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Forecasting pan evaporation with an integrated artificial neural network quantum-behaved particle swarm optimization model: a case study in Talesh, Northern Iran

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ABSTRACT

Accurate simulation of evaporation plays an important role in the efficient management of water Resources. Generally, evaporation is measured using the direct method where Class A pan-evaporimeter is used, and an indirect method that includes empirical equations. However, despite its widespread usage, Class A pan-evaporimeter method can be affected by human and instrumentation errors. Empirical equations, on the other hand, are generally linked to the different climatic factors that should provide initial or boundary conditions in the mathematical equations that affect the rate of evaporation. Considering these challenging, heuristic soft computing approaches that do not need key information about the physics of evaporation. In this study, a Quantum-behaved Particle Swarm Optimization algorithm, embedded into a multi-layer perceptron technique, is developed to estimate the evaporation rates over a daily forecast horizon. The measured evaporation data from 2012–2014 for Talesh meteorological station located in Northern Iran are employed. The predictive accuracy of the MLP-QPSO model is evaluated with existing methods: i.e. a hybrid MLP-PSO and a standalone MLP model. The results are evaluated in respect to statistical performance criterion: the mean absolute error, root mean square error (RMSE), Willmott's Index and the Nash–Sutcliffe coefficient. In conjunction with these metrics, Taylor diagrams are also utilized to assess the level of agreement between the forecasted and observed evaporation data. Evidently, the hybrid MLP-QPSO model is confirmed to be an optimal forecasting tool applied for estimating daily pan evaporation, outperforming both the hybrid MLP-PSO and the standalone model. In light of these results, the present study justifies the potential utility of the hybrid MLP-QPSO model to be applied for estimating daily evaporation rates in North of Iran.

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QPSO; forecasting; hybrid model; pan evaporation; PSO

1. Introduction

Evaporation is an integral component of the global hydrological cycle. Therefore, the accurate estimation of evaporation rates using novel learning algorithms is a vital task for hydrologic engineering, water resources management and agriculture, particularly in arid and semi-arid regions (Deo & Samui, 2017; Deo, Samui, & Kim, 2016; Goyal, Bharti, Quilty, Adamowski, & Pandey, 2014; Kim, Shiri, Singh, Kisi, & Landaras, 2015; Kisi, 2015). Acquisition of pan evaporation by means of direct measurements can be an expensive and a tedious task, so the evaporation rate are routinely estimated by statistical regression and parametric methods such as the Thornthwaite and Hargreaves approaches (Jacobs, Heusinkveld, & Lucassen, 1998; Tabari, Marofi, & Sabziparvar, 2010;

Thornthwaite, 1948). However, among the several statistical regression models, the widely Penman-Monteith approach (Linacre, 1994) can incur a potential challenge if the boundary conditions data in the physical equations are unavailable or if they are unrealistic and a reasonable assumption in this regard needs to be made (Almedeij, 2012). Any errors in estimating the water mass balance on which the parametric equation is intrinsically reliant, can produce significant errors in the estimated evaporation rate (McJannet, Webster, Stenson, & Sherman, 2008). It is also important to note that the physical processes related to evaporation rates are highly non-linear (Kisi, 2007), therefore, consistent and powerful forecasting methods should be able to analyze the non-linear trends related with the predictor variables for the evaporation rate,

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in order to accurately predict this important hydrological variable. Hence non-linear forecast models, do not depend on the physical processes, require less information (e.g. initial or boundary conditions) are useful for decision-making for data-sparse regions compared to the other types of parametric methods (Deo & Şahin, 2015a).

Over the last several decades, the evolution of soft computing, data-driven learning algorithms coupled with new artificial intelligence (AI) tools (Deo et al., 2016; Garousi-Nejad, Bozorg-Haddad, & Loáiciga, 2016) based on artificial neural network-multi-layer perceptron and Particle Swarm Optimization (MLP-PSO) have successfully led to an extensive number of investigations that attempted to model the evaporation rates. As these models are completely non-parametric (and assumption-free), they provide considerable advantage compared to the physically-based models. This is because prior information about the relationships between inputs and objective variables are not required (e.g. Ghorbani et al., 2017; Ghorbani, Deo, Yaseen, Kashani, & Mohammadi, 2018; Ghorbani, Zadeh, Isazadeh, & Terzi, 2016; Gocić et al., 2015; Khatibi et al., 2013; Khatibi, Ghorbani, Kashani, & Kisi, 2011). An important and a primary advantageous feature of AI-based techniques is that they can be generally be applied at local scales. As a result of this advantage, the AI-models have a greater applicability for practical implementations that require estimated evaporation rates.

A brief summary of the previous research works that have applied AI-based methods for water resources forecasting can be presented in the following. A hybrid neural network model, which incorporated the fuzzy pattern-recognition ability was proposed to forecast downstream river flows based on upstream river flow data and areal average precipitation (Chen, Chau, & Busari, 2015). A genetic algorithm based artificial neural networks, was employed for flood forecasting purposes (Wu & Chau, 2006) Another research work applied an ANN model together with dendrochronology (tree-rings) datasets to forecast groundwater level fluctuations (Gholami, Chau, Fadaee, Torkaman, & Ghaffari, 2015) whereas an ANN model was used for river forecasting with base flow separation and binary-coded swarm optimization and a Binary-coded swarm optimization technique to identify filter parameters and model structures (Taormina, Chau, & Sivakumar, 2015).

Other than the aforementioned studies, several researchers have validated the utility of a standalone ANN and a hybrid MLP-PSO model for forecasting pan evaporation rates (Abudu, Cui, King, Moreno, & Bawazir, 2011; Deo & Şahin, 2015a; Deo & Samui, 2017; Keshtegar, Piri, & Kisi, 2016; Kisi, Genc, Dinc, & Zounemat-Kermani, 2016). On the other hand, regardless of the

profusely testified prospects of using AI-based methods for their relatively accurate performance, a large proportion of these research works have utilized a standalone AI method. In such models, there was no algorithm that enabled a pre-processing of input and target data and did not use a feature optimizer algorithm. It is noteworthy that in the hybridized form, a neural network model connected with an optimizer algorithm is normally implemented to attain consistently optimal values of the internal parameters of the standalone model. Notwithstanding this limitation in the current standalone model, recent research works have also advocated the application of several optimizer algorithms (within a standalone forecast model). In fact, the statistical performance of the hybrid (or integrated) AI-based model has seemingly been better than their non-optimized counterpart models (e.g. Garousi-Nejad et al., 2016; Olatomiwa et al., 2015; Yang, 2010). Having stated that, the application of an optimizer algorithm within a standalone model for the forecasting of daily pan evaporation is yet to be fully explored, especially in the context of data-sparse (i.e. both arid and semi-arid) regions such as Northern Iran.

