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# Emerging techniques for enhancing the practical application of city logistics models

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**Abstract**

This paper presents a review of emerging techniques for enhancing the practical application of city logistics models. A number of models have been applied to practical problems for evaluating policy measures of city logistics. These models can be categorised into two types: optimisation models, and simulation models. Optimisation models incorporate dynamic and stochastic elements, since the real urban freight transport faces varying demands and travel times. Simulation models typically use multi-agent systems, as multiple stakeholders are involved in planning city logistics schemes. Evaluation methodology is directly related to decision making of policy measures. Models for supporting decision making have become more important for obtaining a social acceptance as well as governance among private and public entities.

*Keywords:* City logistics; optimisation; simulation; evaluation

## 1. Introduction

There have been increasing concerns about the environmental issues relating to urban freight transport due to the congestion which is caused by the increase of passenger and freight vehicles in urban areas. Considering sustainable development of urban areas as well as mobility of goods has focused more attention towards coordinating traffic and logistics problems. We need efficient and effective freight transport systems in terms of logistics costs with the full consideration of environmental issues including

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noise, air pollution, vibration and visual intrusion. In that sense, the idea of city logistics (Taniguchi *et al.*, 2001) has been proposed to establish efficient and environmentally friendly urban logistics systems.

Recently liveability within urban areas has become a more important concern for ensuring the well-being of community. We need to incorporate traffic safety as well as security issues in the planning and implementing urban distribution systems. People are worrying about crashes and damage to their health caused by freight vehicles, although they request higher levels of service for their delivered commodities. Especially increasing demand for e-commerce requires more frequent home deliveries which may result in the increase of pickup-delivery trucks in community. Therefore, city logistics must incorporate liveability as an essential principle to be enhanced.

In addition to mobility, sustainability and liveability, resilience has gained more attention in presenting city logistics. Huge damage to people, buildings and industry was experienced after the massive earthquake and tsunami in Tohoku, Japan on 11 March 2011. Nobody could have imagined such cascading disasters caused by the M9.0 earthquake. Unfortunately 26,466 people died, 5,314 people were injured, and about 440,000 people evacuated from the disasters area to temporary housing. Humanitarian logistics played an important role for delivering water, food, clothes and other daily commodities to many displaced persons after the disasters. In this context, we have learned that the mitigation of damage and quick recovery of logistics systems is crucial for keeping a good quality of life. In particular, as the proportion of elderly people becomes higher, a higher level of medical treatment and care is required.

Another difficulty in modelling city logistics comes from the complicated interactions between private and public stakeholders who are involved in urban freight transport. Shippers, freight carriers, administrators and residents (consumers) are the main stakeholders who hold different objectives and perspectives towards their own goals. For example, estimating the responses of freight carriers to policy measures which are implemented by municipality is difficult for modellers. Therefore, it is quite challenging to model the behaviour of these stakeholders within the framework of coordination and competition in a market economy. Minimising the costs for a firm may be good for them, but consolidation systems with competitive companies might be even better for the private companies as well as the society at large. These type of city logistics measures can be well studied in advance using emergent modelling techniques for incorporating the behaviour of private and public entities.

To cope with these complicated issues of city logistics, great efforts have been devoted for modelling the phenomena and evaluating policy measures to solve urban freight transport problems. A number of models have been developed and deployed with the help of technological advances in computer and communication, which are known as ICT (Information and Communication Technology) and ITS (Intelligent Transport Systems). Modelling city logistics is based on the systems approach which requires high quality of data for identifying problems, developing models, verifying and validating models as well as evaluating the results which are obtained by applying models. The systems approach depends largely on collecting good data of traffic, capacity of resources, and the environment in urban areas. The development of ICT and ITS is very helpful to fully support the systems approach in city logistics modelling.

This review paper presents recent advances in modelling city logistics and focuses on practical applications of models in realistic cases. Optimisation and simulation are main areas of discussion. A number of efforts have been made to evaluate policy measures using models including dynamic and stochastic vehicle routing, multi-objective systems, multi-agent systems and reliability analysis.

## 2. Optimisation

### 2.1. Vehicle routing and scheduling

Models of vehicle routing and scheduling problems (VRP) or vehicle routing and scheduling problems with time windows (VRPTW) are basic tools for understanding goods distribution in urban areas. A number of papers on VRP and VRPTW have been published by operations researchers and practitioners. The dynamic and stochastic nature of demands as well as travel times is incorporated in the VRP and VRPTW models.

