Engineering Applications of Artificial Intelligence 76 (2018) 55–66

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Integrating forecasting in metaheuristic methods to solve dynamic routing problems: Evidence from the logistic processes of tuna vessels

Carlos Groba, Antonio Sartal *, Xosé H. Vázquez

University of Vigo, Spain

ARTICLE INFO

Keywords:
Multiple traveling salesman problem
Genetic algorithm
Vehicle routing problem
Fish aggregating devices
Moving targets

ABSTRACT

The multiple Traveling Salesman Problem (mTSP) is a widespread phenomenon in real-life scenarios, and in fact it has been addressed from multiple perspectives in recent decades. However, mTSP in dynamic circumstances entails a greater complexity that recent approaches are still trying to grasp. Beyond time windows, capacity and other parameters that characterize the dynamics of each scenario, moving targets is one of the underdeveloped issues in the field of mTSP. The approach of this paper harnesses a simple prediction method to prove that integrating forecasting within a metaheuristic evolutionary-based method, such as genetic algorithms, can yield better results in a dynamic scenario than their simple non-predictive version. Real data is used from the retrieval of Fish Aggregating Devices (FADs) by tuna vessels in the Indian Ocean. Based on historical data registered by the GPS system of the buoys attached to the devices, their trajectory is firstly forecast to feed subsequently the functioning of a genetic algorithm that searches for the optimal route of tuna vessels in terms of total distance traveled. Thus, although valid for static cases and for the Vehicle Routing Problem (VRP), the main contribution of this method over existing literature lies in its application as a global search method to solve the multiple TSP with moving targets in many dynamic real-life optimization problems.

1. Introduction

This paper addresses the synergies in combining a predictive technique with a metaheuristic evolutionary-based method to solve the multiple Traveling Salesman Problem (mTSP) with moving targets (mTSP-MT). The mTSP-MT is the generalization of the well-known Traveling Salesman Problem (TSP). It deals with multiple salesmen, and targets (e.g., customers or objects) are not fixed. As in any TSP, however, the aim is to minimize the total distance traveled by all salesmen.

The mTSP-MT is therefore more suitable than the ordinary TSP for a wider range of real-world problems. In fact, this is the method used, for example, in the defense sector to protect an airport or a security zone from mobile intruders (raiders, animals, vehicles, etc.), or in the logistics sector to supply a fleet of boats or mobile ground units (Stieber et al., 2015; Stieber and Fügenschuh, 2017). It can also be applied to the Vehicle Routing Problem (VRP) with multiple vehicles, time windows or capacity restrictions (Sundar et al., 2017; Bae and Chung, 2017). New potential uses are also emerging every day in mobility and delivery services (e.g., delivery services, real-time mobility requirements, drones scheduling and collaboration, etc.) conducted by companies such as Uber and Amazon (Menezes et al., 2015).

Whereas the diverse perspectives and problem-solving methods have helped practitioners and scholars to address a multitude of TSPs, including mTSPs in various industries (Menezes et al., 2015), the literature on mTSP-MT is still scarce. This is possibly due to the greater complexity of this type of problems compared to conventional TSP approximations, which may also explain why ad hoc experiments with many restrictions (small distances, planned routes, fixed starting-points, etc.) have often ended with few or not applicable solutions for real-life problems. For example, Liu (2013) and Jiang et al. (2005) proposed various solutions for the mTSP-MT problem by narrowing the scope of analysis to one dimension and limiting the working speed. Similarly, other studies have restricted the positions of the salesmen (e.g., by having them start at the same point, located in the middle of the area) or the possible targets' movements (e.g., by forcing customers to move in a structured path) (Menezes et al., 2015; Stieber and Fügenschuh, 2017). In addition, regarding the calculation methodology, the most recent approaches have worked on a real-time basis and have been recalculated to find the changes between nodes (Zhou et al., 2003; Hajjam et al., 2013). However, they have not anticipated the targets' future movement, so the optimal solutions appear only when the changes are communicated and the algorithms have been recalculated.

