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Incorporating risks in City Logistics

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Abstract

This paper presents a review on incorporating risks caused by natural and manmade hazards in city logistics modelling. We describe the classification of risks related to city logistics based on the source of difficulty for assessing risks caused by events. Methodologies for modelling risks for urban freight transport are outlined including, stochastic programming, multi-objective optimisation, robust optimisation, multi-agent simulation, and traffic simulation. New concepts of human security engineering are presented and discussed focusing on natural disasters, manmade disasters, hazardous material transport, traffic safety, and health issues. Human security engineering is very important to provide appropriate tools for decision making related to urban freight policy incorporating risks due to natural and manmade hazards.

Keywords: Risk modelling; human security engineering; disaster planning and management

1. Introduction

There has been increasing concern about the risks caused by natural hazards including earthquakes, flooding, tsunamis, snowfall and bushfires as well as manmade hazards of crashes and terrorist attacks. Although in principle these risks should be well assessed and incorporated in city logistics, they are not fully taken into account in modelling city logistics (Taniguchi et al., 2001) and implementing city logistics schemes in urban areas. The reasons are:

- assessing the risks related to city logistics is hard due to uncertainty of these events,
- incorporating risks of natural and manmade hazards incurs additional costs on logistical operations, and
- natural and manmade disasters are not regarded as being within the logistics managers' responsibility.

Recently we have encountered extremely destructive disasters generated by the tsunami after Northern Sumatra earthquake in the Indian sea region in 2004, Hurricane Catharina in the Mexican bay area in the USA in 2005,

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Sichuan earthquake in China in 2008 and bushfires in Melbourne, Australia in 2009. As well, there was a chemical attack using saran on the subways in Tokyo in 1995, terrorism in New York on September 11 in 2001, blast attack in London in 2005 and piracy attacks off the Somalia coast in 2009. These threats triggered a change in the mindsets of stakeholders to start taking into account risks due to natural and manmade hazards.

In private firms these risks are discussed from the viewpoint of business continuity management. We can find a typical case of critical disruption of supply chain caused by the collapse of a small firm named Riken by the Niigataken Chuetsu-oki earthquake in 2007, which produced piston rings for automobile manufacturers in Japan. The disruption of the factory of Riken generated the shutdown of many automobile assembly factories for a week, since small inventory of such parts in Just-In-Time production systems were so vulnerable against the threats of earthquake with too much dependence on the supply of a critical part from a single firm. After that most of logistics companies realized the importance of incorporating risks of natural disasters in logistics systems from the point of business continuity.

In the public sector, risks due to natural and manmade hazards in urban freight transport system are directly related to public welfare and public health in emergency cases. The public sector is interested in how to mitigate the damage to urban logistics facilities and recover quickly after disasters from the viewpoint of delivering goods needed for maintaining a high quality of life in urban areas.

In this context we need to consider multiple stakeholders involved in urban freight transport systems, namely shippers, freight carriers, administrators and residents (consumers) to incorporate risks in city logistics. As there are different motivations, objectives and behaviours among these stakeholders in facing risks, advanced modelling methods including multi-agent models are required for modelling behaviours of stakeholders.

In general city logistics takes into account the day to day risks of delay when arriving at customers for delivering or picking up goods due to recurrent congestion generated by the concentration of traffic in peak periods, crashes and sporting events. However, we need to incorporate less frequent and severe effects caused by cyclones, earthquakes and floods and others extreme weather events. Figure 1 illustrates the classification of risks related to city logistics. The horizontal axis shows the source of difficulty for assessing risks caused by events and the vertical axis indicates the frequency of events.

The first level of difficulty comes from complexity. The effects of congestion on road networks are complex and it is hard to anticipate the travel times due to congestion, since the demand of passenger and freight traffic fluctuates. If we use vehicle routing and scheduling with time windows (VRPTW) models, conventional VRPTW models can be applied for duplicating the movements of pickup/deliver trucks in urban areas.

