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A Stochastic Discrete Optimization Model for Multimodal Freight Transportation Network Design

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Abstract: Since the freight transport mostly incorporates several modes and transshipments, the uncertainty issue becomes more and more important. This uncertainty can be influenced by several factors, which essentially affect the transportation cost. This paper presents a stochastic discrete optimization model for designing multimodal freight transportation network, which includes the decision of transshipment location and mode choice. Taking different direction from the previous researches, the model takes into account the variation effect of traffic flow, capacity and loading/unloading productivity to the freight cycle time which directly influences the transportation cost. A Monte Carlo simulation is then applied to propagate those variations by following the observed distribution. A combinatorial optimization model is also incorporated to find the right combination of transportation alternatives, where genetic local search (GLS) is invoked. Its applicability is then tested to an actual multimodal network, which consists of sea and land transportation modes and several transshipment terminals.
Keyword — Multimodal Transportation Network, Metaheuristics, Monte Carlo Simulation, Stochastic Discrete Optimization, Genetic Local Search

1. INTRODUCTION

Since freight transport plays important roles in goods movement along a supply chain (e.g., Yamada et al., 2009; Yamada and Febri, 2015), it essentially grows in line with the increasing interaction among economic actors (i.e., producers, distributors, retailers, and consumers), who are geographically apart from each other. In addition, the interaction frequently includes the long-haul transportation, which requires the combination of several modes and transshipments. This multimodality basically offers the more efficient and flexible freight transportation, although the uncertainty issues need to be carefully handled for ensuring the efficient movement. In term of multimodal freight transportation, the uncertainty issues can be relied on the travel time (e.g., Sim et al., 2009; Andersen and Christiansen, 2009; Bock, 2010; Goel, 2010), the operating times in transshipments (e.g., Ishfaq and Sox, 2012), the demand (e.g., Smilowitz and Daganzo, 2007; Hoff et al., 2010; Meng et al., 2012) as well as the disruption issue (e.g., Huang et al., 2011; Chen and Miller-Hooks, 2012; Di Francesco et al., 2013).

The decision in freight transportation is essentially related to the determination of supply resources (e.g., mode, capacity, timing, and location) in order to meet the demand (e.g., quantity, frequency etc.). Since the multimodal freight transportation network combines the advantages of single-mode to offer potential cost savings, it practically consists of the collection of transshipment terminal for transferring the freight loads from one transportation mode to another. Therefore, the fundamental decision of multimodal freight transportation is closely related to the determination of terminal location, route and transportation modes. The decision should be carefully tackled in order to minimize the transportation cost and to satisfy the demand. However, the decision becomes more challenging due to the lack of future knowledge when the plan is implemented.

1.1 Literature Review

Due to its importance to the freight transportation field, the multimodal transportation research obtains growing attention during the last decade. Crainic and Kim (2007), Christiansen et al., (2007), Bektas and Crainic (2008) and SteadieSeifi et al. (2014) provide the comprehensive review papers on multimodal transportation subjects.

The different terminologies also spread out for describing the transportation multimodality, such as, multimodal, intermodal, co-modal (CEC, 2006) and synchromodal (Verweij, 2011), where the two first term is widely used in the literature. For avoiding the ambiguity, both terms are firstly defined. The multimodal freight transportation describes the sequencing goods transportation uses at least two different modes of transportation (UNECE, 2009), in which if it involves the similar transportation unit among modes and it does not require the

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goods handling, the intermodal freight transportation term is practically applied (SteadieSeifi, 2014). Based on the definition, the intermodal term is thus extensively employed on the container handling (Bektas and Crainic, 2008). For the sake of generality, this paper uses the multimodal term for developing the model.

The decision planning horizon is considered in the multimodal transportation literatures, which includes the strategic level, tactical level and operational level. At the strategic level, the decision focuses on the infrastructure network design, such as, the terminal, the type of equipment, the quantity of equipment, the capacity expansion of infrastructures and facilities, and the customer service coverages. The tactical planning takes a huge attention on the cost-efficient utilization of resources, and hence, the decision determine the mode type, the mode route, the frequency and the load allocation of terminal in order to meet the demand satisfaction. In term of operational planning, the fleet management is practically considered. The tactical planning in the multimodal transportation is then emphasised in this paper. As the multimodal transportation incorporates various different modes, the elaboration of mode considered in the literature is firstly conducted. Anghinolfi et al. (2011) involve the tactical planning procedure of railway network by taking into account the fast transfer equipment at terminals. Several studies have been conducted by considering ship mode (e.g., Hsu and Hsieh, 2007; Meng and Wang, 2011, Meng et al., 2012), train mode (e.g., Andersen and Christiansen, 2009, Verma and Verter, 2010; Verma et al., 2012,), and road base mode (e.g., Lium et al., 2009; Hoff et al., 2010). There are a few case that explicitly capture the collaboration and competition among modes, which is captured in this study.

The increment of disaster events bring a high pressure to logistic industry for providing the service at reasonable cost with sufficient protection from external forces. Several researches attract to study the multimode transportation by incorporating the disruption issues (e.g., Huang et al., 2011; Chen and Miller-Hooks, 2012; Miller-Hooks et al., 2012), which tried to quantify the performance of multimodal transportation network in the natural and human disaster events. Taking different perspective of uncertainty issue in multimodal transportation, the variation of demand (e.g., Hoff et al., 2010; Meng et al., 2012) and travel time (e.g., Andersen and Christiansen, 2009; Sim et al., 2009) are discovered. Previous works mostly consider the uncertainty of travel time by constructing its variation on the link, which follows certain distribution. However, this work specifically counts the interaction of capacity and transportation flow for governing the uncertainty condition. The capacity variation illustrates the extreme event that is possibly occurred, whereas the variety of flow depicts the natural phenomena of transportation demand.

Since the logistic service should offer the reasonable cost, the transportation cost attained a huge consideration in the multimodal transportation network design. Several cost parameters have thus been incorporated for designing the multimodal transportation network, namely, travel cost (e.g., Crainic et al., 2006), operating and handling cost (Hoff et al., 2010), transhipment cost (e.g., Anghinolfi et al., 2011), and system cost (e.g., Lium et al., 2009). In spite of its growth consideration, there are the few cases that investigates the effect of congestion to the multimodal system (SteadieSeifi et al., 2014). Therefore, this study comprises the cycle time for calculating the transportation cost. The cycle time is basically a function of round trip travel time, waiting time, loading and unloading time, which varies as an interaction result of capacity and flow variation. In practical, the cycle time is used by the freight carrier company for determining the unit of transportation cost. Therefore, by considering the variation of cycle time, the effect of uncertainty to the transportation cost can be properly investigated, as conducted in this paper.