The dynamic and stochastic nature of demands of customers have been studied within the framework of VRP and VRPTW models (Powell, 1987, Jaillet and Odoni, 1988, Bertsimas, *et al.*, 1990, Gendreau, *et al.*, 1996, Figliozzi, *et al.* 2007, Wen *et al.*, 2010). Since travel times on roads change with time, the time varying and stochastic nature should be taken into account in VRP and VRPTW models (Stewart and Golden, 1983, Laporte, *et al.*, 1992, Laporte and Louveaux, 1993).

Within congested urban road networks, dynamic and stochastic characteristics of travel times are important for efficiently operating distribution systems. Taniguchi and Shimamoto (2004) investigated dynamic VRPTW with real time information of travel times based on ITS application. They found that the dynamic VRPTW is beneficial for both carriers in terms of cost reduction and community by alleviating congestion. Woensel *et al.* (2008) applied a queuing approach for the VRP with dynamic travel times. Soler *et al.* (2009) presented a generalization of the VRPTW that considers time-dependent travel times and costs. Figliozzi (2010) discussed the impacts of congestion on commercial vehicle tour characteristics and costs of deliveries. Kok, *et al.* (2010) studied the VRPTW with time-dependent travel times and driving hours regulations using dynamic programming heuristics. Maden, *et al.* (2010) presented case studies of the VRPTW with time varying data, showing that using the proposed approach in the UK can lead to saving in $CO_2$ emissions of about 7%. Thompson *et al.* (2011) estimated the benefits of considering travel time variability in urban distribution using stochastic programming and robust optimization procedures.

A number of new challenges have been observed in city logistics systems. Crainic, *et al.* (2009) discussed models for evaluating and planning city logistics and focusing on two-tiered distribution systems. Nguyen *et al*. (2010) presented meta-heuristic approach for the two-echelon Location Routing Problem. Perboli, *et al.* (2010) proposed new cuts for the two-echelon VRP.

Concerning time windows included in the VRP, soft time windows are new challenges relating to city logistics. Ioachim, *et al.* (1998) studied a dynamic programming algorithm for the shortest path problem with time windows and linear node costs. Gendreaqu, *et al.* (1999) applied parallel tabu search for the VRP with soft time windows. Tagmouti, *et al.* (2007) investigated arc routing problems with time-dependent service costs. Qureshi, *et al.* (2009) presented an exact solution approach for the VRP with soft time windows using column generation.

### 2.2. Multiobjective optimisation

Optimisation modelling has typically been undertaken with a single objective function. However, optimal solutions may vary depending on the evaluation criteria used, especially when multiple objective functions must be taken into account. As such, decision-making in logistics and supply chain management often faces the simultaneous consideration of several mutually conflicting criteria. This can commonly be modelled and solved within the framework of multicriteria decision-making problems and multi-objective optimisation problem (i.e., multiobjective programming problem (MOP)) (e.g., Chancong and Haimes, 1983; Sawaragi *et al*., 1985).

One of the key topics to be dealt with in the MOP is to identify the Pareto optimal set, since all objective functions cannot be simultaneously optimised. In the case of minimisation problem, the Pareto optimal solutions (i.e. non-inferior or non-dominated solutions) are those obtained such that the value of at least one objective function must be increased in order to decrease the value of a certain objective function.

It can be observed that most MOPs have been focused on heuristic algorithms to obtain approximate solutions, such as genetic algorithms (GA) or evolutionary algorithm (EA) (e.g., Deb *et al*., 2002; Vieira *et al*., 2004; Avila *et al*., 2006 ), particle swarm optimization (PSO) (e.g., Baumgartner *et al*., 2004), simulated annealing (SA) (e.g., Ho *et al*., 2003; Bandyopadhyay *et al*., 2008), Tabu search  (e.g., Baykasogluab *et al*., 1999; Ho *et al*., 2002; Jaeggi *et al*., 2008) and ant colony optimisation (ACO) (e.g., Alaya *et al*., 2007; Jaqueline and Barbosa, 2011).