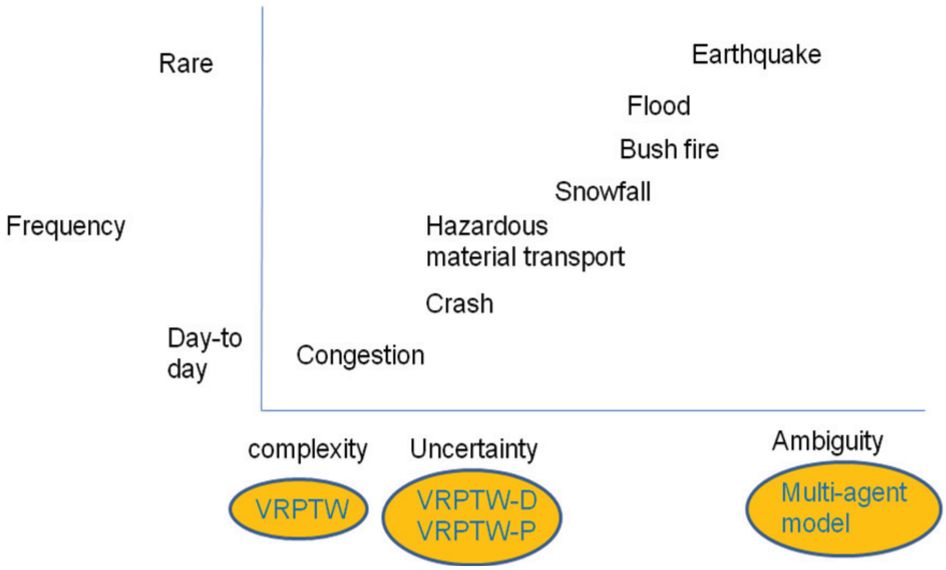

Figure 1 Classification of risks related to city logistics

The second level of difficulty comes from uncertainty. Crashes on roadways are not predictable and in particular vehicles carrying hazardous materials often generate huge health problems for residents and damage to buildings. In this class of difficulty, we need to develop models taking into account the dynamic and stochastic nature of travel times and connectivity of road networks. Then VRPTW-D (vehicle routing and scheduling with time windows – dynamic) or VRPTW-P (vehicle routing and scheduling with time windows – probabilistic) models are available to duplicate the dynamic adaptation of starting time and route choice of pickup/deliver trucks in urban areas based on ITS (Intelligent Transport Systems) applications.

The third class of difficulty comes from ambiguity. Bad weather conditions and natural hazards are included in this class and these events occur less often but greatly affect urban freight transport systems. In this class more sophisticated treatment is required for duplicating the behaviour of stakeholders. The VRPTW-D or VRPTW-P models are not sufficient in ambiguous situations, while multi-objective models or multi-agent models and simulation are effective to assess the effects of these events and evaluate initiatives for responding to them. The ambiguity of the situation is generated by the unpredictable interaction among stakeholders as well as the action-reaction relationships between stakeholders and the environment.

For coping with the risks of complexity, uncertainty and ambiguity, the concept of risk governance has been proposed (Kröger, 2008). The idea of risk governance is beyond risk management and includes the cycle of pre-assessment, appraisal, characterisation and evaluation, and management. The comprehensive framework of risk governance allows us to understand the dependency of each stakeholder related to city logistics initiatives and the critical infrastructure as well as the critical points in supply chains.

Risk has been defined as, "the chance of something happening that will have an impact on objectives" (AS/NZS, 2004). City Logistics aims to reduce the total costs including economic, social and environmental associated with urban goods movement. There are a number of aims and objectives of urban freight systems that are under threat such as the health and safety of citizens and the drivers of vehicles, the fulfilment of delivery contracts (eg. city curfews and time windows) as well as reducing climate change.

There is a need to incorporate uncertainty into models for city logistics to ensure that schemes will perform well into the future. A variety of methods have been used to incorporate uncertainty in supply chain modelling such as scenario and contingency planning, decision trees and stochastic programming (Shapiro, 2007).

2. Methodology

2.1. *Robustness*

There is often considerable uncertainty in the input data such as parameters, resources and operational limits within optimisation models that are used to plan, design and evaluate city logistics schemes. Mathematical programming represents systems by an objective function, decision variables and constraints. A feasible solution is one that satisfies the constraints of a system. An optimal solution is defined a feasible solution where the values of the decision variables provide the best value of the objective function.

