Forecasting River Flow in the USA Using a Hybrid Metaheuristic Algorithm with Back-Propagation Algorithm

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Received 15 April 2015 - Accepted 5 November 2015

ABSTRACT

Water resource management is a very complex and important challenge in this century; most of the political analysts consider that the world is going to face a problem of water management and reservation in the future. water management and estimation in the short and long term is an essential tool in planning, maintaining, managing and controlling the unexpected events. In this work, a Metaheuristic Algorithm which hybridizes Tabu search and Genetic algorithms with Back-propagation Algorithm (MABP) were proposed for managing, controlling and predicting water flow. The proposed algorithm used the statistical data set of the Ontonagon River near Rockland in USA as a case study. Back-propagation algorithm was used to train the Artificial Neural Network (ANN) using 550 daily data sets and was tested for other different 550 daily data sets. Metaheuristic algorithm (MA) was used to enhance and improve the obtained weights (solutions quality) from Back-propagation Algorithm (BP) by increasing and enhancing the fitness cost number. The estimated time series, ANN convergence, training and tested graphs were also explored.

Key Words: Artificial Neural Networks, Back-propagation algorithm, Metaheuristic algorithm, River flow forecasting, Water resource management.

INTRODUCTION

Water is the sustaining source of all creatures. Forecasting river flow protects from flood damage, water shortage, and helps in agriculture management. Water management is a continuous problem that varies according to state, region within a country, and among countries. Many African countries suffered from water shortage that caused death of, animals, plants, and human beings.

Water resource management and reservation have an important role in controlling, directing and governing countries in the future as expected by many political analysts. Successful understanding of water management requires knowing the available resources accurately (Biswas, 2004), the nature of water, its uasage, its estiamted demands, in addition to the needed parameters and measures to predict future events to prevent possible flood or shortage disasters. Water management and estimation are very complex, important and random processes. The flow system varies according to location, weather, and seasonal changes. They are also affected by several factors including distribution, ground aquifers, cover, soil types, river water consumption, vegetation, evaporation losses, channel characteristics, rainfall, and many other factors. several challenges arise when forecasting the stream flow (Fan, 1994, and Alkasassbeh, 2013). The reason behind that is the multi-dimensional processes of nature of flows which can be represented by several factors such as timing, duration, magnitude, and velocity.

Kobayashi and Porter (2012) and IBM (2015), introduced that a good water management process should include the following important points:

- Using dynamic process in planning and managing the natural water systems.
- Sufficient balances in using water resources through an efficient distribution that considers the social values, cost effectiveness, and environmental benefits and costs.
- Coordination and participation of all the governments' units in water management decision-making.
- Encourage water conservation, reuse, protection, and enhancing water quality.

The important safety chain of protection, prevention, preparation, repression, and normalization that help in decision making to reduce uncertainties consists of three elements as shown in figure 1.

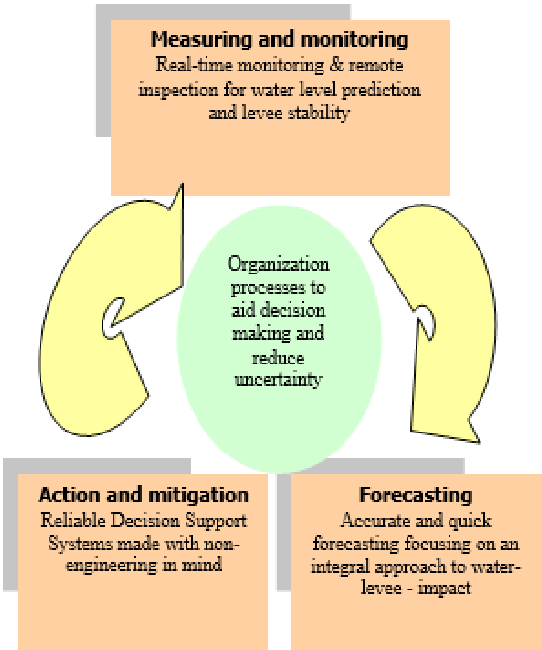

Figure (1): Organization processes to aid decision-making and reduce uncertainty (IBM, 2015).

The problem of modeling for forecasting can be solved in two steps according to Baareh et *al.,* (2006). The first is building a suitable model structure with some parameters. Estimating the developed model parameters comes second.

Many solutions have been proposed for both steps. Most of these solutions consider linear behavior approach with less solutions interested in nonlinear one. Linear models have been proposed as a solution for system identification process (Kothyari *et al.,* 1993). These models are simple, like the Moving Average (MA) model. Thus, simple algorithms like Least-Square Estimation (LSE) may be used to estimate the model parameters (Ljung and Söderström, 1983, and Ljung, 1987). LSE has been used as a useful tool in solving parameter estimation problem for a known system structure. This structure can be either linear or nonlinear. Although, most nonlinear systems can be linearized by representation with differential or difference equations, modeling nonlinear systems using linear models involves many approximations. This approximation is called modeling error. These approximations are sometimes not sufficient to reflect the real behavior of the nonlinear systems. Thus, to get a good model structure which reflects real system information, there is usually an increase in cost. This cost is due to the need for more advanced algorithms which can handle complex model structures.

As a solution to the identification problem for nonlinear systems several works were proposed (Gibson, 1963, Johansson, 1993, and Isidori, 1995). Such proposed model structures were proved theoretically to conduct and explain real and clear knowledge regarding nonlinear systems.

Examples of these models include Hammerstein, Winer, Winer-Hammerstein, and Volterra-series. Nonlinear models have characterized physical processes (Gelb, 1974). Unfortunately, most of these models have some problems. For example, one problem is the large number of parameters in these models that need to be identified (Nam *et al.,* 1990, and Tummala, 1990). Another problem is the selection of the optimal parameters which contribute to the modeling process. One solution for this problem is the use of the Artificial Neural Network (ANN) and Metaheuristic Algorithm (Badawi and Alsmadi, 2014). ANN was recognized and applied to many applications like the stock returns (Gibson, 1963), shift failures (Ljung and Söderström, 1983), estimating prices (Ljung, 1987), and sales prediction (Kothyari *et al.,* 1993). ANN was used by a number of researchers to predict the river flow complicity (Shamseldin, 2010, Selventhiran *et al.,* 2012, and Kalteh, 2013).

Biological neural networks consist of real neurons which are functionally related or connected in the nervous system. These networks consist of groups of neurons, where each group has special functions. ANNs contain interconnecting artificial neurons simulating the biological neural networks roles. These artificial networks have the ability to solve the problems of artificial intelligence without the necessity to create a real biological system model. Different number of neural network types are used to train the data set in a way similar to the human brain information processing. Back-propagation neural network in this case is used as famous neural type (Cigizoglu and Kisi, 2005, Baareh *et al.,* 2006, Alsmadi *et al.,* 2009, Alsmadi *et al.,* 2010, and Selventhiran *et al.,* 2012).

Genetic algorithm (GA) is a well-studied and common evolutionary method. This search method, which is a directed technique, evaluates multi thousands possible solutions and concentrates on the optimum solution options (global optimum). It has three main steps which are selection, crossover and mutation. Michalewicz (1996) identified some mechanisms for selection of solutions from the matting pool such as, Tournament Selection, and Roulette Wheel Selection. The most important part of GA is crossover which finds new solutions within the search space. GA has mutation operator which performs like a local search in order to explore the solutions in the neighborhood. To improve the quality of the matting pool if a better solution is reached, the algorithm keeps updating the population (Goldberg, 1989). For further explanations about GA please refer to (Alsmadi *et al*., 2011, and Badawi and Alsmadi, 2014).

Tabu Search is one of the most common meta-heuristic algorithms. After it was proposed by Glover (1989), it was used in optimization and artificial intelligence fields. For further explanations about Tabu search algorithm please refer to (Baareh, 2013).

The aim this work is to design and develope a robust and effective hybrid method, which hybridizes Tabu search and Genetic algorithms with Back-propagation Algorithm (MABP) for forecasting, managing, controlling and predicting water flow.

MATERIALS AND METHODS

A neural network with three types of layers was generated in this work. The input layer is the first layer which receives the input data from the outside environment, and the number of neurons in this layer equals the model input number. The second layer is the hidden layer which receives input data from earlier layer. The final layer in the neural work is the output layer; the neurons of this layer are the network output. The neurons in every layer are completely connected to the next layer neurons. Oppositely, the neurons within each layer are not interconnected to each other. Figure 2 shows a three layer feed forward ANN. This example simulates a model with one output and seven inputs; the complexity of the problem determines the neurons number in the hidden layer.

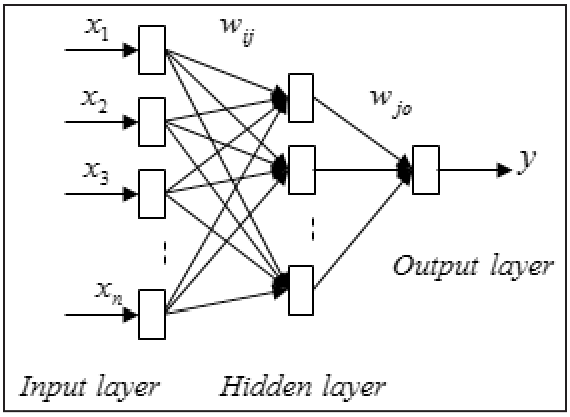

Figure (2): A Feed forward ANN structure with three layers.

