International Journal of Cognitive Informatics and Natural Intelligence
Volume 17 • Issue 1

A Coevolution Algorithm Based on Spatial Division and Hybrid Matching Strategy

Hong-Bo Wang, University of Science and Technology, Beijing, China*
https://orcid.org/0000-0002-4765-4584

Wei Huang, University of Science and Technology, Beijing, China

ABSTRACT

With the rapid development of social economy, people's demand for diversified and precise goals is increasingly prominent. In the face of a specific engineering application practice, how to find a satisfactory equilibrium solution among multiple objectives has been the focus of researchers at home and abroad. Aiming at the convergence and diversity imbalance in the current high-dimensional multi-objective evolutionary algorithm based on reference points, this article suggests a constrained evolutionary algorithm based on spatial division, angle culling, and hybrid matching selection strategy. Experimental practices show that the proposed algorithm has better performance compared with other related variants on DTLZ/WFG benchmark functions and in solving the problem of electricity market price.

KEYWORDS

Integrative Strategy, Multi-Objective Optimization, Power Dispatching

INTRODUCTION

Many practices need consider multiple objective problem (MOP) (Cohon, 1978) at the same time to optimize the overall effect in recent years. Typical work includes the second generation non-dominant sequencing genetic algorithm (NSGA-II) proposed by Deb et al. Furthermore, Zitzler et al. put forward the second-generation strength Pareto evolutionary (SPEA2) (Deb et al., 2002). NSGA-II and SPEA2 perform well in solving 2-3 objective problems with high operating efficiency and good distribution of solutions. However, when they face with higher dimensions (more than 4 targets), their disadvantages of low efficiency and poor diversity will occur, just like works in (Ikeda et al., 2001, & Khare et al., 2003) and (Purshouse et al., 2003).

Therefore, a high-dimensional multi-objective evolutionary algorithm has become a hotspot in this field. The latest MOEA/D-M2M (Liu et al., 2014) can overcome two shortcomings of MOEA/D (Zhang et al., 2007). A new improved algorithm based on MOEA(Deb et al., 2003, & Ghoreishi et al., 2015), as well as the high dimensional multi-objective evolutionary algorithm based on corner point sorting are proposed with non-dominant sorting and etc. Due to it is more difficult to calculate

DOI: 10.4018/IJCINI.326752
*Corresponding Author

the performance index, the following problems exist. (1) The inefficiency of Pareto dominance may lead to density-based diversity methods according to the pressure of environmental selection. (2) The recombination operator may be invalid. (3) The visualization of Pareto's optimal front is very difficult.

In order to trade off the relationship between convergence and diversity in high-dimensional evolutionary algorithms based on reference points and constrained multi-objective optimization problems, a Many-Objective Optimization Algorithm based on Space-Partition and Angle-based culling strategy (MaOEA-SDAC) is proposed in this paper. To meet the requirements of high-dimensional multi-objective problems with constraints, a Constrained Many-Objective Evolutionary Algorithms based on Hybrid Mating Selection (CMaOEA-HMS) is suggested in this article, which is integrated an approach of reference-point with non-dominated sorting.

The remainder of this paper is organized in the following. In the second section, two coevolution strategies and their corresponding implementation are proposed. Section III and IV design some experiments and compare the two new variants (MaOEA-SDAC and CMaOEA-HMS) with practicable strategies with the related algorithms, and summarizes the experimental results. Section V discusses that MaOEA-SDAC is applied into a joint calculation problem of residential ladder and peak-to-valley time-of-use electricity price. Conclusions are made in Section VI.

TWO IMPLEMENTATION STRATEGIES

The Framework of MaOEA-SDAC

Algorithm 1 in Table 1 is the overall pseudo code of Many-Objective Optimization Algorithm based on Space-Partition and Angle-based culling strategy (MaOEA-SDAC). In Table 1, λ represents a vector of reference points, P_0 represents an initial population, t represents an iterator, P_t represents the current generation t of a population, Q_t represents its offspring population generated by the recombination operation, R_t represents a population generated after the merger of P_t and Q_t, P_{t+1} represents the next generation produced by P_t environmental selection.

In Table 1, lines 01-03 in algorithm MaOEA-SDAC initialize some operations for a population. Lines 05-21 are an iterative process of the population, which is also its core part. Lines 08-20 run some actions in its environmental selection stage of the population.

The specific process of MaOEA-SDAC is as follows. The first step generates reference points λ, initialize the population P_0 and set the number of iterations t=0. The second step enters a loop, and the condition of the loop judgment is whether the maximum number of iterations is reached. If the related condition is met, the solution set is output; otherwise, the loop is entered. In the cycle, P_t is first matched and is selected to generate $P_t^{'}$, then $P_t^{'}$ is cross-mutated to generate Q_t, and R_t is generated by combining P_t and Q_t. Do non-dominated sorting on R_t, and merge the sorted result with P_{t+1} to generate new P_{t+1}. Then, a judgement condition will be entered, which is to generate the next population through environmental selection operation on R_t. Lines 12 and 18 are two the strategies of spatial partitioning and angle-based Culling introduced by this algorithm MaOEA-SDAC.

The Framework of CMaOEA-HMS

Algorithm 2 in Table 2 is the overall pseudo code for CMaOEA-HMS. Lines 01-03 include some initial operations. Lines 05-25 are population iterations, and lines 05-19 are its core part in this stage, which carries out matching and selection operations on a population. Lines 20-21 run the crossover mutation, and lines 22-25 are the environmental selection stage of the population. Among them, $CV\left(x\right)$ represents a degree of constraint violation of an individual, $d_{i,j}\left(x_i, x_j\right)$ is the Euclidean distance between individuals, $d\left(x, \lambda\right)$ represents the distance between an individual and its reference vector.