The present study embraces a global optimizer, the Quantum-Performed Particle Swarm Optimization (QPSO) algorithm (Sun, Feng, & Xu, 2004). In general, the QPSO is a novel learning algorithm inspired by the fundamental theory of the Particle Swarms, integrated with characteristic features within the field of quantum mechanics. This involves the application of Schrodinger equation and the potential field distributions applied to solve the optimization problem (Fang, Sun, Ding, Wu, & Xu, 2010). Due to its growing popularity, the QPSO algorithm has been applied in many research areas. For example, the study of (Cheng, Niu, Feng, Shen, & Chau, 2015) proposed an ANN model integrated with the QPSO algorithm for forecasting daily reservoir runoffs. QPSO has also been applied in streamflow forecasting problems (Ch, Anand, Panigrahi, & Mathur, 2013), groundwater level forecasting (Sudheer, Shrivastava, Panigrahi, & Mathur, 2011), evaluation of fused images (Le et al., 2013) and in solving economic dispatch problems (Niu, Zhou, Zhang, & Deng, 2012). However, the application of the QPSO model for daily pan evaporation forecasting in arid and semi-arid regions (e.g. the region studied in this paper) where it can potentially aid decision-makers to apply the tool in hydrological and water resources problems, is yet to be undertaken.

In this paper, a new hybrid forecast model to integrate the multi-layer perceptron (MLP) technique (i.e. a specific architecture of an ANN model) with the QPSO algorithm has been designed and applied to a case study problem for the estimation of pan evaporation at Talesh

station. In this paper, QPSO was integrated with the MLP algorithm to identify the optimal weights and neuronal parameters of the forecasting model. Due to the integration of the two algorithms (i.e. QPSO for weight optimization and ANN for prediction purposes), the mean square error produced by the fully trained forecast model can be minimized in respect to the error encountered by the standalone MLP model. While the QPSO algorithm has been effectively applied in several different contexts, in literature review, there exist no previous study testing the MLP-QPSO capability to forecast daily evaporation rates. In this study, the cross-validation of the hybrid MLP-QPSO model has been performed in respect to the standalone MLP and the earlier hybrid version, the hybrid MLP-PSO model. The novelty of this study is therefore, to develop a hybrid MLP-QPSO model for the forecasting of the daily evaporation rates in the data-sparse region of Northern Iran.

The purpose of this research paper is as follows. (1) To develop and evaluate the performance of a hybrid MLP-QPSO model applied in a problem of forecasting the daily pan evaporation rate for Talesh meteorological station in Northern Iran using data for the period 2012–2014. For the first time in this study region, the study aims to also: (2) evaluate the predictive ability of the hybrid MLP-QPSO model in respect to the standalone and the hybrid MLP-PSO model (i.e. a non-quantum-behaved counterpart) by means of statistical metrics, diagnostic plots and visual model performance measures in an independent testing phase. To make it easily understandable by the non-expert readers of this paper, it is important to also clarify that, the multi-layer perception is an AI technique applied for forecasting the pan evaporation data, but the Quantum-Behaved Particle Swarm Optimization algorithm has been integrated with the MLP (standalone) model to screen the model's internal parameters (i.e. the synaptic weights and thresholds), resulting in the final hybrid MLP-QPSO model. The rest of the paper is organized as follows. In Section 2, the Methods and Materials are presented, including a brief account of the model's theory, study area, required model development data and the performance evaluation criterion. In Section 3, the Results and Discussions are presented, followed by Section where the Conclusions in regards to the forecasting ability of the integrated MLP-QPSO model are made.

2. Materials and method

2.1. Multi-layer perceptron neural networks

The multi-layer perceptron (MLP) has an input, hidden and the output as layer with the Levenberg–Marquardt

(LM) back propagation learning procedure as the general MLP structure. The sigmoid and the linear activation functions are normally adopted in the hidden and the output layer to analyze the input data characteristics (Deo & Şahin, 2015a; Lima, Cannon, & Hsieh, 2016). The choice of the Levenberg–Marquardt algorithm in this study is relevant to the problem of interest, as this algorithm is a variation of the commonly used Newton's method (Hagan & Menhaj, 1994) applied in the computational phase to identify the model's neuronal weights. In this study, the LM algorithm has been employed as a well-established approximation tool to the Newton's method. This model offers robustness, speed and a better ability to determine and model the local minima or maximum present in the training data in respect to the other learning algorithms (Adamowski, Fung Chan, Prasher, Ozga-Zielinski, & Sliusarieva, 2012; Tiwari & Adamowski, 2013). This makes the LM algorithm an attractive modeling tool for the MLP-based model (Sapna, Tamilarasi, & Kumar, 2012). For further details and application, the authors can refer to several previous works (e.g. Ghorbani et al., 2016, 2018; Raheli, Aalami, El-Shafie, Ghorbani, & Deo, 2017).

2.2. Particle swarm optimization

In this paper we apply the Particle Swarm Optimization (PSO), as a novel learning method proposed originally by Kennedy and Eberhart in 1995 (Eberhart & Kennedy, 1995). PSO is used to progressive population-based procedure for optimization of the global problems and has been used in a number of optimization problems (e.g. Al-Musaylh, Deo, Adamowski, & Li, 2018). The theory of the PSO is based on the biological analogy and sociological feeding performances of the bird swarm. In the context of predictive modeling, the PSO algorithm is firstly adjusted with random solutions in the search of an ideal situation through the flying problem space. The flight of each particle is then conducted constantly based on the best known situation (i.e. the personal best situation 'pbest'), besides the best known situation of the whole population (i.e. the global best solution, 'gbest').

Each particle has velocity and a location vector, and by a utilization of these parameters, it is able to discover the penetrating space using simple formulas. A wider and thoughtful similarity is found between the PSO and some of the other evolutionary computation methods, such as a genetic algorithm. Offering a better alternative compared to the genetic algorithm, the PSO algorithm is generally faster in the convergence speed, and it does not contain the evolution operators as crossover and selection procedure in other algorithms. Furthermore, the PSO algorithm contains fewer

parameters that require an adjustment, which is depend directly on task values relatively than the information on derivatives.

Consequently, the PSO algorithm can simply be trapped into a local optima (rather than the global optima) despite its fast convergence rates (Clerc & Kennedy, 2002; Ren et al., 2014). For this reason, alternative forms of the PSO algorithm, such as the Quantum-Behaved PSO applied in our study, can potentially be used as an alternative optimization tool to improve the performance of the traditional PSO algorithm.

2.3. MLP based on quantum-behaved particle swarm optimization (QPSO)

In this paper, the QPSO algorithm, which is an advanced modeling algorithm compared to the original PSO algorithm, has been applied. In the QPSO, the particles prevail in the perfect D -dimensional examination space through the iterative phase. In current literature the application of the QPSO algorithm for solving hydrological modeling problems, particularly in pan evaporation forecasting area remains very limited. We have therefore, adopted this improved version of the original PSO algorithm into the present case study-based research paper.

