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Sperm whale algorithm: An effective metaheuristic algorithm for production optimization problems

A. Ebrahimi, E. Khamehchi*

Faculty of Petroleum Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

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ABSTRACT

A new optimization algorithm called sperm whale algorithm (SWA) is proposed to solve production optimization problems. This algorithm is based on the sperm whale's lifestyle. Like other population-based algorithms, SWA uses a population of solutions to find the optimum answer. One of the advantages of this method over others is that it uses two contradictory types of answers: it uses the worst and the best answers to reach the optimum point. The SWA algorithm was tested on 26 benchmarks and three benchmarks in several dimensions and one production optimization problem. The results and comparison of its performance with other algorithms show that SWA's performance is superior to other algorithms and it could be confidently used in optimization tasks.

1. Introduction

Production optimization has been offered as a response to the increasing world demand for oil and gas. Optimization algorithms have many applications, and optimization techniques have proved very effective in various problems such as reserves development, well testing, distribution of natural gas reserves, design of conditions in operational production, development of production and injection projects, solving problems related to gas lift systems, and other problems. Simply stated, optimization is the selection of the best choice from among available options. Optimization algorithms can be divided into deterministic and stochastic classes. Deterministic methods themselves are classified into evaluation and gradient-based methods. In purely computational methods, there is no need for calculating gradient functions, but they are extremely slow and ineffective methods. Gradient-based algorithms use gradients or derivations of objective functions to direct the search. However, these methods do not guarantee convergence to the global optimum point, unless when the objective function is flat and smooth. Briefly, we can say that in deterministic methods, whether they use information on derivatives or receive help from methods without derivatives, the fact remains that the answers will still be local, the final answer will be greatly dependent on the initial guess, and they will fail if there are many local optimum points in the problem. In fact, the problems which have high dimensionality, multimodality, epistasis (parameter interaction), and non-differentiability are difficult or impossible to solve using this class of methods (Storn and Price, 1995).

However, stochastic methods try to find the global optimum point. They do not require gradient information but rather search for the global optimum point through calling the objective function many times. These methods can be divided into several general classes: the methods of random search, evolutionary methods, intelligent population methods, and other methods such as harmony search, etc. (Rangaiah, 2010). However, in general, they can be divided into two categories: the single-based solution methods and the population-based solution methods (Storn and Price, 1995; Boussaïd et al., 2013). The following algorithms are classified in the single-based category:

Simulated Annealing (SA) (Kirkpatrick et al., 1983), Tabu Search (TS) (Glover, 1986), Iterated Local Search (ITS) (Lourenço et al., 2010), Guided Local Search (GLS) (Alsheddy, 2011), Pattern Search (PS) (Hooke and Jeeves, 1961), Random Search (RS) (Rastrigin, 1963), Variable Neighborhood Search (VNS) (Hansen et al., Perez) and Vortex Search algorithm (VS) (Dogan and. Ölmez, 2015).

There are various population-base algorithms: the genetic algorithm (GA) based on Darwin's theory (Golberg, 1989), the Particle Swarm Optimization (PSO) algorithm based on the swarm movement of birds (Kenndy and Eberhart, 1995), Differential Evolution (DE) (Storn and Price, 1995, 1997), Estimation of Distribution

* Corresponding author.
E-mail address: khamehchi@aut.ac.ir (E. Khamehchi).

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Algorithms (EDA) (Larrañaga and Lozano, 2002), Ant Colony.

Optimization (ACO) (Dorigo and Birattari, 2010), Artificial Bee Colony algorithm (ABC) (Basturk and Karaboga, 2006; Karaboga, 2005; Karaboga and Basturk, 2007, 2008), Harmony Search (Geem et al., 2001), Bacterial Foraging Optimization Algorithm (BFOA) (Passino, 2002), League Championship Algorithm (LCA) (Kashan, 2009), Firefly Algorithm (FA) (Yang, 2008, 2009), Group Search Optimizer (GSO) (He et al., 2009), Cuckoo Search algorithm (CS) (Gandomi et al., 2011), Krill Herd algorithm (KH) (Gandomi and Alavi, 2012), Artificial Chemical Reaction Optimization Algorithm (ACROA) (Alatas, 2012), Stochastic Fractal Search (SFS) (Salimi, 2014), Symbiotic Organisms Search (SOS) (Cheng and Prayogo, 2014) and Optics Inspired Optimization (OIO) (Husseinzadeh Kashan, 2015) that are characterized by their names.

These algorithms find the solution by effectively searching the search space and reducing its size. The main difference between different algorithms is in fact in their approach to balance between exploration (global search capability) and exploitation (local search capability around the near-optimal solution) (Boussaïd et al., 2013). Most of the algorithms use the best sections of solution to reach an optimal solution and discard bad ones. In fact, they do not make utmost use of the existing data. That is why it seems necessary to develop an algorithm that uses all solutions, extracts maximum information from existing data for solving a problem, and shortens the time to reach an optimal solution.

