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Research paper

Support Vector Machine and Neural Network based Model for Monthly Stream Flow Forecasting

Nuratiah Zaini[1] *, Marlinda Abdul Malek[2], Marina Yusoff[3], Siti Fatimah Che Osmi[4], Nurul Hani Mardi[5], Shuhairy Norhisham[6]

[1] *Department of Civil Engineering, Universiti Tenaga Nasional, 43000 Kajang, Selangor, Malaysia*
[2] *Institute of Sustainable Energy, Universiti Tenaga Nasional, 43000 Kajang, Selangor, Malaysia*
[3] *Institute for Infrastructure Engineering and Sustainable Management, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia*
[4] *Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia*
**Corresponding author E-mail: Nur_Atiah@uniten.edu.my*

Abstract

Accurate forecasting of streamflow is desired in many water resources planning and management, flood prevention and design development. In this study, the accuracy of two hybrid model, support vector machine - particle swarm optimization (SVM-PSO) and bat algorithm – backpropagation neural network (BA-BPNN) for monthly streamflow forecasting at Kuantan River located in Peninsular Malaysia are investigated and compared to regular SVM and BPNN model. Heuristic optimization namely PSO and BA are introduced to find the optimum SVM and BPNN parameters. The input parameters to the forecasting models are antecedent streamflow, historical rainfall and meteorological parameters namely evaporation, temperature, relative humidity and mean wind speed. Two performance evaluation measure, root mean square error (RMSE) and coefficient of determination (R^2) were employed to evaluate the performance of developed forecasting model. It is found that, RMSE and R^2 for hybrid SVM-PSO are 24.8267 m^3/s and 0.9651 respectively while general SVM model yields RMSE of 27.5086 m^3/s and 0.9305 of R^2 for testing phase. Besides that, hybrid BA-BPNN produces RMSE, 17.7579 m^3/s and R^2, 0.7740 while BPNN model produces lower RMSE and R^2 of 28.1396 m^3/s and 0.5015 respectively. Therefore, the results indicate that hybrid model, SVM-PSO and Bat-BPNN yield better performance as compared to general SVM and BPNN, respectively in streamflow forecasting.

Keywords: *Bat algorithm; Forecasting; Optimization; Streamflow; Support vector machine*

1. Introduction

Application of artificial intelligence (AI) technique is an essential approach in streamflow forecasting. The accuracy and reliability of the forecasting model is desired for water resources planning and management, flood prevention and design development. Streamflow is known as multidimensional and highly nonlinear nature, therefore forecasting accurate streamflow is very challenging [1, 2, 3]. In the past few decades, there are various application of AI in streamflow forecasting, for instance, artificial neural network (ANN) [4, 5, 6], fuzzy logic [7, 8], genetic programming (GP) [9, 10, 11], support vector machine [12, 13, 14, 15] and hybrid model [16, 17, 18, 19].
ANN has the ability of mapping nonlinear data and found to be a reliable method for streamflow forecasting as it able to learn and generalize non-linear time series data [20, 21, 22]. Besides that, SVM based on statistical learning theory that employed structural risk minimization principle has the advantage to compute large nonlinear time series data. Previous study stated that SVM can avoid underfitting and overfitting in ANN and very convenience to many researchers [1, 2, 23].
One of the popular method in ANN called BPNN is use in this study. General BPNN and SVM forecasting model is found to have drawbacks during the learning process and the performance of the models depending on the choice of parameters [1, 18, 24]. To find the optimum parameters is time consuming and there is no rigid guideline to define the parameters [24]. Therefore, metaheuristic method is introduced in this study as an optimization tool to find the optimum parameter for BPNN and SVM called particle swarm optimization and bat algorithm [1]. Particle swarm optimization (PSO) is a heuristic technique travels out the search space and find out the optimum parameter of SVM [2]. Another efficient optimization algorithm is Bat algorithm (BA) proposed by Yang, (2010) [25]. BA is based on echolocation capability of microbats that guide them to find their food [26, 27].
Various study on implementation of SVM-PSO can be found in literature such as Sudheer et al., [2] studied forecasting of streamflow considering streamflow and rainfall as the input parameters, Wang et al. [28] conducted rainfall forecasting and Xuan et al. [29] studied forecasting of water quality. At present, there are small number of applications of BA in streamflow forecasting. However, BA is successfully implemented in other field such as price forecasting [24, 26], output power prediction [30] and optimization [31, 27].
This study focuses on the application of support vector machine and neural network based model to forecast monthly streamflow for the study dataset at Kuantan River, Peninsular Malaysia. Monthly dataset used in this study consist of antecedent streamflow data, historical rainfall data and meteorology parameters namely evaporation, temperature, relative humidity and mean wind speed. The performance of general SVM and ANN forecast-

ing models then being compared to hybrid SVM-PSO and BA-BPNN, respectively.