The QPSO, which has been adopted in the present study to optimize the standalone MLP model, was developed by Sun (Sun et al., 2004). The formulation of the QPSO algorithm essentially involves solving the appropriate time-dependent Schrödinger equation where $\psi(y, t)$ is the wave task. It is applied to define the term of a particle as an alternative of location X and velocity V in conventional mechanics (Xi, Sun, & Xu, 2008). In fact, the term $|\psi(y, t)|^2$ represents the probability density function of its situation (Sun et al., 2004):

$$\int_{-\infty}^{\infty} |\psi(y, t)|^2 dy = 1 \quad (1)$$

The situation of the particle updates follows the equation (Sun et al., 2004):

$$X_{ij}(k+1) = p_{ij}(k) \pm \alpha(k) |C_{ij}(k) - X_{ij}(k)| \ln\left(\frac{1}{u}\right) \quad (2)$$

In Equation (2), $X_{ij}(k)$ is the location for j th dimension of i th particle in k th generation, and u shows a randomly generated number distributed uniformly in (0, 1) (Cheng et al., 2015). The inputs for i are 1, 2, ..., M , for j are 1, 2, ..., d , and for k are 1, 2, ..., k . Here $p_{ij}(k)$ denotes the j th dimension of local attractor i in the k th generation. α is the representative of the contraction extension coefficient. It is the individual factor in QPSO to regulate the convergence rate.

A popular control strategy of α is set to decrease linearly from 1.0 to 0.5 viz:

$$\alpha(k) = 1.0 - 0.5 \frac{k}{k_{\max}} \quad (3)$$

where $C_{ij}(k)$ is the mean finest location:

$$C_{ij}(k) = \left(\frac{1}{M} \sum_{i=1}^M P_{i1}(k), \frac{1}{M} \sum_{i=1}^M P_{i2}(k), \dots, \frac{1}{M} \sum_{i=1}^M P_{iD}(k) \right) \quad (4)$$

In order to integrate the standalone MLP model with the QPSO algorithm, in this study, the optimum weights applied to the MLP algorithm were calculated by the QPSO algorithm as an add-in optimizer tool. As this research work is in the early stage of developing and applying the QPSO algorithm for pan evaporation forecasting, our paper has aimed to demonstrate the usefulness of the quantum-behaved PSO-MLP hybrid model for a particular study region: that is, the Talesh stations (the site used as a case study).

Figure 1 displays the hybrid modeling mechanism. In general, the process involves the determination of input variables based on the combinations of maximum and minimum temperatures, relative humidity (%), duration of sunshine, and wind speed (km hr^{-1}) which are the predictor variables used for forecasting pan evaporation data. (Jacobs et al., 1998; Wintle, McCarthy, Volinsky, & Kavanagh, 2003)

It is noteworthy that the MLP-based approaches adopted in this research paper are well-established predictive tools, also applied for several other study locations (e.g. Altunkaynak, 2013; Gardner & Dorling, 1998; Pham & Sagioglu, 2001; SaralaThambavani & Uma Mageswari, 2014; Singh, Imtiyaz, Isaac, & Denis, 2012; Tabari, Talae, & Abghari, 2012) but their application to the present data-scarce region has been very limited.

The novelty of this work, is off course, is that our study provide a valuable contribution to the science that aims to report a unique dataset and a respective case study region with a more improved version of PSO-MLP (i.e. we introduced quantum-behaved model) to construct the hybrid MLP-QPSO predictive model.

2.4. Study region and datasets

In order to construct the hybrid MLP-QPSO model, the daily meteorological data for a case study region (Talesh meteorological station) located in Northern Iran has been utilized.

Figure 2 shows the geographic location of the tested station and Figure 3 plots a time-series of the daily variation in pan evaporation over the study period 2012–2014, acquired from Talesh meteorological station.