Solution robustness investigates whether the optimal solution is maintained when there are changes to the input data. In particular, solution robustness considers how close the original optimal solution is to the new optimal solution when the input data changes.

Model robustness considers the effect on feasibility for changes to the input data. This involves determining how close to feasible the optimal solution is when there are changes to the input data.

The concept of robustness in mathematical programming analyses the effect of uncertainty in a models input data represented by parameters and constraints. Robustness of logistics and supply chain networks has received considerable attention recently (Bok et al., 1998; Christopher and Peck, 2004; Mo and Harrison, 2005; Yu and Li, 2000).

It is desirable to develop procedures for identifying solutions that remain close to optimal and close to feasible when there are changes to the values of the input variables due to their uncertainty. Robust optimisation analyses the trade-off's between solution robustness and model robustness (Mulvey et al., 1995). A number of methods have been developed for representing uncertainty in optimisation models, including probability distributions, fuzzy logic and scenario-based techniques.

2.2. Stochastic programming

Stochastic programming formulates a system as a probabilistic (stochastic) model that explicitly incorporates the distribution of random variables within the problem formulation (Birge and Louveaux, 1997). This is contrast to approaches such as linear programming where the parameters are assumed to be constant. Stochastic programming can identify solutions that perform better when parameters vary from their mean or estimated values.

The value of the stochastic solution (VSS) measures the possible gain from solving the Probabilistic (Stochastic). It represents the value of knowing and using the distributions of future outcomes. VSS is relevant to problems where the future is uncertain and no further information about the future is available. It measures the cost of ignoring uncertainty when making a decision (ie. determining a solution).

Although the actual travel time between customers is uncertain in static vehicle routing and scheduling problems a single value estimate (forecast) is usually made (Psaraftis, 1995). Stochastic (probabilistic) models allow random inputs that are assumed to follow a probability distribution

With the Probabilistic (stochastic) Vehicle Routing Problem with Soft Time Windows (VRPSTW) model an expected penalty cost must be estimated (Laporte et al., 1992). The expected penalty cost associated with accounts for the uncertainty of predicting the arrival time of trucks visiting customers.

A two stage procedure was developed for estimating the benefits (cost savings) of using stochastic programming for vehicle routing and scheduling with time window and variable travel times (Taniguchi et al., 2001).

Late deliveries in urban areas can lead to missed sales in retailing as well as delivery failure in home deliveries. Vehicles running late may also not be allowed to enter inner urban areas where strict curfews for delivery vehicles have been implemented.

Stochastic programming has recently been applied to the design of supply chain networks (Santoso et al., 2005; Shapiro, 2007; Shapiro, 2008; Snyder, 2006).

2.3. Simulation

Simulation can be a useful tool for designing urban logistics systems. It has been used widely in the design of loading/unloading facilities and the layout within distribution centres. Operational performance measures can be estimated for varying physical designs and demand levels. This can allow contingency plans to be developed for extreme conditions.

A micro-simulation was developed to determine a congestion management strategy of the Kallang-Paya Lebar Expressway (KPE) in Singapore (Keenan et al., 2009). The KPE involves a 9 kilometre road tunnel and the level of service was estimated for various traffic levels including freight vehicle to ensure reasonable safety levels using the VISSIM simulation software.

Simulation can be used to design security and scheduling procedures for reducing the threat of terrorism. A delivery vehicle scheduling system was developed using the Planimate simulation software for use in planning and operations of the Sydney 2000 Olympics (Pearson and Gray, 2001). Animation of transport activities assisted in the effective communication between key stakeholders including security forces. This system was used to determine specific time-slots of deliveries to Olympic venues and produce a master delivery schedule (MDS). It provided the capability to verify the robustness of the final schedule and to analyse scenarios including terrorist events.

2.4. Multiobjective optimisation

Decision-making in supply chain and logistics management often faces simultaneous consideration of several criteria. In most cases, a simple approach is used, where multiple objectives are weighted into a single one. However, it is difficult to set the weights for each objective in advance. Thus, it can typically be modelled and solved within the framework of the multi-criteria decision-making problem and the multi-objective optimisation problem (i.e., multi-objective programming problem (MOP)). These problems commonly have the characteristic that there does not generally exist a unique optimal solution. In cases where the values of objective functions are mutually conflicting, all objective functions cannot be simultaneously optimised. A set of so-called Pareto optimal solutions (e.g. Chancong and Haimes, 1983; Sawaragi et al., 1985), which also imply non-inferior or non-dominated solutions, are determined in that case.