Moreover, the transhipment processes play a crucial role in the multimodal network design, in which ignoring it in design may toward to the suboptimal or infeasible results. However, the exploration of feasibility, capacity, operation time and cost of transshipment in network is relatively obtained small attention (e.g., Ishfaq and Sox, 2010; Ishfaq and Sox, 2012). Therefore, recent literature review locates it as a potential future research area (SteadieSeifi et al., 2014). This paper thus includes the transhipment capacity and cost in the multimodal transportation design, which substantially affect the selection of transhipment location.

Decision in the multimodal transportation basically contains the large set of variables, which is difficult to be solved. Therefore, within the framework of optimization problem, heuristic (e.g., Agarwal and Ergun, 2008; Huang et al., 2011) and metaheuristic based approaches are the first-rate choice for solving the problem. In term of metaheuristic solution methods, Tabu Search (TS) is widely used in the multimodal transportation network field (e.g., Crainic et al., 2006; Pedersen et al., 2009; Bai et al., 2012; Verma et al., 2012). Moreover, as implied by SteadieSeifi et al. (2014), it has a great opportunity to study population-based metaheuristic for solving the multimodal freight transportation problem, which is conducted in this paper.

1.2 Objectives and Contributions

This paper aims to investigate the proposed stochastic optimization model for designing multimodal freight transportation network, which includes the decision of transshipment location and mode choice. The optimization model tends to minimize the total cost for transporting goods from origin to destination. The total cost is originated from the related costs summation, namely, the transportation and transit cost, the penalty cost, and the investment cost for operating the selected modes (i.e. capacity expansion cost). The transportation cost is computed by utilizing the cycle time, daily operation cost and payload capacity. To characterize the uncertainty, it is assumed that the required cycle time is resulted from the interaction of capacity and flow, which is varied. A Monte Carlo simulation, which is a stochastic technique, is then invoked to derive the expected value of cycle time components. It incorporates random number and probability statistics to construct problem scenarios for representing the uncertainty condition. Furthermore, in order to govern the multiple problem scenarios, the random process is repeatedly conducted by taking values from a probability distribution of selected variable. The cycle time variation potentially affects the delay on the goods delivering, and it possibly toward to the inability of demand fulfillment, which may result in a company having to compensate it. This compensation is possibly estimated by referring the penalty cost. However, the penalty needs to be taken into account not only the lateness, which is mostly considered (e.g., Ando and Taniguchi, 2006; Zhang et al., 2013; S. Binart et al., 2016), but also the fulfillment of demand.

As one of the most important problems in optimization, the approach of optimization under uncertainty has been rapidly developed. While the efficient technique has been widely implemented in the deterministic optimization problem, the approach merely turn out to be unsatisfactory in term of stochastic optimization, due to the size. This paper then presents the metaheuristics based approach for solving the stochastic optimization. This problem can further be formulated as the combinatorial optimization problem, in which the decision variables are related to the determination of transit location and transportation mode in order to minimize the total cost. The genetic local search (GLS) is thus adopted for solving the problem.

The applicability of model is also elaborated by applying the model to an actual freight transportation network for transporting a goods from an origin to a destination, which includes sea and land transportation modes and several transit terminals. Existing literature (e.g., Nelldal, 2000; SteadieSeifi et al., 2014) reflects that the train mode normally provide the more competitive transport cost for long-haul trip rather than the truck mode. However, this paper elaborates the competition between rail and road modes by assuming both unit transport costs are not significantly different as it is practically occurred in Indonesia. In addition, by considering the uncertainty issue, the reliability aspects of competition can interestingly be explored. A comparison is conducted between the deterministic (with certainty) optimization and the stochastic (with uncertainty) optimization to observe the differences of both solution results, as well as the loss and benefit between the two points of view.

Based on the literature reviews above, the contributions of this study are remarkably located in three aspects. First, it contributes to the literature by presenting a realistic stochastic optimization model to the multimodal transportation network design. Second, the uncertainty condition is taken place in term of facilities demand (i.e., transportation flow) and supply (i.e., capacity, productivity), which is not sufficiently explored in the literatures. By evaluating the cycle time variation to determine the transport cost, the effect of uncertainty to the transportation cost can be properly investigated, which can be regarded as the third contributions.

The rest of the paper is organized as follows. In the following section, the modeling framework is described. In the third section, the model is then tested and applied to an actual test network, where the implication of uncertainty on multimodal freight transportation is also explored. Finally, in the fourth section, the methodologies, results, and analyses in the paper are summarized.

2. A STOCHASTIC DISCRETE OPTIMIZATION MODEL

2.1 General

The total cost minimization is set as the objective function of optimization problem. While the A certain amount of freight in a certain time period must be transported from an origin to a destination through the public transportation network. It is then need to be decided, how to assign the freight amount to the alternative transshipment points, to the alternative modes, and also to the routes. Since the transshipment and transportation network to be use is public facilities, it has the current performances due to its current demand. This create constrains in the available capacity that can be use and the dynamic performance and cost according to the freight amount share to be assigned upon. On the other side, the use of a particular transportation and transshipment facilities might require costs of capacity expansion (i.e. for the stock yard, additional loading/unloading equipment).