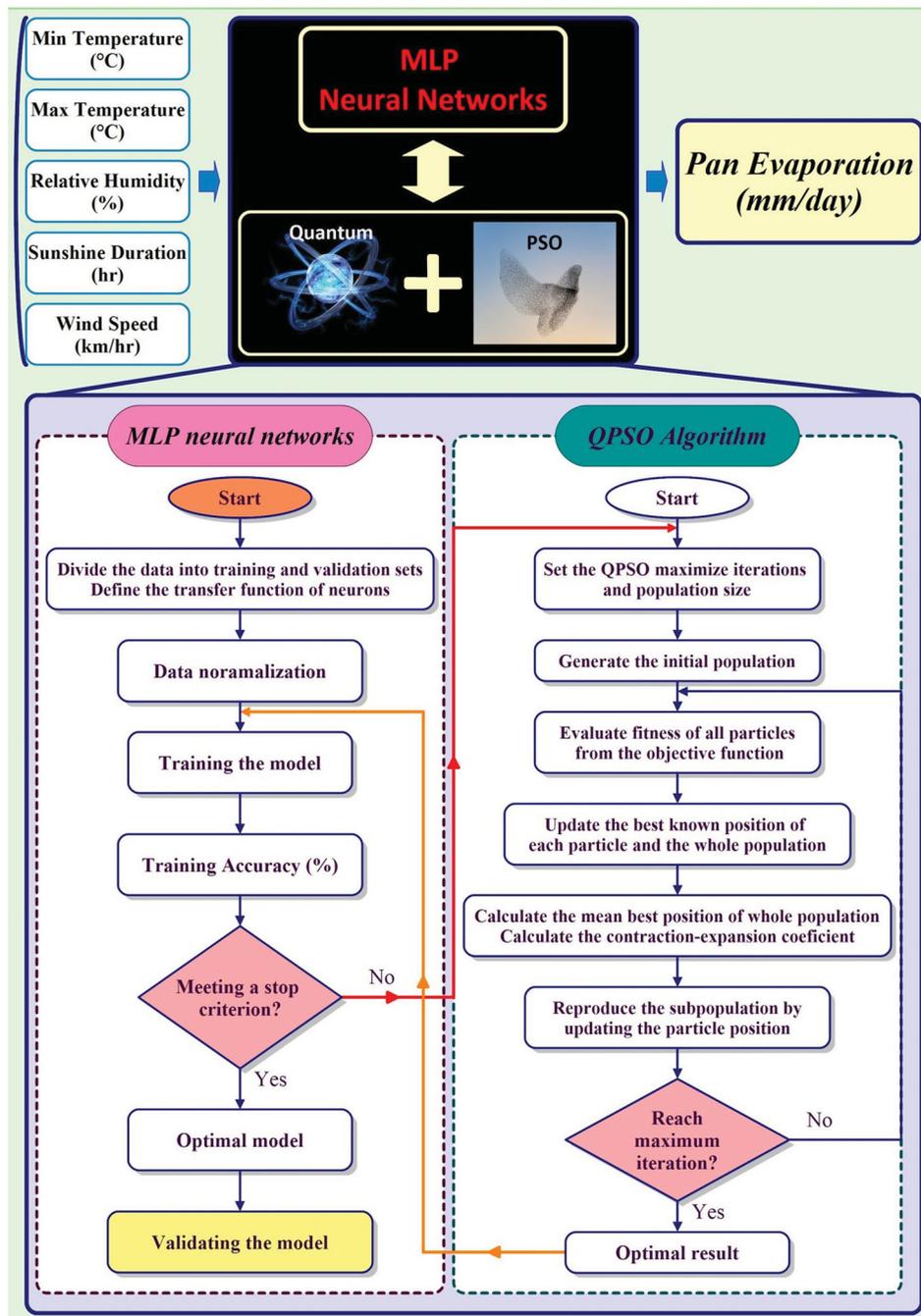


Figure 1. Flowchart of the proposed MLP-QPSO model structure.

Daily meteorological data from 2012 to 2014 were applied as the predictor (or the model input) variables. These data composed of a time-series of maximum temperature (T_{\max}) ($^{\circ}\text{C}$), minimum temperature (T_{\min}) ($^{\circ}\text{C}$), wind speed (WS) (km hr^{-1}), sunshine hours (SSH), mean relative humidity (RH) (%), while the objective variable modeled by the hybrid MLP-FFA model was the daily pan evaporation (E_{pan}) (mm day^{-1}) (Ghorbani et al., 2018; Wintle et al., 2003) The development of the hybrid predictive model required an appropriate separation of the measured

meteorological data into two different groups via: the training set (which had a total of 822 records or 75% of the entire dataset) and the testing subsets (which had an overall of 274 records or 25% of the entire dataset).

Table 1 shows the training and testing data for Talesh meteorological station. It is evident that the maximum temperature and sunshine hours are considered as the primary variables that are likely to carry the most significant predictive features used for forecasting the daily pan evaporation data for this study region.

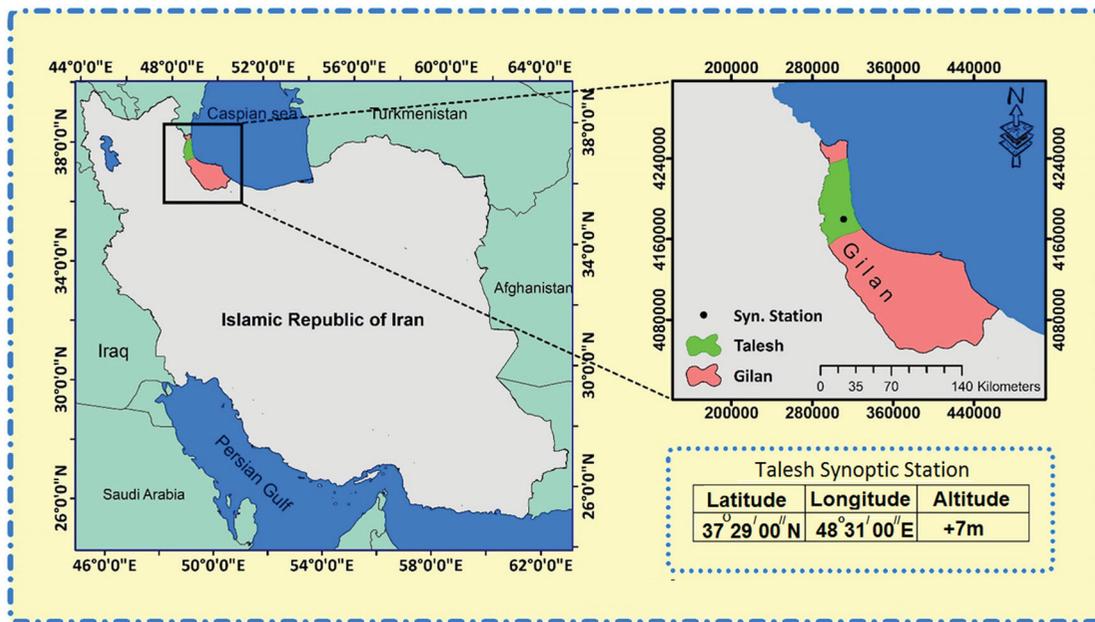


Figure 2. Geographic location of the Talesh meteorological station.

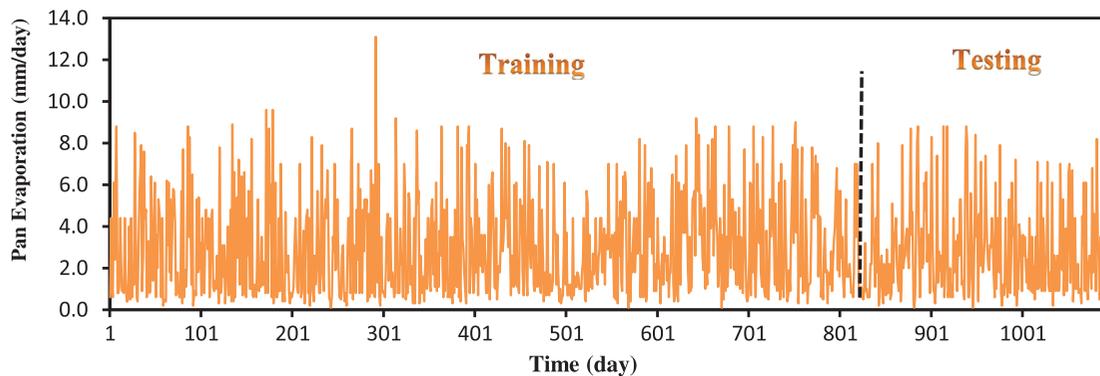


Figure 3. Variation of the daily evaporation time-series for the period 2012-2014 depicting the training and testing datasets.

2.5. Predictive model development

In order to construct an accurate hybrid MLP-QPSO model, a total of 6 different input combinations of the predictor variables (related to the problem of forecasting daily pan evaporation), comprised of the maximum and minimum air temperatures, wind speed, mean relative humidity and sunshine hours, were considered (Table 2). The order of properly incorporating each predictor variable into the inputs defined by the former variable was distinguished in harmony with a sensitivity test (i.e. correlation coefficients) of the predictors with the target variable (Table 1). All predictive models were assessed subsequently. To evaluate the accuracy of the compatibility of different input variables with the model's forecasting reply, the order of inputs for the hybrid MLP-QPSO and the counterpart comparative models (i.e. MLP-PSO and the standalone MLP) was kept identical.