In the management of supply chain and/or logistics, both costs and risks are required to be simultaneously evaluated, and these are often conflicting. Thus, the MOP has increasingly been used as a decision-making tool in such fields (e.g., Yamada *et al*., 1999; Iakovou, 2001; Chen *et al*., 2003, 2004; Zografos and Androutsopoulos, 2004; Chang *et al*., 2005; List *et al*., 2006; Yong *et al*., 2007; Tan *et al*., 2007; Sheu, 2008; Sundar Raj and Lakshminarayanan, 2008; Mansouri *et al*., 2010; Franca *et al*., 2010; Garcia-Najera and Bullinaria, 2011; Moncayo-Martínez and Zhang, 2011).

## 2.3. Intelligent agents

Intelligent agent software can automate a number of complex tasks relating to the operation of City Logistics schemes. Software agents are a, "encapsulated computer system, situated in some environment, and capable of flexible autonomous action in that environment in order to meet its design objectives" (Wooldridge, 2002).

Software agent's autonomy allows them to control their internal state and behaviour. Agents are able to gain experiences through sensors and learn by usage experience. Flexibility allows agents to able to react to changes in the environment. They can also be proactive.

Intelligent agents can perform in open, dynamic and unpredictable environments. Due to advances in information and communication technology they can communicate with sensor networks both at a local level (eg. wireless networks) and globally using the internet. They have the potential for incorporating more intelligence in software. Intelligent Agents can be designed to cope with changing situations and solve problems.

Developing intelligent agent software involves specifying a number of elements of the system, including the roles, interactions, types of agents, system goals, capabilities and services. Events are defined from the processing of percepts (information gained from the environment) and situated agents are capable of performing actions or tasks.

Intelligent agents are often designed using the Belief Desires and Intentions (BDI) architecture (Rao, and Georgeff, 1991). They can also be characterized by their situatedness, subjective rationality, autonomy, robustness, coherence, personalizability and cooperation (Schleifer, 2002). Intelligent agents can either serve as an automated system or as a decision support system (Davidson *et al*, 2005).

An agent based system outperformed an on-line system for optimising the drayage problem when service time durations were highly uncertain (Máhr *et al* 2010). Intelligent agents can be used to solve complex optimisation problems in dynamic environments such as the allocation of aircraft to gates at airport (Lam *et al* 2002). There are a number of areas where intelligent agents can assist in implementing City Logistics schemes such as determining optimal paths for delivery vehicles in road networks and dynamic vehicle routing and scheduling.

There are many challenges for truck drivers in determining the traffic links to use travelling between customers in urban areas. Intelligent agents could be used to aid route guidance, incorporating real time information concerning non-recurrent congestion and parking availability. The position of the vehicle in real time can be combined with traffic and parking information to reduce delays.

Intelligent agents could also be used to facilitate dynamic routing and scheduling for collaborative distribution systems (Fischer *et al*, 1993). Real time information regarding new requests from customers could be used to allocate trucks to customers based on available capacity and the proximity of vehicles to construct more efficient routes in urban areas.

## 3. Simulation

### 3.1. Systems dynamics

Systems dynamics is a simulation modelling approach for predicting the behaviour of complex systems. It allows the effects of feedback loops and time lags to be predicted providing a tool for aiding understanding the behaviour of dynamic complex systems (Sterman, 2000). Systems dynamics was originally developed to aid understanding of industrial processes but has more recently used for policy analysis. Systems dynamics models can be used to gain insights into the effects of freight policies considering the complex interactions between stakeholders.

Developing a systems dynamics model involves identifying major stocks and flows, the factors that impact flows as well as the main feedback loops. Causal diagrams are used to link stocks, flows and information sources. Equations are developed for representing flow levels.

Systems dynamics permits linked systems to be specified with delay and feedback loops allowing counterintuitive behaviour to be understood. Tools for expressing mental models can be utilised for studying human systems.

A number of diagramming methods including causal loop diagrams and system dynamic flow diagrams as well as simulation software tools have been developed to aid the construction of system dynamics models (Pidd, 2009).

A systems dynamics model was developed to investigate intermodal planning issues associated with the Port of Lewiston in the US (Sebo, 1996). The impacts of infrastructure development, policies and regulations were analysed incorporating concerns and interactions between modes and key stakeholders. This model allowed  a number of leverage points, hidden assumptions and second order effects to be identified.

A systems dynamics model was used to investigate the effects of freight consolidation a distribution strategy (Luan, 2010). This study analysed the operational status of influencing factors associated with implementing freight consolidation. It showed that freight consolidation increased the vehicle load factor as well as the goods delivery costs.

### 3.2. Multi-agent systems and game theory

There are four major stakeholders relating to city logistics; (a) Shippers, (b) Freight carriers, (c) Residents and (d) Administrators. These stakeholders have different objectives and different types of behaviour. Shippers try to minimise their costs in supply chains. Freight carriers try to meet shippers' requests to collect and deliver goods within strict time windows. Residents desire quiet, noiseless atmosphere and clean air in their community. Finally administrators hope to activate the vitality of city with sustainable transport systems. Understanding the behaviour of the stakeholders and interaction among them is needed for evaluating city logistics measures before implementing them.

Multi-agent modelling techniques allow complicated urban freight transport systems with multiple actors to be investigated (e.g. Weiss, 1999; Ferber, 1999; Wooldridge, 2002). Multi-agent models generally deal with the behaviour and interaction among multiple agents, which are most suitable to understand and study the behaviour of stakeholders in urban freight transport systems and their response to policy measures. Davidsson *et al.* (2005) provided a survey of existing research on agent-based approaches in freight transport and noted that agent-based approaches seem very suitable for this domain. Jiao *et al.* (2006) presented an agent based framework in the global manufacturing supply chain network. Roorda(2010) presented an agent-based micro-simulation framework for freight systems. The literature shows a number interesting examples of multi-agent approaches to transport logistics problems but most of them do not directly focus on urban freight transport systems.

Taniguchi *et al.* (2007) presented multi-agent models for treating city logistics schemes in which shippers, freight carriers and administrators are involved. Multi-agent simulation on a small test road network demonstrated that the VRPTW-D model which dynamically adjusted vehicle routing planning to the current travel times generated good performance in terms of increasing profits for freight carriers and decreasing costs for shippers. After applying multi-agent models on a large test road network, it was observed that introducing the VRPTW-D model generated a win-win situation by increasing profits for freight carriers and decreasing costs for shippers. Tamagawa *et al.* (2010) presented multi-agent models in which five stakeholders, freight carriers, shippers, residents, administrators, and urban motorway operators are involved. They embedded the Q-learning process in decision making of policy by agents taking into account the reward of previous action. After applying multi-agent models in urban road network, they examined the performance of several city logistics measures including road pricing and truck bans. In spite of the implementation of the city logistics measures and the increase of using urban motorways, freight carriers could keep their transport cost at the level of the situation without any city logistics measures or tolling, and they could keep the delivery charge at the same level.

Duin *et al.* (2007) studied auctions between carriers and shippers and re-scheduling process for urban freight delivery systems. Boussier *et al.* (2009) investigated the distribution of goods with electric vans using a multi-agent based simulation. They studied impacts and benefits of sharing parking spaces with passenger cars on-street. Donnelly (2009) modelled urban goods movement using hybrid models based on aggregate macroeconomic interactions, discrete event micro simulation and agent-based modelling. He successfully applied the models in the practical domain of road network in Portland City, US for examining some city logistics scenarios using existing data sets. Duin *et al.* (2011) modelled the dynamic usage of urban distribution centres using multi-agent simulation. Their model incorporated the behaviour of freight carriers, an UDC operator, truck drivers, and the municipality. They analysed the impacts of dynamic fee for using the UDC on the usage rate, income of UDC as well as the environment. Mes, *et al.* (2010) applied a multi-agent simulation model to dynamic pickup and delivery problems and proposed a pricing and scheduling strategy based on a dynamic programming. Mahr, *et al.* (2010) compared the multi-agent simulation and on-line optimisation approach for drayage problem with two types of uncertainty: service time duration and job-arrival uncertainty.

Game theory is a common tool to understand the gaming situation of multiple stakeholders involved in city logistics systems. Bell (2004) used the game theoretic approach for studying risk averseness in vehicle routing problems. He assumed two players, a dispatcher who seeks a least cost of tour and a demon with the power to cause one link to fail. Engevall and Gothe-Lundgren (2004) applied cooperative game theory to heterogeneous vehicle routing problems. Cost allocation methods based on the concepts of core and nucleolus were discussed. Holguin-Veras , *et al.* (2008) analysed the behaviour of carriers and receivers based on game theory.

## 3.3. Traffic simulation

Transport networks are one of the systems where computer simulation models have typically been applied, since it is not practical to experiment with real networks. Existing traffic simulation models can be classified into several ways: the division between macroscopic, microscopic and mesoscopic, and between continuous and discrete time approach.

