Journal of Manufacturing Systems 33 (2014) 188–195

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

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

Bi-criterion optimisation for configuring an assembly supply chain using Pareto ant colony meta-heuristic

Luis A. Moncayo-Martínez [a,*], Gustavo Recio [b,1]

[a] Department of Industrial and Operations Engineering, Instituto Tecnológico Autónomo de México (ITAM), Río Hondo No. 1, Col. Progreso Tizapán, C.P. 01080 Mexico City, Mexico

[b] Department of Computer Science, Carlos III University of Madrid, Avda. de la Universidad No 30, Sabatini Building, 28911 Leganés, Madrid, Spain

ARTICLE INFO

Article history:
Received 24 October 2012
Received in revised form
25 September 2013
Accepted 2 December 2013
Available online 4 January 2014

Keywords:
Supply chain configuration
Multi-objective optimisation
Pareto set
Ant colony system

ABSTRACT

An assembly supply chain (SC) is composed of stages that provide the components, assemble both sub-assemblies and final products, and deliver products to the customer. The activities carried out in each stage could be performed by one or more options, thus the decision-maker must select the set of options that minimises the cost of goods sold (CoGS) and the lead time (LT), simultaneously. In this paper, an ant colony-based algorithm is proposed to generate a set of SC configurations using the concept of Pareto optimality. The pheromones are updated using an equation that is a function of the CoGS and LT. The algorithm is tested using a notebook SC problem, widely used in literature. The results show that the ratio between the size of the Pareto Front computed by the proposed algorithm and the size of the one computed by exhaustive enumeration is 90%. Other metrics regarding error ratio and generational distance are provided as well as the CPU time to measure the performance of the proposed algorithm.

1. Introduction

In recent years, the problem of supply chain (SC) configuration has attracted the attention of researchers in combinatorial optimisation and practitioners in SC management due to the effect on performance of an optimum design. Typically, optimum design decreases costs by 5–60% with 10% typical and coordinates and improves service time, decreasing it by 25–75% with 40% typical [1]. In addition, the SC configuration provides the basic structure for the SC operations, from the strategic to operational level, and it represents a competitive advantage for companies and a significant area of capital investment.

We model the SC by means of stages, which can be of three different kinds: supplying, manufacturing, and modes of delivery. Every stage is connected to one or more stages according to the products' bill of materials in which the sub- and final assemblies are represented by manufacturer stages, whereas components or raw materials are represented by the supplier stages. The modes of delivery are stages that include information about which customer asks for which product. They are connected to the manufacturers' stages that represent the final assembly. It is assumed that every stage could be performed by at least one option, thus a manufacturer stage could have one or more plants or production lines (options) in which an assembly could be assembled, a supplier stage could have at least one option that represents a supplier able to supply the component, and a delivery stage that represents different modes of delivery, e.g. normal or fast delivery. Every option that could perform a stage is associated with a certain time and cost, e.g. for a manufacturing stage, these correspond to the cost and time of producing either the final-assembly or sub-assembly.

Therefore, the problem of configuring the SC is about selecting an option for every stage given that the cost of goods sold (CoGS) and the products' lead time (LT) are minimised, simultaneously. This is not a trivial decision because the decision-maker could have many options, differentiated by their lead times and costs, that could perform the tasks of supplying a component, assembling a product, and delivering the final product to the customer. In order to select an option to perform a stage, the decision maker must take into account the trade-off between the time and cost added to the CoGS and LT, respectively.

So far, the approaches used to solve the SC configuration problem deal with optimising the CoGS and the most common techniques used to solve it are evolutionary computation and traditional operational research techniques. In this paper, we test a meta-heuristic called ant colony optimisation (ACO) to solve a bi-objective SC configuration problem. ACO has been proved to solve efficiently and effectively many real world and theoretical problems, specially hard combinatorial problems [2]. Moreover, ACO

* Corresponding author. Tel.: +52 55 5490 4618; fax: +52 55 5490 4611.
E-mail addresses: luis.moncayo@itam.mx (L.A. Moncayo-Martínez), grecio@inf.uc3m.es (G. Recio).
1 Tel.: +34 91 624 8843.

0278-6125/$ – see front matter
http://dx.doi.org/10.1016/j.jmsy.2013.12.003

can be used in dynamic environments due to its inherent parallelism, i.e. many ants look for a solution at the same time, and positive feedback accounts for rapid discovery of promising solutions.

Since the SC configuration problem is related to the selection of an option to perform a stage (i.e. a combinatorial problem) that minimises both CoGS and LT, we test the performance of ACO to solve the bi-objective problem applying the concept of Pareto optimality criterion to the solutions found by the ants.

We proposed not only applying the Pareto ACO (P-ACO) to the bi-objective SC configuration problem, but also comparing the results with the optimum Pareto set computed by exhaustive enumeration of a notebook SC widely used in literature.

One novelty in our paper is the comparison of the Pareto sets computed by exhaustive enumerations and the one returned by P-ACO to this problem. One of the latest surveys in the SC design problem conducted by Chandra and Grabis [3] shows that the most widely used meta-heuristic applied to SC design problem is the genetic algorithm (GA). Additionally, a survey published by Jones et al. [4] regarding the application of meta-heuristics to multi-objective problems shows that 70% of the articles utilise GA, 24% simulated annealing, and 6% tabu search, thus the application of ACO is relatively new in the SC configuration. A similar survey is published by Giagkiozis et al. [5].

