A Pollution Estimating Approach by Discrete Particle Swarm Optimization with Hierarchical Structure

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Abstract

A pollution estimating approach by discrete particle swarm optimization with hierarchical structure is proposed in this paper. Discrete particle swarm optimization with hierarchical structure aims to improve the performance of PSO by offering accurate best solution and faster convergence speed. The discrete particle swarm optimization with hierarchical structure is used to optimize the SVR. It can be seen that the pollution estimating results of SVR optimized by discrete particle swarm optimization with hierarchical structure are better than those of SVR optimized by particle swarm optimization, and SVR. Therefore, discrete particle swarm optimization with hierarchical structure has very high application value in pollution estimating.

Keywords: Pollution; Estimating Technology; Discrete Particle Swarm Optimization; Optimization Technique

1 Introduction

A pollution estimating approach by discrete particle swarm optimization with hierarchical structure is proposed in this paper. Particle swarm optimization (PSO) is a population-based optimization technique, which simulates social behavior of bird flocking. In PSO, the best position of the particle can be gained by adjusting the direction towards its own best location and the best particle of the swarm [1-5]. PSO is generally used to solve continuous optimization problems. When the continuous PSO is applied to discrete combinatorial optimization problems, a transformation method is needed to translate the continuous particle into a discrete solution [6-8]. Discrete particle swarm optimization with hierarchical structure aims to improve the performance...
of PSO by offering accurate best solution and faster convergence speed. The swarms are grouped based on the similar properties and allowed to undergo conventional PSO, every swarm discovers the similarly converging neighbor swarms and selects the best neighbor swarm using orthogonal analysis.

The cases are applied to testify the pollution estimating performance of discrete particle swarm optimization with hierarchical structure. The discrete particle swarm optimization with hierarchical structure is used to optimize the SVR. It can be seen that the pollution estimating results of SVR optimized by discrete particle swarm optimization with hierarchical structure are better than those of SVR optimized by particle swarm optimization, and SVR. Therefore, discrete particle swarm optimization with hierarchical structure has very high application value in pollution estimating.

2 Pollution Estimating Method Based on Discrete Particle Swarm Optimization with Hierarchical Structure

Particle swarm optimization (PSO) is a population-based optimization technique, which simulates social behavior of bird flocking [9-12]. In PSO, the best position of the particle can be gained by adjusting the direction towards its own best location and the best particle of the swarm [13-15].

In the L-dimensional space, some parameters are represented as followings:

\[ x_i = (x_{i,1}, x_{i,2}, ..., x_{i,L}) \] represents the current position of the \( i \)-th particle;

\[ p_i = (p_{i,1}, p_{i,2}, ..., p_{i,L}) \] represents the best position of the \( i \)-th particle;

\[ v_i = (v_{i,1}, v_{i,2}, ..., v_{i,L}) \] represents the current velocity of the \( i \)-th particle;

\[ p^n_g \] represents the best position of the swarm.

Then, the best position of the \( i \)-th particle can be computed by updating the following formulation:

\[ v_i^{j+1} = \omega \cdot v_i^j + c_1 \cdot \text{rand} \cdot (p_i^j - x_i^j) + c_2 \cdot \text{rand} \cdot (p^n_g - x_i^j) \] (1)

\[ x_i^{j+1} = x_i^j + v_i^{j+1} \] (2)

where \( \text{rand} \) means the random value in the range from 0 to 1. \( \omega \) represents the inertia weight, which controls the impact of the previous velocity of the particle on its current one. \( c_1 \) and \( c_2 \) are the acceleration coefficients.

PSO is generally used to solve continuous optimization problems. When the continuous PSO is applied to discrete combinatorial optimization problems, a transformation method is needed to translate the continuous particle into a discrete solution. Discrete particle swarm optimization with hierarchical structure aims to improve the performance of dynamic PSO by offering accurate best solution and faster convergence speed. The swarms are grouped based on the similar properties and allowed to undergo conventional PSO, every swarm discovers the similarly converging neighbor swarms and selects the best neighbor swarm using orthogonal analysis. The proposed discrete particle swarm optimization with hierarchical structure algorithm is found to be suitable for numerous applications. Based on the abnormality percentage, the proposed discrete particle swarm optimization with hierarchical structure algorithm identifies the optimal particles to be served with minimum waiting time and schedules them by using dynamic round robin scheduler.
The following function describes the nonlinear mapping relationship between input variable and target output variable.

$$f(x) = w'\varphi(x) + b$$  \hspace{1cm} (3)

where $w$ denotes the weight, which can control the smoothness of the model; $b$ is the bias.

We introduce the slack variables $\xi_i$, $\xi_i^*$ to make the above optimization problem become a feasible convex optimization problem: minimize $\frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)$; subject to

$$\begin{cases}
y_i - \langle w, \theta(x_i) \rangle - b \leq \varepsilon + \xi_i \\
\langle w, \theta(x_i) \rangle + b - y_i \leq \varepsilon + \xi_i^* \\
\xi_i^* \geq 0
\end{cases}$$

The Lagrange multipliers $\alpha_i$ and $\alpha_i^*$ are introduced, and the regression hyperplane for solving regression problem is written by

$$f(x) = \sum_{i=1}^{n} (a_i - a_i^*)k(x_i, x) + b$$  \hspace{1cm} (4)

where only parts of $\alpha_i$ and $\alpha_i^*$ have non-zero values, $k(x_i, x)$ is called the kernel function.

The parameters $C$, $\sigma$, $\varepsilon$ of SVR are important influence on its forecasting performance. Discrete particle swarm optimization with hierarchical structure is used to select the parameters $C$, $\sigma$, $\varepsilon$ of SVR in the paper. The process of selecting the training parameters of SVR by discrete particle swarm optimization with hierarchical structure is presented as followings:

**Step 1** Produce a population of initial particles randomly;

**Step 2** Compute the fitness function;

**Step 3** If the fitness value of current position of the particle is better than its previous best fitness value, then its best fitness value is replaced by the fitness value of current position of the particle. If the best value of current position of all particles is better than the previous global best, then the value of the global best is replaced by the best value of current position of all particles. The velocity and position of the particles are updated;

**Step 4** The evolutionary process proceeds until maximum iterations are met. Otherwise, go to Step 2.

### 3 Experimental Results

The cases are applied to testify the pollution estimating performance of discrete particle swarm optimization with hierarchical structure. The actual estimating values of the cases are given in Fig. 1. The discrete particle swarm optimization with hierarchical structure is used to optimize the SVR. The pollution estimating results of SVR optimized by discrete particle swarm optimization with hierarchical structure are given in Fig. 2; and the pollution estimating errors of SVR optimized by discrete particle swarm optimization with hierarchical structure are given in Fig. 3. Then, particle swarm optimization is used to optimize the SVR. The pollution estimating results of SVR optimized by particle swarm optimization are given in Fig. 4; and the pollution estimating errors of SVR optimized by particle swarm optimization are given in Fig. 5. The pollution
estimating results of SVR are given in Fig. 6; and the pollution estimating errors of SVR are given in Fig. 7. It can be seen that the pollution estimating results of SVR optimized by discrete particle swarm optimization with hierarchical structure are better than those of SVR optimized by particle swarm optimization, and SVR. Therefore, discrete particle swarm optimization with hierarchical structure has very high application value in pollution estimating.

Fig. 1: The actual estimating values of the cases

Fig. 2: The pollution estimating results of SVR optimized by discrete particle swarm optimization with hierarchical structure
Fig. 3: The pollution estimating errors of SVR optimized by discrete particle swarm optimization with hierarchical structure

Fig. 4: The pollution estimating results of SVR optimized by particle swarm optimization

4 Conclusion

A pollution estimating approach by discrete particle swarm optimization with hierarchical structure is proposed in this paper. Discrete particle swarm optimization with hierarchical structure aims to improve the performance of PSO by offering accurate best solution and faster convergence speed. The swarms are grouped based on the similar properties and allowed to undergo conventional PSO, every swarm discovers the similarly converging neighbor swarms and selects
Fig. 5: The pollution estimating errors of SVR optimized by particle swarm optimization

Fig. 6: The pollution estimating results of SVR

developed the best neighbor swarm using orthogonal analysis. The discrete particle swarm optimization with hierarchical structure is used to optimize the SVR. It can be seen that the pollution estimating results of SVR optimized by discrete particle swarm optimization with hierarchical structure are better than those of SVR optimized by particle swarm optimization, and SVR. Therefore, discrete particle swarm optimization with hierarchical structure has very high application value in pollution estimating.
Fig. 7: The pollution estimating errors of SVR

References


