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# A Glowworm Swarm Optimization algorithm for the Vehicle Routing Problem with Stochastic Demands

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ABSTRACT

The Glowworm Swarm Optimization (GSO) algorithm is a relatively new swarm intelligence algorithm that simulates the movement of the glowworms in a swarm based on the distance between them and on a luminescent quantity called luciferin. This algorithm has been proven very efficient in the problems that has been applied. However, there is no application of this algorithm, at least to our knowledge, in routing type problems. In this paper, this nature inspired algorithm is used in a hybrid scheme (denoted as Combinatorial Neighborhood Topology Glowworm Swarm Optimization (CNTGSO)) with other metaheuristic algorithms (Variable Neighborhood Search (VNS) algorithm and Path Relinking (PR) algorithm) for successfully solving the Vehicle Routing Problem with Stochastic Demands. The major challenge is to prove that the proposed algorithm could efficiently be applied in a difficult combinatorial optimization problem as most of the applications of the GSO algorithm concern solutions of continuous optimization problems. Thus, two different solution vectors are used, the one in the continuous space (which is updated as in the classic GSO algorithm) and the other in the discrete space and it represents the path representation of the route and is updated using Combinatorial Neighborhood Topology technique. A migration (restart) phase is, also, applied in order to replace not promising solutions and to exchange information between solutions that are in different places in the solution space. Finally, a VNS strategy is used in order to improve each glowworm separately. The algorithm is tested in two problems, the Capacitated Vehicle Routing Problem and the Vehicle Routing Problem with Stochastic Demands in a number of sets of benchmark instances giving competitive and in some instances better results compared to other algorithms from the literature.



## 1. Introduction

The improvement of routing decisions is one of the most important problems in the Supply Chain Management as the reduction of the routing decisions' cost is crucial for a company in order to increase its profit. The difficulty in the solution of the routing problems is that most of them belong to the class of combinatorial optimization problems that are characterized as NP-hard and, thus, heuristic and metaheuristic techniques have been used in order to find high quality solutions in reasonable computational time. Moreover, it has been proven that some Stochastic Combinatorial Optimization problems are #P-hard (Dyer & Stougie, 2006; Weyland, 2014). In this paper, the proposed algorithm is used for the solution of the **Vehicle Routing Problem with Stochastic Demands (VRPSD)** where the customers' demands are stochastic variables. It should be noted that in Stochastic Vehicle Routing Problems (SVRPs), one parameter of the problem is a stochastic variable that follows a known (or unknown) probability distribution. This parameter could be the customers, the demands of the customers or the travel and service times of the customers. SVRPs differ from the Capacitated Vehicle Routing Problems (CVRPs) in several fundamental aspects, like the concept of a solution. The solutions methodologies are considerably more complicated in the SVRPs.

The algorithm proposed for the solution of the VRPSD is a swarm intelligence algorithm. In the last few years, a number of new swarm intelligence algorithms have been proposed. A very interesting new population-based swarm intelligence algorithm that simulates the movement of the glowworms in a swarm based on the distance between them and on a luminescent quantity called **luciferin** is the Glowworm Swarm Optimization (GSO) algorithm presented by Krishnanand and Ghose (2006), Krishnanand and Ghose (2009a), Krishnanand and Ghose (2009b). The Glowworm Swarm

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Optimization was, initially, presented for the optimization of multimodal functions (Krishnanand and Ghose (2006, 2009a, 2009b, 2011)). In Krishnanand and Ghose (2008a) a modified version of the algorithm is presented and applied in hazardous situations in ubiquitous environments. In Krishnanand and Ghose (2009b) the algorithm is used in searching higher dimensional spaces. The results reported are from tests conducted up to a maximum of eight dimensions and show the efficacy of GSO in capturing multiple peaks in high dimensions. In Krishnanand and Ghose (2009c) a multi-robot system is implemented using a modified version of the algorithm and addresses the problem of multiple signal source localization where robotic swarms are used to locate multiple signal sources. In Mannar and Omkar (2011) a new suit-repair system is presented which is exhaustively defined and has high implementation feasibility. This system provides a new innovative space suit puncture-repair mechanism using a Wireless Sensor Network of micro-robots optimized using a GSO algorithm. In Krishnanand and Ghose (2008b) theoretical foundations for a variation of the multi-agent problem using GSO are presented. In Wu, Qian, Ni, and Fan (2012) a GSO algorithm for continuous optimization problems is presented while a hybridized version of the algorithm for the solution of the same kind of problems is presented in Ghandehari, Miranian, and Maddahi (2013). In Liao, Kao, and Li (2011) a sensor deployment scheme based on GSO to enhance the coverage after an initial random deployment of the sensors is presented. Chaotic versions of the algorithm are presented in Zhou (2012), Zhang, Zhou, and Zhou (2012). The GSO algorithm has been used for solving numerical integration in Yang and Zhou (2011). The only application, at least to our knowledge, that concerns a combinatorial optimization problem is an application of the GSO algorithm for the solution of the multidimensional Knapsack problem in Gong, Zhou, and Luo (2011).

