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Algal Bloom Prediction with Particle Swarm Optimization Algorithm

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Abstract. Precise prediction of algal booms is beneficial to fisheries and environmental management since it enables the fish farmers to gain more ample time to take appropriate precautionary measures. Since a variety of existing water quality models involve exogenous input and different assumptions, artificial neural networks have the potential to be a cost-effective solution. However, in order to accomplish this goal successfully, usual problems and drawbacks in the training with gradient algorithms, i.e., slow convergence and easy entrapment in a local minimum, should be overcome first. This paper presents the application of a particle swarm optimization model for training perceptrons to forecast real-time algal bloom dynamics in Tolo Harbour of Hong Kong, with different lead times on the basis of several input hydrodynamic and/or water quality variables. It is shown that, when compared with the benchmark backward propagation algorithm, its results can be attained both more accurately and speedily.

1 Introduction

Owing to the semi-enclosed nature and the nutrient enrichment through municipal and livestock waste discharges in Tolo Harbour, frequent algal blooms with occasional massive fish kills have been recorded over the past two decades. Precise prediction of algal booms is beneficial to fisheries and environmental management since it enables the fish farmers to gain more ample time to take appropriate precautionary measures. However, the causality and dynamics of algal blooms, which are related to various pertinent factors such as time-lagged chlorophyll-a, secchi disc depth, nitrogen, phosphorus, dissolved oxygen, rainfall, water temperature, solar radiation, wind speed, tidal range, and so on, are extremely complicated and not well-understood.

Existing water quality models require exogenous input and embrace different assumptions. In numerical modeling, the physical problem is represented by a highly coupled, non-linear, partial differential equation set. The involving processes are highly complex and uncertain which may demand huge computing cost and time. Process-based models are not completely satisfactory in representing the highly complex inter-relationships. Recently, owing to various advantages (built-in dynamism, data-error tolerance and no need to have exogenous input), artificial neural networks (ANN), and in particular, the feed forward back-propagation (BP) perceptrons, have been widely applied in water resources engineering [1]. However, slow training convergence speed and easy entrapment in a local minimum are inherent drawbacks of the commonly used BP algorithm.

In this paper, the particle swarm optimization (PSO) algorithm is employed to train multi-layer perceptrons for algal bloom prediction in Tolo Harbour of Hong Kong with different lead times and input variables.

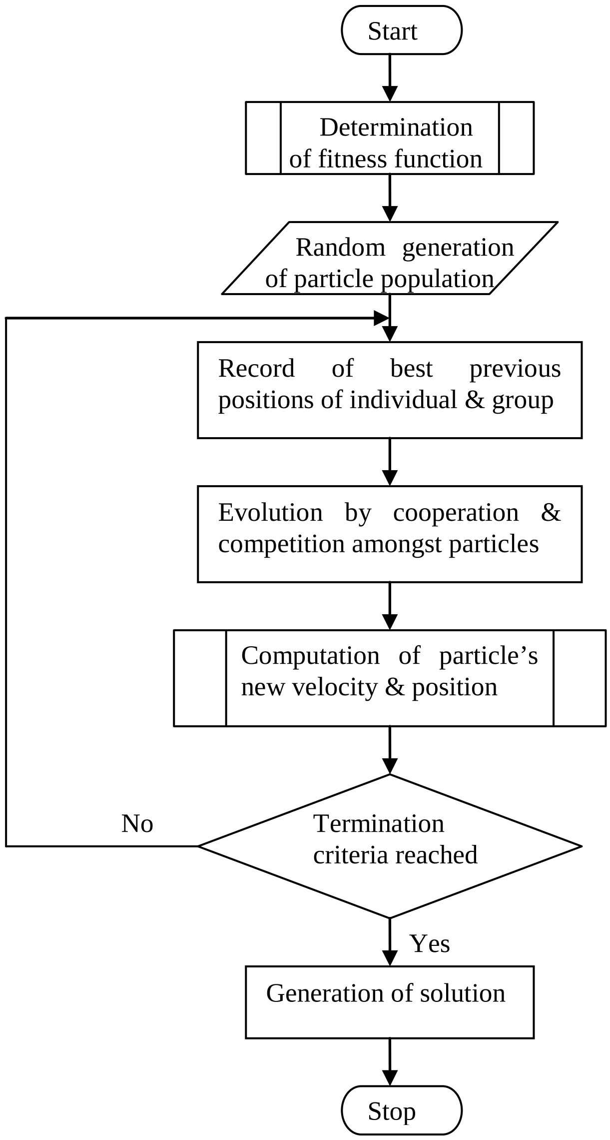

Fig. 1. Overall flow chart of PSO algorithm

2 Attributes of PSO Algorithm

During its inception, PSO algorithm is developed as a tool for modeling social behavior and is able to optimize hard numerical functions [2-3]. It is currently adapted as a computational intelligence technique intimately related to evolutionary algorithms [4]. It is an optimization paradigm that mimics the ability of human societies to process knowledge. It has roots in two main component methodologies: artificial life on bird swarming; and, evolutionary computation. The PSO technique has been applied in hydrological problems and accomplished satisfactory results [5-6].Its principle is founded on the assumption that potential solutions will be flown through hyperspace with acceleration towards more optimum solutions. PSO is a populated search method for optimization of continuous nonlinear functions resembling the movement of organisms in a bird flock or fish school. Each particle adjusts its flying according to the flying experiences of both itself and its companions. In doing so, it keeps track of its coordinates in hyperspace which are associated with its previous best fitness solution, and also of its counterpart corresponding to the overall best value acquired thus far by any other particle in the population. Vector, as a convenient form for optimization problems, is used as the variable presentation to represent particles. Figure 1 shows the overall flow chart of PSO algorithm.

The principal advantages of PSO are relatively simple coding and hence computationally inexpensive. A similarity between PSO and a genetic algorithm is the initialization of the system with a population of random solutions and the employment of the fitness concept. However, the evolution of generations of a population of these individuals in such a system is by cooperation and competition among the individuals themselves. The population is responding to the quality factors of the previous best individual values and the previous best group values. The allocation of responses between the individual and group values ensures a diversity of response. The principle of stability is adhered to since the population changes its state if and only if the best group value changes. It is adaptive corresponding to the change of the best group value. The capability of stochastic PSO algorithm to determine the global optimum with high probability and fast convergence rate has been shown in other cases. PSO is adopted to train the multi-layer perceptrons here.

3 Application in Network Training

For a three-layered preceptron, $W^{[1]}$ and $W^{[2]}$ represent the connection weight matrix between the input layer and the hidden layer, and that between the hidden layer and the output layer, respectively. During training of the multi-layer preceptrons, the i-th particle is denoted by $W_i = \{W^{[1]}, W^{[2]}\}$ whilst the velocity of particle i is denoted by V_i. The position representing the previous best fitness value of any particle is denoted by P_i whilst the best matrix among all the particles in the population is recorded as P_b. Let m and n represent the index of matrix row and column, respectively, the following equation represents the computation of the new velocity of the particle based on its previous velocity and the distances of its current position from the best experiences both in its own and as a group.

$$V_i^{[j]}(m,n) = V_i^{[j]}(m,n) + r\alpha[P_i^{[j]}(m,n) - W_i^{[j]}(m,n)] + s\beta[P_b^{[j]}(m,n) - W_i^{[j]}(m,n)] \quad (1)$$

where j = 1, 2; m = 1, …, M_j; n= 1, …, N_j; M_j and N_j are the row and column sizes of the matrices W, P, and V; r and s are positive constants; α and β are random numbers in the range from 0 to 1. In the context of social behavior, the cognition part $r\alpha[P_i^{[j]}(m,n) - W_i^{[j]}(m,n)]$ represents the private thinking of the particle itself whilst the social part $s\beta[P_b^{[j]}(m,n) - W_i^{[j]}(m,n)]$ denotes the collaboration among the particles as a group. The new position is then determined based on the new velocity as follows.

$$W_i^{[j]} = W_i^{[j]} + V_i^{[j]} \quad (2)$$

The following equation is used to determine the fitness of the i-th particle in term of an output mean squared error of the neural networks

$$f(W_i) = \frac{1}{S}\sum_{k=1}^{S}\left[\sum_{l=1}^{O}\{t_{kl} - p_{kl}(W_i)\}^2\right] \quad (3)$$

where f is the fitness value, t_{kl} is the target output; p_{kl} is the predicted output based on W_i; S is the number of training set samples; and, O is the number of output neurons.

4 Prototype Prediction

A necessary procedure to test the usefulness of a system is to verify its capability to mimic a particular case study with accurate depiction of real phenomena. This system has been verified and validated by applying to predict the algal bloom dynamics in Tolo Harbour of Hong Kong [7]. It is observed that the life cycle of algal blooms is in the order of 1 to 2 weeks. Thus, algal biomass, represented as chlorophyll-a, is forecasted with a lead time of 1 and 2 weeks based on comprehensive biweekly water quality data at Tolo Harbour from year 1982 to year 2002. The data of 1982-1995 and those of 1996-2002 are used for training and testing/validation, respectively. They are so chosen such that extreme frequency and intensity are contained in both data sets. Depth-averaged values, derived from the data for surface, mean and bottom of the water column, are adopted for analysis purpose. Ten input variables are generally considered to be significant on the algal dynamics of Tolo Harbour.

Hence, different perceptrons are tried which have an input layer with from one to ten neurons, a hidden layer with three to five neurons, and an output layer with one neuron. The input neurons represent the combinations of the time-lagged chlorophyll-a (Chl-a), phosphorus (PO_4), nitrogen (TIN), dissolved oxygen (DO), secchi disc depth (SD), rainfall, water temperature, solar radiation, wind speed, tidal range whilst the output node represents chlorophyll-a. Three scenarios are attempted with 10, 5 and 1 input variables for scenario 1, 2, and 3, respectively. Figure 2 shows the general network for 1 week lead time chlorophyll-a prediction for scenario 1. Table 1 lists the neural network parameters for the 3 scenarios. All source data are normalized into the range between 0 and 1, by using the maximum and minimum values of the variable over the whole data sets. The number of population is set to be 30 whilst the maximum and minimum velocity values are 0.3 and -0.3 respectively.

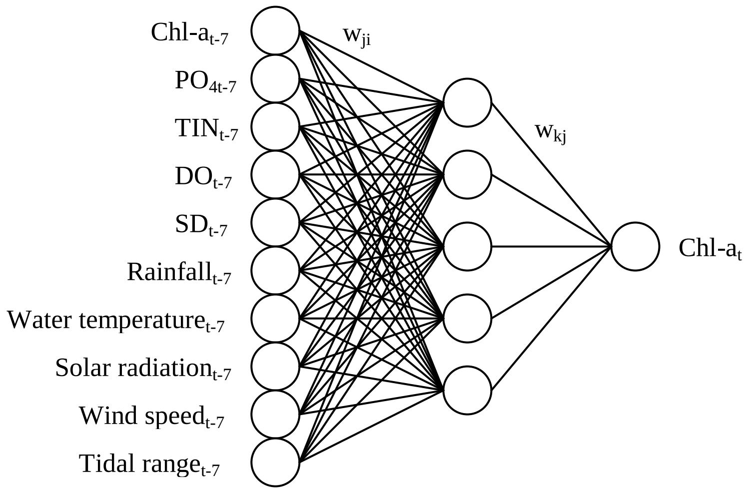

Fig. 2. General network for 1 week lead time chlorophyll-a prediction for scenario 1