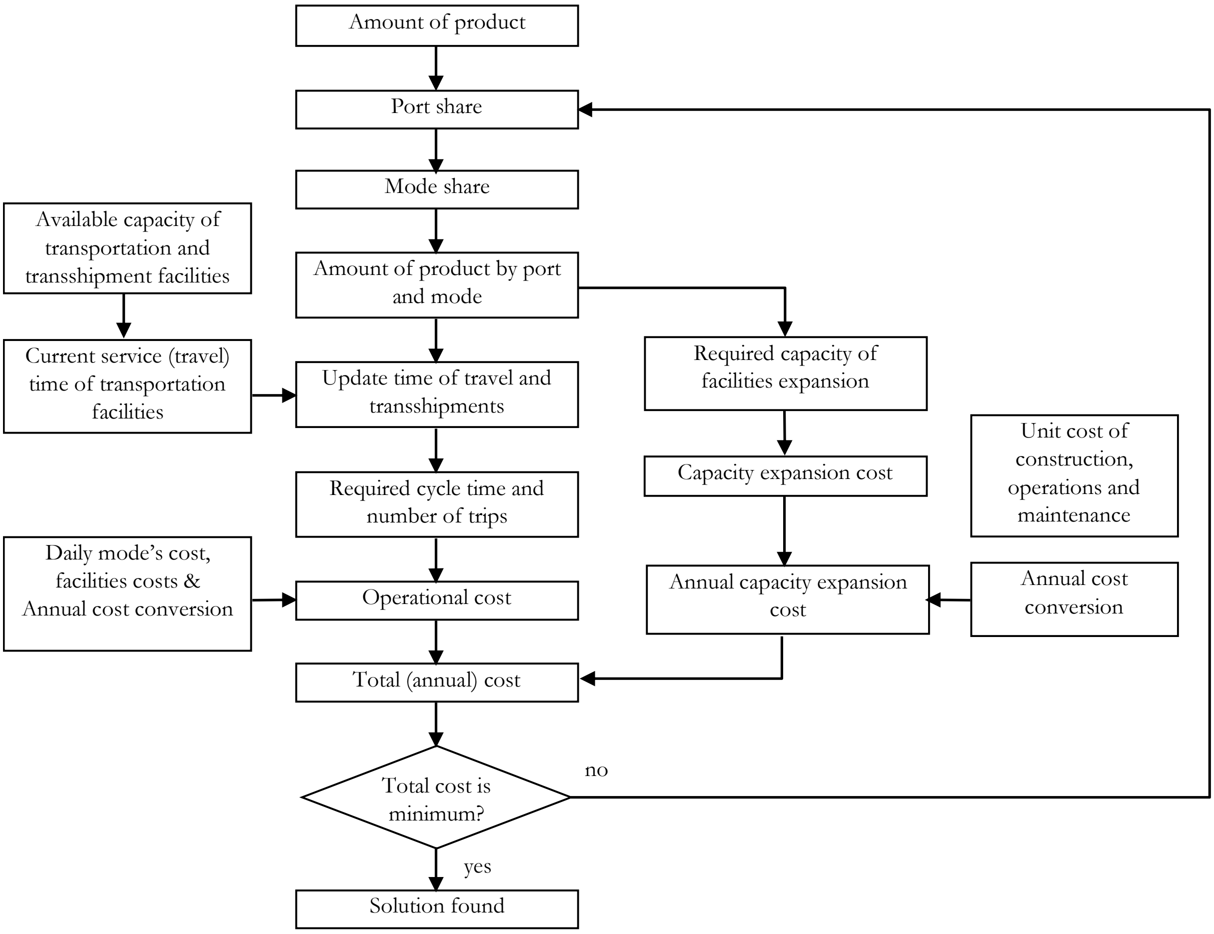

Figure 1. Framework of total cost optimization of multimodal transport and transshipment network design.

The total cost minimization is set as the objective function of this optimization problem, by changing the transshipment terminal share and mode share. The total cost is comprised of operational costs and capacity expansion costs. With known data on: (1) Amount of freight that is transported from origin to destination, (2) Available capacity of the transportation and transshipment facilities, (3) Current productivity, service time and travel time, under the current actual demand, (4) Unit costs of capacity expansion and operational cost, in term of daily operational cost for transportation and service cost per unit freight.

The operational cost of transportation is derived from the cycle time, as the results of total time required to transport the freight between transshipment point and the back haul, that has a stochastic properties and differed for each mode, where the sea mode includes the terminal time at loading port (origin) and unloading port (transshipment point). For the rail mode, the cycle time involves the terminal time for loading at stock yard (transshipment point) and unloading at rail station (transshipment point), while truck mode requires terminal time at stock yard and at destination point. The framework of the optimization is following the procedure in Figure 1.

2.2 Formulation

A standard formulation of stochastic optimization model is then presented below. τ is a random variable from a probability space (i.e., A, θ, $\boldsymbol{\Omega}$), A denote the collection of random events, in which each event A is then associated with probability θ. Uncertainty condition is represented by random process with outcomes denoted by τ, where the set of all outcomes is represented by $\boldsymbol{\Omega}$. The expectation value is then denoted by E.

$$\min\left(\alpha_l X + E_{\tau\in\Omega}\left[f(X,\tau)\right]\right) \qquad x,y,z \in X \tag{1}$$

$$f(X,\tau) = \min\left(\sum_j^J \xi_j(Q^1,\tau)x_j + \sum_i^I\sum_j^J\sum_l^L q_{lij}c_{lij}\left(\tau\right)y_l + \sum_j^J\sum_k^K\sum_l^L q_{ljk}c_{ljk}\left(\tau\right)z_l + p(Q^2)\right) \tag{2}$$

subject to:

$$\sum_i^I\sum_j^J\sum_l^L q_{lij} - \sum_j^J\sum_k^K\sum_l^L q_{ljk} = 0 \tag{3}$$

$$\sum_i^I\sum_j^J\sum_l^L q_{lij} \le \sum_j^J \varpi_j x_j \tag{4}$$

$$q_{lij}, q_{ljk} \ge 0 \tag{5}$$

where,

q_{lij} : amount of freight transported by mode *l* between origin *i* and transshipment point *j*,

q_{ljk} : amount of freight transported by mode *l* from transshipment point *j* to destination *k*,

c_{lij} : unit transportation cost charged by mode *l* for transporting freight from origin *i* to transshipment point *j*,

c_{ljk} : unit transportation cost charged by mode *l* for transporting freight from transshipment point *j* to destination *k*,

α_l : investment cost required for operating mode *l*,

$\xi_j(Q^1)$: transit cost at transshipment point *j*,

$p(Q^2)$: penalty cost incurred,

Q^1 : *LIJ*-dimensional vector with component *lij* denoted by q_{lij} ,

Q^2 : *LJK*-dimensional vector with component *ljk* denoted by q_{ljk} ,

ϖ_j : capacity of transshipment point *j*,

x_j : binary value of 1 if freight transit in transshipment point *j* ; 0 if it is otherwise,

y_l : binary value of 1 if mode *l* is transported the freight from origin *i* to transshipment point *j*; 0 if it is otherwise,

z_l : binary value of 1 if mode *l* is transported the freight from transshipment point *j* to destination *k*; 0 if it is otherwise.

Equation (1) reflects the minimization problems, in which the total cost for transporting from origin i to the destination j is minimized. The total cost takes into account not only the travel cost, the penalty cost, and transit cost, but also the investment cost for operating the selected modes. The investment cost deals with the related cost for utilizing the transportation modes, such as the infrastructure development cost and the equipment purchasing cost. Furthermore, the travel cost and transit takes into account the uncertainty condition by considering random variable as it is shown in the Equation (2). The penalty cost is estimated by taking into account the amount of freight that cannot be satisfied by the combination of terminal location and transportation modes. Hence, the penalty cost is charged if the total amount of freight received in the destination is less than the total amount freight. Equation (3) describes the flow conservation constraint to ensure that the entire flow is delivered to its destination. The Equation (4) are illustrated the maximum flow at transit terminal is limited by its capacity. The latter equation is described the non-negativity variable. This optimization problem further needs to decide which transshipment terminals and modes to be assigned.

2.3 Transportation Cost Function

The transportation cost can be simply estimated by multiplying the unit cost and the amount of freight transported. However, different from the preceding related paper, the unit transportation cost is calculated by considering the cycle time, daily operation cost and payload capacity (see Equation (6)), which is practically applied by the freight carrier company. The cycle time is a function of round trip travel time, waiting time, loading and unloading time. The daily operation cost is then derived from the mode purchasing cost, the depreciation cost, the routine cost for operating the mode and the maintenance cost.

$$c_l = \frac{u_l t_l\left(\tau\right)}{T_l \; s_l} \tag{6}$$

where:

c_l : unit transportation cost charged by modes (Rp./ton),

u_l : daily operation cost of mode (Rp.),

t_l : mode cycle time for transporting freight in an origin-destination pair (hour),

T_l : daily operational hour (hour),

s_l : mode's vehicle size (i.e., carried payload or loading/unloading volume per unit mode, in ton).

The cycle time includes the travel time (outbound and inbound) and transshipment time, which varies according to the performance of mode's travel and transshipment point's level of services. The general formulation for the cycle time is described as follow:

$$t_l\left(\tau\right) = \sum_{w=1}^{W}\left(\beta_w(\tau) + \frac{s_l}{(n_w r_w(\tau) e_w)}\right) + 2a_l\ (\tau) \tag{7}$$

where:

β_w : waiting time to be served (loading/unloading) at the terminal *w*. The terminal might be a transshipment point *j*. It could also the point of origin *i* or the point of destination *k* (hour).

n_w : number of unloading equipment at terminal *w*,

r_w : loading/unloading equipment productivity at terminal *w* (ton/hour),

e_w : effective working time at terminal *w* (hour),

a_l : travel time of the mode *l* on the prevailing condition of vehicle, traffic and infrastructures.

The waiting time to be served (β) is estimated based on the queuing theory, which can be described as follow:

$$\beta_w = \left(\omega\ e^{\eta\left(\frac{\mu_w}{\lambda}\right)}\right) \tag{8}$$

where:

ω, η : coefficients, calibrated for the particular terminal

μ_w : service rate of the terminal *w*, as the function of equipment, productivity and operational time (vehicle/hour),

λ : arrival rate of the mode's vehicle (vehicle/hour),

In this paper, the travel time of railway mode might be considered to be deterministic, while for the sea mode, the speed variation during the voyage is randomly propagated based on the observed distribution, which can be illustrated as follow:

$$a_{sea} = \frac{d}{v(\tau)} \tag{9}$$

where:

a_{sea} : travel time of sea transportation mode (hour),

d : trip distance (nautical mile),

v : speed (knot),

Since the variation of traffic flow and capacity of roads along the route strongly affect the truck travel time, the BPR function (see Equation (10)) is thus utilized for estimating the travel time at link by considering the uncertainty of traffic and road capacity. The most practical application to approach the future knowledge (i.e., uncertainty) is conducted by applying the statistical distributions derived from the historical data, which is conducted in this study.

$$a_{truck} = \sum_{g}^{G}\left(t^{0}_{\ g} * \left(1 + 0.5 * \left(\frac{f_g(\tau)\,\delta}{Cap_g(\tau)}\right)^{1.5}\right)\right) \tag{10}$$

where:

a_{truck} : travel time of truck mode (hour),

$t^{0}_{\ g}$: travel time of link g at free flow condition (hour),

f_g : traffic flow (daily vehicle) of link g,

δ : passenger car equivalent factor,

Cap_g : capacity of link g (in passenger car unit/hour),

2.4 Solution Technique

As indicated in Equation (1), the objective function is to minimize the total transportation cost by determining the proper combination of transshipments terminal and transportation modes. Furthermore, the problem can be represented using binary-based approach, where it corresponds to the decision which the transit terminal and modes to be employed. Let $M = (\bar{J}, A)$ be a graph representing a freight transportation network with node set $\bar{J}$ and arc set A. Define $J(J \neq \bar{J})$ as the transshipment terminal set, where x_j is the binary decision variable (i.e., $x_j \in \{0,1\}$ and $j \in J$). The transportation mode set L is moved along arc set A for transporting goods in an origin-destination pair. The variables y_l and z_l then describe the mode decision, taking values 0 or 1 (i.e., $y_l \in \{0,1\}$ and $z_l \in \{0,1\}$), depending on utilization or misused of transportation mode $l \in L$.

Due to its lack of facility and equipment capacity, the transshipment terminal is commonly regarded as the bottleneck of freight distribution. As illustrated in Eqs. (7)−(9), the lack will affect the loading/unloading and waiting time, then it influences the amount of freight which can be carried by transportation mode from the transit terminal. In order to determine the amount of freight transported and depict the competition among modes, this paper thus presents the integer decoding method. This method puts the different perspective of binary representation and considers the maximum payload of transportation mode (see Eqs. (11) and (12)).

$$q_{ljk} = \frac{\left(\sum_{m}^{M} 2^{M-m} y_m\right)}{2^{M-1}} * \rho_{lj} \quad \forall m \in l \tag{11}$$

$$q_{lij} = \frac{\left(\sum_{m}^{M} 2^{M-m} y_m\right)}{2^{M-1}} * \sum_{l}^{L}\sum_{k}^{K} q_{ljk} \quad \forall m \in l \tag{12}$$

where, ρ_{lj} is the maximum payload capacity which can be carried by transportation mode l from transshipment j.