A lot of techniques have been proposed to model and optimise the SC configuration (SCC) problem. We solve this problem using an algorithm based in ACO and modify it by minimising not only the CoGS but also the LT. As the aim of this research is to apply a new approach (Pareto ant colony optimisation) to solve the SCC problem. We identify mainly the mathematical, genetic-algorithm, and computational techniques.

When a mathematical approach is utilised, a mixed-integer programming (MIP) model must be built. The MIP models have two important disadvantages: (a) they provide a relatively simple and compact approximation of complex decision problems and (b) the computational complexity remains an important issue in their application [3]. In order to cope with problem complexity, only some entities of the SC are modelled and one objective is optimised.

When the MIP model has linear or quadratic objective functions or restrictions, it is solved using standard optimisation software as Tsiakis and Papageorgiou [6], Kouvelis et al. [7], Sadjady and Davoudpour [8], and Amin and Zhang [9]. Although the general-purpose optimisation software has high performance and is flexible, the SCC problem does not rely on some kind of linear or quadratic functions that oversimplify key issues such as demand uncertainty or cost and time of SC operations [10]. In order to reduce the computational complexity in mathematical approaches, other techniques such as meta-heuristics and simulation are utilised. The solutions generated by meta-heuristics could not be proved to be optimal but experiences during the past decades have shown that meta-heuristics find the solution or a very "good" solution rapidly and effectively [11].

Another technique used for solving the SC design problem is simulation. Although simulation is a useful tool for modelling the SC, it is not an optimisation technique in itself [12]. Therefore, attempts have been made to combine simulation and optimisation techniques in order to design the SC, see a complete survey by Terzi and Cavalieri [13].

There is no published attempt to solve the bi-objective SC configuration by means of ACO as shown in recent surveys published by Chandra and Grabis [3], van der Vaart and van Donk [14], Tako and Robinson [15], and Kleijnen [16], specialised in SC, and the surveys published by Dorigo and Stützle [2], Mohan and Baskaran [17], and Blum [18] about problems which have been solved by ACO. Some SC topics include order fulfilment by Silva et al. [19]; vehicle routing by Reimann et al. [20], and shop scheduling by Blum and Sampels [21].

2. Ant colony and Pareto optimisation

The ACO is a novel, nature-inspired meta-heuristic that mimics the real foraging behaviour of ant colonies and the concentration/evaporation of chemical substances called pheromones [2].

When ants begin looking for food, they explore the forage area randomly depositing a quantity of pheromones all along their trail. As soon as an ant finds food, it returns to the nest using the path built on its forward trip, reinforcing the pheromones deposited over it. While other ants are looking for food or when ants leave the nest, they tend to choose (in probability) trails that have a strong concentration of pheromones. As a general rule: the higher the quantity of pheromones over a trail, the higher the probability that ants follow it. The quantity of pheromones concentrates over a path because they are a function of time, i.e. if pheromones are not reinforced in short periods of time, they evaporate. It is clear that the shorter the distance from the nest to the food, the faster the ants complete the tour, thus the concentration of pheromones is higher in short trails than in long ones. As pheromones over long trails are not reinforced at the same rate, they evaporate.

As in real ants, the artificial ones (A), also called agents, cooperate to find solutions to hard combinatorial problems by reacting to changes in their environment using an indirect communication process based on artificial pheromones (τ), thus near- and optimum solutions emerge from agent's cooperative interaction. The problem to be solved is represented by a graph in which the pheromones are deposited over the set of either vertices or edges. An initial and a final condition represent the nest and the food, respectively. Ants build a solution by stepping from vertex to vertex based on: (a) a probabilistic decision rule that is a function of the quantity of τ over either vertices or edges and the heuristic information (η) which is a source of information that is not related to ants' parameters and gives A the opportunity of exploiting the specific knowledge of the problem; and (b) the set of problem constraints.

The ACO meta-heuristic has three basic procedures that can take place simultaneously or one at a time. The first procedure is the *construct ant solution* which allows A to build a solution, i.e. A travel around a graph which represents the problem. They know they have to stop travelling when they reach the final condition. The *apply local search* is the second sub-process. This is optional and aims to improve the ant's solution by applying a local search. Finally, in the third procedure called *update pheromones*, the pheromones trails are reinforced according to the solution's "quality" and are evaporated by an evaporation factor (ρ) to avoid stagnation due to an indiscriminate concentration of pheromones.

Multi-objective (MO) optimisation is a growing area of research, thus many techniques have been proposed over the years. Those techniques are broadly divided into preference-based methods and generating methods [22]. In the first ones, a solution is generated based on the preference of the decision maker who can provide this information before or while the solution process is run. On the other hand, generating methods are based on the idea of calculating a set of possible solutions from which the decision maker could select one according to his or her criteria.

In our case, we compute a set of solutions (thus we use the generating method) and then the concept of Pareto optimality is applied to it, thus the decision maker is able to select the "best" solution according to his or her criterion.

Angus [23] proposed an early taxonomy in MO-ACO that is based on the following common features: choice of pheromone model, solution construction process, solution evaluation, pheromone update, and treatment of Pareto optimal solutions.