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Evolutionary memetic algorithms supported by metaheuristic profiling effectively applied to the optimization of discrete routing problems

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ABSTRACT

Optimizing the routing of resources to multiple remote sites is a complex issue confronting many sectors of the gas an oil industries with significant cost implications. When significant numbers of sites are involved the optimum solutions become difficult to find and require complex algorithms to do so. Memetic algorithms (MA), combining multiple metaheuristics and heuristics that can be easily activated or deactivated offer a potentially effective and flexible approach to complex routing optimization problems. By combining MAs with the recently proposed tool of metaheuristic profiling (MHP) it is possible to establish and monitor the contributions of the component metaheuristics and heuristics in finding the lowest-distance tour solutions for routing problems. MHP also facilitates the identification of synergies between specific metaheuristics, potential conflicts or duplication among others, and computational time consumption issues with certain combinations. Applying MHP as a monitoring tool during the development of MAs helps to develop balanced algorithms combining multiple metaheuristics focused on specific tasks, such as exploring the global solution space and/or exploiting the space locally around specific solutions. Memetic algorithms make it possible to consider the classic evolutionary algorithms and other well-known heuristics each as components in a "toolbox" of metaheuristics/heuristics available to be combined and configured to form flexible, fit-for-purpose optimization tools. A routing memetic algorithm is described in detail and tested using well-studied examples of the travelling salesman problem (TSP). MHP is applied, using the Excel-VBA platform, to reveal the relative contribution of the nine metaheuristics involved in the routing MA developed here, which incorporates some of the metaheuristics derived from bat-flight principles. The study identifies how these metaheuristics function together with integrational synergies. The MHP information is displayed in graphic and tabular form, alongside the optimum values obtained from multiple executions of the algorithm to illustrate the guidance and level of insight that can be provided by the MHP technique. Memetic algorithms typically involve multiple control variables that can be (and often need to be) tuned to improve their efficiency in finding the optima of specific problems. This makes them flexible, but potentially time consuming to setup and operate. The successful application of the MA to the TSP routing problem suggests scope for its development to address more complex routing problems.

1. Introduction

Optimization of the routing of services, supplies, human resources and vehicles to multiple locations is a problem relevant to many industries and therefore is studied extensively with many algorithms proposed to provide efficient solutions. When significant numbers of sites are involved the optimum solutions become difficult to find and require complex algorithms to do so. It is a problem with particular relevance to several sectors of the gas and oil industry, e.g., distribution of resources to onshore and offshore drilling and/or production sites, routing of gas, oil and petroleum product supply through transmission and distribution networks, scheduling maintenance operations across multiple sites, etc. Some recent developments have actually increased its importance to the gas and oil industry, such as the rapidly increasing use of automated surveillance vehicles, such as drones and autonomous underwater vehicles (AUVs) to monitor integrity of equipment at remote sites, flowlines in gathering systems and pipelines. In addition, the expansion of unconventional gas developments, particularly shale gas and coalbed methane, typically means that

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more surface locations and more complex gathering systems are involved in that type of resource developments. This results in routing problems involving more locations than would be associated with conventional gas resource developments, and therefore complicates the associated routing optimizations problems.

Previous gas and oil industry studies directed at optimizing routing problems include those focused on helicopter transport of rig crews (Menezes et al., 2010), routing of supply vessels to petroleum installations (Aas et al., 2007,Gribkovskaia et al., 2008a, b; Halvorsen-Weare et al., 2012), pipeline network layouts and flow movements (Brimberg et al., 2003; Li et al., 2015), LNG ship route planning (Cho et al., 2014), and vehicle routing for fuel oil distribution (Rizzoli et al., 2003).

The classic routing challenge for combinatorial optimization algorithms is the travelling salesman problem (TSP) (Merz and Freisleben, 2001). A combinatorial optimization problem, also referred to as a discrete optimization problem, involves finding the optimal combination of a finite set of objects or locations knowing that there is a discrete set of feasible solutions (Schrijver, 2003). The early algorithms applied to the TSP involved construction heuristics commonly referred to as nearest neighbour, insertion, and greedy (multi-fragment) (Bentley, 1990; Johnson and McGeoch, 1997; Reinelt, 1994), the savings heuristic (Clarke and Wright, 1964), and the spanning tree algorithm (Christofides, 1979). Combining these heuristics, particularly the greedy heuristic, with insertion methods (i.e., deleting up to three nodes from a tour and re-inserting them elsewhere, e.g. 2-opt and 3-opt exchange algorithms) focused on local search (Lin and Kernighan, 1973) in some cases improves outcomes, but the greedy heuristic has its limitations when applied to the TSP (Gutin et al., 2002). Other algorithms and heuristics applied to TSP with varying degrees of success include simulated annealing (Jeong and Kim, 1991; Zhan et al., 2016), Tabu search (Fiechter, 1994), genetic algorithms (Fox and McMahon, 1991; Ahmed, 2010; Erol &Bulkan, 2012), ant colony systems (Dorigo and Gambardella, 1997; Shimomura et al., 2010), many other evolutionary algorithms (e.g., Abdel-Rahman and Khalafallah, 2013) state transition (Yang et al., 2012).