The argument of activation function is specified by the neuron inputs weighted sum, assuming that activation function is nonlinear. Where represents network inputs, and represents the estimated output. The Back-propagation ANN function can be denoted according to Negnevitsky (2005 and 2011). The following equation (Equation 1) calculates the output of the hidden layer

$$y_j(p) = sigmoid[\sum_{i=1}^{n} x_i(p) \times w_j(p) - \theta_j] \quad (1)$$

Where w_{ij} represents the weights between the input and the hidden layers, and between the hidden and the output layers, θ is a threshold value. The sigmoid function adopted in this study is given in Equation 2.

$$y_j(p) = \frac{1}{1 + e^{-x_j(p)}} \quad (2)$$

Equation 3 calculates the output layer output:

$$y_j(p) = sigmoid[\sum_{i=1}^{n} x_i(p) \times w_j(p) - \theta_j] \quad (3)$$

Calculating the output layer Error Gradient is as seen in Equation 4.

$$\delta_k(p) = y_k(p) \times [1 - y_k(p)] \times e_k(p) \quad (4)$$

Where $e_k(p)$ is the error at the output layer

$$e_k(p) = y_{d,k}(p) - y_k(p) \quad (5)$$

The weights of the ANNs can be calculated as in Equation 6.

$$\Delta w_{jk}(p) = \alpha \times y_j(p) + \delta_k(p) \quad (6)$$

Equation 7 is used for ANNs weights readjustment

$$w_{jk}(p+1) = w_{jk}(p) + \Delta w_{jk}(p) \quad (7)$$

Equation 8 is used to calculate the hidden layer gradient error.

$$\delta_k(p) = y_j(p) \times [1 - y_j(p)] \times \sum_{k=1}^{l} \delta_k(p) \times w_{jk}(p) \quad (8)$$

Equation 9 recalculates the weights.

$$\Delta w_{ij}(p) = \alpha \times x_i(p) + \delta_j(p) \quad (9)$$

Equation 10 readjusts the weights.

$$w_{ij}(p+1) = w_{ij}(p) + \Delta w_{ij}(p) \quad (10)$$

A Metaheuristic algorithm which hyberdizes tabu search and genetic algorithm with back-propagation algorithm (MABP).

Metaheuristic algorithm (MA) is an extension of the genetic algorithm GA (Baareh, 2013, and Costa *et al.,* 2014). MA differs from the GA as MA is applied individually after the operators of the GA such as (Tabu search, Great deluge and iterated Local search algorithms). The exploitation process is enhanced by inserting a local search algorithm. In this work, a metaheuristic algorithm (Tabu search and Genetic algorithms) is used to tune the parameters' weights of the Back-propagation algorithm, in order to enhance and improve the performance of the Back-propagation algorithm. Figure 3 illustrates the metaheuristic algorithm pseudo-code that was used in this research.

```
Metaheuristic Algorithm
begin
Population:=generate initial solutions;
repeat the following until stopping criterion
Select two parents
Apply genetic operators (crossover and mutation)
Apply Tabu search algorithm
Update population
end
end;
```

Figure (3): illustrates the metaheuristic algorithm pseudo-code Adopted from (Goldberg, 1989).

The metaheuristic algorithm (Tabu search with Genetic algorithm) was used in this work to optimize and enhance the weights between neural network layers. MA algorithm has several advantages such as the ability of avoiding getting trapped in the local optima compared with the back-propagation algorithm.

In order to enhance the performance of the back-propagation algorithm, some genetic mechanisms and operators were implemented such as generating new population using crossover and/or mutation operators. Figure 4 shows the flowchart of the proposed hybrid MABP algorithm. In the proposed MABP, the obtained weights from the the back-propagation algorithm are encoded to form a long chromosome and tuned using the proposed metaheuristic algorithm.

