

Chapter 4

City Group Optimization: An Optimizer for Continuous Problems

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ABSTRACT

City group refers to a collection of cities. Through the development and growth, these cities form a chain of metropolitan areas. In a city group, cities are divided into central cities and subordinate cities. Generally, central cities have greater chances to develop. However, subordinate cities may not have great chances to develop unless they are adjacent to central cities. Thus, a city is more likely to develop well if it is near a central city. In the process, the spatial distribution of cities changes all the time. Urbanologists call the above phenomena the evolution of city groups. In this chapter, the city group optimization algorithm is presented, which is based on urbanology and mimics the evolution of city groups. The robustness and evolutionary process of the proposed city group optimization algorithm are validated by testing it on 15 benchmark functions. The comparative results show that the proposed algorithm is effective for solving complexly continuous problems due to a stronger ability to escape from local optima.

1. INTRODUCTION

City group, the sub-discipline of urbanology, first, is found by the twentieth century urbanologist, i.e., Ebenezer (Ebenezer, 2010). Until 1915, Patrick wrote a book “Cities in Evolution” and first presented “city-region” (Patrick, 1968). The “city-region” is defined as “conurbation” by Patrick, a chain of inter-linked urban districts or metropolitan areas. In 1957, Gottmann used “megalopolis” to describe a chain of metropolitan areas along the northeastern seaboard of U.S. According to the research of urbanologists, they discovered that different terms are used to denote the concept of metropolitan areas. Thus, to avoid confusion, we use a constant term “city group” to express the same concept in this chapter. By now, many scholars have researched abundant information about city groups (Peter, & Kathy, 2006). During twenty-first century, a quick population growth leads to the expansion of cities. City groups have drawn more people’s attention, especially in China (Yao, et al., 2006). With the fast development of China, many city groups, such as the Pearl River Delta, Beijing-Tianjin-Hebei Region and Central

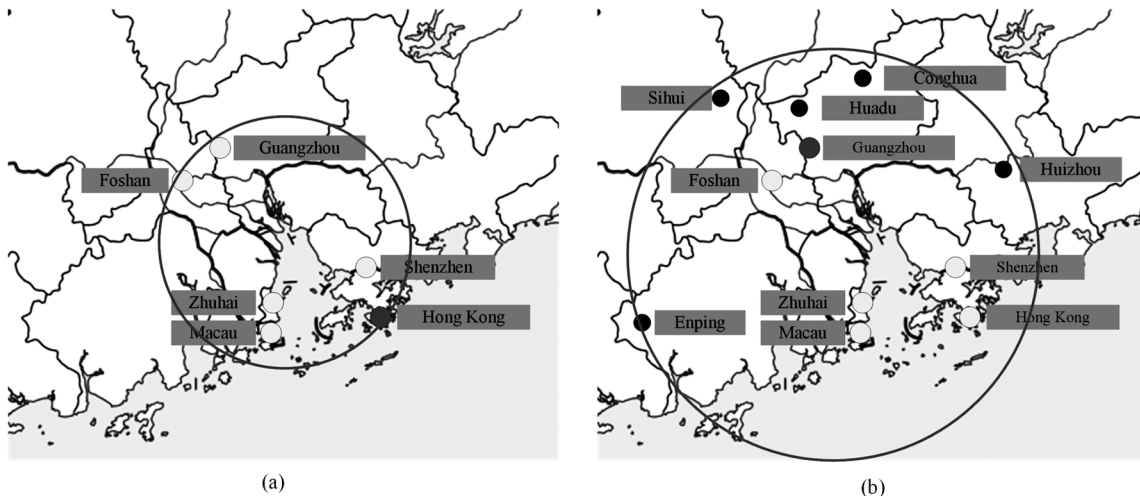
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Plains Urban Agglomeration, have already deeply influenced the public life. City groups have become common phenomena. However, we investigate the Engineering Index (EI) and Science Citation Index Expanded (SCIE), and discover that no one tries to utilize advantages of city groups to solve optimization problems. Therefore, this chapter is written to study advantages of city groups, and these may contribute to design new metaheuristics.

The development of city group is an evolutionary process. The process can be classified into the following two stages. In the first stage, cities cluster together in a group. A city with more residents is deemed to have a higher population size index (*PSI*). A city has prosperous economies, excellent geographic positions and convenient transportations, naturally, its *PSI* is high. A city group contains central cities and subordinate cities. It is obvious that *PSI*s of central cities are higher than subordinate cities. Usually, subordinate cities that are nearer central cities are easier to improve their *PSI*s. Hence, the central cities are magnetic for subordinate cities. In this case, subordinate cities will be gathered around central cities as shown in Figure 1(a). In the second stage, cities are diffused in a limit area. Suppose subordinate cities have higher *PSI*s than central cities over time, and then the subordinate cities will displace former central cities. So the center of city group will change from the previous position to another position. New central cities will be surrounded by subordinate cities, thus the cities are diffused as shown in Figure 1(b). Due to the unceasing clustering and diffusion, a city group maintains the internal balance and development (Gregory, 2002).

In the last decade, more and more metaheuristics are presented and developed to balance the population diversity and convergence speed. For metaheuristics, fine population diversity is beneficial to escape from local optima, and a fast convergence speed contributes the improvement of efficiency in solving problems. Genetic algorithm (GA) adopts evolutionary operators. Because of a series of genetic transformations, selection, mutation and crossover, GA preserves population diversity. But GA lacks effective mechanisms to accelerate convergence. Particle swarm optimization (PSO) adopts kinetic particle swarms to find the best solutions. Swarms follow leaders, and search the solution space of a problem. Due to the directivity of particles, PSO exhibits a fast convergence speed. But on multimodal problems, the leader located at a local optimum may lead to the premature convergence of swarms. In order to solve this problem, many

Figure 1. (a) Clustering (b) Diffusion



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