Behavioral Factors in City Logistics from an Operations Research Perspective

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Abstract. In the face of sharp urbanization around the world, metropolitan areas have started different initiatives and projects to make cities more efficient and sustainable. Hereby logistics and transportation activities have a major impact in the development of so called 'Smart Cities'. By addressing complex decision making problems through simulation and optimization, the Operations Research community has contributed to the development of sustainable city logistic systems. While technical and structural problems have been extensively discussed in the literature, many models neglect the importance of behavioral issues arising from risk aversion, stakeholder interaction and human factors that play an important role in the consolidation and optimization of logistical activities. This paper reviews existing work considering behavioral factors from an OR perspective. Simulation and optimization models to major problem settings in City Logistics are discussed and methodologies to conquer real-life urban L&T challenges are presented.

Keywords: Smart Cities · City Logistics · Operations Research · Behavioral research · Simulation-optimization

1 Introduction

Cities are the driving forces of economies around the world with 85 % of the Gross Domestic Product (GDP) of the European Union (EU) already produced in urban areas [25]. The importance of metropolitan areas is fostered by the fact that the world's urban population is expected to double from 2.6 billion in 2010 to 5.2 billion people until 2050 [20]. This urbanization trend has both positive and negative effects on a global level. On the one hand it leads to wealth, jobs, and an increase in cultural activities. On the other hand, increasing city populations augment carbon dioxide and greenhouse gas emissions, traffic jams and waste development [13,15].

Especially activities related to logistics and transportation (L&T) of urban freight has a major impact on urban society, environment, and economy [29,42]. In Europe alone traffic jams yield yearly costs of 100 Billion US$, equal to 1 % of the EU's GDP [26]. Furthermore, transportation vehicles lead to excessive

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noise levels in urban areas affecting as much as 41 million Europeans [26], while the sector accounts for 27 % in total greenhouse gas emissions in the USA [56]. In the development of sustainable urban areas (often addressed in 'Smart City' innovations and projects, see [6,27]), the planning of a sustainable and effective logistical environment is therefore of major importance.

In an approach to reduce the impact of urban freight transportation, the concept of *City Logistics* (CL) has emerged as new area of L&T planning [42]. Through the coordination and consolidation of logistic activities of different stakeholders, the aim is to develop integrated and sustainable urban logistics systems by reducing freight vehicles numbers, control their dimensions and characteristics, and optimize vehicle usage by reducing empty vehicle mileage [8]. Hereby Operations Research (OR) plays an important role by developing models to optimize and evaluate complex problem settings, e.g. the location of freight consolidation centers, routing of electric vehicles with limited driving ranges [33], or the scheduling of driver workplans.

Different simulation and optimization techniques to solve various real-life problem settings concerning technological-, process- and structural challenges have been presented by the OR community. However, behavioral issues such as lack of trust, natural risk aversion, or decision biases of people and companies typically lead to some kind of uncertainty in OR models, which has not yet been discussed to the same extend [10,28]. Within the OR community the people dimension in L&T is mainly addressed in the field of simulation to evaluate the behavior of different stakeholders (usually shippers, freight carriers, administrators and consumers) concerning different urban L&T measures [53]. In optimization issues of arising in the development of CL systems however, behavioral factors of individual decisions and stakeholder interaction has received less formal attention [5].

This paper contributes to this research line by reviewing how behavioral aspects of different CL stakeholders in main urban L&T problem settings such as the location of freight consolidation centers, development of routing plans, or workforce scheduling is addressed in existing operational research. The structure is hereby as follows: Sect. 2 highlights main concepts of CL and stresses the importance of considering human behavior to develop realistic and sustainable L&T systems; Sect. 3 reviews OR approaches addressing human factors in CL; Sect. 4 discusses possible future research work and concludes this paper.

2 Considering Behavioral Issues in City Logistics Concepts

2.1 City Logistics Concepts and Related Optimization Problems

CL is defined by Taniguchi et al. [51] as "totally optimizing urban logistics activities by considering the social, economic, and environmental impact of urban freight movement while providing an opportunity for the development of innovative solutions that allow to improve the quality of life in urban areas."

Crainic et al. [18] focus more on the optimization and utilization of transportation resources, by defining CL as "reducing and controlling the number, dimensions, and characteristics of freight vehicles operating within city limits, improving the efficiency of freight movements, and reducing the number of empty vehicle kilometers". The main goal is to make urban freight L&T more efficient while reducing the negative environmental impacts by viewing CL as integrated system instead of focusing on individual stakeholders. This process requires planning at a strategical, tactical, and operational level, in which behavior of macro- and micro stakeholders play a decisive role [5,8].

On a strategic level, especially the development of multi-tier transportation systems has been discussed [39]. The aim is to keep delivery-trucks away from city centers by consolidating logistics activities of different companies in so called Urban Consolidation Centers (UCCs). Instead of delivering products to the final customer, companies transport their freight to consolidation hubs which are usually located in direct proximity to the geographic areas of interest (e.g. the city center or a shopping mall). From the UCC, consolidated deliveries and other logistics services such as storing or packaging are then carried out [5,21].