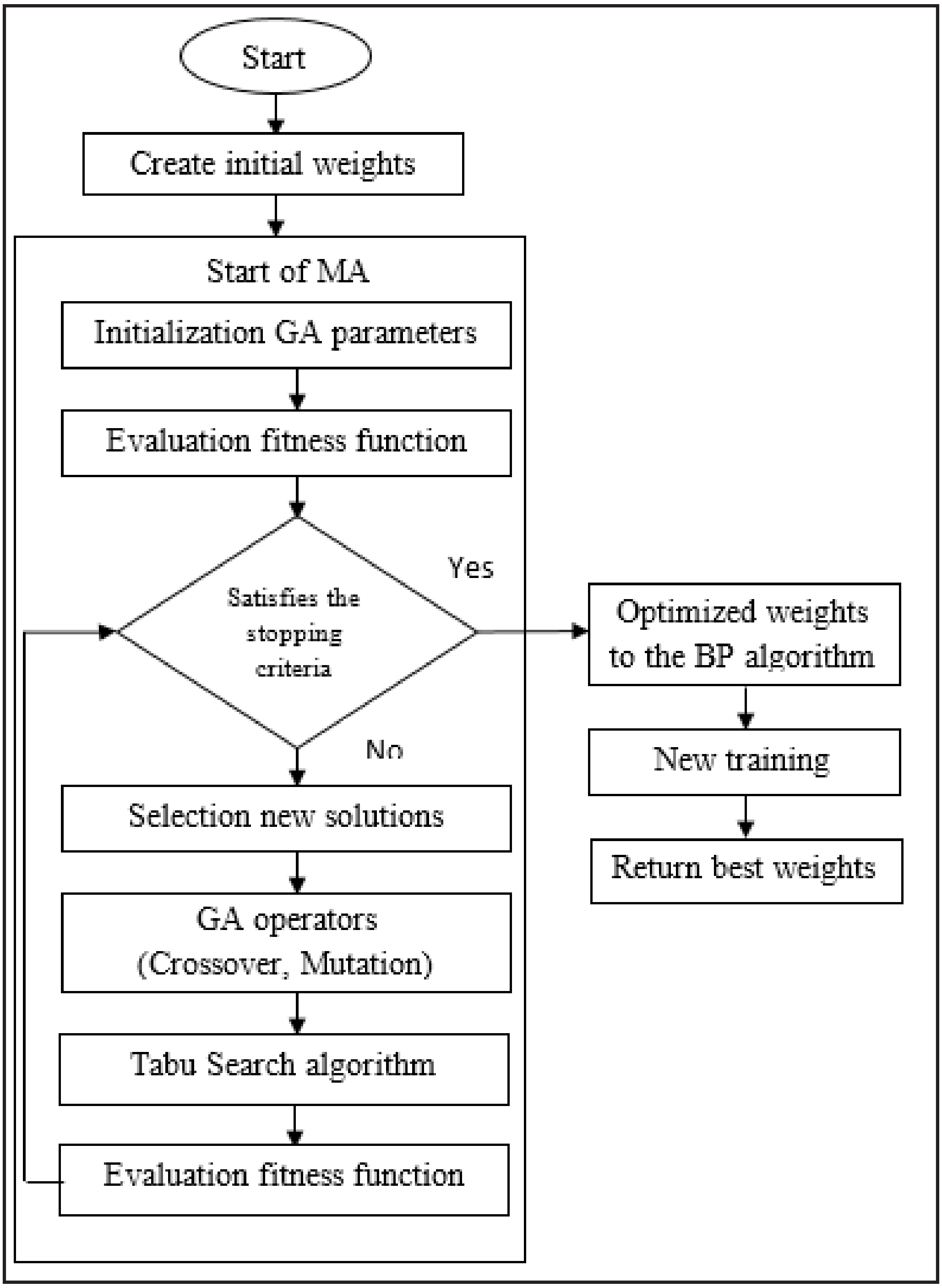

Figure (4): The flowchart of the proposed hybrid MABP algorithm.

Initialization

Representation of chromosome is very important element for successful genetic algorithm. In this work, a binary representation was used for each solution. Thus the chromosome represents a random number (real values in the form of fraction numbers) from the weight matrix. The real values represent the genes in the chromosome in the form of binary strings.

Figure 5 shows the representation of the population, chromosomes and genes.

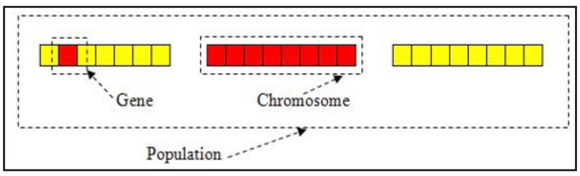

Figure (5): The representation of the population, chromosome and gene.

Selection

The aim of the selection mechanisms is to select chromosomes (individuals) from the population for reproduction based on their fitness values. Chromosomes with higher fitness values are more likely to be selected as parents and used to generate new solutions (chromosomes). Crossover and mutation mechanisms are used to formulate these chromosomes (Alsmadi *et al.*, 2011, and Baareh, 2013).