MOP is generally formulated as follows:

$$\min \ \mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})]^{\mathrm{T}} \tag{1}$$

$$\text{subject to} \ \ \mathbf{x} \in \mathbf{S} \tag{2}$$

where **f** is a vector of *m* objective functions to be minimised, **x** is a vector of decision variables, and **S** is a set of all feasible solutions. A solution to the above problem **x*** is called Pareto optimal solution if and only if $f_i(\mathbf{x}^*) \leq f_i(\mathbf{x}') \ \forall i$ and $f_i(\mathbf{x}^*) < f_i(\mathbf{x}') \ \exists i$. In other words, the Pareto optimal solution can be defined as a solution if no objective function value of **x*** is greater than that of $\mathbf{x}'$, and there is at least one objective function value of **x*** that is less than that of $\mathbf{x}'$.

In general, there are lots of such optimal solutions, and a set of Pareto optimal solutions are only obtained. Decision-makers have to choose a final preferred one from among the Pareto optimal solutions based on personal preferences or additional criteria. There have been a variety of approaches to obtain the Pareto optimal solutions as well as to select the final preferred one, many of which are reviewed in the surveys recently collected by Ehrgott and Gandibleux (2002) and Figueira et al. (2005), providing a comprehensive overview of multi-criteria decision-making and multi-objective optimisation.

Several MOP models have been proposed to facilitate decision-making for supply chain and logistics optimisation under the conditions of risk due to the consideration of different demand risk from many different customers (e.g., Weber and Ellram (1992); Weber and Current (1993); Ghodsypour and O'Brien (2001); Wu and Olson (2008)). Recently, MOP has increasingly been used for a decision-making tool in the field of green supply chain management and reverse logistics, including hazardous material transport and hazmat waste management (e.g., Iakovou, 2001; Zografos and Androutsopoulos, 2004; Chang et al., 2005; List et al., 2006; Yong et al., 2007; Sheu, 2008), since these have uncertainty, complexity, and potential risks for people in nature, in the process of transport, transactions and purchasing.

In supply chain and logistics management, both costs and risks are required to be simultaneously evaluated, and these are often conflicting. In that case, total operational costs are typically estimated, consisting of transport costs, inventory costs, reprocessing costs and final disposal costs, while the assessment is undertaken at the same time for the operational risks generated for transportation, storage, reprocessing and final disposal. This leads problems associated with supply chain and logistics management when using MOP.

2.5. Multi-agent simulation

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 want quiet, noiseless atmosphere and clean air in their community. Finally administrators hope to activate the vitality of the 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. Duin et al. (1998) showed dynamic actor network analysis for complex logistics problems. Ossowski et al. (2005) presented multi-agent approaches to decision support systems in traffic management. Jiao et al. (2006) presented an agent based framework in the global manufacturing supply chain network. 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. This model included a reinforcement learning process to take better policies into the next step based on a reward which was given as a result of the previous action of the agent. This paper presents multi-agent models for evaluating the behaviour and interaction among stakeholders who are involved in urban freight transport systems as well as the effects of city logistics measures. 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 the VRPTW-D model generated a win-win situation by increasing profits for freight carriers and decreasing the costs for shippers. The results also show that implementing road pricing can reduce NO_x emissions but may increase costs for shippers. To avoid such effects, introducing co-operative freight transport systems helps shippers reduce their costs.

Tamagawa et al. (2009) presented a multi-agent model in which five stakeholders, freight carriers, shippers, residents, administrators, and urban motorway operators were involved. They embedded a Q-learning process in decision making of policies made by agents taking into account the reward from the previous action. After applying multi-agent models in an urban road network, they examined the performance of several city logistics measures including road pricing and truck bans. In spite of implementing of city logistics measures and the increase of using urban motorways, freight carriers could keep their transport costs at the level of the situation without any city logistics measures or tolling, and they could keep their delivery charges at the same level. As a result, shippers could also keep their delivery costs at the same level as before. They conclude that the implementation of these measures had the effect of improving the environment for all stakeholders.

Donnelly (2009) modelled urban goods movement using hybrid models based on aggregate macroeconomic interactions, discrete event micro simulation and agent-based modelling. These models were successfully applied in Portland City, US for examining several city logistics scenarios using existing data sets.

2.6. Health

The health of persons involved in urban distribution is an important element of the vision for city logistics (Taniguchi et al., 2004). Occupational health and safety of employees is a substantial issue and there is increasing pressure on employers to be more proactive with respect to protecting the health of their employees. This section outlines approaches used to model the effects of air quality and physical activity of drivers.

2.7. Air quality

Carriers are a major stakeholder in City Logistics and the drivers of trucks and vans are often exposed to high levels of emissions for extended periods. A number of research studies have shown that there is higher air pollution inside road vehicles compared to ambient air quality (Chertok, 2004; Fruin, 2004; Rodes et al., 1998). The level of in-cabin exposure to air pollutants is a function of the time a person spends in the cabin in urban streets. Therefore, drivers have an increased risk of cancer and respiratory diseases, such as asthma.

The disability adjusted life year (DALY) measurement is an indicator of the burden of disease (BoD) in the community. One DALY represents one lost year of 'healthy' life and is a combination of years of life lost (YLL) as a result of premature mortality plus an equivalent number of 'healthy' years of life lost as a result of disability (YLD). DALYs are the summation of years due to premature mortality (YLL) in the population and the years lost due to disability (YLD). DALYs are regularly determined for particular States and cities and typically calculated for particular diseases such as diabetes mellitus and cardiovascular disease (Murray and Lopez, 1996).

Kayak and Thompson (2007) report that the possible contribution to the BoD for the population of the Melbourne Statistical Division (MSD) jurisdictions from exposure to diesel fuel emissions, by in-vehicle diesel engine environments is multiples greater than that to the population outside the vehicles.

Improved methods are needed to develop and identify cost effective methods to reduce the risk of health problems for drivers from air pollution. There is a need to incorporate public health impact evaluation using tools such as the DALY health measurement for avoidable deaths into city logistics planning.

2.8. Physical activity

There are increasing concerns relating to the rising levels of obesity in many countries with most residents leading increasingly sedentary life-styles. Physical activity is most commonly undertaken at work, home or during recreation and transport. Drivers of freight vehicles face increased risks of not undertaking sufficient levels of physical activity at work.

The current Australian physical activity guidelines are, “Put together at least 30 minutes of moderate-intensity physical activity on most, preferably all, days.” (Commonwealth Department of Health and Family Services, 1998)

A classic epidemiological study of bus conductors in London, concluded that the higher physical activity of conductors on double-decker buses in London contributed to the lower incidence and mortality in the conductors (Morris, 1953).

There is a need to incorporate more physical activity in urban distribution since many logistics tasks have been mechanised in the last 50 years. A significant amount of physical activity has taken out of contemporary daily distribution system in cities, with typical motorisation of delivery of newspapers and mail as well as the collection of garbage. Drivers often experience long periods sitting in vehicles driving or waiting.

Accelerometers can be used to accurately measure the amount of energy expenditure undertaken due to physical activity. Activity diaries can also be used to estimate the frequency, intensity and duration of physical activities undertaken by individuals.

A person’s weight is largely determined by the amount of energy expenditure and food energy intake. Combining levels of predicted energy expenditure (including that from non-motorised distribution) with dietary details the weight of individuals can be simulated (Westerterp et al., 1995; Payne and Dugdale, 1977). The health benefits can then be determined since many burden of disease studies relate the risk of chronic diseases to Body Mass Index (BMI).

Daily Physical Activity Levels (PALs) can be determined by estimating the total energy expenditure, expressed as a multiple of the basal metabolic rate (Ainsworth et al., 2000). It is recommended that average PALs should be above 1.6 (AICR, 2007).

Estimating energy expenditure for an individual over a daily period is a complex and challenging task. There are several methods of calculating physical activity levels. A simple method has developed for determining basal, activity and total energy expenditure levels based on personal attributes such as age, height, weight and gender as well the duration and metabolic rate of activities undertaken (Ainsworth, 2000; Gerrior et al., 2006).

There has been a recent trend in the delivery of mail within Australian cities towards using trolleys and bicycles instead of motor cycles and vans. This is due to the difficulty in recruiting licensed motorcycle riders as well as the increasing number of motorcycle riders that are becoming overweight. Distribution of mail to dwellings in residential areas by bicycle has many health benefits for riders. In addition, there are environmental benefits of less air pollution as well as social benefits associated with reduced safety costs associated with crashes (number and severity).

2.9. Human security engineering

Cities can experience a range of natural and man-made disasters that can cause disruptions to urban distribution systems. Following the emergency response and relief phases, urban logistics systems often need to be redesigned as reconstruction and recover efforts are undertaken.

There is a need to build more resilience into urban transport systems to limit the effect of disasters (Murray-Tuite and Mahmassani, 2004; Murray-Tuite, 2006). Traffic systems are often disrupted as a result of disasters and city logistics schemes can provide an efficient means of continuing distribution services when the capacity of the urban traffic system has been reduced.

Following a disaster the capacity of traffic links is lost or reduced resulting is increased travel time, delays and delay penalties. Changes in the origin and destination patterns for freight vehicle trips can result due to links being blocked leading to changed routes within urban areas.

Models can assist in designing appropriate city logistics schemes to operate throughout the reconstruction period following a disaster. Models can also assist in identifying vulnerable links as well as determining the most efficient schedule of reconstruction projects.

Economic loss modelling involves estimating the direct losses including the reconstruction of traffic links and traffic management as well as the indirect losses such as business disruption and increase delay (Buckle, 2005).

Catastrophe models predict the financial loss from disasters (Grossi and Kunreuther, 2005). Hazard and inventory modules provide the information to estimate the vulnerability of structures to damage from a disaster. Losses are predicted by direct costs of repair or reconstruction as well as indirect costs such as business interruption and evacuation.

Hazard modules involve consideration of the location, frequency and severity of disasters that is largely based on analysis of historical data. The inventory module provides information on the type and strength of structures. Vulnerability modelling predicts the damage to structure for given disaster events. Loss models estimate the financial loss incurred from the physical damage.

The Risk from Earthquake Damage to Roadway Systems (REDARS) model (Werner et al., 2005; 2007) estimates post disaster trip demands and this is used to identify vulnerable transport links (including bridges). It provides guidance for making decisions to reduce risks and can assist in developing response and recovery strategies.

2.10. Manmade disasters

Manmade disasters is a challenging topic to be tackled in terms of City Logistics. It includes war, terrorism, epidemics and pandemics, traffic accidents, nuclear accidents, food or water contamination, building collapses and so on. Tansel (1995) compares the characteristics of manmade disasters with that of natural disasters and states that manmade disasters could happen anywhere where there is human activity, while natural disasters are generally regional. He also indicates that hazardous waste was the most serious environmental problem among manmade disasters, confronting risk managers in the 1990s. Risk management in hazardous material transport has therefore been a major research topic relating to manmade disasters (e.g., Gopalan et al., 1990; List et al., 1991; Beroggi and Wallace, 1995; Nozick et al., 1997; Miller-Hooks and Mahmassani, 1998).

There is an increasing need to further secure transportation infrastructure due to terrorist threats and incidents seen since September 11th, 2001. Sheffi (2001) points out that supply chains are particularly vulnerable to intentional or accidental disruptions and suggest multi-supplier strategy as a possible approach for alleviating the vulnerability.

Tang (2006) reviewed quantitative models that deal with supply chain risks and classifies supply chain risks into two types: operational risks and disruption risks. The disruption caused by manmade disasters include disruption risks, whilst the operational risks refer to those inherent uncertainties that inevitably exist in supply chains, such as uncertain customer demands and uncertain costs. In addition, robust supply chain strategies are proposed for mitigating disruption risks that would enhance efficiency and resiliency. Lau et al. (2008) proposed a real-time supply chain management model based on multi-agent simulation with its application in the event of bird flu (avian influenza) or terrorist attacks. Mohan et al. (2009) investigated the risks faced by poultry supply chains in the avian influenza epidemic, identifying risk factors, losses and gains, and mitigation strategies used by different players in the supply chain.