Through tactical planning, efficient transportation plans concerning resource utilization and demand satisfaction are established. This leads to several OR problems, for example the well-known Vehicle Routing Problem (VRP) and its variants considering time windows, different load levels, and uncertainty. Also, the use of Electric Vehicles (EVs) in freight transportation brings new challenges to the OR community [12,33,34,36].

Operationally, human factors such as fatigue, education, or learning abilities have to be considered in the development of employee work schedules. Also the operational control and adjustment of transportation plans through the use of ICT, e.g. GPS to dynamically adjust routing plans and vehicle schedules, has been discussed in the literature [18].

2.2 The Importance of Behavioral Issues in City Logistics

The editorial for a special issue on behavioral operations of the Journal of Operations Management [19] defines behavioral operations "the study of potentially non-hyper-rational actors in operational contexts". Behavior of stakeholders is often ignored in mathematical modeling of complex decision problems. Indeed, most work in OR research considers them to be (i) a minor factor of the system, (ii) deterministic, (iii) independent, (iv) non-developing, (v) emotionless, and (vi) observable [10,47,55]. This is a drawback in the development of realistic problem-solving support tools, as they often proof to be difficult to implement in practice as they ignore important system characteristics related to behavioral influences [7].

In the context of CL, behavior plays an important role as the integration and cooperation among different stakeholders (public and private) and system planning does not only depend on technical and physical components, but also human and behavioral factors. Current research in supply chain management mostly neglects this fact and forgets about the "crucial importance of the behavioral and people dimension [48]", arising from risk-aversion of decision takers or the lack of trust and incentive misalignment between companies and their managers [7].

Urban freight transportation is the product of the interaction between different stakeholders, mainly from the commodity, transport and infrastructure sector. Even though most situations in L&T systems can be described and solved mathematically, the complete environment needs to be understood for the development of realistic and suitable optimization models. In CL the integration of logistical activities comes down to relationships between individuals, teams, and companies which in essence consist of people [2,49].

3 OR Problems Considering Behavioral Issues in City Logistics: A Review

OR models describing CL concepts can be generally categorized into: *simulation models* and *optimization models*. In the field of simulation, behavior of different stakeholders to different CL measures such as municipal subsidies of UCCs, road-pricing, or time windows in city centers has been addressed. Concerning optimization, different real-life algorithms to consider various combinatorial optimization problems (COPs) have been presented. These approaches (with special focus on publications considering human factors and stakeholder interactions) are reviewed in Sects. 3.1 and 3.2 respectively. Recently, some interesting methodologies combining simulation into optimization (mainly metaheuristic) based frameworks have been presented. As these techniques (e.g. simheuristics)

Table 1. Summary of reviewed papers

OR-Technique	Reviewed Papers	Behavioral Issues addressed
Simulation	[23]	Stakeholder interactions in UCCs
	[57]	Stakeholder interactions in joint delivery systems and car-park management
	[54]	Stakeholder behavior in e-commerce delivery
	[50,52]	Evaluation of CL measures from the point of view of different stakeholders
	[11,37]	Stakeholder behavior concerning local traffic regulations in multi-modal transportation
Optimization	[17,24,40,44,45]	VRPs with different constraints (e.g. time windows, load factors)
	[39,41]	Multi-criteria, multi-echelon LRPs
Sim-Opt	[30]	LRP with stochastic demands and travel times
	[32]	Different Safety-Stocks in the VRP with stochastic demands
	[31]	Scheduling problem with stochastic times

could be a promising tool to integrate behavioral issues such as different risk-attitudes of route dispatchers, they are outlined in Sect. 3.3. An overview over the discussed papers their relation to behavioral issues is given in Table 1.

3.1 Simulation Models

Simulation is often used to evaluate complex CL systems and predict the effects of measures such as the implementation of UCCs, road pricing, truck bans in city centers, time windows, load factor controls, or operational subsidies. Hereby, especially Agent-Based Modeling and Simulation (ABMS) allows the consideration of the behavior of different actors [38].

Stakeholder behavior in the opening of a UCC concerning different urban congestion levels, minimum vehicle loads, and time windows in city centers is discussed by Duin et al. [23]. Wangapisit et al. [57] use ABMS to fine tune the implementation of UCCs in congested cities considering stakeholder interaction and cooperation in joint delivery systems and car parking management. Teo et al. [54] evaluate CL measures in urban road networks in a e-commerce delivery system environment. Similar ABMS models to evaluate CL systems are presented by Tangawa et al. [50] and Tanguchi et al. [52]. The use of multi-modal transportation systems incorporating the use of EVs in consolidated logistics systems is modeled as result of interaction between different stakeholders and their reactions to local traffic regulations using ABMS by Boussier et al. [11]. Lebeau et al. [37] test the impact of using electric vehicles in UCCs using discrete event simulation.

