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An ensemble of intelligent water drop algorithms and its application to optimization problems

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ABSTRACT

The Intelligent Water Drop (IWD) algorithm is a recent stochastic swarm-based method that is useful for solving combinatorial and function optimization problems. In this paper, we propose an IWD ensemble known as the Master-River, Multiple-Creek IWD (MRMC-IWD) model, which serves as an extension of the modified IWD algorithm. The MRMC-IWD model aims to improve the exploration capability of the modified IWD algorithm. It comprises a master river which cooperates with multiple independent creeks to undertake optimization problems based on the divide-and-conquer strategy. A technique to decompose the original problem into a number of sub-problems is first devised. Each sub-problem is then assigned to a creek, while the overall solution is handled by the master river. To empower the exploitation capability, a hybrid MRMC-IWD model is introduced. It integrates the iterative improvement local search method with the MRMC-IWD model to allow a local search to be conducted, therefore enhancing the quality of solutions provided by the master river. To evaluate the effectiveness of the proposed models, a series of experiments pertaining to two combinatorial problems, i.e., the travelling salesman problem (TSP) and rough set feature subset selection (RSFS), are conducted. The results indicate that the MRMC-IWD model can satisfactorily solve optimization problems using the divide-and-conquer strategy. By incorporating a local search method, the resulting hybrid MRMC-IWD model not only is able to balance exploration and exploitation, but also to enable convergence towards the optimal solutions, by employing a local search method. In all seven selected TSPLIB problems, the hybrid MRMC-IWD model achieves good results, with an average deviation of 0.021% from the best known optimal tour lengths. Compared with other state-of-the-art methods, the hybrid MRMC-IWD model produces the best results (i.e. the shortest and uniform reducts of 20 runs) for all13 selected RSFS problems.

1. Introduction

Optimization is a process that is concerned with finding the best solution of a given problem from among a range of possible solutions, within an affordable time and cost [66]. Optimization can be applied to many real-world problems, in a large variety of domains. As an example, mathematicians apply optimization methods to identify the best outcome pertaining to some

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Table 1
Applications of the IWD algorithm.

Disciplines	Applications	Ref.
Engineering	Multi-dimensional knapsack, *n*-queen puzzle	[51,53,54]
	Vehicle routing	[2]
	Economic load dispatch	[41,45]
	Flow-shop scheduling	[72]
	Reactive power dispatch	[32]
	Safety and in-transit inventory in manufacturing supply chains	[40]
	Robot path planning	[16,48]
	Printed circuit boards drill routing process	[59]
	Parallel machine scheduling	[26]
	Aerospace and defense	[60]
Networking and routing	QoS-aware routing algorithm for MANETs	[49]
	Routing protocol in mobile ad–hoc networks	[28]
	Sensor node organization in wireless sensor networks	[21]
Machine learning	Feature selection for an irrigation system	[20]
	Rough set feature subset selection	[3]
	Clustering algorithm	[55]
	Gene selection and cancer classification	[36]
	Fault detection	[5]
	Optimization of neural network weight parameters	[17]
Multi-objective optimization	Multi-objective job shop scheduling	[43]
	Vehicle guidance in road graph networks	[61]
Continuous optimization	Mathematical optimization function	[54]

mathematical functions within a range of variables [63]. In the presence of conflicting criteria, engineers often use optimization methods to find the best performance of a model subject to certain criteria, e.g. cost, profit, and quality [37]. Numerous methods have been developed and used to solve many NP-hard (i.e. problems that have no known solutions in polynomial time) [33] optimization problems [39,64,69]. A number of recent survey papers that provide comprehensive information on optimization methods and their associated categorizations are also available in the literature [11,30,33,35]. In this study, we focus on the Swarm Intelligence (SI) methodology for undertaking optimization problems.

Among a variety of optimization methods, SI constitutes an innovative family of nature inspired models that has attracted much interest from researchers [8]. SI models stem from different natural phenomena pertaining to different swarms, e.g. ant colony optimization (ACO) is inspired by the foraging behavior of ants [13,14], while particle swarm optimization (PSO) is inspired by the social behaviors of bird flocking or fish schooling [56]. In this paper, we investigate a relatively recent swarm-based model known as the intelligent water drop (IWD) algorithm [50]. IWD is inspired by the natural phenomenon of water drops flowing with soil and velocity along a river. It imitates the natural phenomena of water drops flowing through an easier path, i.e., a path with less barriers and obstacles, from upstream to downstream. Specifically, IWD is a constructive-based, meta-heuristic algorithm, comprising a set of cooperative computational agents (water drops), that iteratively constructs the solution pertaining to a problem. The solution is formulated by water drops that traverse a path with a finite set of discrete movements. A water drop begins its journey with an initial state. It iteratively moves step-by-step passing through several intermediate states (partial solutions), until a final state (complete solution) is reached. A probabilistic method is used to control the movements of the water drops. Specifically, each water drop in the IWD algorithm has two key attributes: soil and velocity. They are used to control the probability distribution of selecting the movement of the water drop, and to find the partial solution. The soil represents an indirect communication mechanism, and enables the water drop to cooperate with other nearby water drops. The soil level indicates the cumulative proficiency of a particular movement. Contrary to the ant colony algorithm [15], in which the pheromone level is constantly updated, the soil level is dynamically updated with respect to the velocity of the water drop. In other words, the velocity influences the dynamics of updating the soil level, which is used to compute the probability of the movement of the water drop from the current state to the next. In addition, the velocity is related to heuristic information pertaining to the problem under scrutiny. This information is used to guide the water drop to move from one state to another.

The IWD algorithm is useful for tackling combinatorial optimization problems [53]. IWD initially was applied for solving the travelling salesman problem (TSP) [50]. Over the past few years, it has been successfully adopted to solve different NP-hard optimization problems [57]. Table 1 summarizes a number of applications that have been successfully solved using the IWD algorithm. The success of the IWD algorithm stems from two salient properties [4,52,53]: (i) its cooperative learning mechanism allows water drops to exchange their search knowledge and (ii) the algorithm is able to memorize the search history.

As can be seen in Table 1, most of the reported IWD investigations in the literature focus on solving optimization problems in different application domains. Only a small number of studies pertaining to the theoretical aspects of the IWD algorithm to improve its performance are available in the literature. As an example, an Enhanced IWD (EIWD) algorithm to solve job-shop scheduling problems was proposed by Niu et al. [42]. The following schemes have been introduced to increase diversity of