All forecasting models were firstly designed with an MLP model and then improved with the QPSO algorithm, under the MATLAB programming software (Inc, 2015). Prior to the modeling process, the datasets were normalized to be between [0, 1] to ensure that the larger numeric attributes within the predictor variable do not dominate the importance of the features provided by those of smaller numeric ranges (Hsu, Chang, & Lin, 2003; Lin & Lin, 2003). As an extensively applied procedure in neural networks, the current MLP method was applied with a back propagation feed forward training procedure, and a linear transfer and a logarithmic sigmoid function, in the output and hidden layer, respectively. An extensive model optimization process was also implemented whereby the best neuronal architecture and model weights for optimal feature extraction from the predictor datasets were attained by a trial and error process following earlier work (Deo & Şahin, 2015a).

Table 1. Summary statistics of the used data at Talesh weather.

Data Partition	Statistics	Predictor Variables					Objective Variable
		T_{\max} (°C)	T_{\min} (°C)	RH (%)	WS (km hr ⁻¹)	SSH (Wintle, et al.)	E_{pan} (mm day ⁻¹)
All data	Standard deviation	8.2	7.3	11.9	2.5	4.1	2.3
	Maximum	37.0	32.0	99.0	28.0	12.6	13.1
	Minimum	-0.4	-4.2	19.0	2.0	0.0	0.1
	Correlation Coefficient with E_{pan}	0.74	0.61	-0.63	0.18	0.71	1.00
Training	Standard deviation	8.2	7.2	12.3	2.7	4.1	2.3
	Maximum	37.0	26.0	99.0	28.0	12.6	13.1
	Minimum	-0.2	-4.2	19.0	0	0	0.1
	Correlation Coefficient with E_{pan}	0.76	0.62	-0.65	0.20	0.72	1.00
Testing	Standard deviation	7.9	7.4	10.8	2.0	4.0	2.2
	Maximum	35.0	32.0	99.0	23.0	12.2	8.8
	Minimum	-0.4	-3.0	44.0	0.0	0.0	0.1
	Correlation Coefficient with E_{pan}	0.70	0.59	-0.55	0.08	0.69	1.00

Table 2. The different input combinations and model designations used in this study.

No.	Input	Output	Models		
			MLP	MLP-PSO	MLP-QPSO
1	$T_{\max}, T_{\min}, \text{RH}, \text{WS}, \text{SSH}$	E_{pan}	MLP1	MLP-PSO1	MLP-QPSO1
2	$T_{\max}, T_{\min}, \text{RH}, \text{WS}$	E_{pan}	MLP2	MLP-PSO2	MLP-QPSO2
3	$T_{\max}, \text{WS}, \text{RH}, \text{SSH}$	E_{pan}	MLP3	MLP-PSO3	MLP-QPSO3
4	$T_{\max}, T_{\min}, \text{RH}$	E_{pan}	MLP4	MLP-PSO4	MLP-QPSO4
5	T_{\max}, WS	E_{pan}	MLP5	MLP-PSO5	MLP-QPSO5
6	T_{\max}	E_{pan}	MLP6	MLP-PSO6	MLP-QPSO6

In this paper, we aimed to attain an optimal forecast model by setting the network training parameters accordance to previous research works (Deo & Şahin, 2017; Prasad, Deo, Li, & Maraseni, 2017). Notwithstanding this, a noteworthy point in the experimental design is also that we have used the LM learning procedure (i.e. one of the most general algorithm applied to train a neural network model). The notion of using this algorithm has been advocated in previous studies (Tiwari & Adamowski, 2013; Tiwari & Chatterjee, 2010, 2011) by virtue of its relatively faster execution time (i.e. computational efficiency) and superior training performance.

In a study by (Deo, Kisi, & Singh, 2017), the LM method was applied to forecast drought index through an ANN model, demonstrating it as a well-established tool. Implemented as a second-order training rule, this learning method was able to minimize the mean square error between the forecasted and observed data in the training period. It is pertinent to also mention that the neurons in hidden layer were recognized by trial and error process. This is approach is an acceptable norm, in accordance with other studies (Deo & Şahin, 2015b, 2017; Deo, Tiwari, Adamowski, & Quilty, 2017; Prasad et al., 2017) for selecting the best model with lowest mean square error in the training dataset.

2.6. Model performance criteria

Performance measures are assessed by comparing predicted with their corresponding observed values using

the following criteria: I: Nash–Sutcliffe coefficient (NS) (Nash & Sutcliffe, 1970), written as

$$NS = 1 - \frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (O_i - \bar{O}_i)^2}, \quad -\infty < NS \leq 1 \quad (5)$$

II: Root mean square error (RMSE) (Willmott & Matsuura, 2005) written as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2} \quad (6)$$

III: Mean absolute error (MAE) (Chai & Draxler, 2014) written as

$$MAE = \frac{1}{N} \sum_{i=1}^N |P_i - O_i| \quad (7)$$

IV: Willmott's Index of Agreement (Willmott, Robeson, & Matsuura, 2012; Wintle et al., 2003) written as

$$WI = 1 - \left[\frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (|P_i - \bar{O}_i| + |O_i - \bar{O}_i|)^2} \right], \quad 0 \leq WI \leq 1 \quad (8)$$

In all equations, O_i and P_i are the observed and forecasted i th value of the E_{pan} , \bar{O} is the average of observed O .

Other than the performance metrics outlined in Equations (10–13), we have also employed the Taylor diagram (Taylor, 2001) to explore its usage in current hydrological context.

3. Results and discussion

In Table 3 we provide the integrated hybrid MLP-QPSO (vs. MLP-PSO and MLP) model training performances as well as the performances in the evaluative phase (i.e. the testing period). Referring to the results of the testing period, it was evident that the MLP-PSO method was capable to estimate daily evaporation amounts more sufficient than the standalone MLP method. It was found that the model error was lower and also Willmott's Index and Nash-Sutcliffe's coefficients were the largest for the developed PSO-based model. As reported by Table 3, the model marked as MLP3 where T_{\max} , T_{\min} , RH and WS data were used could be chosen as the optimal and the most favorable model for the Talesh station. This was also indicated for all models where a progressive extension of all predictors' variable inspire a slowly growth in the amount of the WI and NS , and reduce in $RMSE/MAE$ (Tables 2 and 3. In the face of the similar tendency for the standalone MLP and the hybrid MLP-PSO models, the efficiency of the MLP-PSO hybrid model was much better than the standalone MLP method.

With an inclusive objective to enhance the predictive correctness of the MLP method, the more advanced, integrated MLP-QPSO modeling procedure was assessed. Optimum weights of the MLP method was recognized by the novel Quantum-Behaved Particle Swarm Optimization algorithm. According to Table 3, the model represented as MLP-QPSO3 showed the smallest amount

of MAE (0.521 mm day⁻¹) and $RMSE$ (0.755 mm day⁻¹) and the highest amount of NS (0.882) and WI (0.963) in the test period compared to any other model for the station of Talesh. Such an optimum model, the most appropriate neuronal architecture has 4 input layer neurons, 4 hidden layer neurons, and 1 output layer neuron (denoted as 4-4-1).

Attained by means of rigorous a trial-and-error procedure, Table 3 shows the optimal neuronal arrangement in the single hidden layer of each model, which remains unique to a particular designated model. It is noteworthy that the optimal number of neurons was recognized in a trial and error practice (e.g. Deo & Şahin, 2015a) to select a method that reached the lowest $RMSE$ in the competent dataset. It is important to note that training $RMSE$ is a popular metric, providing a balanced evaluation of the goodness of fit of the developed model. For a perfect method, $RMSE$ value is expected to be near to zero (Table 3). Accordingly, the model designated as MLP3 for all three types of algorithms (i.e. standalone, MLP-PSO and MLP-QPSO) is seen as a better performing model among all 6 model structures based on the $RMSE$, MAE , NS and WI (i.e. 1.099 mm day⁻¹, 0.833 mm day⁻¹, 0.789 and 0.934, respectively) for the training dataset. Likewise, the table presents these values for the best model in the test dataset with $RMSE = 1.303$ mm day⁻¹, $MAE = 0.921$ mm day⁻¹, $NS = 0.646$ and $WI = 0.878$, respectively).

In spite of the internal consistency between training and testing sets among different designated models, it is generally true that the quality of the optimal model performance drops from the training to the testing phase and this is the case for all of the 6 model structures in accordance with each of performance metrics.

Table 3. The performance metrics in the training and testing phases for the station of Talesh. Units for $RMSE/MAE$ ((mm day⁻¹) and neuronal architecture is denoted as per input-hidden-output neurons. Optimal model is shown in **boldface**.

	Model Designation	Neuronal Structure	Training				Testing			
			RMSE	MAE	NS	WI	RMSE	MAE	NS	WI
Standalone Model	MLP1	5-2-1	1.106	0.836	0.777	0.932	1.356	0.932	0.621	0.873
	MLP2	4-20-1	1.196	0.870	0.740	0.925	1.511	1.0422	0.5303	0.829
	MLP3	4-4-1	1.099	0.833	0.789	0.934	1.303	0.921	0.646	0.878
	MLP4	3-12-1	1.181	0.861	0.746	0.922	1.529	1.090	0.519	0.806
	MLP5	2-3-1	1.384	1.050	0.652	0.883	1.536	1.094	0.514	0.811
	MLP6	1-2-1	1.400	1.037	0.644	0.882	1.591	1.114	0.479	0.804
MLP-PSO hybrid model	MLP-PSO1	5-2-1	0.961	0.733	0.813	0.946	1.357	0.963	0.620	0.851
	MLP-PSO2	4-20-1	1.005	0.745	0.816	0.949	1.308	0.893	0.647	0.872
	MLP-PSO3	4-4-1	0.951	0.725	0.832	0.950	1.221	0.840	0.693	0.884
	MLP-PSO4	3-12-1	1.014	0.753	0.835	0.952	1.208	0.829	0.699	0.900
	MLP-PSO5	2-3-1	1.200	0.923	0.738	0.918	1.378	0.978	0.609	0.850
	MLP-PSO6	1-2-1	1.199	0.899	0.738	0.920	1.424	0.995	0.582	0.845
Hybrid MLP-QPSO Model	MLP-QPSO1	5-2-1	0.778	0.612	0.890	0.974	0.770	0.529	0.877	0.962
	MLP-QPSO2	4-20-1	0.798	0.636	0.884	0.972	0.802	0.552	0.867	0.956
	MLP-QPSO3	4-4-1	0.778	0.583	0.890	0.974	0.755	0.521	0.882	0.963
	MLP-QPSO4	3-12-1	0.864	0.677	0.864	0.968	0.850	0.594	0.851	0.949
	MLP-QPSO5	2-3-1	0.921	0.754	0.845	0.962	0.922	0.645	0.824	0.940
	MLP-QPSO6	1-2-1	0.972	0.783	0.828	0.959	0.937	0.653	0.819	0.939

It is imperative to mention that we have developed 3 sets of simulations (i.e. MLP, MLP-PSO and MLP-QPSO) with several different neuronal structures for each predictive model considered to investigate the performance of the stochastic algorithm. In each case, we followed

the notion of earlier works (e.g. Deo et al., 2016; Deo & Şahin, 2015a, 2015b) where, initially several MLP models were developed with different neuronal architectures and finally, the best model that yielded the smallest *RMSE* was selected. The comparison results indicate that different