While many simulation-based models have been applied to evaluate the behavior of stakeholders in the context of CL, the consideration of humans and companies as non-rational factors has not been done to the same extend. Badin et al. [4] use a representative EV simulator to test the impact of driver aggressiveness in the energy consumption of EVs by considering ordinary, economic, and aggressive drivers.

3.2 Optimization Models

Different complex COPs for optimizing CL processes with real-life constraints have been addressed by with OR solution methodologies, generally divided into exact- and approximate methods. While exact methods (e.g. Branch-and-Bound) are usually applied to smaller instances, approximate metaheuristics (e.g. GRASP, Tabu Search, Simulated Annealing, etc.) are able to solve large problem settings in short calculation times.

An overview over VRPs in the context of CL is given in Cattaruzza et al. [14]. Main VRP variants are hereby the VRP with access time windows in city centers, multi-modal heterogeneous vehicle fleets, routing problems with restricted zones for certain vehicle types, the 2-Echelon VRP or dynamic re-routing of vehicles according to real-time travel information [17,24,40,44].

Very current in the optimal integration of UCCs in CL systems is also the complex location-routing problem and its variants, in which facility locations and connected routing activities are planned together [22]. In this context, an exact

Branch &Cut algorithm to solve small and medium sized instances exactly of the capacitated 2-Echelon Loading Routing Problem (2E-LRP) is proposed by [16]. Metaheuristics such as Variable Neighborhood search (VNS), GRASP, and Iterated Local Search (ILS) to address different 2E-LRPs are presented by Nguyen et al. [41] and Schwengerer et al. [46].

Behavioral issues regarding problem owners have not been considered in much detail, and the interaction of stakeholders is also not considered in the works cited above. Awasthi et al. [3] employ a fuzzy model in the location planning of UCCs, in which different evaluation criteria such as accessibility, security, connectivity to multi-modal transport, costs, environmental impact, resource availability and the possibility for expansion are considered. Othman et al. [43] incorporate human factors into a workforce scheduling case, including aspects such as skills, training, workers personalities, breaks, fatigues, and recovery levels. Even though their problem setting is related to workforce scheduling in the context of production scheduling, their multi-objective mixed programming model could also be applied to workplan scheduling problems of drivers and UCC operative personal.

Other human factors such as the route-choice behavior of drivers are not yet considered in optimization approaches. They are more addressed in the field of behavioral research, done for example by Albert et al. [1], who use advanced traveler information systems to test the differences concerning geographic ability and sensation seeking of drivers experimentally. However, some promising research work considering uncertainty through human behavior and risk-aversion of decision-takers have been presented recently by combining simulation in optimization based frameworks, which is surveyed in the following sub-section.

3.3 Combining Simulation with Metaheuristics to Model Behavioral Issues

One of the main issues when modeling behavioral issues in the problem settings discussed above is the inclusion of uncertainty arising through stakeholder interactions and human factors. Simulation seems to be the method of choice in artificially reproducing complex systems to evaluate certain measures. But simulation itself is not an optimization tool. In this context, the combination of simulation with optimization is becoming very popular and seems a promising methodology to model different behavioral aspects in OR [9].

Juan et al. [35] discuss the concept of simheuristics to consider uncertainty in COPs. By implementing simulation techniques in metaheuristic optimization approaches, established COP plans (e.g. vehicle routing solutions) can be assessed by showing their behavior in stochastic scenarios. In this context, for example the VRP with stochastic demands has been discussed [32]. After finding promising VRP solutions with a metaheuristic, the authors evaluate the effect of different safety capacity factors (representing route planners willingness to take risks) by using Monte Carlo simulation. Herazo-Padilla et al. [30] apply a similar approach by combining Ant Colony Optimization with discrete-event simulation to consider stochastic demands and stochastic travel times (occurring for example through different driver behavior) in the LRP. Not directly related to CL problem settings, Juan et al. [31] discuss a simheuristic approach to the permutation flow shop problem with stochastic time, a well-known COP in which stochastic job termination times can be related to difference employee working speeds. A similar approach could be implemented in the context of CL.

4 Future Research Work and Conclusions

This paper has identified typical OR problems in the context of the development of City Logistics concepts and related behavioral issues. Especially simulation (through agent-based models) has contributed to research concerning the evaluation of stakeholder behavior and the interaction of different public and private actors concerning different urban L&T measures. In the context of optimization to establish efficient location-, routing-, and scheduling plans behavioral factors of individuals and their interactions are only scarcely considered. The reason for this seems to be the difficulty in including uncertainty (as one of the outcomes when considering behavior) in traditional optimization models. The combination of simulation and optimization seems to overcome this drawback, and has recently been successfully applied to logistical problem settings. As such, this could be a promising future research line to overcome existing drawbacks in modeling behavioral issues in OR.

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