2. Support Vector Machine

Support vector machine (SVM) is a machine learning methodology based statistical learning theory was first developed by Vapnik, (1995) [32, 2]. SVM implements structural risk minimization (SRM) that able to minimize empirical and confidence interval of the learning machine to attain good generalization capability [33, 23]. Besides that, SVM was a promising technique for classification and regression [34, 2]. Assume that, N training data $[(x_1, y_1), (x_2, y_2), \ldots.(x_N, y_N)]$, where $N = 1,2,\ldots,N$, where N is the size of training data, x is the input, y is the output. SVM solves optimization problem based on sequential minimal optimization (SMO):

Minimize $$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i') \quad (1)$$

subject to $$\begin{cases} y_i - (w\phi(x_i) + b) \le \varepsilon + \xi_i \\ (w\phi(x_i) + b) - y_i \le \varepsilon + \xi_i' \\ \xi_i, \xi_i' \ge 0 \qquad i = 1,2,\ldots,l \end{cases}$$

where ξ_i and ξ_i' are slack variables, indicating upper and lower training errors.

Parameter C, the width of the tube controls the regression quality and ε is the tube size and equivalent to the approximation accuracy placed on training dataset. The most kernel function, radial basis function (RBF) was decided to use in this study [23, 2]. The equation can be derived as,

$$K(x_i, x) = exp(-\gamma|x_i - x|^2) \quad (2)$$

where x_i represent the ith support vector and x is input vector. □ is RBF parameter which gives the width of the kernel. SVM model developed in this study is standard SVM that has three mutually dependent parameter C, ε and γ [2, 35].

3. Backpropagation Neural Network

BPNN is based on layered feed forward ANN, organized in layers that consist of three different layers. BPNN algorithm is implements to reduce the error until ANN learns the training data. The training is starts with random weights and BPNN used to adjust the weights to minimize the error [36]. A basic three-layered feedforward neural network includes other elements namely nodes and connection pathway to connect them. As neural network method is based on biological neural network of the human brain, the nodes are called neurons which is to process the elements of the network [37]. Fig. 1 illustrates standard architecture of neural network.

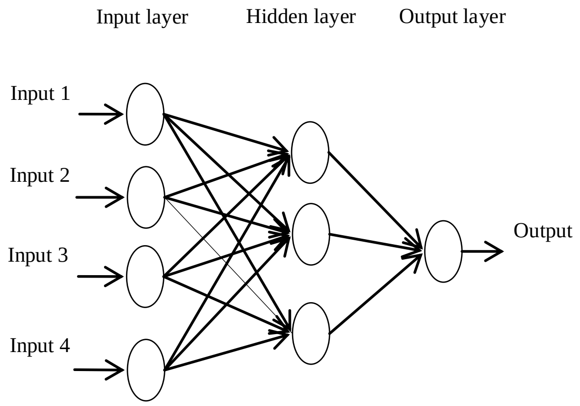

Fig. 1: Basic architecture of neural network

4. Metaheuristic Method

4.1. Particle Swarm Optimization

Particle swarm optimization (PSO) is an optimization technique is based on the metaphor of social behaviour. In an analogy, a swarm represent population while a particle is like an individual. The particles move through a multidimensional search space where the position of each particle is adjusted based on its own experience and neighbours [38]. In this study PSO is used to find optimum parameters of SVM, γ [2]. Changes of particle file to a new position by calculating the velocity corresponding to the equations, [38, 2]

Velocity,

$$v_{ij}(t) = [\omega v_{ij}(t-1) + c_1 r_1(pbest_{ij}(t-1) - x_{ij}(t-1) + c_2 r_2(gbest_j(t-1) - x_{ij}(t-1)] \quad (3)$$

Position,

$$x_{ij}(t) = x_{ij}(t-1) + v_{ij}(t) \quad (4)$$

where $v_{ij}(t)$ is the velocity of particles i in dimension $j = 1,\ldots,n_x$ at time step t, $x_{ij}(t)$ is the position of particles i in dimension j at time step t, c_1 and c_2 are positive acceleration constant, r_1 and r_2 are random numbers between 0 to 1 [2]. Next, ω represents the inertia weight to control the impact of velocity's history on the current value.

Flow chart of hybrid SVM-PSO architecture is demonstrated in Fig. 2. From the chart, the fitness function values are repetitively determined until meet the stopping criteria. In this study, the stopping criteria to stop the iterative search process is when the maximum allowable number of iterations reaches to 30 [39, 2]. The acceleration constant, c_1 and c_2 were set to 2.0 [2].

4.2. Bat Algorithm

Bat algorithm (BA) is inspired from search of bats to find their food. It is based on the echolocation behaviour of bats. The characteristic of echolocation is idealized from the following three rules [25]:

i. All bats practice echolocation to sense distance and able to identify the difference between food/prey and background barriers in some magical way.
ii. Bats fly randomly with velocity v_i at position x_i with a fixed frequency f_{min}, varying wavelength λ and loudness A_0 to seek for prey. They are able to adjust the wavelength/ frequency of their emitted pulse and the rate of pulse emission $r \in [0, 1]$ automatically depends on the proximity of their target.
iii. It is assumed that the loudness varies from a large (positive) A_0 to a minimum constant value A_{min} even though the loudness can be varied in many ways.

The new position x_i, frequency f_i and velocities v_i at time step t as in the equation below:

$$f_i = f_{min} + (f_{max} - f_{min})\beta \quad (5)$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*)f_i \quad (6)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (7)$$

where f_{min} and f_{max} are the pre-defined minimum and maximum frequencies, β is a random number between 0 and 1, v_i^{t-1} is the velocity of ith bat at iteration t - 1, x_i^{t-1} is the position of ith bat at iteration t - 1, x_* is the position of the best bat at this iteration. These three equations are applied to every bat [27, 25].

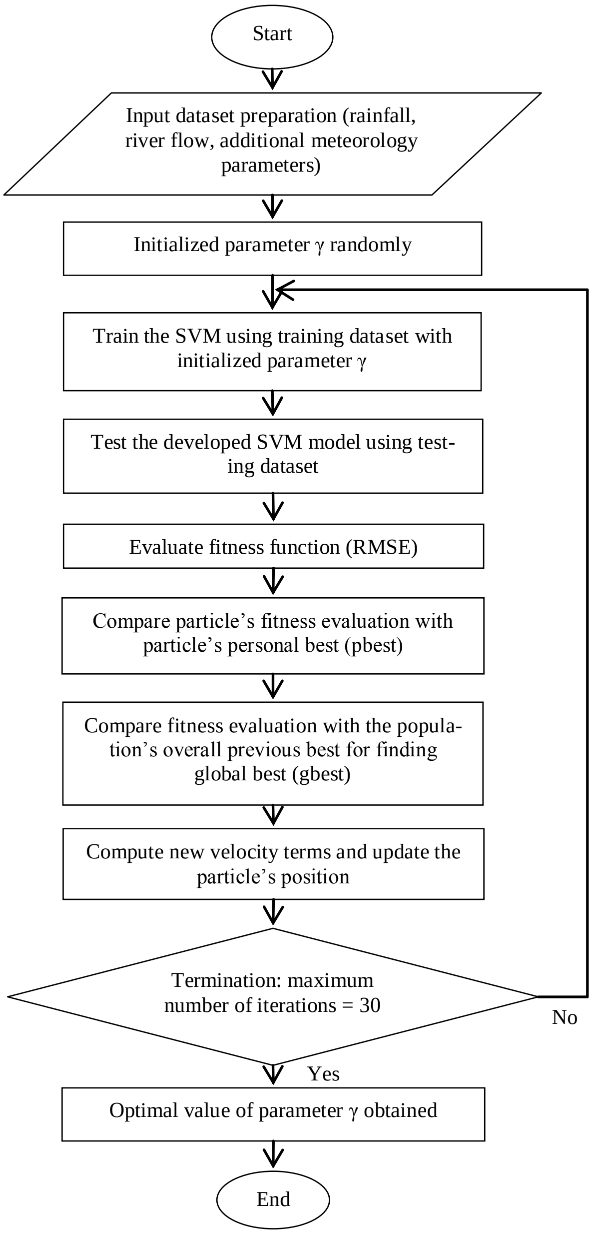

Fig. 2: Hybrid SVM-PSO architecture

A solution is selected among the current best solution for location search. New solution is generated locally using random walk [1, 30]

$$x_{new} = x_{old} + \theta A^t \quad (8)$$

where θ is random number between -1 to 1 and A^t is average loudness of all bats at time t.
The loudness, A_i usually decrease while the emission pulse rate, r_i increase once the prey is found. Therefore, A_i and r_i are updated based on the following equations [1, 30]

$$A_i^{t+1} = \alpha A_i^t \quad (9)$$

$$r_i^{t+1} = r_i^0[1 - exp(-\gamma t)] \quad (10)$$

where α is loudness decay factor and γ is pulse increase factor. Both parameters are constant and assumed to be equal, $\alpha = \gamma$. The value is set to 0.9 [1]. Flowchart of hybrid BA-BPNN as illustrated in Fig. 3.

