Population Based Equilibrium in Hybrid SA/PSO for Combinatorial Optimization: Hybrid SA/PSO for Combinatorial Optimization

Kenneth Brezinski, University of Manitoba, Winnipeg, Canada  
Michael Guevarra, University of Manitoba, Winnipeg, Canada  
Ken Ferens, University of Manitoba, Winnipeg, Canada  
https://orcid.org/0000-0002-1031-0518

ABSTRACT

This article introduces a hybrid algorithm combining simulated annealing (SA) and particle swarm optimization (PSO) to improve the convergence time of a series of combinatorial optimization problems. The implementation carried out a dynamic determination of the equilibrium loops in SA through a simple, yet effective determination based on the recent performance of the swarm members. In particular, the authors demonstrated that strong improvements in convergence time followed from a marginal decrease in global search efficiency compared to that of SA alone, for several benchmark instances of the traveling salesperson problem (TSP). Following testing on 4 additional city list TSP problems, a 30% decrease in convergence time was achieved. All in all, the hybrid implementation minimized the reliance on parameter tuning of SA, leading to significant improvements to convergence time compared to those obtained with SA alone for the 15 benchmark problems tested.

KEYWORDS

Cognition, Combinatorial Optimization, Global Optimization, Metaheuristics, Particle Swarm Optimization, Simulated Annealing, Swarm Intelligence, Traveling Salesperson Problem

1. INTRODUCTION

Simulated Annealing (SA) is a well-known stochastic technique, belonging to a family of optimization algorithms for the purposes of solving unconstrained and bound-constrained engineering optimization problems. It was originally developed by (Kirkpatrick et al., 1983) and was inspired by the process of metal annealing; whereby the atoms that make up the crystal lattice of a solid go from a high energy state to a low energy one through the steady and controlled decrease in temperature of the system state. SA has found a bevy of applications in both combinatorial and continuous optimization problems, as it is able to approximate a global optimum for fairly large search spaces. As a result, it has been successfully applied in fields such as flow shop scheduling (Bewoor et al., 2018). In the process of SA defects are introduced as a potential candidate solution, and only when the temperature - initialized as a Boltzman probability - is high enough is the defect potentially accepted as the solution for the next iteration of annealing. This allows the algorithm to accept candidate solutions that may not immediately result in a better evaluation of an objective function - as is done by default - but
rather, creates the possibility of exploiting a better global solution in future evaluations by exiting an existing local minima/maximum.

One of the more popular applications of SA is for solving the Traveling Salesperson Problem (TSP). The TSP was established as an NP-Hard problem by (Karp, 1972), and has the goal of determining the shortest route among a set of cities, while visiting each city exactly once and returning to the starting city at the end. The problem becomes exponentially more complex when more cities are involved, and therefore requires intelligent algorithms to provide approximate solutions through the use of heuristics. The main goal of SA is to make small alterations to the TSP city route, in the form of perturbations or as mutations in the context of genetic algorithms, in order to provide a balance between exploitation and exploration of solution space.

In order to tackle this problem with balancing exploitation and exploration, this paper presents an improved hybrid Particle Swarm Optimization (PSO)/SA algorithm called Hybrid Particle Swarm Simulated Annealing Dynamic Equilibria (HPSOSADE) to overcome the complexity and computational overhead of other implementations of SA. This strategy inserts Particle Swarm Optimization (PSO) into the equilibrium process of SA in order to lower the computational cost of exploitation within the perturbation step in SA. This is done through an additional evaluation function based on standard deviation to coordinate swarm members to an optimal number of equilibrium loops in according to the needs of the problem. In conventional SA equilibrium loops are set at run-time, and do not change as the problem progresses or as computational resources are wasted.

This paper is structured as follows: Section 2 presents an overview of the relevant literature pertaining to SA and its use in hybrid strategies and other combinatorial optimization applications. Section 3 outlines the hybrid heuristic developed in this work, as well as the conventional forms of PSO and SA. Finally, Section 4 and 5 presents the computational results and conclusions made in this work, respectively.

2. BACKGROUND

Metaheuristics have been developed over the years as a means in which to tackle computationally difficult problems. One of the most well studied metaheuristics is SA, which was originally applied for solving the TSP in the work of (Černý, 1985). One of the core properties that makes SA so appealing as a metaheuristic is the ability for it to accept worse solutions that would have otherwise been discarded as they lead to poorer short-term solutions (Franzin & Stützle, 2019). Alternatively, SA is regarded as relying too heavily on initial parameters (Trelea, 2003; van den Bergh & Engelbrecht, 2006); thereby requiring significant domain-level and application-level knowledge of the problem before initializing. Researchers have stayed on top of this problem by introducing hybrid strategies that complement the shortcomings of SA alone. These strategies will be discussed in the following section.

2.1. Summary of Hybrid Implementations

Hybridization of metaheuristics provides the advantage of potentially addressing the shortcomings of one heuristic with the strengths of another. PSO is one of such complementary strategies to SA, which uses the concept of birds flocking together in search of food for survival as a means to guide global progress (Kennedy & Eberhart, 1995). Particles are initialized as members of a swarm and can communicate their best solutions to other particles and update their own personal positions and velocities accordingly. This strategy can potentially provide better local exploitation through coordination of the population members, while SA incorporates global exploration to navigate the vastness of the search space. For significantly more difficult problems, introducing PSO with SA has shown to vastly improved convergence speed on 4 benchmark functions of increasing complexity (Yan et al., 2012). For a more practical application, this was demonstrated in the work of (Bewoor et al., 2018) for a flow shop scheduling problem which translated continuous values of particles to discrete ones; combining the evolutionary search of PSO with local search of SA. In the work of (Sudibyo et al.,
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