The binary genetic local search (GLS) is then invoked to tackle this optimization problem, which has been successfully applied to handle optimization problem in term of freight transportation network design (e.g., Yamada et al., 2009; Yamada and Febri, 2015). GLS is a variant genetic algorithm (GA), which utilizes the local search operator after crossover and mutation. This operator searches two other variations of individuals, by choosing a random location and swapping the neighbors. Three variant individuals further compare to investigate the best among them (see Yamada et al., 2009 for the detail procedures).

3. CASE STUDY

3.1 Description

To examine the proposed model, it is then applied an actual case of transporting 800 thousand tons/year of dry bulk freight in Indonesia (see Figure 2). The origin is located in the South Sumatera Province, whereas the destination is placed in the Yogyakarta Province. Several sea ports are regarded as the transshipment point alternatives, which is positioned in Banten Province (i.e., Cigading Port), West Java Province (i.e., Cirebon Port), East Java Province (i.e., Tanjung Emas Port) and Central Java Province (i.e., Cilacap Port). There are many other ports in Java Island, but they are not considered as alternative transshipment point, because they are certainly have far higher travel cost to the destination point than the before mentioned ports. Since the origin and destination is separated by sea, the ship is employed for distributing goods from the origin to the transshipment point using the sea lines. Sea network data (i.e., port and lines) are gained from the Directorate General of Sea Communication under the Ministry of Transportation.

Table 1. Network of Case Study

Route	Mode	Travel Distance (km)	Number of Link*
Origin to Transhipment Port #1 (Cigading Port)	Sea	288	
Origin to Transhipment Port #2 (Cirebon Port)	Sea	458	
Origin to Transhipment Port #3 (Semarang Port)	Sea	560	
Origin to Transhipment Port #4 (Cilacap Port)	Sea	659	
Transhipment Port #1 (Cigading Port) to Destination	Truck	590	90
	Rail		
Transhipment Port #2 (Cirebon Port) to Destination	Truck	271	83
	Rail		
Transhipment Port #3 (Semarang Port) to Destination	Truck	153	42
	Rail		
Transhipment Port #4 (Cilacap Port) to Destination	Truck	140	16
	Rail		

*Note: Number of link only for road that is separated by major intersections. Each link has a different capacity and traffic condition, thus it has different level of travel time reliability

The truck and train are then competed or cooperated to transport the goods along terminal transshipment and destination. The truck route is derived from the actual allowable routes, which is determined by the local government. The parameter values of road link are mainly gathered from the Indonesian Inter-urban Road Management System (IRMS) and the Indonesian toll road operator PT. Jasa Marga. The rail route follows the existing railway line in Java Island, in which the railway related data are collected from the Department of Communications and the national railway company (i.e., PT. KAI). The summarized of parameter values is then presented in Table 1, which comprises the network information (e.g., distance, number of link).

3.2 Key Issues

It is generally well accepted that a particular mode is more efficient for a certain range of distance for freight transporting, regardless the geographical fitness of the mode. For long haul freight transportation, the most efficient modes will be railway or even sea transportation. But, this is not the case, if the patronage of the regulators is not equal among the modes, as happened in Indonesia. The trucks, which may use subsidized fuel, with less enforcement on the driver's salary and insurance, vehicle age, overloading, etc., obtain more advantages compare to the other modes, beside their natural main feature as the most flexible mode that can provide a door-to-door services. Table 2 presents the calculation for unit transportation costs by modes for 100 km hauling based on typical travel time and loading/unloading time.

Table 2. Typical daily and unit transportation costs by mode

Mode	Unit Daily Cost	Payload	Travel Time	Cycle Time	Unit Transportation Cost
	(USD)	**(ton)**	**(hour)**	**(hour)**	**(USD/ton)**
Truck (3 axles dump truck)	310.0	20.0	2.9	9.0	5.8
Rail Mode (20 wagons @ 20 t)	3,470.0	400.0	2.5	13.0	4.7
Sea Mode (Barge)	5,770.0	8,000.0	10.0	100.0	3.1

(*Source: observation and interview to the operators*)

Note that the unit transportation cost for truck already consider cost to its final destination, while other modes still require loading-unloading, inventory (at the stock pile) and short haul trucking costs. Then, for the door-to-door transportation cost, the other-than-truck mode requires additional 5.0 to 7.5 USD/ton. Furthermore, by overloading practices, neglecting insurances and other costs (i.e. depreciation cost), the unit daily cost of truck might be lowered to around 200 USD. This is one of the reasons that the mode share of truck is very far greater than other modes in Indonesia.

However, the main drawback of the truck mode is the reliability (uncertainty), especially due to the traffic conditions. Since the traffic condition tends to get worse in the future as the high growth of vehicle and mobility, then it can be expected the mode shifting to other-than-truck modes due to the higher truck transportation cost. The stochastic optimization is then possibly used for obtaining the more understanding of this phenomena.

3.3 The Optimization

To address the issues above, the case study examines several different scenarios and their combinations for the optimization, as follows:

- Deterministic Scenario
  This scenario does not consider the uncertainty issue of problem, and hence, the transportation related parameters are derived based on its average values.
- Stochastic Scenario
  The uncertainty issue is then reflected by stochastic scenario, where the variation of transportation related parameter follow the distribution. In addition, the Monte Carlo simulation is invoked for performing the random process repeatedly.

As depicted in Equations (5) − (8), the uncertainty phenomena can be lied in the transportation link and the transit terminal due to the variation of flow, capacity, speed, and productivity variation. In this case study, the parameter value for representing those variations is derived from the observed data, and the distribution is approached by the triangle distribution. The equipment productivity is randomly set based on the actual productivity range, which is collected during the port stakeholder interview. The waiting time in transshipment point is estimated by constructing the delay function that considers the transit point productivity and arrival rate of mode's vehicle. Furthermore, Monte Carlo simulation is utilized for governing multiple problem scenarios by conducting the random process repeatedly. The random process is applied 1500 times by taking values from a probability distribution.

The performance of GLS is then tested for determining the best solution in term of transit terminal and modes combination. The best solution contains the location of transit terminal and the modes transportation required for minimizing the total transportation cost and satisfying the total freight amount to be transported. As illustrated before, the amount of freight unloaded in the transit terminal and distributed by transportation modes is thus estimated by changing the perspective of binary position (see Figure 3).

Cigading Port		Cirebon Port		Semarang Port		Cilacap Port	
Truck	Train	Truck	Train	Truck	Train	Truck	Train
0 0 1 1	0 0 0 1	1 0 0 1	0 0 0 0	0 1 0 1	0 1 0 0	0 1 0 1	0 1 1 1
20.0%	6.7%	60.0%	0.0%	33.3%	26.7%	33.3%	46.7%

Binary Representation.

% of maximum payload capacity (see Eq. (10)) which can be carried by truck from Cigading Port.

% of maximum payload capacity (see Eq. (10)) which can be carried by train from Cilacap Port.

Figure 3. Binary representation for optimization model.

The maximum payload capacity is estimated by considering the distance of transshipment port and destination, the capacity of transportation link, the port productivity, the waiting time at transshipment port and the mode payload capacity. The maximum mode capacity is thus approximately determined as Table 3.

Table 3. Maximum capacity of each mode at each port of transshipment

Transshipment Port	**Maximum Payload Capacity (1000 ton/year)**	
	Truck	**Train**
Cigading	420	280
Cirebon	420	140
Semarang (Tanjung Emas)	420	140
Cilacap (Tanjung Intan)	420	280

(*Source: interview to the port's operators*)

Parameter values of GLS is decided based the numerical examination for determining the best parameter sets. The examination is applied for 10 runs with different random seeds. The chromosome length is determined to be 32 for obtaining the more precision result, and the maximum number of combination evaluated set as 4,500, as it is practically implemented in the literatures (e.g., Yamada et al., 2009; Yamada and Febri, 2015). In term of deterministic scenario, the crossover rate is set to 0.6 and the mutation rate to 0.07. The population in each generation comprises 20 individuals with 2 elites preserved in each generation. Furthermore, the number of generations (i.e., stopping criterion) is set to 75.

Using the similar approach, the parameter setting examination is also conducted for the stochastic scenario, where in each generation comprises 30 individuals with 8 elites preserved. In addition, the crossover and mutation rate is set as that in the deterministic scenario. By conducting the sensitivity analysis, the number of runs in the Monte Carlo Simulation is set to 1500 times, since the results of 1500 runs is very small difference with the higher number of runs.

3.4 Optimization Results

With the total demand of 800,000 ton/year (the total available payload capacity is 2,520,000 ton/year), the mode share by transshipment port is then searched to minimize the total operational (and investment) costs, under a particular scenario.

By using a deterministic calculation, the optimum solution is firstly found in fifth generation, while in the stochastic calculation the solution is found in fourth generation as can be seen in Figure 4. This faster finding of optimum solution might cause by the initial solution (individual) that is set to the lowest operational cost route. The result for deterministic scenario suggest the use of trucks with the transshipment port through Cilacap (Transshipment Port #4) and Semarang (Transshipment Port #3), with the amount of freight and operational costs depict in Figure 5. It can be noticed that the amount of freight by sea mode will be equal to the total amount of freight by rail and truck modes at the same port. The total amount of freight by sea mode is equal to the total freight. If the stochastic effect is considered, in this deterministic optimization case, the total operational cost is predicted might be increased to 28%, which will be borne by the freight carrier.

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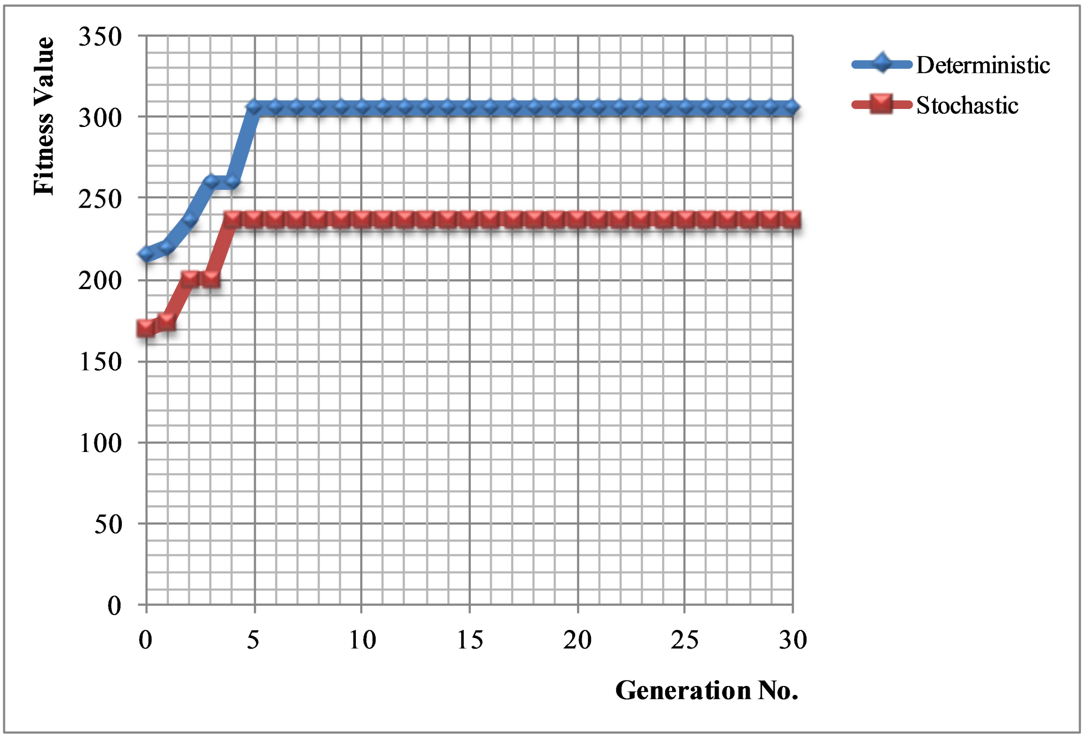

Figure 4. The maximum objective function value of generations for the deterministic and stochastic scenario.