There are a number of other well-studied routing scenarios that consider more complex situations than TSP that are relevant to some of the routing problems encountered by the gas and oil industry. For example, the capacitated vehicle routing problem (CVRP) often encountered is one in which a number of vehicles with a fixed carrying capacity are required to satisfy varying delivery requirements at a number of locations starting and finishing from a specific location (Dantzig and Ramser, 1959; Iori and Martello, 2010). A further complication of the CVRP is the dynamic vehicle routing problem (DVRP) that takes into account periodic changes in road traffic conditions (Mavrovouniotis and Yang, 2013). On the other hand, arc routing problems (ARP and their capacitated equivalents) focus on route selection from a network of options between locations rather than the relative position of the fixed nodes to be visited (Xing et al., 2011). Other routing scenarios to consider are VRP with simultaneous delivery and pick-up (VRPSDP) (Potvin, 2009).

Despite many variations on routing scenarios ultimately worthy of optimization, TSP is frequently used as a benchmark testing and verification problem for a wide range of optimization algorithms (e.g. Antosiewicz et al., 2013; Laporte, 2010), including some novel ones (e.g., Perle, 2013). TSP is therefore considered an appropriate routing problem to test the memetic algorithm proposed and to demonstrate the benefits of the metaheuristic profiling technique in assessing its performance.

Memetic algorithms (MA) were first introduced and applied as modifications to genetic algorithms (i.e., hybridizing a genetic algorithm with simulated annealing) applied to the TSP (Moscato, 1989; Moscato and Norman, 1989, 1992). A memetic algorithm consists of a combination of several metaheuristics and heuristics, referred to by some as memes (Neri and Cotta, 2012). MAs are essentially search strategies in which, to make them effective, the component metaheuristics both cooperate and compete to achieve improved solutions (Norman and Moscato, 1989; Moscato and Cotta, 2003). Memetic algorithms, combining multiple metaheuristics and heuristics that can be easily activated or deactivated offer a potentially effective and flexible approach to complex routing optimization problems.

The MA evaluated here is a hybrid evolutionary algorithm incorporating multiple metaheuristics and heuristics operating collectively, focused on global and local search, and incorporating knowledge of the problem as it unfolds, and communicating that knowledge to its component parts, in order that it might be further processed and enhanced. The communication and sharing of knowledge is an important feature of MAs that help them to overcome the "no-free lunch theorem" limiting the benefits of combining metaheuristics (Wolpert and Macready, 1997).

The objective of this study is to describe a novel memetic algorithm focused on optimizing routing problems. The algorithm and its metaheuristic and heuristic components are described and applied to the TSP. The performance of the memetic algorithm is evaluated using detailed metaheuristic profiling (MHP) to demonstrate the usefulness of that technique (Wood, 2016) in identifying the respective and collective contributions of the component metaheuristics and heuristics to its performance. The memetic algorithm evaluated was developed in Excel Visual Basic for Applications (VBA), because that platform facilitates the collection and display of the intermediate calculations performed by the algorithm to provide the detail necessary for metaheuristic profiling. The results presented were obtained by running the algorithm on a standard laptop computer (i.e., Samsung 350V5C-A06 Laptop, Intel Core i7, 2.4 GHz, 8 GB RAM). If the intermediate data collection capabilities of the algorithm were to be reduced then significantly faster execution times of the algorithm would be possible by recoding the algorithm in other computer languages focused more on speed.

2. Travelling salesman problem (TSP) and memetic Algorithm's tour construction principles

The combinatorial optimization problem known as the TSP involves the objective of finding the shortest tour that visits each node (i.e., location, city etc.) in a set of n nodes [N] only once and returns at the end of the tour to the node from which the tour started. The distances between, the cities either straight lines or arcs, are typically defined in a distance matrix (D) with elements consisting of the distances between specific node sequences in set [N], d_{ij} where i and $j = 1, \ldots, n$. The objective function is then to minimize the total-tour distance, which can be expressed as:

$$Minimize \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} \tag{1}$$

Two key constraints typically applied in the TSP problem are: $d_{ij} = 0$ and $d_{ij} = d_{ji}$. The latter constraint makes it a symmetrical problem. Although it is possible to consider asymmetrical TSP scenarios where, for at least some elements, $d_{ij} \neq d_{ji}$, in this study it is symmetrical TSP that are considered.

The city sequence selection process, to build city tours for testing and adaption, applied in the evolutionary memetic algorithm developed and described here is a stochastic method based upon probabilities derived from a scoring system inspired in part by