Table 1. Neural network parameters for the 3 scenarios

Scenario	NN structure	Input variables
1	10-5-1	Chl-a, PO_4, TIN, DO, SD, rainfall, water temperature, solar radiation, wind speed, tidal range
2	5-3-1	Chl-a, PO_4, TIN, DO, SD
3	1-3-1	Chl-a

5 Analysis of Results

The performance of the PSO-based multi-layer ANN is evaluated in comparison with the benchmarking standard BP-based network. In order to provide a fair and common initial ground for comparison purpose, the training process of the BP-based perceptron commences from the best initial population of the corresponding PSO-based perceptron. Figure 3 shows the 1 week lead time normalized chlorophyll-a prediction for scenario 3 by both perceptrons in the validation process. Table 2 shows comparison of the results for chlorophyll-a forecasting with both 1 week and 2 weeks lead times for scenarios 1 to 3. It should be noted that the results do not exhibit a significant advantage of using more environmental variables as the network inputs and that 1 week lead time is better than its counterparts of 2 weeks. Moreover, the PSO-based perceptron exhibits much faster convergence and better prediction ability than those by the BP-based perceptron.

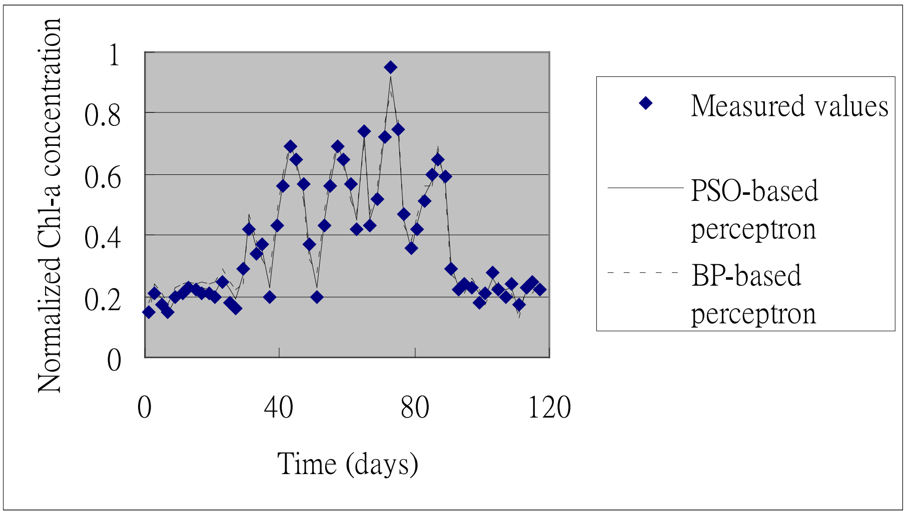

Fig. 3. 1 week lead time chlorophyll-a prediction for scenario 3 in the validation process

Table 2. Results for chlorophyll-a forecasting based on scenarios 1 to 3

Input data	Algorithm	Coefficient of correlation			
		Training		Validation	
		1 week ahead	2 weeks ahead	1 week ahead	2 weeks ahead
Scenario 1	BP-based	0.964	0.935	0.947	0.924
	PSO-based	0.988	0.977	0.968	0.963
Scenario 2	BP-based	0.962	0.934	0.948	0.924
	PSO-based	0.986	0.978	0.969	0.959
Scenario 3	BP-based	0.961	0.938	0.953	0.923
	PSO-based	0.989	0.976	0.966	0.961

6 Conclusions

In this paper, a perceptron approach based on the PSO paradigm is employed for real-time prediction of algal blooms at Tolo Harbour in Hong Kong with different lead times and input variables. The results do not exhibit any advantage of using more environmental variables as the network inputs. The chlorophyll-a output from the 1 week time-lagged chlorophyll-a input can be a robust forewarning and decisionsupport tool. The results also show that the PSO-based perceptron consistently performs better than the benchmarking BP-based perceptron in algal bloom prediction.

7 Acknowledgement

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