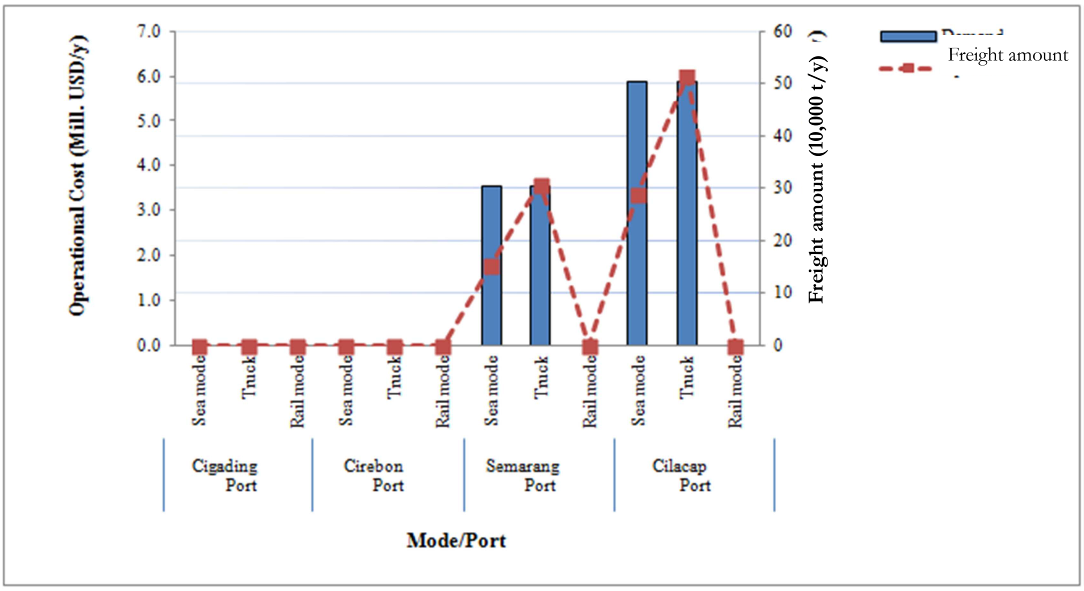

Figure 5. Amount of freight and operational costs by modes and transshipment ports as the solution for the deterministic scenario.

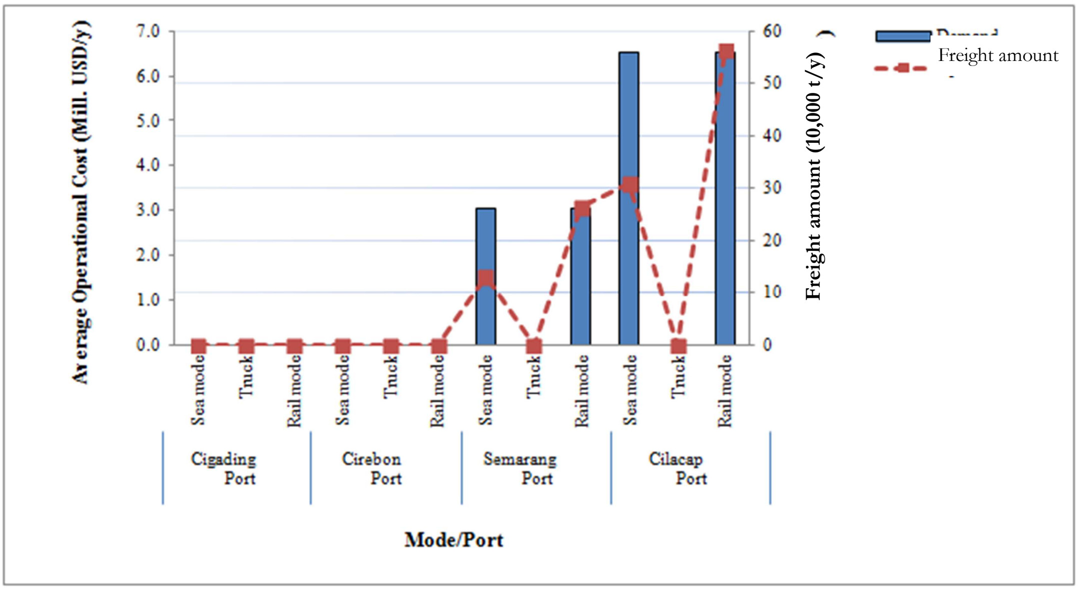

Figure 6. Amount of freight and operational costs by modes and transshipment ports as the solution for the stochastic scenario.

The stochastic optimization scenario further uses the sum of investment cost and the expected value of 90 percentile operational cost distribution as the fitness value. For capturing the uncertainty condition in transport network, the stochastic scenario also takes account of the different condition of road traffic by each link in the route. This consideration becomes more important due to the increasing of congestion in Indonesia practically influences the logistic cost. Compared to the deterministic scenario, the stochastic scenarios gain a lower fitness value (i.e., higher total costs), although its convergences performance remains similar, as it is previously illustrated in Figure 4. This different results are caused by the wide range of cost variation in due to the consideration of the stochastic effects in the transportation network. Furthermore, the stochastic effect possibly drives the mode shifting truck to train (see Figure 6). In the case of deterministic, the truck is more favorable for freight distribution, although in the case of stochastic, the rail-based mode is more efficient for moving freight. The uncertainty issues in the road network (i.e., traffic condition), which strongly affect the operational cost, is regarded as main factor of this mode shifting results.

4. CONCLUSION

A stochastic optimization model of multimodal freight transportation network has been presented. This model is particularly implemented in the tactical level to identify the lowest cost for transporting a goods between a pair of source and destination. The model is able to elaborate the more detail of actual modes characteristics, especially in the uncertainty point of view. The uncertainty aspects is derived from the actual condition of freight transport in Indonesia, in which the most uncertain time will be relied in waiting for berth and unloading for sea mode, while for truck mode, it will be positioned in the travel time that due to the variation of traffic conditions. Such uncertainty conditions then influence the cycle time, which is utilized for estimating the transportation cost.

This paper then substantially proposed the method for converting the time uncertainty to the cost based on the Monte Carlo simulation. By considering such uncertainties and the practical modes operational costs, the more realistic costs can be assessed, even in the less efficient and less reliable transportation network. The GLS is invoked for solving the optimization problem, which is firstly developed for deterministic problem. The further research is prospectively conducted by proposing the different variant of population-based metaheuristic, such as Particle Swarm Optimization (PSO) or Glow-worm Swarm Optimization (GSO), which attains the growth concern. In addition, the multiproduct analysis is interestingly to be included in the model.

REFERENCES

1. Agarwal, R., and Ergun, O. (2008). Ship scheduling and network design for cargo routing in liner shipping. *Transportation Science*, 42, 175–196.
2. Andersen, J., and Christiansen, M. (2009). Designing new european rail freight services. *Journal of the Operational Research Society*, 60, 348–360.
3. Ando, N., and Taniguchi, E. (2006). Travel time reliability in vehicle routing and scheduling with time windows. *Netw. Spat. Econ.,* 6, 293–311.
4. Anghinolfi, D., Paolucci, M., Sacone, S., and Siri, S. (2011). Freight transportation in railway networks with automated terminals: A mathematical model and MIP heuristic approaches. *European Journal of Operational Research*, 214, 588–594.
5. Bai, R., Kendall, G., Qu, R., and Atkin, J. (2012). Tabu assisted guided local search approaches for freight service network design. *Information Sciences*, 189, 266–281.
6. Bektas, T., & Crainic, T. (2008). A brief overview of intermodal transportation. In G. Taylor (Ed.), *Logistics Engineering Handbook*, 1–16.
7. Binart, S., Dejax, P., Gendreau, M., Semet, F. (2016). A 2-stage method for a field service routing problem with stochastic travel and service times. *Computers &Operations Research*, 65, 64–75.
8. Bock, S. (2010). Real-time control of freight forwarder transportation networks by integrating multimodal transport chains. *European Journal of Operational Research*, 200, 733–746.
9. CEC. (2006). Keep Europe moving – Sustainable mobility for our continent. ISBN: 92-79-02312-8.
10. Chen, L., and Miller-Hooks, E. (2012). Resilience: An indicator of recovery capability in intermodal freight transport. *Transportation Science*, 46, 109–123.
11. Christiansen, M., Fagerholt, K., Nygreen, B., and Ronen, D. (2007). Maritime transportation. In C. Barnhart, & G. Laporte (Eds.), *Transportation. Handbooks in operations research and management science,* Vol. 14, 189–284.
12. Crainic, T., Li, Y., and Toulouse, M. (2006). A first multilevel cooperative algorithm for capacitated multicommodity network design. *Computers and Operations Research*, 33, 2602–2622.
13. Crainic, T., and Kim, K. (2007). Intermodal transportation. In C. Barnhart, & G. Laporte (Eds.), Transportation. *Handbooks in operations research and management science*, Vol. 14, 467–537.
14. Di Francesco, M., Lai, M., and Zuddas, P. (2013). Maritime repositioning of empty containers under uncertain port disruptions. *Computers and Industrial Engineering*, 64, 827–837.
15. Goel, A. (2010). The value of in-transit visibility for supply chains with multiple modes of transport. *International Journal of Logistics Research and Application*, 13, 475–492.
16. Hsu, C., and Hsieh, Y. (2007). Routing, ship size, and sailing frequency decision-making for a maritime hub-and-spoke container network. *Mathematical and Computer Modelling*, 45, 899–916.
17. Hoff, A., Lium, A., Løkketangen, A., and Crainic, T. (2010). A metaheuristic for stochastic service network design. *Journal of Heuristics*, 16, 653–679.
18. Huang, M., Hu, X., and Zhang, L. (2011). A decision method for disruption management problem in intermodal freight transport. *Intelligent Decision Technologies*, 10, 13–21.
19. Ishfaq, R., and Sox, C. (2010). Intermodal logistics: The interplay of financial, operational and service issues. *Transportation Research Part E*, 46, 926–949.
20. Ishfaq, R., and Sox, C. (2012). Design of intermodal logistics networks with hub delays. *European Journal of Operational Research*, 629–641.
21. Lium, A., Crainic, T., and Wallace, S. (2009). A study of demand stochasticity in service network design. *Transportation Science*, 43, 144–157.
22. Meng, Q., and Wang, S. (2011). Liner shipping service network design with empty container repositioning. *Transportation Research Part E*, 47, 695–708.
23. Meng, Q., Wang, T., and Wang, S. (2012). Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand. *European Journal of Operational Research*, 223, 96–105.
24. Miller-Hooks, E., Zhang, X., and Faturechi, R. (2012). Measuring and maximizing resilience of freight transportation networks. *Computers and Operations Research*, 39, 1633–1643.
25. Nelldal, B.L. (2000). Competition and co-operation between railways and trucking in long distance freight transport an economic analysis. Proceedings of 3nd KFB-Research conference "Transport Systems – Organisation and Planning".
26. Pedersen, M., Crainic, T., and Madsen, O. (2009). Models and tabu search metaheuristics for service network design with asset-balance requirements. *Transportation Science*, 43, 158–177.
27. Sim, T., Lowe, T., and Thomas, B. (2009). The stochastic p-hub center problem with service-level constraints. *Computers and Operations Research*, 36, 3166–3177.
28. Smilowitz, K., and Daganzo, C. (2007). Continuum approximation techniques for the design of integrated package distribution systems. *Networks*, 50, 183–196.

29. SteadieSeifi, M., Dellaert, N., P., Nuijten, W., Van Woensel, T., Raoufi, R. (2014). Multimodal freight transportation planning: A literature review. E*uropean Journal of Operational Research*, 233, 1–15.
30. UNECE. (2009). Illustrated glossary for transport statistics. ISBN: 978-92-79- 17082-9
31. Verma, M., and Verter, V. (2010). A lead-time based approach for planning rail truck intermodal transportation of dangerous goods. *European Journal of Operational Research*, 202, 696–706.
32. Verma, M., Verter, V., and Zufferey, N. (2012). A bi-objective model for planning and managing rail-truck intermodal transportation of hazardous materials. *Transportation Research Part E*, 48, 132–149.
33. Verweij, K. (2011). Synchronic modalities – Critical success factors. In P. J. van der Sterre (Ed.), Logistics yearbook edition 2011, 75–88.
34. Yamada, T., Russ, B.F., Castro, J., Taniguchi, E. (2009). Designing multimodal freight transport networks: a heuristic approach and applications. *Transportation Science*, 43, 129–143.
35. Yamada, T., Imai, K., Nakamura, T., Taniguchi, E. (2011). A supply chain-transport supernetwork equilibrium model with behaviour of freight carriers. *Transportation Research Part E,* Vol. 47, No.6, 887-907.
36. Yamada, T., and Febri, Z. (2015). Freight transport network design using particle swarm optimisation in supply chain–transport supernetwork equilibrium. *Transportation Research Part E,* Vol. 75, 164-187.
37. Zhang, J., Lam, W., H., K., Chen, B., Y. (2013). A stochastic vehicle routing problem with travel time uncertainty: trade-off between cost and customer service. *Networks and Spatial Economics,* 13, 471–496.