“Time” is one of the major challenges in *petroleum production optimization* because each execution of the model by a simulator (like Eclipse) takes a long time and the large number of parameters of such problems in a real condition requires the reservoir model to be executed thousands of times by the simulator. It is practically impossible to reach optimal solution in some reservoirs with a large number of grids (Ebrahimi and Khamehchi, 2016; Abdolhosseini and Khamehchi, 2015). Therefore, it seemed necessary to develop an algorithm, which provided a better solution in lower NFE.

A new metaheuristic usually utilizes a new metaphor as the search directory. In this article, the SWA algorithm is introduced as a population-based method for solving optimization problems. One of the advantages of this method over others is that it uses two contradictory types of answers: it uses the worst and the best answers to reach the optimum point. The whale's life style was used as a model in creating this algorithm. Therefore, this animal is described first.

2. Sperm whale related background

The sperm whale belongs to the Odontocete suborder of the Class Mammalia, is a toothed whale, and the largest predator. Its senses of taste and smell are weak (Oelschläger and Kemp, 1998), but its sense of hearing is so strong that whales can use it when communicating with one another. The sperm whale emits sounds to inform other members of the group that prey is nearby. Its eyes cannot roll in the eye sockets and, hence, the eyes are not very strong, but sperm whales can retract and protrude their eyes due to the presence of thick retractor muscles attached around the eyes (Bjergager et al., 2003; Clarke et al., 1993). This helps them to catch squids (Fristrup and Harbison, 2002). They take approximately 1000 kg each day (Lockyer, 1981). Sperm whales have an average length of 16 m, mean weight of about 45 tons, and the largest brain (weighing up to 18 kg) among all the creatures living on earth. Sperm whales feed on squids that live deep in the water. To catch squids, they must go down to the depths of the water (2000–3000 m deep) while they need to come to the surface to breathe (Lee, 2014). That is why they experience two opposite poles of their environment in each cycle of breathing and feeding: the surface and, usually, the bottom of the sea. It is believed that sperm whales can stop breathing for up to 90 min (Perrin et al., 2009).

Sperm whales usually travel in groups of 6–9 and the males and females live in the same group. Moreover, the males may also form weak all-male groups of their own. Of course, most males live alone except for the mating season. Their mating pattern is like this: males fight each other and the final superior male mates with several female whales (Whitehead and Weilgart, 2000). Other animals such as orcas (killer whales) may catch weak sperm whales (such as the kids and the females), but male sperm whales are not caught by any animal (Pitman and et al., 2001).

3. Sperm whale algorithm

In this research, life style of sperm whales described above was mathematically modeled to introduce a new efficient algorithm called SWA. In this algorithm, each answer represents a sperm whale. Taking the formation of social units of sperm whales into consideration, $m \times n$ number of answers were first created, evaluated, and ordered as the initial population. This ordered population was then divided into n Temporary Sub-Groups (TSG) each with m members, and one member was randomly selected from each of the temporary subgroups for every Main Sub-Group (MSG). Fig. 1 shows the grouping process. This process, which is the simulation of sperm whale grouping and both male and female exist in each group, somewhat ensures the distribution of solutions in different groups and prevents early local stuck.

Then the following operations were carried out on each of the main subgroups:

1. Each sperm whale experiences two opposite places in its breathing–feeding cycle (it has to come to the surface to breathe and go down to the seabed to feed). Therefore, for each whale, one answer for its current place and another answer for its mirror place were considered, and the objective functions for both points were estimated. However, the problem here was that the mirror reflection of the best answer did not help in finding the optimum answer and only increased the time needed for finding it. That was why only the worst answer was reflected. In the case where the problem had constraints, the reflection to the center of the search space might transfer the point out of the desired space. It was for this reason, and considering the information exchange between whales, that the worst answer was transferred to a random point on the spatial line connecting the worst and the best answers. The best and the worst whale in each group were called the X_{best} and the X_{worst}, respectively. So:

$$X_{center} = X_{worst} + c \times X_{best} \tag{1}$$

$$X_{reflex} = X_{worst} + 2 \times (X_{center} - X_{worst}) = 2X_{center} - X_{worst} \tag{2}$$

In the above equation, X_{center} is the reflection center and X_{reflex} is the obtained result from the reflection of the worst answer to the reflection point. Moreover, c is called center factor that could be any number.

If X_{reflex} is located outside of the search space, c should decrease in this way: $c = r \times c_i$ which c_i is initial center factor and r is contraction coefficient that is a value less than 1. r and c_i should be set as algorithm parameters. Fig. 2 shows the concept of Equations (1) and (2). In the case of bound-constrained global optimization problems, the range of the parameter c can be selected in a way that X_{reflex} does not fall beyond the search space range. Let C be a $1 \times n$ vector, with n being the number of decision variables. In this case, we can write: