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Transportation decision tool for optimisation of integrated biomass flow with vehicle capacity constraints

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ABSTRACT

In this paper, an improved mathematical model is proposed to solve the multi-echelon biomass supply chain synthesis problem, including processing hubs selection, biomass allocation design and transportation mode selection, with the consideration of vehicle capacity constraint (weight and volume). On top of that, carbon emission penalty is introduced in the model in order to evaluate the environmental impact in the supply chain. The entire problem is modelled through mixed integer non-linear programming with the aim of maximising the overall profit, at the same time ensuring the minimal CO_2 emission. A comparative study between the model developed in the previous work (vehicle capacity constraint and environmental performance are not considered) and the current improved model is carried out to compare the reliability of the outcomes. Both models are illustrated by using a same case study in Johor, Malaysia. In order to fill the gap of lacking user-friendly decision-making tool for the transportation design in supply chain management, a novel graphical decision-making tool, called smart vehicle selection diagram is proposed in this paper. The diagrams are constructed based on the optimised results obtained from the formulated model. The user manual for the proposed decision-making tool is given in this paper. Besides, five sets of sensitivity analysis are conducted to identify the sensitivity of the assumed realistic factors (i.e. terrain profile, weather changes, traffic congestion, fuel price fluctuation and individual environmental preference) to the optimal results obtained from the proposed tools. This paper shows the potential of the proposed tools in providing rigid optimal solution for the proposed research problem. Finally, several potential future works is suggested in this paper to fill up some of the remaining research gaps.

1. Introduction

As the population grows, biomass supply chains have to expand to meet the growing market. On top of that, customers nowadays are becoming more demanding not only in terms of product quality but also concerns on the consistence and efficient supply of product (Christopher, 2012). In order to keep pace with the expanding demands of an increasingly economy and to meet the snowballing customers' expectations, business companies started to become more reliant on logistics and supply chain management. In fact, this field has received great attention from academia partners too. Generally, these researchers have been focusing on three topics, i.e. (1) Demand Forecasting, (2) Inventory Planning and (3) Transportation Design.

Demand forecasts are essential for supply chain management (SCM), but generating a reliable and accurate forecasts are often challenging due to the absence of information sharing from the downstream supply chain members to support the forecasting procedure (Holweg et al., 2005). Numerous works regarding to the forecasting methods and techniques have been published since last 20 y Leung (1995) claims that artificial neutral networks (ANNs) were suitable for supply chain forecasting. Auto-regressive integrated moving average (ARIMA) demand model is another time series method which has been widely used for forecasting (e.g. Graves (1999) presents a model for a single-item inventory system with a deterministic lead-time but subject to a stochastic, non-stationary demand process; Gilbert (2005) explains the cause of the bullwhip effect by using a multi-stage supply chain model that is based on ARIMA time-series model; Babai et al. (2013) analyse the relationship between forecasting accuracy and inventory

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performance in a two-stage supply chain with ARIMA (0,1,1) demand.). Kuo (2001) develops an advanced statistical tool which utilised genetic algorithm in order to predict the future market demand. More recently, hybrid forecasting models which incorporate ARIMA, ANNs and fuzzy logic have received great attention in the research field. For instances, Pai and Lin (2005) combine support vector machine (SVM) with ARIMA to strengthen the predict performance; Efendigil et al. (2009) and Chang et al. (2011) incorporate fuzzy logics into ANNs to improve the decision-making process; Jaipuria and Mahapatra (2014) propose an integrated approach which combined discrete wavelet transforms (DWT) and ANNs for demand forecasting.

Location-inventory problems (LIPs) are integrated problems which determine location-allocation and inventory decisions simultaneously. These problems basically have considered both inventory planning and transportation design. LIPs have received much attention in literature since 15 y ago. Most of these excellent works have set the primary objective as cost-minimisation (e.g. Erlebacher and Meller (2000) proposes an analytical model to determine the optimal design of distribution system with the aim of minimising the operating cost; Teo et al. (2001) discusses the effect on facility investment and inventory costs during the consolidation of distribution centers by using the developed analytical model; Shen (2005) determines the optimal multi-commodity supply chain design with the aim of minimising the total cost by using nonlinear integer programming; Ozsen et al. (2008) introduce a capacitated warehouse location model with risk pooling to minimise the fixed facility location, transportation and inventory carrying cost; Atamtürk et al. (2012) proposes a novel conic integer programming approach to solve the joint facility location and inventory management problem with the aim of minimising the total location, shipment and inventory costs while ensuring a specific level of service; Lam et al. (2013a, b) develops a two-stage optimisation to determine the minimum transportation cost for the palm oil biomass supply chain in Peninsular Malaysia.) and profit-maximisation (e.g. Zhang (2001) introduces a locational model with a profit-maximising objective to determine the optimal location of the warehouse and the suitable product pricing; Shen (2006) presents a profit-maximising supply chain design model in which a company has flexibility in determining which customers to serve; Shu et al. (2012) formulate the logistic network design with a profit-maximising objective problem as a set-packing model; Ahmadi-Javid and Hoseinpour (2015) study a profit-maximisation LIP in a multi-commodity supply chain distribution network incorporates with price-sensitive demands; How et al. (2016) propose a decomposition approach which integrates both mathematical modelling and P-graph framework to determine the optimal design of multiple biomass corridor in Johor, Malaysia with a profit-maximising objective.). Others even considered multi-objectives in their model. For instances, Liao et al. (2011) develop a multi-objective location-inventory model which considered cost, customer service level and flexibility; Ghodratnama et al. (2015) have solved hub allocation problem with minimisation of cost, service time and greenhouse gas emission; Mota et al. (2015) propose a generic multi-objective mathematical programming model for SCM synthesis problem which take into account of economic potential, environment impact and social performance.

Transportation design is another common decision-making problem in supply chain synthesis. There are quite a number of works contributed in this area. Song et al. (2002) develop a mixed integer linear programming (MILP) to solve a multi-product, multi-echelon supply chain problem. Carle et al. (2012) propose a hybrid agent-based meta-heuristic called Collaborative Agent Team (CAT) to solve a large-scale multi-period supply chain synthesis problem. Odeyale et al. (2014) illustrate the selection of the transportation modes by incorporating fuzzy sets into Saaty's priority theory. Sahay et al. (2014) use agent-based simulation model and embedded optimization model to study the behaviour of the supply chain entities.

All the aforementioned works are admirable, but most of them do not consider physical capacity limits of the vehicles (i.e. volume and weight) in their proposed transportation design models (e.g. Ng et al. (2013a, b) and How et al. (2016) utilise a generalise cost factor [RM/km/t] to calculate the overall transportation required without considering the vehicle capacity constraint; Bertazzi and Maggioni (2014) determine the service zone of a stochastic capacitated traveling salesmen location problem that minimise the expected cost of the travelled routes without including the vehicle capacity constraint into the model; Király et al. (2015) solves the multiple traveling salesmen problem without considering the capacity limit of vehicle by using a multi-chromosome based genetic algorithm.). Only few works have considered the eight and volume constraint of vehicle. For instances, Hamelinck et al. (2005) consider weight limit of the transportation mode in their model; Iori and Martello (2010) solve the routing problem which associated with two- and three-dimensional loading constraint; Cheang et al. (2012) extend the traveling salesmen problem with last-in-first-out loading constraint; Odeyale et al. (2013) includes vehicle capacity as one of the selection criteria in their proposed model. However, none of them have developed a user-friendly tool for the decision makers in SCM in order to improve the effectiveness of the decision-making process.

This paper represents the extended work of a master project in University of Nottingham Malaysia Campus (Tan et al., 2015). In this paper, an improved mathematical model which has considered the physical capacity limitation of transportation mode and environmental performance is developed in order to solve the biomass supply chain synthesis problem. Based on this model, a graphical decision-making tool is generated to help decision makers in the transportation design. It is worthy to note that the decision makers do not have to be a professional in programming in order to use the proposed tool. With the proposed tool, one can easily determine the optimal mode of transportation and the total number of vehicles required according to the specific circumstances. In addition, a wise decision is also a key that lead the SCM into a more sustainable future (less transportation cost and less carbon emission).

This paper is organised as follows. The biomass supply chain problem is described in Section 2. Section 3 outlines the model formulation for this problem. The development of decision-making tool is presented in Section 4. In Section 5, background of the case study used in this paper is given. It is then followed by the results and discussion in Section 6. Finally, concluding remarks are stated in Section 7.

2. Problem statement

The problem described in this paper aim to determine the optimal biomass allocation networks and the optimal transportation decisions that minimise transportation cost and reduce carbon emission. It is formally stated as follows: given a set of biomass types r supplied from a set of source points i is planned to be delivered through a set of transportation modes m to a set of processing hubs j. Then, it is converted into a set of products p via a set of technologies t and t' and delivered to a set of customers k through a set of transportation mode m'. All the intermediates are denoted as l. The superstructure of the model is illustrated in Fig. 1.

In order to provide readers a better understanding and insight into the proposed research problem, several underlying assumptions are stated: