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Multi-objective modeling of production and pollution routing problem with time window: A self-learning particle swarm optimization approach

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ABSTRACT

Production routing and pollution routing problems are two important issues of vehicle routing problem (VRP) of the supply chain planning system. Both determine an optimum path for the vehicle, in addition, production routing problem (PRP) deals with production and distribution whereas pollution routing problem deals with carbon footprint. In this paper, we develop a VRP that simultaneously considers production and pollution routing problems with time window (PPRP-TW). The proposed PPRP-TW is a NP-hard problem concentrating to optimize the routing problem over the periods. A fleet of identical capacitated vehicles leave from a production plant to a set of customers scattered in different locations. The transportation part of PPRP-TW is concerned with carbon footprint. Thus, a multi-objective multi-vehicle PPRP-TW (MMPPRP-TW) is formulated with two objectives: minimization of the total operational cost and minimization of the total emissions (equivalently, minimization of the fuel consumption). A hybrid Self-Learning Particle Swarm Optimization (SLPSO) algorithm in multi-objective framework is proposed to solve the MMPPRP-TW. To establish superior computational efficiency of hybrid SLPSO algorithm, a comparison with the well-known Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is performed.

1. Introduction

A globally optimized supply chain network and logistic system that includes inventory routing problem (IRP), production routing problem (PRP) and its variants as of major concern, is the core issue for enterprises. The problem that involves simultaneous optimization of total inventory and vehicle routing costs in a supply chain network is termed as IRP. Furthermore, when production lot-size decision is incorporated into the IRP, the resulting problem is called PRP (Adulyasak, Cordeau, & Jans, 2014a). In general, a fleet of vehicles through road transportation perform the delivery process in the network. There are mainly two types of inventory replenishment policies. First, if a visited customer's store is replenished by the exact amount that brings the inventory level up to a pre-defined target-point, then it is called over-up-to-level (OU) policy (Solyali & Süral, 2009). Second is the maximum level (ML) policy, in which any quantity can be added, but the resulting inventory level cannot exceed a pre-defined maximum stock level (Archetti, Bertazzi, Laporte, & Speranza, 2007).

Globalization of supply chain has resulted in geographical expansion of marketplace with increased transportation distances, and air pollution from carbon emissions (Govindan, Jafarian, Khodaverdi, & Devika, 2014). According to a report of Integrated Transport Commission published by the climate change working group, 22% of CO_2 emissions in transportation sector in the United Kingdom (UK) is due to freight transportation, which is

Abbreviations: ALNS, adaptive large neighborhood search; IRP, inventory routing problem; MMPPRP, multi-objective multi-period production and pollution routing problem; MMPPRP-TW, MMPPRP with time window; NSGA-II, Non-dominated sorting genetic algorithm-II; PRP, production routing problem; PPRP, production and pollution routing problem; PSO, particle swarm optimization; SLPSO, self learning PSO; MOSLPSO, multi-objective SLPSO; VRP, vehicle routing problem.

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6% of the total CO_2 emissions in the country (Demir, Bektaş, & Laporte, 2014). A report of TERM 2011 published by the European Environment Agency testified similar observations for the year 2009. Transportation sector is responsible for 24% of the overall green house gas (GHG) emissions in the EU-27 countries, and road transportation is contributor of 17% of total GHG emissions (Vicente, 2011). According to Wright, Kemp, and Williams (2011), CO_2 and CH_4 are the two most hazardous anthropogenic GHGs which are significant contributors of emissions. CO_2 emissions is proportional to the fuel consumption rate of vehicle, which in turn is dependent on vehicle type, environment and traffic-related parameters such as vehicle speed, load, acceleration and congestion (Demir, Bektaş, & Laporte, 2011). Besides GHG, freight transportation emits considerable amount of carbon monoxide (produced when carbon containing fuel is not burned completely), ozone, volatile organic compound (chemically react in the presence of sunlight), and air toxics (a chemical spread into the atmosphere that may be a cause of cancer or other severe health effects), along with particulate matters such as dust, soot and organic matters (Demir et al., 2014).

In this paper, we develop a supply chain planning model that simultaneously deals with production routing and pollution routing problems, and is termed as production and pollution routing problem (PPRP). We consider a production-distribution network that deals with single product, and consists of a plant node and a set of geographically dispersed customers with their own storage space. In a supply chain, production and distribution are the most important operational functions (Chen, 2004), whereas joint lot sizing and finished product delivery with finite/infinite horizon for discrete time period are tactical level decisions (Armentano, Shiguemoto, & Løkketangen, 2011). In order to facilitate smooth functioning at tactical level, it is assumed that the production plant and customers may maintain initial inventory at the beginning of the planning horizon. Shortage is strictly prohibited at any node. In each period, each customer holds sufficient inventory to satisfy demand. In case of PRP, operational decisions such as volume of production quantity, and production set-up time, are in general taken by the plant. If production takes place in a period, a fixed set-up cost and unit production cost are incurred. A fleet of identical capacitated vehicles transport the finished items to customers who possess limited storage capacity. In the entire process, vehicle routing and inventory holding costs are incurred. The proposed PPRP model also incorporates carbon emissions resulting from the total fuel consumption.

In order to evaluate trade-off between total operational cost and total carbon emissions due to fuel consumption, we formulate a multi-objective model for multi-vehicle PPRP with time window (MMPPRP-TW). The first objective is to minimize the total operational cost which is the sum of set-up, production, inventory holding, transportation and waiting penalty costs. The second objective is to minimize the total emissions which can be achieved by minimization of total fuel consumption. According to Demir et al. (2014), each vehicle has an optimal speed which yields minimum fuel consumption, but, in general, this speed is lower than the speed preferred by vehicle drivers. Fuel consumption and resulting carbon emissions are directly proportional to the distance traversed. Now, if a firm incurs high inventory holding cost, then it may decide not to hold extra inventory and receive replenishments every time period. Consequently, the higher frequency of vehicle movement will result in higher emissions due to increased traveling distance. Thus, the two objectives: minimization of total operational cost and minimization of total fuel consumption (representing minimization of total emissions) are conflicting in nature. The problem demands Pareto-based multi-objective optimization to evaluate the trade-off between the objectives. To achieve the same, we extend the population-based stochastic optimization algorithm self-learning particle swarm optimizer (SLPSO) (Li, Yang, & Nguyen, 2012) in a multi-objective framework (MOSLPSO).

Novelty of proposed MMPPRP-TW is fourfold. (1) The multi-period multi-vehicle PRP with ML policy is extended by incorporating the time window flexibility in replenishment to the customers. (2) The single-period pollution routing problem with time window is extended for multi-period. (3) The two most important problems of integrated supply chain planning system, namely, PRP and pollution routing problem are integrated in multi-objective framework with minimization of total operational cost and minimization of total fuel consumption (for total emissions) as conflicting objectives. (4) Enhancement of SLPSO algorithm for multi-objective optimization problem. The rest of the article is organized as follows: Section 2 presents the literature review of VRP and its variants inventory routing, production routing and pollution routing problems. Section 3 starts with notations and assumptions followed by mathematical formulation of the MMPPRP-TW. The proposed multi-objective SLPSO and its parameter setting along with NSGA-II are discussed in Section 4. Section 5 illustrates the methodology in a case study with comprehensive discussion of the outputs. Finally, Section 6 concludes the paper with directions for future research.

2. Literature review

A supply chain sequentially performs the activities of production, storage and distribution, wherein each upcoming activity is planned and optimized using decisions obtained from previous activity (Adulyasak, Cordeau, & Jans, 2014b). In an integrated supply chain planning system, stakeholders collaboratively optimize planning decision in order to leverage the additional benefits derived from co-ordination. In the similar context, IRPs and PRPs are the vendor managed integrated supply chain planning problems; wherein supplier acts as a central decision maker, monitors inventory of retailers and takes decisions regarding replenishment policy, etc. In recent years, the integrated planning problem for IRP and PRP has been increasingly explored by the researchers, and adopted by enterprises. It has been engendered from VRP, and is recognized as a NP-hard problem. Archetti et al. (2007) modeled an IPR with single vehicle and developed a branch-and-cut approach to obtain the global optimal solution. Solyali and Süral (2011) enhanced Archetti et al. (2007) with a stronger mathematical formulation in shortest path network representation framework and adopted OU replenishment policy at customer node. An exhaustive literature review of IRP is presented by Andersson, Hoff, Christiansen, Hasle, and Løkketangen (2010).

IRP ignores the production part which is one of the most important aspects of integrated supply chain planning system. This deficiency of IRP is addressed by PRP, which includes determination of production related decisions such as set-up time and lot-sizing. Chandra and Fisher (1994) first studied the benefits of co-ordination in PRP, and noticed 3–20% cost savings as compared to non-aligned decision making. Chen and Ji (2007) proposed a mixed integer programming (MIP) formulation for advanced planning and scheduling (APS) that comprises of production routing and shop floor scheduling. Recently, several heuristic and meta-heuristic approaches have been employed to solve the MIP formulation of PRPs (see, Adulyasak, Cordeau, & Jans, 2015) such as memetic algorithm (Boudia & Prins, 2009), tabu search (Armentano et al., 2011). Though PRP is a NP-hard problem, some researchers have proposed exact algorithms or methods to compute the tight lower bounds. Fumero and Vercellis (1999) and Solyali and Süral (2009) developed Lagrangian relaxation approaches to obtain the lower bounds. The Lagrangian relaxation approach of Fumero and Vercellis (1999) determine the routing decision by solving a