In order to avoid the slow convergence of Glowworm Swarm Optimization algorithm Zhou, Zhou, and Chen (2013) proposed an artificial Glowworm Swarm Optimization algorithm based on cloud model. In Tang, Zhou, and Chen (2013) an improved version of GSO algorithm is presented denoted as parallel hybrid mutation Glowworm Swarm Optimization. A multiobjective version of GSO algorithm for finding the optimal pareto set was presented by Sanseverino, Di Silvestre, and Gallea (2013), while in Mo, Liu, and Ma (2013) an application of GSO in modern finance for finding the parameters of an option pricing model was presented. In Zhou, Luo, and Liu (2014) a GSO algorithm was used in order to find the optimum scheduling in a transit vehicle scheduling optimization problem. In Nelson Jayakumar and Venkatesh (2014) a GSO algorithm was used for finding the optimal solution for the multiple objective environmental economic dispatch (MOEED) problem while in Li, Wang, Gong, Liu, and Jiang (2014) a binary GSO algorithm was proposed for the solution of a unit commitment problem. In Cui, Feng, Guo, and Wang (2015) the GSO algorithm was used as a method for training the parameters of a neural network for using on time series prediction, while in Mageshvaran and Jayabarathi (2015) the GSO algorithm was used in order to minimize the amount of load to be shed in order to prevent excessive load shedding to avoid the cascaded tripping and blackout in power systems during generation contingencies. In Yepes, Marti, and Garcia-Segura (2015) a hybridization of the Glowworm Swarm Optimization algorithm with a simulated annealing algorithm was presented in order to optimize cost and $CO_2$ emissions when designing precast-prestressed concrete road bridges with a double U-shape cross-section. In Singh and Deep (2015) two major contributions concerning the GSO algorithm were made. Initially, a mathematical result was proved which shown that the step size of GSO has a significant influence on the convergence of GSO. Secondly, three variants of GSO were proposed with different step size each one of them. In Nair, Gupta, and Valadi (2015) a GSO algorithm was presented for solving the feature selection and classification problem. In Singh and Deep (2014) a recent review of GSO algorithm was presented.

As there are not any competitive nature inspired methods based on Glowworm Swarm Optimization, at least to our knowledge, for the solution of any kind of vehicle routing problems, we would like to develop such an algorithm and to test its efficiency compared to other nature inspired algorithms in a variant of the Vehicle Routing Problem, the Vehicle Routing Problem with Stochastic Demands (VRPSD). Also, a second challenge was to find an efficient hybridization with two very powerful metaheuristics, the Path Relinking (Glover, Laguna, and Marti (2003) and the Variable Neighborhood Search (Hansen and Mladenovic (2001), in such a way that the metaheuristic algorithms will be incorporated inside the Glowworm Swarm Optimization algorithm improving its main characteristics and, also, improving the performance of the algorithm. The main innovative features of the hybridized algorithm presented in this paper are:

- Two different solutions vectors are used, the one is in the continuous space and it is used in the equation of the movement and in the equation of the expanding of the circle where the glowworms search for their neighbors and the other is in the discrete space where it represents the path representation of the tour and it is used in the calculation of the fitness function of the solution.
- In the movement phase of the algorithm, two different subphases are used independently. In the first one, the update of the vector in the continuous space is realized as in the initially proposed GSO algorithm while in the second subphase the update of the vector in the discrete space is performed using a novel Path Relinking (PR) procedure, the Combinatorial Neighborhood Topology (Marinakis and Marinaki (2013c)). The reason that we perform this modification is that the movement equation needs the transformation of the values into a floating point in the interval [0,1] which is not efficient for a stochastic combinatorial optimization problem like the Vehicle Routing Problem with Stochastic Demands. Thus, using the PR procedures we do not transform at all the solution of each glowworm from the path representation of the tours into continuous values and, thus, we speed up the whole algorithm and there is no any losing of information in each phase of the algorithm.
- A migration policy for the glowworms is used in two cases. First, when a glowworm cannot attract or be attracted from any other glowworm for a number of iterations and, second, when for a number of iterations a glowworm is the brighter inside a circle. The migration policy is used in the solution in the continuous space (and not in the solution in the discrete space) and, thus, the fitness function is not affected from this strategy. The reason that it is performed is that we would like to exchange information between good glowworms which are in very different places in the solution space. Many researchers use a kind of migration policy in a number of evolutionary algorithms either by using the term "migration" or by using the term "restart" as in the Max-Min Ant System (Stutzle and Hoos (1997)) and in the Artificial Bee Colony algorithm (Karaboga & Basturk, 2007).
- The use of a local search algorithm (Variable Neighborhood Search (VNS) (Hansen & Mladenovic, 2001) for improving the solution of each of the glowworms separately. This is performed in order to give to each glowworm more exploitation abilities in the solution space and the possibility to work independently from the other glowworms.

The development of an efficient algorithm is very crucial for the problem studied in this paper. It should, also, be mentioned that an expert and intelligent system is used in order to replace the human expert when he/she cannot solve the problem by hand or with a simpler method. The problem studied in this paper is a combinatorial optimization NP-hard problem. It is, also, very difficult to solve a Vehicle Routing Problem with Stochastic Demands using an exact algorithm. Thus, the main task of the research community dealing with this problem is to find an efficient algorithm that solves it. There is a