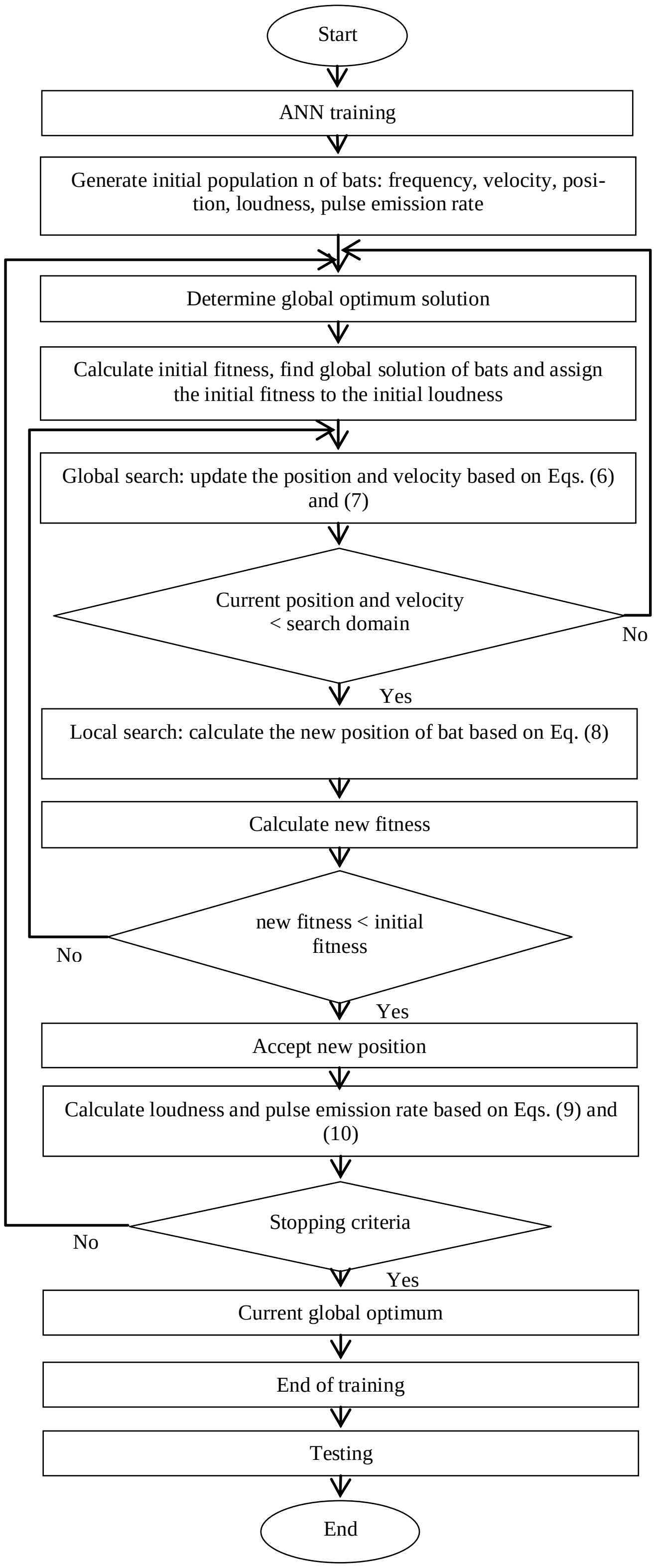

Fig. 3: Hybrid BA-BPNN architecture

5. Study Area and Dataset

5.1. Study Area

The study area is Kuantan River located in Peninsular Malaysia. Fig. 4 shows the study area and the location of streamflow and rainfall stations. Two rainfall station used namely Ldg. Kuala Reman station and Ldg. Nada station. Only one available streamflow station at the study area namely Sg. Kuantan station. This study also limited to data that only available at the study area.

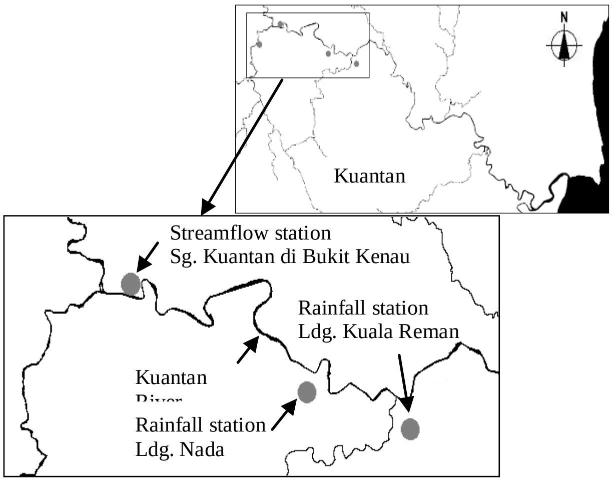

Fig. 4: Study area

5.2. Dataset

This study considered monthly historical rainfall data from two different rainfall stations at Kuantan River. In addition, monthly antecedent streamflow data and meteorology parameters namely evaporation, temperature, relative humidity and mean wind speed from 2008 to 2015 were used as the input parameters to the forecasting model. In the application, 70 percent of the total data were used for training and 30 percent were used for testing. Table 1 indicates the description of study dataset. It is important to normalize the dataset to avoid error that caused by magnitude. In this study, the dataset was normalized to [0, 1] implementing equation below,

$$x' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{11}$$

where *x'* is scaled value, dimensionless; x_i, x_{min} and x_{max} represent actual data, minimum and maximum value of the dataset respectively.