A roulette wheel selection is used in this work. roulette wheel selection was established by Baker (1987) and it is the simplest selection technique. This technique chooses solution with the highest fitness number to generate the next generation. The fittest individuals will have more chance to survive than the weaker ones.

Crossover

Crossover is the main operator in the genetic algorithm. This operator is used to generate a new chromosomes (solutions) in the search space by combining the contained information in two or more parents (Baareh, 2013, Alsmadi *et al.,* 2011). Population chromosomes are paired randomly in the standard crossover operator. Using this operator, two mating individuals are cut once at randomly determined point and the resulted segments are exchanged (resulting offsprings) as shown in figure 6.

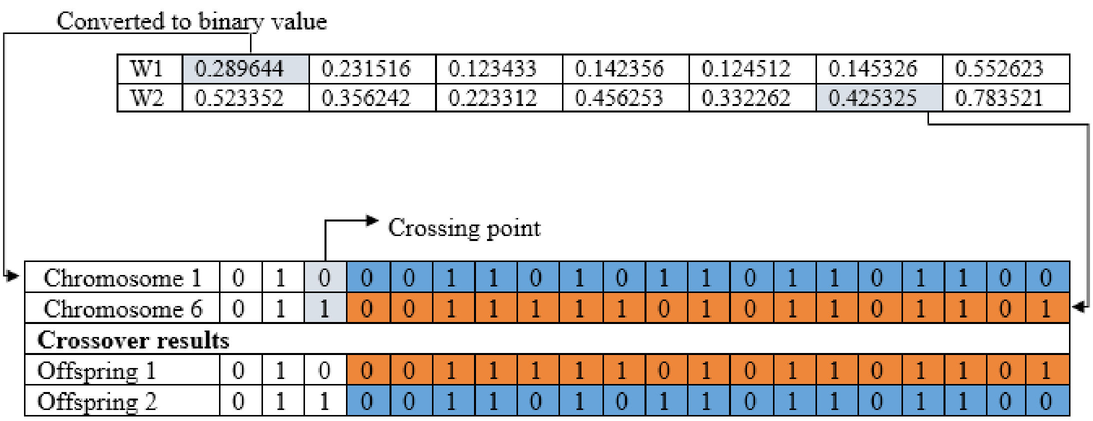

Figure (6): Single point crossover.

Mutation

Mutation operator in the GA works as a local search to discover the neighbor solutions and used to maintain the diversity of the GA from one generation to the next generation (Alsmadi *et al.*,(2011) and Baareh (2013)). After crossover operator, the new chromosomes (weights) are subjected to the mutation operator. The aim of the mutation is to help the GA to avoid getting trapped in the local minima by ensuring that chromosomes population are not similar to each other, which leads to slowing down or stopping of the evaluation process. This work uses the non-uniform mutation, via the non-uniform distribution of probability. Non-uniform mutation exchanges only one of the parent genes as shown in figure 7.

Mutated bit

Offspring	0	1	0	0	0	1	1	1	1	1	0	1	0	1	1	0	1	1	0	1
Mutated Offspring	0	1	0	0	0	1	1	1	0	1	0	1	0	1	1	0	1	1	0	1

Figure (7): Mutation process.

Problem formulation

To solve water management problem for the Ontagon River, this resaerch built a model structure taking into consideration the historical measurements of water flow during the previous years. A seven years delay has been selected in this research. This means that there is a need to build a model structure having the characteristics given in Equation (11).

$$y(k) = f(y(k-1), y(k-2), \ldots, y(k-7)) \quad (11)$$

In addition, this research used the Variance-Account-For (VAF) formula to evaluate the performance and the correctness of the developed models, where the performance and the correctness will be measured by comparing the estimated output with the real output of the model. The VAF criteria helps in measuring the closeness between the two characteristics. The higher the value of the VAF the better the performance is. The VAF is calculated using the following equation:

$$VAF = \frac{\mathrm{var}(y - \hat{y})}{\mathrm{var}(y)} x100\% \quad (12)$$

The real flow is represented as $y(k)$ and the predicted flow is represented as $\hat{y}(k)$.

The Ontagon River flow estimation was performed using the developed neural network model. This was done by implementing multiple networks with a varying number of input delays. The proposed neural network had three layers. Regarding the developed model order, the input layer has 7 neurons and hidden layer contains 7 hidden nodes. These numbers were chosen experimentally. The back-propagation learning algorithm was used to adjust the weights from the Input layer to the hidden layer and from the hidden layer to the output layer. The output layer has one output neuron to predict the flow. In this work, a metaheuristic algorithm (Tabu search and Genetic algorithms) was used to tune the parameters (weights) of the Back-propagation algorithm, in order to enhance and improve the performance of the Back-propagation algorithm.