Surface transport systems, including freight transport, are inherently very vulnerable to terrorist threats. Plant (2004) examined the impact of the terrorist attacks on the North American rail industry and government agencies concerned with railroad security. Okonweze and Nwagboso (2004) placed emphasis on the usage of real-time information systems and categorised intelligent transport subsystems, which can help to protect transport infrastructure and systems against terrorism. Murray-Tuite (2007) presented a framework for evaluating a risk (i.e., capacity loss between an OD) to the road transport network from direct targeting by terrorists.

2.11. Hazardous material transport

Hazardous material transport in urban areas has been an important research area for decades. Once a vehicle carrying hazardous material is involved in a crash on a roadway it may cause a large impact on people and buildings and other traffic by the explosion or spill of hazardous material. These risks should be assessed in advance and well controlled for safer management of transport using ICT (Information and Communication Technology) and ITS. Modelling techniques are required for assessing risks and evaluating measures to manage hazardous material transport in urban traffic environments.

Erkut and Verter (1998) presented an overview of modelling hazardous material transport and pointed out that different risk models suggest different "optimal" paths for a hazmat shipments between a given origin-destination pair. Five categories of risk models were suggested in the literature: (a) Traditional risk, (b) Population exposure, (c) Incident probability, (d) Perceived risk, and (e) Conditional risk.

Incorporating the risks of hazardous material transport often requires multi-objective optimisation models. 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 safest routes and the safest share of traffic between these routes leads to better risk averse strategy based on a game theory approach. Beroggi (1994) proposed a real time routing model for assessing the costs and risks in a real-time environment and pointed out that the ordinal preference model turned out to be superior to the utility approach.

2.12. Traffic safety

There has been a lot of research relating to traffic safety and accidents. Empirical studies have been undertaken to identify the relationship between crash frequency and some or all of the factors including vehicle-kilometres, average hourly traffic volume per lane, average occupancy, lane occupation, average speed, its standard deviation, curvature, road geometry, and ramp section design (e.g., Jovanis and Chang (1986); Miaou and Lum (1993); Shankar et al. (1995); Abdel-Aty and Radwan (2000)). The focus has also been on the relationship between accident rates and traffic characteristics, including hourly traffic volume, level of service, weather, and hourly traffic flow of cars and lorries (e.g., Fridstrøm et al., 1995; Ivan et al., 1999; Martin, 2002). Furthermore, driving behaviour has been considered to be a crucial factor causing traffic accidents. Sleep-related or sleepiness-related driving accidents are investigated by Horne and Reyner (1995), and Sagberg (2001).

However, there have been few studies taking into account the effect of the flow of freight vehicles and heavy goods vehicles (HGVs) on traffic accidents, except for Hiselius (2004), Ramírez et al. (2009). Zaloshnja and Mill (2004) investigate the relationship of ramp design and truck accident rates. Tzamalouka et al. (2005) identify the contributing factors to the probability of falling asleep and crash risk through the interview questionnaire survey to professional drivers including truck drivers. The use of intelligent transport systems are also undertaken in terms of the prevention of traffic accidents caused by freight traffic (Palkovics and Fries, 2001; Sarvi and Kuwahara, 2008).

3. Conclusion

There is a need for transport logistics models to incorporate risk so that urban distribution systems can become more resilient with respect to natural and manmade hazards. Models that take risks into account can assist in designing city logistics schemes to improve the health and safety of persons involved in transport logistics as well as residents.

This paper has outlined how recently developed modelling techniques such as stochastic programming, agent based simulation and robust optimisation methods can be applied to urban freight and supply chain networks. Links between human security engineering and city logistics were described. The need for models to assist in the recovery of transport infrastructure for the public sector as well as to develop plans for business continuity management for the private sector were outlined.

Due to growing urbanisation and the increasing prevalence of extreme weather events as well the continuing threat of terrorism, improved urban freight models are required to minimise the disruptions to urban freight systems from natural and manmade hazards.

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