Table 1: Study dataset

Variable	Dataset	
	Training	Testing
1. Rainfall 2. Streamflow 3. Meteorology parameter i. Evaporation ii. Maximum temperature iii. Minimum temperature iv. Mean wind speed v. Relative humidity	70% (67 months)	30% (29 months)

5.3. Performance Measure

The performance of the model in streamflow forecasting are evaluated using standard statistical performance evaluation namely root mean square error (RMSE) coefficient of determination (R^2) which are defined respectively from equation (10)-(11). RMSE measures the error between forecasted and actual data and R^2 evaluates how well the forecasted streamflow correlates with actual streamflow.

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(Q_t - \hat{Q}_t)^2} \tag{12}$$

$$R^2 = \frac{\left[\sum_{t=1}^{m}(Q_t - Q_{avg})(\hat{Q}_t - \hat{Q}_{avg})\right]^2}{\sum_{t=1}^{m}(Q_t - Q_{avg})^2 \times \sum_{t=1}^{m}(\hat{Q}_t - \hat{Q}_{avg})^2} \tag{13}$$

where Q_t and $\hat{Q}_t$ denote the actual and forecasted river flow at time *t*, respectively and *m* is the number of forecasts. While, Q_{avg} and $\hat{Q}_{avg}$ are the average value of observed and forecast river flow.

6. Result and Discussion

6.1. Comparison of Developed Forecasting Model

This study applied BPNN to forecast monthly streamflow for the study dataset at chosen study area. BPNN forecasting model is organized in three layer which are input, hidden and output layer. Therefore, the number of hidden layers was set to two and population count was set to 20 [26]. Then, SVM forecasting model are developed to compare with BPNN model. Radial basis function (RBF) kernel was used in SVM model and parameter gamma (γ) was set. In addition, another parameter in SVM which are C and ε were set to 1.0 and 0.001 respectively [2].

In order to highlight the efficiency of optimization method introduced, comparison of hybrid SVM-PSO and BA-BPNN model is then being focused. The purpose of PSO is to find the optimum value of SVM parameter (γ), also, BA is to determine optimum parameter for BPNN. For both PSO and BA, constant number of population and iteration were used. The population count is set to 20 and the iteration is 30 [1].

The performance of all foresting model is illustrated in Table 2. For training phase of forecasting, BPNN model yield RMSE of 28.7370 m^3/s and R^2 of 0.7014. The result from BPNN is found to be reliable as the accuracy of the model is 70% for training phase. However, BPNN yield the highest RMSE and lowest R^2 for testing phase which are 28.1396 m^3/s and 0.5015, respectively. Therefore, it is found that BPNN perform the least as compared to other forecasting models [1]. As compared the performance between BPNN and BA-BPNN, it is clear that hybrid BA-BPNN performed better forecasting as the model yield lower RMSE and reliable R^2 for both training (RMSE = 24.2422 m^3/s, R^2 = 0.6702) and testing phase (RMSE = 17.7597 m^3/s, R^2 = 0.7440). Besides that, general SVM model is compared to hybrid SVM-PSO model in streamflow forecasting. SVM yielded lower accuracy as compared to hybrid SVM-PSO model for both training and testing phase [2, 35]. The results tabulated in Table 2 show that for training phase, SVM-PSO yield lower RMSE (24.8267 m^3/s) as compared to SVM (29.6758 m^3/s) and SVM-PSO has higher correlation as compared to SVM model which are the value of R^2 is 0.7013 and 0.6279, respectively. Similar result is found for testing phase which SVM-PSO model performed better as compared to SVM model. RMSE and R^2 for SVM-PSO are 24.8267 m^3/s and 0.9651 while for SVM model are 27.5086 m^3/s and 0.9305, respectively. It is found that, in the optimization process, both BA and PSO efficiently effect the performance of both general SVM and BPNN as hybrid models yield better performance. Optimization technique iterates the number of analysis get optimum value of parameters to get optimum result of forecasting [2, 1, 35].

Table 2: Forecasting performance of developed model

Model	Training		Testing	
	RMSE	R^2	RMSE	R^2
SVM	29.6758	0.6279	27.5086	0.9305
SVM-PSO	**26.5588**	**0.7013**	**24.8267**	**0.9651**
BPNN	28.7370	0.7014	28.1396	0.5015
BA-BPNN	**24.2422**	**0.6702**	**17.7597**	**0.7440**

In addition, as compared between both hybrid model SVM-PSO and BA-BPNN for streamflow forecasting, from this study, it is found that BA-BPNN yield better RMSE as compared to SVM-PSO for both training and testing phase. However, SVM-PSO have higher R^2 for both training and testing phase as compared to BA-BPNN. Therefore, in this case, it is extremely hard to decide which hybrid model are more accurate to forecast streamflow, however the result from both models could be reliable as the models yield good performances.

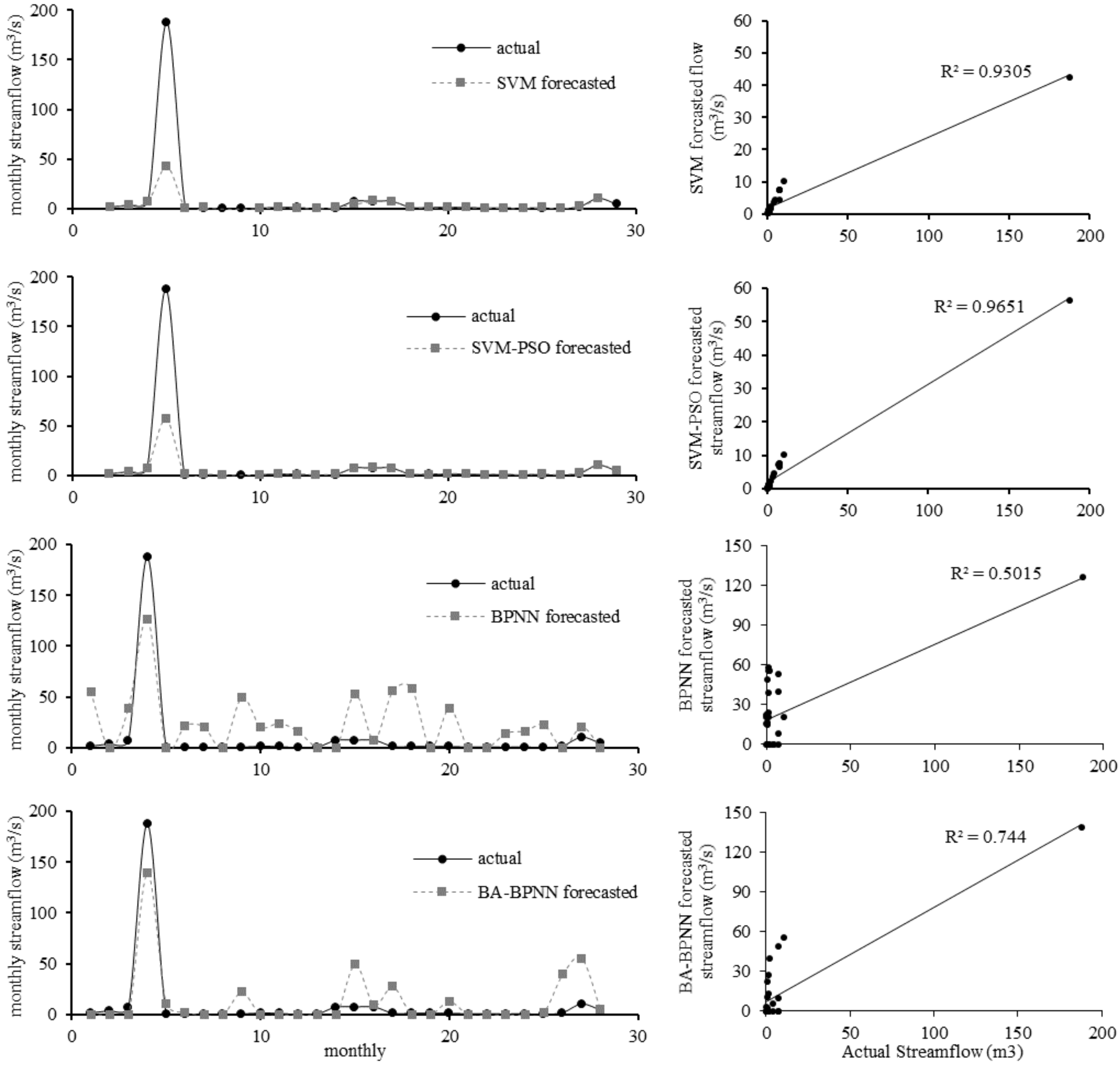

Fig. 5: Actual and forecasted monthly streamflow for testing phase by SVM, SVM-PSO, BPNN and BA-BPNN

7. Conclusion

In this study, four monthly streamflow forecasting models were developed which are BPNN, SVM, BA-BPNN and SVM-PSO. The performances of the models were compared to each other and discussed. From this study that using the study data set at chosen study area, it is found that hybrid model, BA-BPNN and SVM-PSO performed better as compared to general BPNN and SVM, respectively. Optimization method works effectively in determining the optimum value of parameters for SVM and BPNN resulting better performance of forecasting model. Then, this study purposely compared the performance of two hybrid forecasting models, SVM-PSO and BA-BPNN. However, in this study, it is hard to define which hybrid model performed better for streamflow forecasting. Therefore, it is recommended that to compare hybrid BA-SVM and BA-BPNN or BPNN-PSO and SVM-PSO in the next study.

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References

[1] B. Xing, R. Gan, G. Liu, Z. Liu, J. Zhang and Y. Ren, "Monthly Mean Streamflow Prediction Based on Bat Algorithm-Support Vector Machine," Journal of Hyrologic Engineering, vol. 21, no. 2, 2016.

[2] Sudheer, R. Maheswaran , B. K. Panigrahi and S. Mathur, "A Hybrid SVM-PSO Model for Forecasting Monthly Streamflow," Neural Computing and Application, vol. 24, pp. 1381-1389, 2013.

[3] R. Ramesan, M. A. Shamim, D. Han and J. Mathew, "Runoff prediction using an integrated hybrid modelling scheme," Journal of Hydrology, vol. 372, no. 1-4, pp. 48-60, 2009.

[4] S. M. Chen, Y. M. Wang and I. Tsou, "Using Artificial Neural Network Approach for Modeling Rainfall-Runoff due to Typhoon," Journal of Earth System Science, vol. 122, no. 2, pp. 399-405, 2013.
[5] C. Sivapragasam, S. Vanitha, N. Muttil, K. Suganya, S. Suji, M. T. Selvi, R. Selvi and J. S. Sudha, "Monthly flow forecast for Mississippi River basin using artificial neural networks," Neural Computing and Applications, pp. 1785-1793, 2014.
[6] D.-H. Lee and D.-S. Kang, "The Application of the Artificial Neural Network Ensemble Model for Simulating Streamflow," Procedia Engineering, vol. 154, pp. 1217-1224, 2016.
[7] K.-H. Wang and A. Altunkaynak, "Comparative Case Study of Rainfall-Runoff Modeling between SWMM and Fuzzy Logic Approach," Journal of Hydrologic Engineering, vol. 17, no. 2, pp. 283-291, 2012.
[8] Talei, L. H. C. Chua and C. Quek, "A Novel Of a Neuro-Fuzzy Computational Technique in Event-Based Rainfall-Runoff Modeling," Expert System with Applications, vol. 37, pp. 7456-7468, 2010.
[9] D. Mehr, E. Kahya and E. Olyaie, "Streamflow Prediction Using Linear Genetic Programming in Comparison with Neuro-Wavelet Technique," Journal of Hydrology, pp. 240-249, 2013.
[10] D. Mehr, E. Kahya and C. Yerdelen, "Linear genetic programming application for successive-station monthly streamflow prediction," Computer & Geoscience, pp. 63-72, 2014.
[11] D. A. K. Fernando, A. Y. Shamseldin and R. J. Abrahart, "Using Gene Expression Programming to Develop a Combined Runoff Estimate Model from Conventional Rainfall-Runoff Model Outputs," in 18th World IMACS / MODSIM Congress, Cairns, Australia, Cairns, 2009.
[12] H. Chu, J. Wei, T. Li and K. Jia, "Application of Support Vector Regression for Mid- and Long-term Runoff Forecasting in “Yellow River Headwater” Region," Procedia Engineering, vol. 154, pp. 1251-1257, 2016.
[13] J. Guo, J. Zhou, H. Qin, Q. Zou and Q. Li, "Monthly streamflow forecasting based on improved support vector machine," Expert System with Applications, pp. 13073-13081, 2011.
[14] C.-h. Hu, Z.-n. Wu, J.-j. Wang and Lina-Liu, "Application of the Support Vector Machine on Precipitation-Runoff Modeling in Fenhe River," in Water Resource and Environmental Protection (ISWREP), 2011 Intenational Symposium on, Xi'an, 2011.
[15] S. Londhe and S. S. Gavraskar, "Forecasting One Day Ahead Stream Flow Using Support Vector Regression," Aquatic Procedia, vol. 4, pp. 900-907, 2015.
[16] M. A. Ghorbani, R. Khatibi, A. D. Mehr and H. Asadi, "Chaos-based multigene genetic programming: A new hybrid strategy for river flow forecasting," Journal of Hydrology, vol. 562, pp. 455-467, 2018.
[17] G. B. Humprey, M. S. Gibbs, G. C. Dandy and H. R. Maier, "A hybrid approach to monthly streamflow forecasting: Integrating hydrological model outputs into a Bayesian artificial neural network," Journal of Hydrology, vol. 540, pp. 623-640, 2016.
[18] P. G. Nieto, E. Garcia-Gonzalo, J. A. Fernandez and C. D. Muniz, "Hybrid PSO-SVM-based method for long term forecasting of turbidity in the Nalon river basin: A case study in Nothern Spain," Ecology Engineering, pp. 192-200, 2014.
[19] V. Nourani, A. H. Baghanam, J. Adamowski and O. Kisi, "Applications of hybrid wavelet–Artificial Intelligence models in hydrology: A review," Journal of Hydrology, pp. 358-377, 2014.
[20] J. Veintimilla-Reyes, F. Cisneros and P. Vanegas, "Artificial Neural Networks Applied to Flow Prediction: A Use Case for the Tomebamba River," Porcedia Engineering, vol. 162, pp. 153-161, 2016.
[21] K. Kasiviswanathan, J. He, K. Sudheer and J.-H. Tay, "Potential application of wavelet neural network ensemble to forecast streamflow for flood management," Journal of Hydrology, vol. 536, pp. 161-173, 2016.
[22] W.-C. Wang, K.-W. Chau, C.-T. Cheng and L. Qiu, "A Comparison of Performance of Several Artificial Intelligence Methods for Forecasting Monthly Discharge Time Series," Journal of Hydrology, vol. 374, no. 3-4, pp. 294-306, 2009.
[23] G.-F. Lin, G.-P. Chen, P.-Y. Huang and Y.-C. Chou, "Support vector machine-based models for hourly reservoir inflow forecasting during typhoon-warning periods," Journal of Hydrology, pp. 17-29, 2009.
[24] P. Bento, J. Pombo, M. Calado and S. Mariano, "A Bat Optimized Neural Network and Wavelet Transform Approach for Shortterm Price Forecasting," Applied Energy, vol. 210, pp. 88-97, 2018.
[25] X.-S. Yang, "A New Metaheuristic Bat-Inspired Algorithm," in Natured Inspired Cooperative Strategies for Optimization (NICSO 2010), Poland, Springer, 2010, pp. 65-74.
[26] H. Dehgani and B. Dejan, "Copper Price Estimation using Bat Algorithm," Resource Policy, vol. 55, pp. 55-61, 2018.
[27] H. Banati and R. Chaudhary, "Multi-Modal Bat Algorithm with Improved Search (MMBAIS)," Journal of Computational Science, vol. 23, pp. 130-144, 2017.
[28] W.-c. Wang, D.-m. Xu, K.-w. Chau and S. Chen, "Improved Annual Rainfall-Runoff Forecasting Using PSO-SVM Model Based on EEMD," Journal of Hydroinfomatics, pp. 1377-1390, 2013.
[29] W. Xuan, L. V. Jiake and X. Deti, "A hybrid approach of support vector machine with particle swarm optimization for water quality prediction," The 5th International conference on computer science & education Hefei, China, pp. 1158-1163, 2010.
[30] M. K. Ramawan, Z. Othman , S. I. Sulaiman , I. Musirin and N. Othman, "A Hybrid Bat Algorithm Artificial Neural Network for Grid- Connected Photovoltaic System Output Prediction," in 2014 IEEE 8th International Power Engineering and Optimization Conference (PEOCO2014), Malaysia, 2014.
[31] M. A. Al-Betar, M. A. Awadallah, H. Faris, X.-S. Yang, A. T. Khader and O. A. Alomari, "Bat-inspired algorithms with natural selection mechanisms for global optimization," Neurocomputing, vol. 273, pp. 448-465, 2018.
[32] V. N. Vapnik, The nature of statistical learning theory, New Yok,USA: Springer, 1995.
[33] N. S. Raghavendra and P. C. Deka, "Support Vector Machine Application in the Field Hydrology: Areview," Applied Soft Computing, pp. 372-386, 2014.
[34] V. N. Vapnik, Statistical learning theory, New York: Wiley, 1998.
[35] N. Zaini, M. A. Malek, M. Yusoff, N. H. Mardi and S. Norhisham, "Daily River Flow Forecasting with Hybrid Support Vector Machine – Particle Swarm Optimization," in IOP Conf. Series: Earth and Environmental Science, Malaysia, 2018.
[36] Gershenson, "Artificial Neural Networks for Beginners," Cornell University Library, 2003.
[37] Z. He, X. Wen, H. Liu and J. Du, "A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region," Journal of Hydrology, pp. 379-386, 2014.
[38] P. Engelbrecht, Fundamentals of Computational Intelligence, England: Wiley, 2005.
[39] P. Engelbrecht, Computational Intelligence An Introduction, England: Wiley, 2007.