Macroscopic traffic simulation models describe the traffic flow in an aggregated manner without looking at their elements in detail (e.g., behaviour of each vehicle on lane), including the Cell Transmission Model (Daganzo, 1994, 1995, 1999), METACOR (Elloumi *et al*., 1994) and MASTER (Helbing *et al*., 2001). On the other hand, microscopic traffic simulation models represent traffic at the level of individual vehicles and their interactions, and therefore have the potential to be used for representing the behaviour of different types of vehicles. Paramics (Smith *et al*., 1994), CORSIM (FHWA, 1996), AIMSUN2 (Barcelo *et al*. 1997), VISSIM (Fellendorf, 1994; PTV, 2009) and MITSIMLab (Toledo *et al*., 2003) are examples of microscopic models.

Mesoscopic traffic simulation models are intermediate ones. Aggregate approaches of the macroscopic models (e.g., link performance functions and capacities) are embedded within them as wells as the individual interactions of the microscopic models. Several Mesoscopic models has been developed so far, such as CONTRAM (Leonard *et al*., 1989), DYNASMART (Jayakrishnan *et al*., 1994), DYNAMIT (Ben-Akiva *et al*., 1996), TRANSIMS (e.g., Nagel, 1997), FASTLANE (Gawron, 1998) and DTASQ (Mahut, 2001).

With their dynamic and tractable nature, traffic simulation models can generally provide more output than the conventional static demand-supply models, such as user equilibrium traffic assignment models (see Patriksson (1994), Florian and Hearn (1995) and Boyce (2007) for a comprehensive overview of such models; Dafermos (1980), Crainic *et al*. (1990), Guelat *et al*. (1990), Yang (1998), Cascetta (2001), Nagurney and Dong (2001) and Yamada *et al*. (2009, 2011) for multiclass and/or multimodal user equilibrium traffic assignment models). However, the users have to pay attention to what output provided by the model have been validated (compared to actual values), taking into account its inherently adhoc nature.

## 4. Evaluation methodology

The systems approach to City Logistics requires goals, objectives and criteria to be defined before modelling and evaluation is undertaken (Taniguchi *et al*., 2001). Evaluation methods are typically categorised as either single (monetary) criterion or multi-criterion (non-monetary). Monetary methods focus on cost benefit analysis that includes consideration of capital, maintenance and operating costs as well as user and indirect benefits. This involves both quantification and valuation of relevant impacts. Multi-criterion evaluation techniques allow qualitative multi-dimensional effects to also be incorporated. However, quantitative methods such as cost benefit analysis do not encompass all relevant issues for City Logistics schemes. They are poor at evaluating non-quantifiable (but still relevant) issues such as health and the environment, to the extent that it is common practice is not to attempt to evaluate them.

Evaluation methods need to be robust and transparent. Robustness implies two concepts: clarity, simplicity and brevity through precision in reasoning; and the 'sensitivity' testing of recommendations to ensure that, in terms of the range of information provided, they are not likely to be upset by minor order changes to options. Transparency implies that the stakeholders can identify an unbroken chain of logic, an 'audit trail', taking them from the basic identification of issues to the selection of projects.

Evaluation methods should also be rigorous. Any analysis methodology must ensure that the economic, environmental and social effects of all City Logistics projects are considered in the light of all relevant objectives. It is challenging to develop methods that easily support robust, transparent and rigorous evaluation of urban road freight improvement projects.

Multi-criteria analysis methods allow alternatives to be ranked where a number of evaluation criteria are considered important (Nijkamp *et al*, 1990; Voogd, 1983; Janssen 1992; Render *et al*, 2006). This method allows urban freight planners to incorporate a range of sustainability related objectives. Multi-criteria analysis has three main components: a finite number of alternative plans or options; a set of criteria by which the alternatives or options are to be judged; and a method for ranking the alternatives or options according to how well they satisfy the criteria (Resource Assessment Commission, 1992).

Multi-criterion techniques however require the specification or derivation of weightings relating to the relative importance of defined criteria. There are numerous approaches that allow the weightings to be determined but there is no generally accepted preferred method.

From the preference statements, relative importance weightings can be estimated using a root product rule within the analytical hierarchy process (Saaty, 1980).

Mathematical programming can be used to evaluate multi-objective urban freight plans or projects that incorporate a range of city logistics objectives. A set of options can be evaluated using multi-objective decision making techniques (Saaty, 1980; Nijkamp *et al*,1990).

