbers are the best predictions of each station.

the test section discussed here. At first glance, it is clear that, in both stations, as the time windows get bigger, the accuracy of the models also increases. In both stations, the accuracy of the models from low to high is reported in the time windows MSPI₃₋₆, MSPI₃₋₁₂, MSPI₆₋₁₂, MSPI₁₂₋₂₄, and MSPI₂₄₋₄₈, respectively. In all cases, the comparison between the two models, which includes 10 series (5 time windows for each of the stations), and the MLP-ICA hybrid model has higher accuracy in predicting MSPI. This shows that ICA is effective in optimizing the MLP model and is able to improve its performance. The lowest percentage of MLP performance improvement by ICA at Hamedan station belongs to the MSPI₃₋₁₂ time window (about 1.9%) and the highest, which is about 60%, was reported for the MSPI₂₄₋₄₈ time window (where the model error is reduced from 0.32 to 0.20). At Kermanshah station, the MLP-ICA hybrid model has performed much better compared to the simple MLP model. In MSPI₁₂₋₂₄ and MSPI₂₄₋₄₈ time windows, it was able to improve MLP forecasting accuracy by more than 50% (in MSPI₁₂₋₂₄, the model error was reduced from 0.47 to 0.31, and in MSPI₂₄₋₄₈, the model error was reduced from 0.30 to

0.20). The lowest performance improvement from ICA merging with MLP at Kermanshah station belonged to the MSPI₃₋₆ time window, where the model error was reduced from RMSE = 0.73 to RMSE = 0.64 (about 14.1% improvement in prediction accuracy). It can be said that, on average, the ICA algorithm in Hamedan and Kermanshah stations caused 25% and 32% increase in accuracy for the MLP model, respectively. The strongest and weakest performance in Hamedan station was reported in MSPI₂₄₋₄₈ window by the MLP-ICA model (with RMSE = 0.20, MAE = 0.15, and R = 0.95) and MSPI₃₋₆ time window by the MLP model, respectively. In Kermanshah station, the best forecast was reported by the MLP-ICA model and MSPI₂₄₋₄₈ time window (RMSE = 0.20, MAE = 0.15, and R = 0.92) and the weakest was obtained by the simple MLP model in the MSPI₃₋₁₂ time window (RMSE = 0.80, MAE = 0.60, and R = 0.60). These overlays of the models' predictions and their observations are shown in time series plots (Figure 6).

In the MSPI₆₋₁₂ time window of Hamedan station, the models have relatively close estimates of the actual value so

(a)

FIGURE 6: Continued.

FIGURE 6: Time series plots of the observed and predicted values of MSPI in the test period.

that, in most of the months, there are overlaps. During the severe drought from May–October 2013 and March–July 2015, both of the models were overestimated but the MLP-ICA's overestimation is milder so that this model could present an acceptable prediction for the classes of these severe drought months. In the same time window ($MSPI_{6-12}$) at Kermanshah Station, the forecasts are also suitable, but compared to Hamedan Station, the overlap is somewhat weaker. The error was enormous during the months of January through October 2016. The months are in wet conditions, so this underestimation in forecasting does not cause problems. Another remarkable point in $MSPI_{6-12}$ of Kermanshah is the severe and extreme drought status during April–November 2015. In this case, MLP was weak and overestimated, but MLP-ICA could have a highly accurate prediction for these important months.

The prediction of models for the $MSPI_{24-48}$ time window of the two stations was very accurate in most of the months, especially in the diagnosis of the drought classes. At the Hamedan station (Figure 6), the MLP model in all months of 2013 (unlike the MLP-ICA) had a large difference with actual values. However, in the course of May–July 2015 (with a little difference), it could have forecast a long-term severe drought class as well as the MLP-ICA. In this diagram ($MSPI_{24-48}$ of

Hamedan), the proximity of the MLP-ICA prediction curve is clearly visible with the actual value curve compared to the MLP. This comparison between the two models at Kermanshah station, due to the significant difference in the forecast of two more convenient models, shows the superiority of the MLP-ICA hybrid model. The MLP's error in forecasting the $MSPI_{24-48}$ time window is more than MLP-ICA in most of the months. However, in March–December 2012, February–September 2016, and April–Nov 2017, it is too clear that MLP-ICA is more accurate than MLP, with a large difference. The ability of the models in predicting drought severity classes of MSPI has been evaluated in Table 5. In this table, the number of months of the test period that predicted drought severity correctly was divided by the total number of test periods. This method is done for both models in each of the time windows of both stations, and the resulted likelihood is shown by percentage.

Observing all of the comparison cases (a specific time window in a station) between the two models shows the superiority of MLP-ICA's likelihood against the MLP simple form. The error decreasing by increasing the time window size is reported here (evaluation of the class prediction) too. The least likelihood percentage is reported for $MSPI_{3-6}$ of Kermanshah station, which is 65.05%, and resulted in the

TABLE 5: The models' likelihood in determining MSPI drought classes.

Time window	Likelihood percentage of the drought severity classes (%)			
	Hamedan		Kermanshah	
	MLP	MLP-ICA	MLP	MLP-ICA
MSPI ₃₋₆	69.90	73.79	65.05	68.93
MSPI ₆₋₁₂	68.32	77.23	70.30	75.25
MSPI ₃₋₁₂	72.28	75.25	67.33	69.31
MSPI ₁₂₋₂₄	80.00	90.00	86.67	88.89
MSPI ₂₄₋₄₈	79.52	86.75	95.78	96.39

MLP model. The largest likelihood percentage is 96.39%, which is reported for the MLP-ICA model in predicting MSPI₂₄₋₄₈ of Kermanshah station. This can show the good capability of AI methods in forecasting the severity classes of different types of droughts simultaneously. The improvement of drought class prediction by the new hybrid model (MLP-ICA) is clearer in Hamedan station compared to Kermanshah station. The biggest improvement reached by combining ICA with MLP is 10%, which is reported for the MSPI₁₂₋₂₄ time window of Hamedan station. This case can make another confirmation on the ability of the new hybrid model, MLP-ICA. In Figure 7 (regression diagrams), the correlation of the output of the two models with actual values is investigated. It is clear that the distribution of points around the axis of the regression line is greater in smaller time windows, and in larger time windows, the points are closer and more concentrated to the models' regression lines.

This indicates a higher correlation and therefore a more accurate prediction in larger time windows, which is consistent with the results in Table 4. At Hamedan station, MSPI₂₄₋₄₈ forecasts have the highest concentration around their fitted regression lines and as a result, have the highest correlation between the time windows. The R^2 coefficients in these series for the MLP and MLP-ICA models are 0.827 and 0.928, respectively, which shows a very good correlation in predicting socio-economic droughts. The MSPI₃₋₆ time window, which represents drought from the perspectives of soil moisture and surface hydrology simultaneously, had the weakest forecasts in Hamedan (R^2 is equal to 0.605 and 0.654 for MLP and MLP-ICA, respectively). The reason for this difference in accuracy can be the sudden jumps in the time series of the index. Sudden jumps occur more frequently among smaller time windows, but in larger time windows that reflect the long-term effects of lack of precipitation, monthly changes are gradual (see Figure 6 for a better understanding). The index with gradual changes will always have a more accurate prediction, while the presence of sudden jumps in the time series naturally increases the prediction error. Among the time windows smaller than 12 months (MSPI₃₋₆, MSPI₆₋₁₂, and MSPI₃₋₁₂), the MSPI₆₋₁₂ time window, which is associated with both hydrological and agricultural droughts, had the strongest predictions at both stations. From the theoretical point of view, the MSPI₃₋₁₂ time window simultaneously represents 3 types of drought perspectives (drought from soil moisture perspective,

hydrological drought, and agricultural drought), while MSPI₆₋₁₂ simultaneously represents two types of droughts (hydrological drought and agricultural drought). Therefore, it is logical that the simultaneous forecasting of two types of droughts will be more accurate than three types of droughts. At Kermanshah station, the best forecasts for the MSPI₁₂₋₂₄ time window (which could theoretically be a simultaneous indicator of drought from agricultural and groundwater perspectives) and MSPI₂₄₋₄₈ time window were presented. The R^2 value of the MLP-ICA output for the MSPI₁₂₋₂₄ and MSPI₂₄₋₄₈ time windows of Kermanshah are 0.849 and 0.841, respectively. In predicting all cases (all 10 series investigated), the slope of the MLP-ICA regression line is closer to the 1:1 line, and the R^2 value is higher than the simple MLP model. This demonstrates the reliable performance of the ICA algorithm in optimizing the MLP model, which results in a more accurate prediction of simultaneous droughts. The highest increased correlation by the MLP-ICA hybrid model is observed in the MSPI₃₋₁₂ time window of Kermanshah station, where the R^2 value has increased from 0.355 to 0.601. Distribution and concentration of the model error around zero can be another measure of predictability. In this section, the violin plot (Figure 8) is used to examine the distribution of prediction errors.

This diagram was drawn separately for each station, and the power of the two models was compared in each time window. The results of this plot also confirm the strength of the MLP-ICA model compared to the simple MLP model. For example, in Kermanshah's MSPI₃₋₆ time window, the curvature of the MLP-ICA violin around the error = 0 axis is greater than that of the MLP (the so-called wider violin). This indicates a higher percentage of zero errors in MLP-ICA, which shows its superiority against the simple MLP model. This is true of all time windows and is more noticeable in larger time windows. In the MSPI₂₄₋₄₈ time window, the width of the MLP-ICA violin is about twice that of the MLP. Therefore, in predicting larger MSPI time windows, the use of the MLP-ICA hybrid model is highly recommended. The situation is similar at Hamedan station, and MLP-ICA violins are wider than MLP, at error = 0 axis. Also, as the size of the time window increases, the width of the violins increases, the distance between the first and third quartiles (IQR) decreases, and the upper and lower tails of the frequency distributions gradually disappear. This indicates that the prediction error is centered on zero, which is minimized in the largest time window (MSPI₂₄₋₄₈).

4. Discussion

MSPI forecasts were so far only reported in the Aghelpour et al. [12] study, which used the ANFIS model and its hybrid models. In this study, 31 stations from different climates of Iran have been studied, and MSPI has been monitored and predicted from the perspective of agricultural drought (the time window of MSPI₉₋₁₂). In Aghelpour et al. [12] study, the Kermanshah station was also examined, which in its most accurate forecast was RMSE equal to 0.356. While in the present study, the RMSE rate for Kermanshah varies between 0.2 and 0.6. This difference is due to the different dimensions

(a)

FIGURE 7: Continued.

FIGURE 7: Scatter plots to evaluate the correlations between the models' outputs and their observations in the test period.

FIGURE 8: Continued.

FIGURE 8: Violin plots of the error distributions in the test period.

of the time windows of the present study ($MSPI_{3-6}$, $MSPI_{6-12}$, $MSPI_{3-12}$, $MSPI_{12-24}$, and $MSPI_{24-48}$). This difference also conceptually creates a different perspective for MSPI. In other words, the $MSPI_{9-12}$ time window can only comment on one type of drought (agricultural drought), while the time windows examined in the current study are multivariate. These current time windows of MSPI can discuss several different types of droughts simultaneously. The ICA algorithm has been used in drought studies in only one study of Hosseini-Moghari et al. [50] to predict SPI, which has not studied drought in the multivariate type. Also, the MLP-ICA hybrid model has not been compared to its simple form to evaluate the improvement of the hybrid model.

The reason for the discrepancy between the results obtained in the two stations studied in the current study could be due to their microclimatic and topographic differences. Also, the difference in the type and number of atmospheric systems that affect these areas could be another reason for the difference in the accuracy of forecasts [52]. The Mediterranean low-pressure system approaches Iran from the northwest and the Sudanese low-pressure system approaches from the southwest. Due to having the Zagros Mountains in the west, Iran has favorable conditions for intensifying and expanding rainfall and sometimes flooding. Also, the role of the Red Sea is to provide more precipitation moisture to Kermanshah compared to Hamedan. In fact, the existence and role of higher mountains in the Hamedan region can be the main controlling factor of atmospheric systems and fronts. This orographic factor decreases the effects of the systems and consequently decreases the irregularity in precipitation time series in Hamedan compared to Kermanshah. So, while the MSPI is originated from the precipitation regime, this can cause weaker autocorrelation and finally weaker predictions in Kermanshah compared to Hamedan.

5. Conclusion

The results show that the simultaneous forecasting of different drought types can have acceptable accuracies for semiarid climates of western Iran. The best performance will

be resulted in predicting the $MSPI_{24-48}$ time window, which is related to socio-economic drought. Also, the weakest accuracy belongs to the predictions of the short-term effects of precipitation deficit, such as soil moisture and surface hydrological droughts simultaneously ($MSPI_{3-6}$). Evaluating the models shows the significant capability of an imperialistic competitive optimization algorithm in improving MLP's prediction accuracy, which is reported 28.5% on average for the current study. As the first use of the MLP models and its hybrid form MLP-ICA in multivariate drought forecasting, it has been reported to be promising and is suggested for other similar climatic areas. Also, using the other previous well-used optimizers of MLP-like genetic algorithm, particle swarm, and firefly are suggested for future researchers to be compared with the imperialistic competitive algorithm and to choose the best optimizer of MLP in multivariate drought forecasting. One of the most important points in this area is that the current results are theoretically acceptable, and to have an actual or applicable investigation, it would be better to consider some more points. For example, in the simultaneous investigation and consequent prediction of agricultural and hydrological droughts, it is better suggested to investigate the relation of the index with the natural events, such as dam reservoir water content's variations (to validate the index in hydrological drought monitoring) or vegetation cover variations (to validate the index in agricultural drought monitoring). This subject can be another suggestion for future studies. Consequently, according to the acceptable results of the current investigated climate (semiarid and cold climate type), the work has research value for other different climates around the world.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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