DATA ACQUISITION

The data sets used were collected from the station operated by the U.S. Geological Survey (USGS). Station No: 04040000 near Rockland (Guide, 2009). The river location is shown in Figure 8. The period of the training data was from 1/1/2002 to 7/1/2003 and the period of testing data was from 7/2/2003 to 12/31/2004.

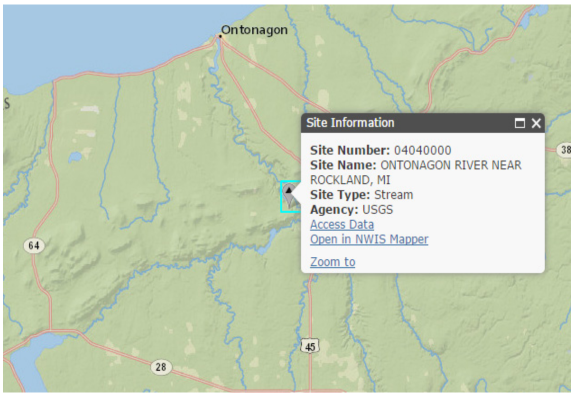

Figure (8): The location of the station operated by the USGS. This map was presented in (USGS, 2015).

RESULTS AND DISCUSSION

In the proposed methods, the parameters learning process consists of two steps, the first step is optimizing and enhancing the initial obtained weights from the ANN by the proposed MA through increasing the fitness cost number. The second step is using BP algorithm to train the optimized weights. The developed ANN convergence is shown in Figure 9.

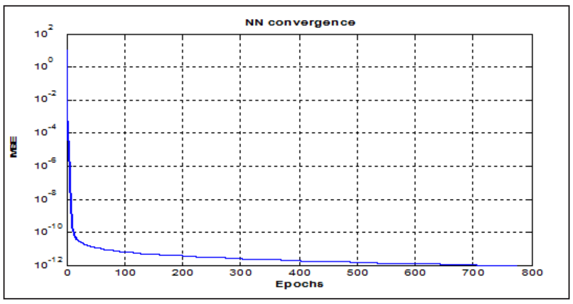

Figure (9): ANN convergence: Ontonagon River.

The convergence of the Mean Squared Error (MSE) at each iteration is shown in figure 9.

The convergence of the mean squared error at each iteration decreases toward zero as the evaluations continue. This indicates the good performance of the proposed model in dealing with the management and prediction of water resource flow.

Table 1 shows the overall training and testing accuracy for traditional BP algorithm and the proposed hybrid MABP algorithm of the Ontonagon River data sets. Training and testing accuracy is the produced performance measures. In this case, the performance was computed as the relationship between the actual and estimated flow. The VAF criteria helps in measuring the closeness between the two characteristics. The higher the value of the VAF the better the performance is.

The obtained results indicated that the hybrid MABP algorithm outperformed the BP algorithm through obtaining better training and testing accuracy results but with more running.

Table (1): The overall training and testing VAF of the Ontonagon River data sets.

Methods	Training Accuracy (VAF)	Testing Accuracy (VAF)
BP algorithm	96%	94.5%
Proposed hybrid MABP algorithm	99.9%	98.5%

Figures 10 and 11 show the obtained results for both of training and testing data sets of Ontonagon River, where the estimated flow is shown with blue dotted line and the actual flow is shown as solid line.