An objective based procedure for evaluating urban road freight projects was developed in Victoria, Australia (Thompson and Hassall, 2006). A number of goals and objectives were defined based on public policy that incorporate a broad range of stakeholder issues. Procedures for estimating weighting of goals and objectives were developed. Qualitative criteria were also developed for each objective. The evaluation procedures were tested for a small number of potential projects.

A methodology aimed at increasing the consistency with which urban goods schemes and projects are evaluated that includes the development of a matrix that takes account of the key ratios that need to be considered within the evaluation approach has been developed in France (Patier and Browne, 2008).

Multi-criteria evaluation techniques can be used to combine a number of performance measures produced from simulation models to aid the identification of optimal City Logistics schemes. Multi-criteria tools were used to analyse the impacts of recurrent and non-recurrent congestion on the reliability, delays and emissions from freight vehicles on freeways in the Portland Metropolitan Area in the US (Wheeler and Figliozzi, 2011). Multi-criteria performance measures were used to evaluate the net benefits of truck lane restrictions on the I-70 freeway in Southern California from both public and private sector standpoints (Yang and Reagan, 2007). Multi-criteria analysis was conducted in Athens to examine the impacts of heavy goods vehicles (Karlaftis *et al*, 2004). This study incorporated several environmental and socioeconomic impacts as well as changes in average network speed.

Multi-criteria approaches can also be used to determine optimal paths for freight vehicles in road networks. The Analytical Hierarchy Process (AHP) was used to identify optimal routes for vehicles carrying hazardous materials in Thailand, where a number of road elements contributing to accidents were incorporated (Sattayaprasert *et al*, 2008). A route choice model for freight vehicles was developed based on multiple criterion including minimum travel time, maximum motorway use and minimum travel cost for the Italian road network (Russo *et al*, 2006).

Location planning of freight terminals often involves consideration of a number of factors that can be evaluated using multi-criteria techniques. The sustainability of inland freight hubs was assessed using multi-criteria decision analysis incorporating a number of qualitative and quantitative criteria addressing the liveability and economic vitality of a region (Lipscomb *et al*, 2011).

Multi-criteria analysis was used to identify the most vulnerable freight related infrastructure to a terrorist attack, providing a tool for developing countermeasures (Tsamboulas and Moraitis, 2008).

A multi-criteria approach was used to evaluate the development of a freight village in Northern Greece (Kapros *et al*, 2005). In developing this process, a number of decision criteria were identified including environmental quality, contributions to local, regional and national economies, attractiveness for private sector financing, land-use changes as well as compatibility with other plans or plans.

### 4.1. Bi-level decision-making

Decision-making processes can often be represented within a bi-level framework, since the behaviour of an entity at one level may influence that of other entities at another level. In the case of reader-follower relationships existing, which are generally assumed in the field of city logistics, bi-level programming technique plays a vital role to determine effective city logistics initiatives.

The upper level typically describes the behaviour of administrators (or system planners) determining the best combination of their actions, which commonly results in combinatorial optimisation. In the lower level, the behaviour of system users (e.g., shippers, freight carriers, consumers and so on in the case of city logistics) is represented using equilibrium models, gaming models or simulation models.

This type of decision-making process is depicted by a bi-level programming problem (BLPP) (Colson *et al*., 2005), when both levels can be formulated with optimisation problems. Bard (1998) and Dempe (2002) described the BLPP in detail. In the case of equilibrium models incorporated within the lower level, the problem involves a mathematical problem with equilibrium constraints (MPEC) (e.g., Luo *et al*., 1996). There has been an increasing amount of research conducted using such approaches in the field of logistics and supply chain management (e.g., Yamada *et al*., 2001, 2006, 2009; Ryu *et al*., 2004; Roghanian *et al*., 2007; Sun *et al*., 2008; Chiou, 2009; Bianco *et al*., 2009; Calvete *et al*., 2011; Kuo and Han, 2011).

### 4.2. Impact analysis of policy measures

Impact analysis of policy measures in city logistics gives important components of evaluation methodology. Policy measures including cooperative delivery systems, urban consolidation centres, off-peak hour delivery, access control, road pricing and access control should be evaluated before implementing in a real situation. Some models have been developed and applied to evaluate these policy measures.

Holguin-Veras, *et al.* (2006) studied the impacts of time of day pricing initiatives on the behaviour of commercial carriers. Holguin-Veras, *et al.* (2007, 2008) investigated the effectiveness of joint receiver-carrier policies to increase truck traffic in off-peak hours. They analysed stated preference data in New York using discrete choice models. Sarhaye, *et al.* (2010) investigated night time deliveries and presented realistic scenarios for two California cities, Los Angeles and Long Beach. They examined diesel exhaust concentration and human intake estimates after temporal redistribution of daily logistics operations.

Munuzuri, *et al.* (2010) investigated modelling peak-hour freight movements with limited data availability in Seville. Russo and Comi (2011) proposed a model system to support ex-ante assessment of city logistics measures. The model systems consist of two levels: commodity and vehicle. Braysy, *et al.* (2009) considered home care, transportation of the elderly and home meal delivery based on efficient scheduling of routing problems in Finland. The results showed that there is a significant potential for cost savings for all applicants considered. Quak and Koster (2009) investigated the government's time-window regulations, the vehicle restrictions and different retailers' logistical concepts on the financial and environmental performance of retailers. They analysed two case studies in the Netherlands.

*4.3. Risk and reliability*

   Risk management relating to natural and manmade disasters is a challenging topic in city logistics. As for natural disasters, humanitarian logistics is important subject associated with city logistics. After natural disasters including earthquakes, floods, tsunamis, hurricanes, tornados and bush fires, people who suffered from the disasters immediately need water, food, clothes and other daily commodities. Providing these required goods to displaced persons is urgent and critical for their lives and health. The objective of humanitarian logistics is minimising the sufferings of affected people, while that of business logistics is minimising the total costs. The constraints are also different in humanitarian logistics, since the commodities are not enough for all displaced persons and the capacity of trucks and drivers is not always enough for deliveries. Moreover, planning deliveries to displaced persons is very hard because their demands are uncertain and the road network is often damaged by disasters. Therefore, planning should be done quickly with very uncertain information.

   Balcik, *et al.* (2010) discussed coordination in humanitarian relief chain among various actors who are involved. Caunhye *et al.* (2011) showed that optimisation models become powerful tools to tackle emergency logistics. They categorised various optimisation models into two groups: (a) short-notice evacuation, facility location, and stock pre-positioning are drafted as the main pre-disaster operations, (b) relief distribution and casualty transportation are categorized as post-disaster operations. Liberatore, *et al.* (2011) studied the disruption caused by disasters focusing on the correlation effects between the facilities. They provided a tri-level formulation of the problem, and proposed an exact solution algorithm which makes use of a tree-search procedure to identify which facilities to protect.

   Hazardous material transport in urban areas has become important research area for decades. Erkut and Verter (1998) presented overview of modelling hazardous material transport and they pointed out that different risk model suggests different "optimal" paths for a hazmat shipment between a given origin-destination pair. Giannikos (1998) presented a multi-objective programming model for this problem taking into account total costs, total perceived risk, individual perceived risk and individual disutility. Chang *et al*. (2005) described a method for finding non-dominated paths for multiple routing objectives in networks where the routing attributes are uncertain, and the probability distributions that describe those attributes vary by time of day. Bell (2006) discussed using a mix of routes by determining the set of the safest routes and the safest share of traffic between these routes leads to better risk averse strategy based on a game theoretic approach. Pradananga, *et al.* (2010) presented a multi-objective model of hazmat transport including vehicle routing for minimizing the costs and risk of exposure of people to explosion of hazmat on roadways.

   Ando and Taniguchi (2006) studied the reliability of travel times in vehicle routing and scheduling in the context of establishing environmentally friendly urban freight transport systems. Bell (2009) presented a multi-path Astar algorithm for risk averse vehicle navigation for improving travel time reliability.

## 5. Conclusions

   Modelling urban freight systems is becoming more challenging due to the increased attention being given to the environmental and social impacts of freight as well as the higher service levels being demanded by consumers. City logistics requires advanced optimisation and simulation modelling approaches to assist in the design, evaluation and operation of schemes that satisfy the concerns of all major stakeholders.

   Recent developments in information and communication technologies allow richer sources of data and information to be used in modelling urban freight and evaluating city logistics schemes. Procedures for

incorporating real time data relating to the performance of the traffic system can provide net benefits for key stakeholders. Developments in agent based software, multi-objective optimisation methods and multi-criteria analysis allow the performance measures for major stakeholders and the interactions between them to be included in city logistics models. Such techniques are most suitable for developing and implementing successful city logistics schemes.

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