* Correspondence to: Facultade de Economía. Rúa Leonardo da Vinci., 36310 Vigo., Spain.
E-mail addresses: cgroba@uvigo.es (C. Groba), antoniosartal@uvigo.es (A. Sartal), xhvv@uvigo.es (X.H. Vázquez).

https://doi.org/10.1016/j.engappai.2018.08.015
Received 25 January 2018; Received in revised form 7 July 2018; Accepted 29 August 2018
0952-1976/

Against this background, the paper addresses the problem of moving targets by combining a predictive technique (Newton's movement equation) with a genetic algorithm (GA). This new approach, which could be named genetic algorithm based in multiple-trajectory prediction (GAMTP), yields a generic solution that not only suits dynamic and static scenarios, but it also applicable to any real-world problem with multiple travelers and mobile targets. GAMTP thus combines prediction and GA in a single method to reach a better global optimization solution than when GAs alone used without internalizing prediction.

Since the objective of this work is to prove that integrating forecasting within a metaheuristic method (e.g., genetic algorithms) better results are achieved than in the simple non-predictive version; we chose Newton's movement equation as our predictive technique over other techniques because it offers a quick, short-term prediction even when provided with very little information (Groba et al., 2015). Analogously, GAs were chosen as metaheuristic method for three reasons: (1) they are evolutionary, which is mandatory for the algorithm implementation; (2) they show fundamental properties in terms of robustness and statistical convergence; and (3) they can reach a solution within an acceptable computational time (Jih and Hsu, 2004).

Data come from different group of tuna vessels retrieving their fish aggregating devices (FADs) in the Indian Ocean during April in 2017. FADs drift in the sea and provide an artificial substrate for attaching organism such as algae and invertebrates. This phenomenon probably stimulates a food chain that attracts different type of fish. Tuna also tends to gather beneath them. All FADs are attached to a buoy with a Global Positioning System (GPS) that transmits its coordinates every 12 h. The people steering the vessels, which work in groups, need to design their routes to recover the constantly moving FADs in order to minimize the total distance traveled. We compare our results with both the most commonly used method, the nearest neighbor (NN) strategy, and a classic mTSP approach based on GA (i.e., without prediction) (Bjarnadottir, 2004).

The paper is organized as follows. The next section provides a review of the literature. Sections 3 and 4 describe, respectively, the data and methodology. Section 5 introduces the model and presents the experimental design. Section 6 discusses results and, finally, Section 7 concludes by highlighting the paper's main contributions and its implications.

2. Literature review

TSP is a well-known of Combinatorial Optimization (CO) problems that is NP-hard (Garey and Johnson, 1983), and in which, assuming that $P \neq NP$, no polynomial time algorithm exists (Karp, 1972).

An extension of TSP involves more than one salesman (mTSP), and assumes that each city must be visited exactly once and by only one salesman (Bektas, 2006a; Venkatesh and Singh, 2015). Thus, given a start-and-end point (a depot), a set of n cities to be visited by one salesman, and m salesmen (where $n > m$ the optimal), then the mTSP consists of finding routes for all m salesmen such that the cost of visiting all cities is minimized. The cost can be defined in terms of distance, time, or other criteria. Thus, although mTSP is NP-hard like TSP but entails a more complicated problem because cities must be assigned firstly to each salesman, and then the optimum order is subsequently determined for each salesman. Two main versions of the mTSP can be defined based on the number of depots. In the first version all m salesmen start and end at one depot. In the second version every salesman begins and ends at a different depot. We address the second variant, which represents a more generalized situation that aims at minimizing the total distance the salesmen travel (i.e., the total length of all routes). This approach reflects the strand of literature dealing with multiple Traveling Salesman Problem (Bektas, 2006b).

Furthermore, the solution shows an additional trait: targets are not fixed and can vary their positions over time. This variant is known as mTSP with moving targets (mTSP-MT), which is a dynamic generalization of the mTSP that makes the problem more suitable to a wider range of real-world situations in various industries. In fact, many mTSP-MT applications exist, for example, in supply logistics (Stieber et al., 2015), robotic patrolling (Pushkarini Agharkar and Bullo, 2015), scheduling and routing (e.g., bank-crew scheduling, workload balancing, and school-bus routing), as well as in the defense sector (e.g., the multiple-weapons-to-multiple-targets assignment problem) (Stieber and Fügenschuh, 2017). On a broad perspective, one of the fields that could highly benefit from this type of analysis in the future is the transportation and delivery service (including unmanned aerial vehicle services) leaded by companies such as Uber, Amazon and others (Agatz et al., 2016; Dorling et al., 2017).

Curiously enough, however, there are relatively few approaches to solve mTSP-MTs. Again, this is possibly due to the greater complexity inherent to the dynamics of mTSP-MT in comparison with traditional TSP (Garcia-Najera and Bullinaria, 2011; Hajjam et al., 2013) or the simpler moving-target TSP (e.g. a supply ship that resupplies patrol boats as they work, a fishing boat collecting its catch at sea, or an airplane that must intercept a number of mobile ground units) (Helbing and Tilch, 1998; Groba et al., 2015). There are also variants of the TSP-MT (including one with resupply) in which the salesmen must return to the depot after intercepting each target (Jiang et al., 2005; Liu et al., 2009; Jindal and Kumar, 2011).

Whereas this specific literature has helped researchers to explore the TSP-MT, it has proceeded so far with a high number of restrictions in order to reach a feasible result (Helvig et al., 2003; Blum and Roli, 2003a). The cost of this strategy, nevertheless, is that they often end up with few or not applicable real-world solutions. For instance, Jiang et al. (2005) described a solution approach based on GA with a fixed number of cities in which the target moved at a constant velocity, which in fact is a very common assumption in this area. The same speed restriction has been considered in moving-target TSP situations (Helbing and Tilch, 1998; Helvig et al., 2003). Similarly, other studies have restricted the salesmen's position (e.g., by requiring that they start at the same point in the middle of the area) or the possible targets' movements (e.g., by having the customers only move in structured paths) (Menezes et al., 2006; Stieber et al., 2015). In the same way, Jindal and Kumar (2011) assumed all targets started from their starting position, were only in one dimension, and moved with constant velocity. In general terms, therefore, this literature shows that the available research can hardly solve practical problems; rather, it is mainly focused on providing structure and analyzing variants of the TSP that answer specific questions in made-to-measure approximations of reality.

Similar arguments hold for VRP (Braekers et al., 2016; Toth and Vigo, 2014), which could be considered as a generalization of mTSP with particular applications to transport and logistic (Montoya-Torres et al., 2015). The main difference between the classic moving TSP and the moving VRP is that the VRP can include additional restrictions beyond distance, such as added vehicle capacity, time constraint, a known non-negative demand for each depot, and a non-negative cost for each route (Eksioglu et al., 2009). Nevertheless, just as it happens with mTSP, research on VRP with moving targets is still underdeveloped. The existing literature focuses on Unmanned Aerial Vehicles (UAVs) (including combat UAVs), surveillance missions, and military needs, but none of these studies offers a generic solution with no restrictions (Shetty et al., 2008; Geng et al., 2014; Shima and Schumacher, 2005). Thus, although our research hinges on mTSP-MT, it can also contribute to solve VRP problems (Cattaruzza et al., 2017).

Summing up, there is a gap in the literature on mTSP and VRP with regard to dynamic scenarios. Research so far has worked with basic settings and simplified parameters that not only lead to a continuous recalculation of the solution, but make this very same solution of limited application to real-life situations. Our proposal, however, addresses simultaneously three key issues that characterize any real-world situation: (1) multiple targets for (2) multiple salesmen and (3) in dynamic scenarios. This makes it a generalized solution for static and dynamic scenarios of mTSP and VRP, and opens multiple real-world applications in many scientific and business fields, from medicine or physics to production and logistics.