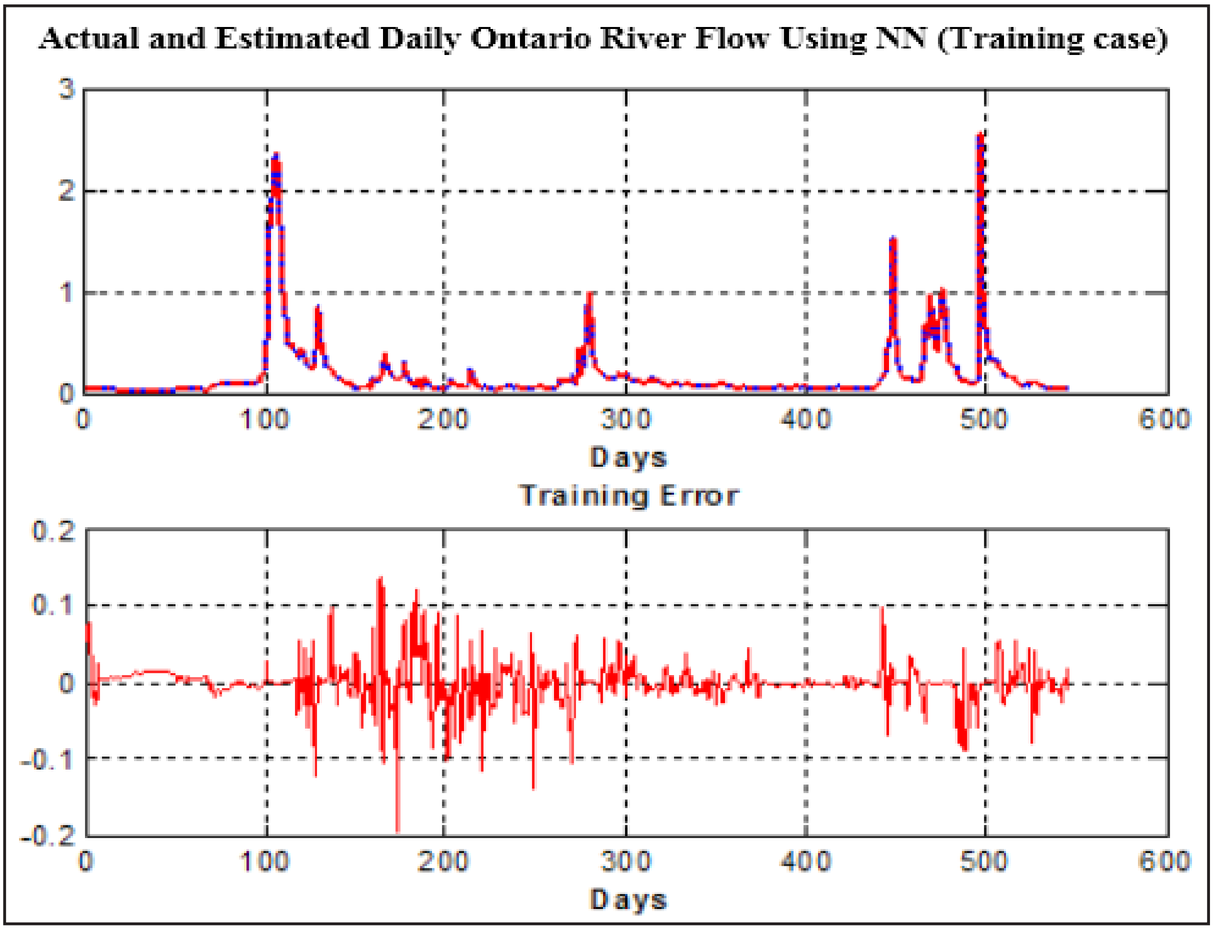

Figure (10): Actual and estimated flow training case.

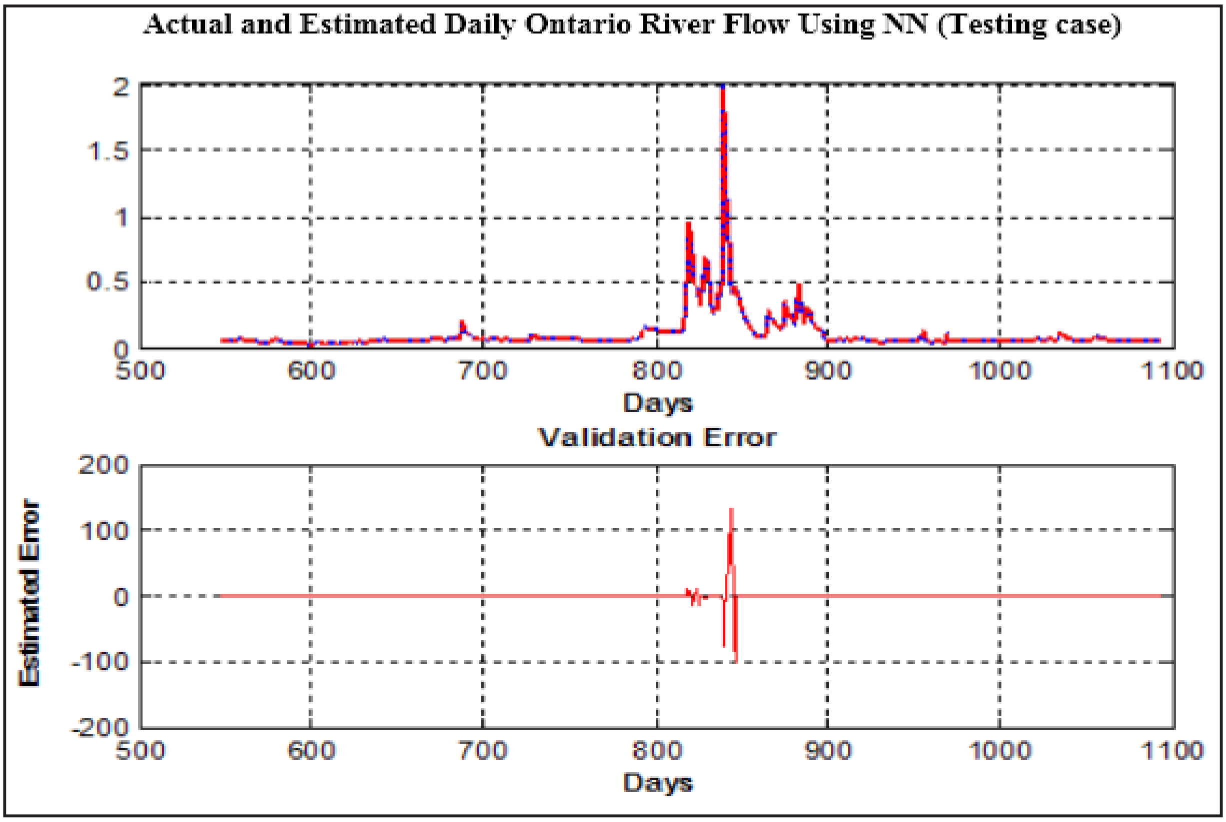

Figure (11): Actual and estimated flow tested case.

Moreover, Figure 11 shows reasonable results, where the error of the test set and the error of the validation set have the same characteristics, with unimportant over-fitting occurred in the data.

CONCLUSION

This research aimed to solve water management and reservation problem to avoid floods, water shortage, or lack of water. In this work, a Metaheuristic Algorithm which hybridizes Tabu search and Genetic algorithms with Back-propagation Algorithm (MABP) was proposed for managing, controlling and predicting water flow. It could be concluded that the proposed hybrid MABP algorithm has many advantages when compared with conventional modeling approaches. For example, it could help in solving forecasting problem by developing a generalized solution from a given set of examples. In cases of testing and training, the performance of the proposed hybrid MABP algorithm was significant and proved its ability to deal with water resource flow management prediction. The obtained results showed that the hybrid MABP algorithm outperformed the BP algorithm through obtaining better training and testing accuracy results but with more running time.

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التنبؤ بفيضان النهر في الولايات المتحدة باستخدام تهجين خوارزمية الميتاهيورستك مع خوارزمية الانتشار الخلفي

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استلام 15 أبريل 2015م - قبول 5 نوفمبر 2015م

الملخص

تعتبر إدارة الموارد المائية إحدى التحديات المعقدة والمهمة في هذا القرن. و يعتبر معظم المحللين السياسيين أن التحدي الرئيسي للعالم في المستقبل هو إدارة المياه والحفاظ عليها. ولذلك فإن إدارة المياه في المستقبل وتقديرها على المدى القريب والبعيد تعتبر أداة أساسية في تخطيط وصيانة وإدارة مصادر المياه والسيطرة على الأحداث غير المتوقعة. في هذه الدراسة تم تطوير طريقة من خلال دمج خوارزمية الميتاهيورستك مع خوارزمية الانتشار الخلفي للمساعدة في إدارة ومراقبة وتوقع تدفق المياه. كدراسة حالة استخدمنا البيانات الإحصائية لنهر أونتوناغون بالقرب من روكلاند في الولايات المتحدة الأمريكية. كما تم استخدام خوارزمية الانتشار الخلفي لتدريب الشبكة العصبية الاصطناعية باستخدام 550 مجموعة من البيانات اليومية واختبارها من خلال 550 مجموعة أخرى، و تم استخدام خوارزمية الميتاهيورستك لتعزيز وتحسين الأوزان التي تم الحصول عليها (جودة الحلول) من خوارزمية الانتشار الخلفي، عن طريق زيادة وتحسين مقدار الملاءمة لقيم الأوزان. وبالإضافة إلى ذلك تم فحص السلسلة الزمنية التقريبية والرسوم البيانية لتدريب واختبار الشبكة العصبية الاصطناعية.

الكلمات المفتاحية: إدارة الموارد المائية، التنبؤ بتدفق النهر، خوارزمية الانتشار الخلفي، خوارزمية الميتاهيورستك، الشبكة العصبية الاصطناعية.