Parameter Identification of RVM Runoff Forecasting Model Based on Improved Particle Swarm Optimization

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Abstract. Runoff forecasting which subjects to model pattern and parameter optimization, has an important significance of reservoir scheduling and water resources management decision-makings. This paper proposed a new forecasting model coupled phase space reconstruction technology with relevance vector machine, and its model parameters is optimized by an improved PSO algorithm. The monthly runoff time series from 1953 to 2003 at Manwan station is selected as an example. The results show that the improved PSO has efficient optimization performance and the proposed forecasting model could obtain higher prediction accuracy.

Keywords: Improved PSO algorithm, Relevance vector machine, Phase space reconstruction, parameter identification, Runoff forecasting.

1 Introduction

Runoff forecasting is very important for reservoir control, water resources planning and management. However, the hydrology system is a highly complex nonlinear system composed of uncertain and deterministic parts under the influence of rainfall system and underlaying surface system[1]. It is difficult to describe it in terms of rigorous physical model. So the data-driven model has become the important model in practice. Many innovated models, such as uncertain reasoning model(RM)[1], Artificial Neural Network (ANN)[2], support vector machine (SVM)[3] are gradually introduced into the hydrological forecasting, and further develop its applications. Tipping[4]puts forward sparse probability model (Relevance Vector Machine, RVM) on basis of SVM and Bayesian theory, this method has been used in the fields of image analysis [5,6], channel equalization [7],etc. and obtained effective performance. The researches show that there two aspects should be mainly involved as: (1) is runoff relevance vector machine choice; (2) is model parameters optimization identification.

Generally, relevance vector based on time series is built in sequence, which is lack of physical basis, this article applied phase space reconstruction technique[1,8] to construct the relevance vectors, and its model parameters is identified by the improved PSO algorithm, which firstly proposed by Kennedy and Eberhart [9] based on the social behavior metaphor, and has been widely applied in global optimization problems as

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well as GA, EA, DE, ACO optimization algorithms. There are many researches[10-13] illustrated PSO algorithm has effectively optimization performance, however, the standard PSO like the others' is easy to entrap the local best fitness, so the crossover and mutation algorithms is developed to expand the search space and applied to the proposed model parameters identification.

This article mainly includes five parts: In Sect.2 Briefly introduces improved PSO algorithms. In Sect.3 Build relevance vector machine runoff forecast model. In Sect.4 Identify RVM model parameter. In Sect.5 Application. In Sect.6 Conclusions.

2 PSO Algorithm

The PSO algorithm is initialized with a population of random candidate solutions, conceptualized as particles. Each individual in PSO algorithm is assigned random velocity in search space, and is iteratively updating according to its own local best fitness and its global best fitness, which is attracted by the particle locations. Each individual in the particle swarm is composed of D-dimensional vector $x_i = [x_{i1}, x_{i2}, \cdots, x_{id}]$ and the ith particle velocity $v_i^k = [v_{i1}^k, v_{i2}^k, \cdots, v_{id}^k]$. During each iteration, the ith particle is updated by the following two best values: $p_i^{best} = [p_{i1}, p_{i2}, \cdots, p_{id}]$, which is the local best value of the ith particle has been achieved so far, and $g^{best} = [g_1, g_2, \cdots, g_d]$, which is the global best value obtained in the swarm so far. Each particle is updated iteratively by

$$v_{id}^k = w_i \cdot v_{id}^{k-1} + c_1 \cdot rand_1 \cdot (p_{id}^{k-1} - x_{id}^{k-1}) + c_2 \cdot rand_2 \cdot (g_d^{k-1} - x_{id}^{k-1}) \tag{1}$$

$$x_{id}^k = x_{id}^{k-1} + v_{id}^k \tag{2}$$

Where c_1=c_2 are acceleration coefficients, w_i is the ith weight, $rand_1$ and $rand_2$ are two independent uniform random number within the range of [0,1]. To ensure convergence and be made much more stable, appropriate values is proposed by Kennedy and Eberhart with c_1=c_2=2 and $w_i \in [0.5, 1.4]$, $v_{id} \in [-v_d^{\max}, v_d^{\max}]$.

Generally, PSO algorithm likes as other evolutionary optimization algorithms, which is easily fall into local optimum. In order to solve the problem and expand particles search space, the crossover and mutation algorithm are applied to improve the search space. r pair of particles are selected randomly from the k-1th iteration to crossover each other, The crossover algorithm is represented as

$$\begin{cases} x_i = rand \cdot x_i + (1 - rand) x_j \\ x_j = rand \cdot x_j + (1 - rand) x_i \end{cases} \tag{3}$$

Where $rand$ is the uniform random number within the range of [0,1].

While the mutation algorithm of the particle velocity is written as[15]:

$$v_{id}^k = \begin{cases} w_i \cdot v_{id}^{k-1} + c_1 \cdot rand_1 \cdot (p_{id}^{k-1} - x_{id}^{k-1}) + c_2 \cdot rand_2 \cdot (g_d^{k-1} - x_{id}^{k-1}) & rand_3 < c_3 \\ 0 & rand_3 \geq c_3 \end{cases} \tag{4}$$