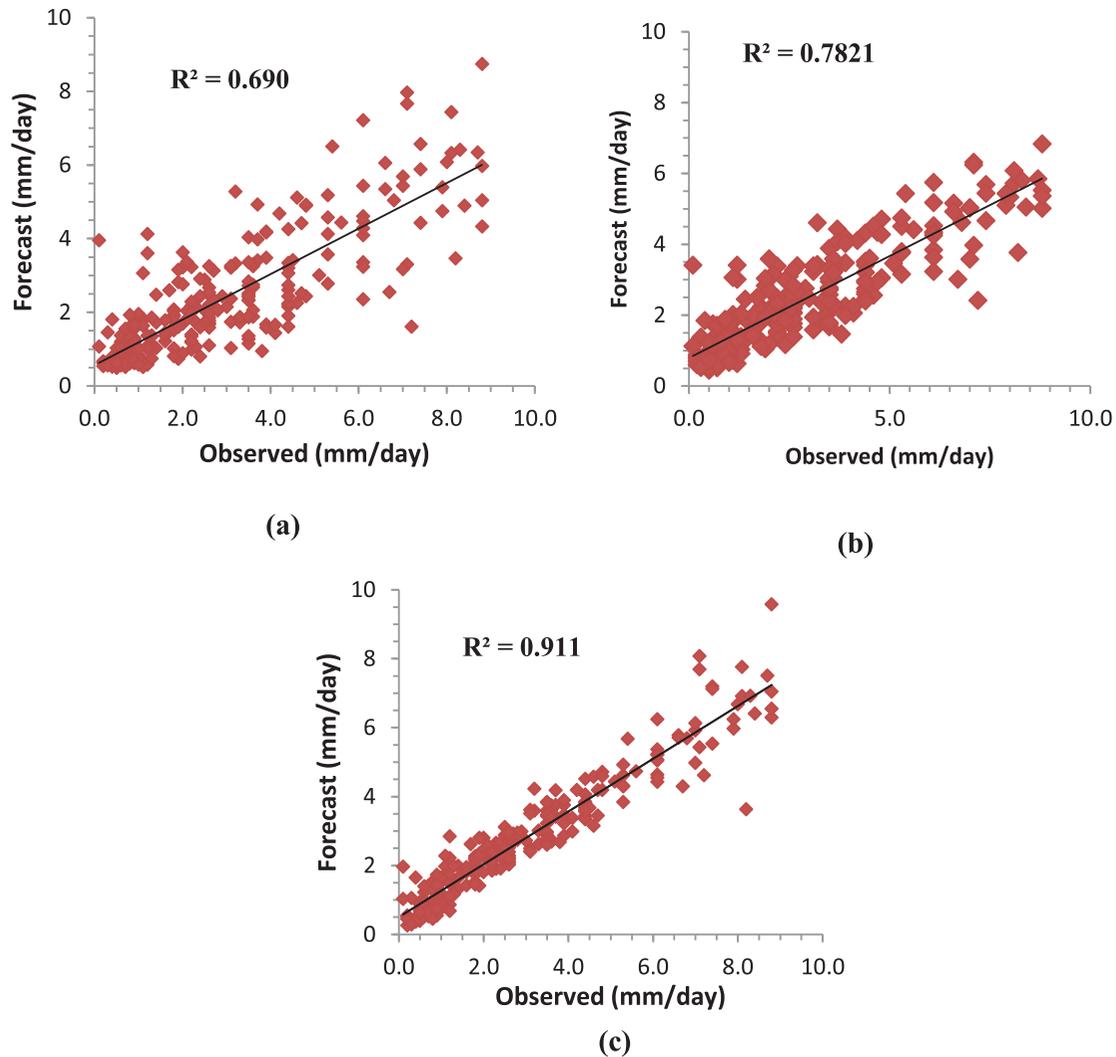


Figure 4. A scatterplot of the forecasted and observed pan evaporation for Talesh station, presented in the testing phase for the optimal hybrid MLP-QPSO model (MLP-QPSO3) relative to the MLP-PSO3 and the standalone MLP3 model. In each panel, the line of best fit with coefficient of determination (R^2) has been included, (a) MLP3; (b) MLP-PSO3; (c) MLP-QPSO3.

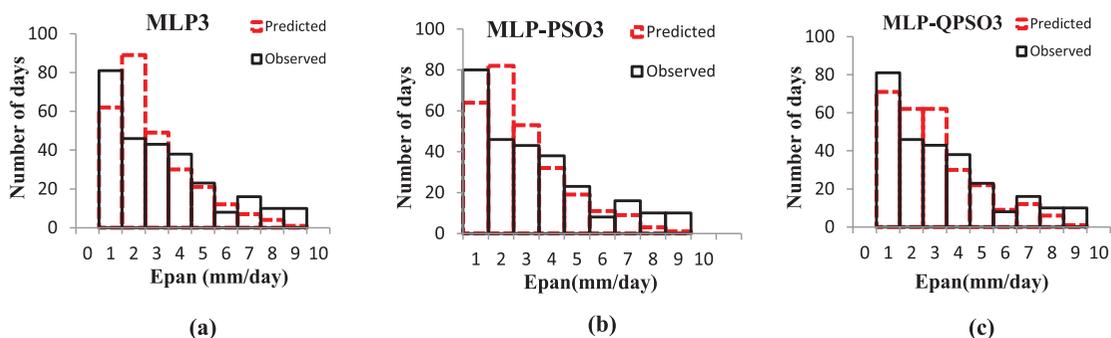


Figure 5. Histogram of the forecasted pan evaporation data in the testing phase, (a) MLP3; (b) MLP-PSO3; (c) MLP-QPSO3.

input combination were attained for the MLP model, as shown in Table 3.

The scatterplots comparing the observed and estimated daily pan evaporation at Talesh weather stations are presented in Figure 4.

Figure 4 reveals that the exactitude of the hybrid MLP-QPSO method was found to be significantly better than the comparative standalone MLP and MLP-PSO hybrid method. The results indicated a lower level of the scattered in the data forecasted-observed data pairs, with a larger magnitude of the R^2 value and a more appropriate fit of the forecasted outcomes compared with the experimental data based on the 1:1 agreement line. Finally, it was distinguished that present results justify the importance of the QPSO as an optimization algorithm in the present case study, bringing an improved calibration of the MLP method with a superior performance in the testing dataset.

More rapidly test of the forecasted and the experimental values of daily evaporation produced by the MLP-QPSO, MLP-PSO and MLP methods are illustrated in Figure 5. Here the histograms represent the possibility scattering of the data within the practical time for the 3 models with their optimal input combination, as indicated in Table 3. These figures are very advantageous for representing the possibility incident of the pan evaporation value contained by a specific interval, which accords with earlier works (e.g. Al-Shammari et al., 2016) Obviously, as stipulated in Figure 5, the analyzing data have been grouped in different classes with 1 (mm day^{-1}) interval. Notably, the highest differences are for interval of 2–4 mm day^{-1} . Also, the histograms show a similar pattern with negatively skewed distribution and the performances are seen to be relatively better at the tail of the histogram, indicating the results with under-estimated pan evaporation in the testing phase.

Figure 6 shows the Taylor diagram of the used models.

Consequently, a forecasting ideal method (with higher agreement with explanations) is noticeable by the orientation point with a correlation coefficient equal to 1, and the same fullness of variations compared to the observation data (Heo et al., 2014). The integrated hybrid MLP-QPSO method significantly produced evaporation predicted results much nearby the experimental evaporations compared to the hybrid MLP-PSO and the standalone MLP method.

In view of the Taylor plot closely, it was revealed that in both panel of results, the hybrid MLP-QPSO outcomes (where a standalone MLP procedure had been integrated with a QPSO as an optimizer tool), has a better result such that a correlation coefficient is approximately 0.95. More interesting is also to note that the root mean square error (represented by the brown points contour lines) for

the hybrid MLP-QPSO model is noticeably lower (< 1.0) as the data for these methods are bundled within this group. Besides, MLP method within the QPSO optimizer algorithms, the hybrid MLP-QPSO3 method where the inputs are defined by T_{\max} , RH , WS and SSH (Table 2) stands out as the best forecasted method in consistent with outcomes.

Finally, Figure 6 also shows that the proposed hybrid MLP-QPSO model provides a significant improvement in the model's overall performance such that the performance may be ranked in order of MLP-QPSO, MLP-PSO and MLP as the best, moderate and worst models, respectively for the present case study area.

4. Conclusion and future research work

A forecast model for daily pan evaporation can be an important decision-support tool in water engineering, agriculture, rural and urban water systems, water policy planning and design of hydrologic structures (e.g. dams or irrigations). The incorporation of an optimizer algorithm where a standalone artificial intelligence model is integrated with a global search algorithm to deduce optimal model's internal parameters, and consequently improving the overall predictive performance, is gaining prominence in hydrologic research. In the present research, the hybrid artificial intelligence procedure based on a multi-layer perceptron framework incorporated with the MLP-QPSO procedure, was established and evaluated for its preciseness in the estimation of daily pan evaporation. For a specific case study region in Northern Iran, the present study has utilized key meteorological parameters including the maximum and minimum temperature, sunshine hours, relative humidity, and wind speed datasets as the predictor variables. Besides this, the predictive ability of the developed hybrid method (i.e. the MLP-QPSO model) was evaluated and compared to a standalone MLP and a hybrid MLP-PSO model. The findings of the present study showed a much improved accuracy of the hybrid MLP-QPSO model in respect to a hybrid MLP-PSO and a standalone MLP model applied in the context of daily pan evaporation.

In the first phase of the forecasting model development, a standalone MLP method was used with the back propagation feed forward approach and the hybrid MLP-PSO method with the smallest root mean square error, was developed. In the next phase, a QPSO procedure was applied to the MLP to improve the model's training accuracy by optimizing the models internal parameters (or hidden neuron weights and biases). In the statistical evaluative phase of the hybrid and standalone model design, the statistical error metrics and other performance parameters were examined in the testing

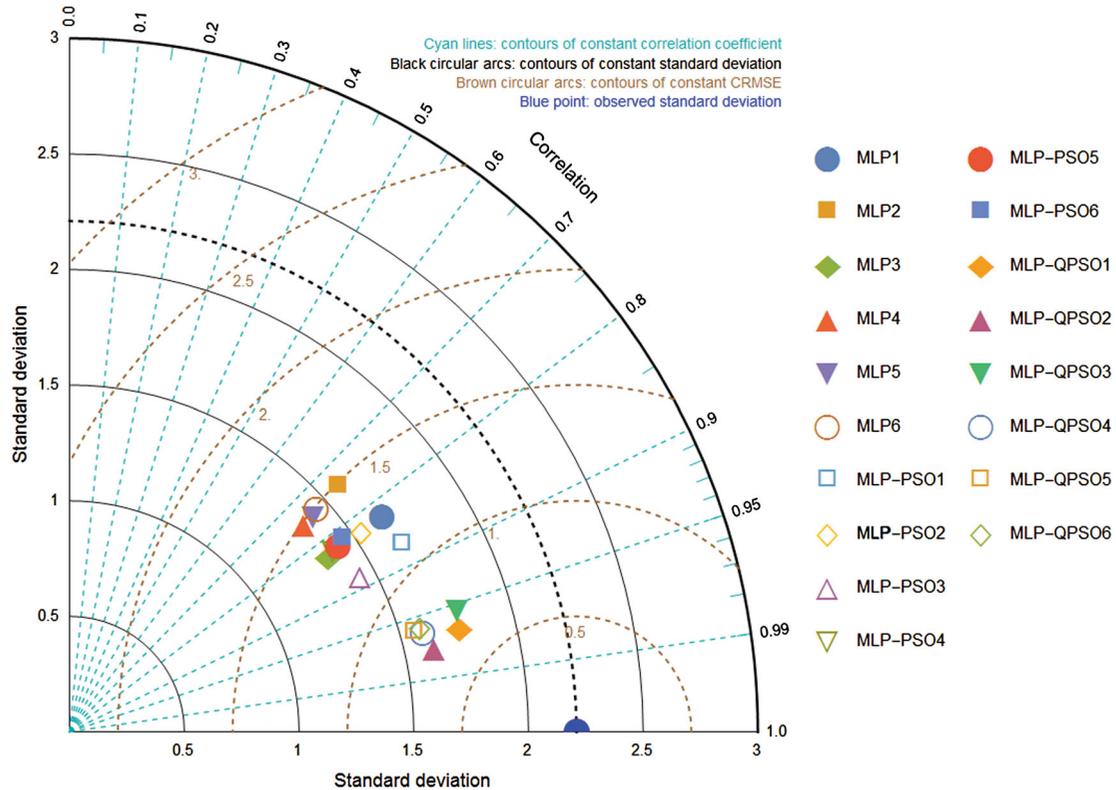


Figure 6. Taylor Diagram comparing a total of 18 predictive models developed for forecasting evaporation of the pan of Talesh station in experimental time. For model designations, readers should see Table 3.

phase to investigate the ability of the model to forecast daily evaporation in the independent testing dataset.

Evaluated over a relatively large list of 18 predictive models developed in this paper, the results confirmed superior ability of the integrated hybrid MLP-QPSO method in comparison with lower accuracy of the standalone MLP and the hybrid MLP-PSO model. Despite a high level of accuracy attained by integrated hybrid MLP-QPSO method relative to the counterpart models, this study does carry some degree of limitations that has created an opportunity for a follow-up research work. In real-time applications, use of these models in decision-making process can be practically appealing if the developed models incorporate some degree of confidence level of the error bounds generated by the simulations, mainly to overcome the lack of understanding on how accurate a forecasted evaporation value could be. Therefore, in-depth studies are thus warranted to address the issues of uncertainty in the forecasted evaporation data which can no doubt assist range of stakeholders (e.g. water resource managers; irrigation managers; farmers, etc.) to avoid decisions linked to over-confident projections and about certain inferences that could be risky due to their decisions. It should also be highlighted that an operational application of the integrated hybrid MLP-QPSO model could be broadened by incorporating the model into

a Bayesian Model Averaging (BMA) algorithm, which is able to assess the model selection uncertainty (Kim, Mohanty, & Shin, 2015; Rathinasamy, Adamowski, & Khosa, 2013; Wintle et al., 2003). The integration of the BMA with the integrated hybrid MLP-QPSO model could lead provide a more coherent mechanism for accounting for the model's uncertainties.

Although in this study we have utilized the fully-optimized, integrated hybrid MLP-QPSO algorithm by constructing a model with a set of best model parameters, an ensemble modeling approach, as applied in previous studies (Efron & Tibshirani, 1994; Tiwari & Adamowski, 2013; Tiwari & Chatterjee, 2010) may also assist in improving the hybrid model, particularly evaluated for its parametric uncertainties (Kim, Mohanty, et al., 2011; Tiwari & Adamowski, 2013). Moreover, issues related to the non-stationarities in the climate datasets, applied as the model inputs, can also be addressed in a separate study by testing the present hybrid model with innovative multi-resolution data pre-processing tools that provide better resolved frequencies that are present within the input dataset. In this regard, the development of an integrated hybrid MLP-QPSO model embedded with empirical mode decomposition (EMD) and non-decimated discrete wavelet transform algorithm (Prasad et al., 2017) can help improve the practical relevance of

the hybrid MLP-QPSO model. Finally, to enhance the practicality of the approach, a follow-up study, one could also consider utilizing several other test locations (subject to the availability of such data) to validate the proposed MLP-QPSO method.

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No potential conflict of interest was reported by the authors.

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