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TOWARDS A MORE SUSTAINABLE FUTURE? SIMULATING THE ENVIRONMENTAL IMPACT OF ONLINE AND OFFLINE GROCERY SUPPLY CHAINS

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ABSTRACT

The negative effects of traffic, such as air quality problems and road congestion, put a strain on the infrastructure of cities and high-populated areas. A potential measure to reduce these negative effects are grocery home deliveries (e-grocery), which can bundle driving activities and, hence, result in decreased traffic and related emission outputs. Several studies have investigated the potential impact of e-grocery on traffic in various last-mile contexts. However, no holistic view on the sustainability of e-grocery across the entire supply chain has yet been proposed. Therefore, this paper presents an agent-based simulation to assess the impact of the e-grocery supply chain compared to the stationary one in terms of mileage and different emission outputs. The simulation shows that a high e-grocery utilization rate can aid in decreasing total driving distances by up to 255 % relative to the optimal value as well as CO_2 emissions by up to 50 %.

1 INTRODUCTION

Sustainability is driven by innovation. Particularly in the logistics sector, increasing transportation activities have a significant impact on the environment. Road traffic contributes a large share of emissions to particulate matter (PM) concentrations, both in an urban as well as a rural and an interregional context (Pant and Harrison 2013). Hence, an important key towards a more sustainable future is the emergence and utilization of innovative business models that aid in reducing traffic and emission outputs. Especially in the retail sector, new information technologies, changing customer preferences, and global supply chain networks feature manifold opportunities to promote business growth, while at the same time fostering more sustainable processes, routines, and systems (Naidoo and Gasparatos 2018). Over the last two decades, home delivery of grocery items has emerged as comprehensive alternative to stationary grocery shopping and can effectively aid in reducing traffic emissions. For instance, in 2017, 17.5 % of the entire traffic volume from motorized private traffic in Germany originated from grocery shopping trips (Auf der Landwehr et al. 2019). Similarly, 19.5 % of all daily vehicle trips in the United States of America are performed for shopping reasons (Federal Highway Administration 2018). Therefore, by promoting utilization as well as growth of e-grocery and consequently reducing or avoiding private errands and shopping trips, traffic loads and traffic-related emissions can potentially be decreased, as delivery tours can substitute customer shopping trips (Mkansi et al. 2018). However, while many studies have dealt with assessing or evaluating the ecological impact of grocery home deliveries within the context of urban last-mile logistics (e.g., Siikavirta et al. 2002; Hardi and Wagner 2019), a holistic view on the entire supply chain is required to ensure reliable and valid propositions regarding the sustainable value of e-grocery compared to stationary shopping.

For reasons of efficiency and profitability, grocery supply chains generally differ according to the given context and market as well as the capabilities and objectives of the retailer. To maximize process efficiency and increase the operational performance, many organizations employ large-scale food fulfillment centers (FFCs), specifically designed for supplying e-grocery orders. These FFCs are supplied with groceries from nationwide or supra-regional warehouses on a regular basis and act as starting point for last-mile deliveries (Hübner et al. 2016). In contrast, in the case of stationary retail activities, supermarkets and store outlets are supplied from these warehouses and act as final point of sales, whereby last-mile traffic does not result from deliveries, but from shopping trips of private individuals (Ge et al. 2019).

To assess the ecological value of e-grocery compared to stationary grocery shopping along the supply chain, we propose a simulation approach to model both mileage as well as emission outputs accruing due to supply, last-mile delivery and private grocery shopping trips. Thereby, we closely cooperate with an industry partner to gain insights into relevant process flows and gather realistic input parameters for our simulation experiments, so that the simulation framework is capable of reproducing and quantifying the entire scope of relevant details (e.g., supply networks) as well as dynamic structures (e.g., behavioral influences) within the respective system. While our proposed simulation results have been generated for a selected pilot area in Hanover, Germany, and the business environment of our industry partner, the general simulation approach can uniformly be employed to assess different peculiarities in various contexts.

Following the introduction, our paper is structured as follows: In Section 2, a synopsis on related literature regarding the ecological assessment of grocery shopping is provided. Subsequently, we outline our methodology in terms of overall research design, assumptions and parameters employed within the course of this simulation study as well as the simulation model and its components (Section 3). Ultimately, we present our simulation results (Section 4) and conclude with a discussion on our findings (Section 5).

2 RELATED WORK

Several studies and research projects have assessed the value of product deliveries compared to customer pickup-scenarios in terms of various objectives. According to Browne et al. (2005), depending on the mode of transport, distances, and shopping basket sizes, shopping trips of consumers can result in a higher energy consumption than delivery activities along the entire supply chain from factory to store outlet. Correspondingly, many studies focus on comparing driving distances between e-grocery and stationary grocery shopping (e.g., Siikavirta et al. 2002). Van Loon et al. (2015) created a Life Cycle Analysis model to quantify CO_2 emissions of various e-fulfillment methods concerning fast-moving consumer goods, indicating that consumer behavior, choice of e-fulfillment method, and basket size are critical factors in determining the environmental sustainability of e-commerce. Moreover, Koç et al. (2016) investigated the combined impact of depot location, fleet composition, and routing decisions on vehicle emissions in city logistics, whereas Kämäräinen et al. (2001) conducted a study to assess how the reception type in e-grocery influences the efficiency of deliveries in terms of distances and costs. Similarly, Durand and Gonzalez-Feliu (2012) evaluated three fulfillment scenarios, indicating that a combined approach consisting of home deliveries and proximity reception points would be most beneficial in terms of reducing mileages. Ultimately, following up the identified potential to reduce traffic and emissions by fostering e-grocery utilization, Hardi and Wagner (2019) conducted a simulation study to determine break-even points for grocery deliveries compared to private customer shopping trips in a given district in Munich, Germany.

Other contributions to the given research area include publications from Tadei et al. (2016), who have simulated and evaluated the environmental and economic benefits of a local food supply chain in e-grocery, as well as Pan et al. (2017), who have proposed a new approach to utilize customer-related data for optimizing the delivery operations regarding grocery items based on absence probabilities derived from electricity consumption information. Recently, Waitz et al. (2018) have developed an agent-based simulation model to investigate the impact of delivery services on different fulfillment variables such as order volumes and customer utility, adumbrating the importance to incorporate shelf life data and customer preferences into e-grocery activities to ensure profitable and efficient operations.

Table 1: Status quo of simulation-based e-grocery research.

Publication	Method	Main Topic	Research Overview	Concept Evaluation	Sustain-ability	Profit-ability	Simulation Approach	Logistical influence
Kämäräinen et al. (2001)	SM	Fulfillment design	○	◑	◑	●	●	●
Punakivi and Saranen (2001)	CS/ SM	Profitability	○	●	◑	●	●	●
Siikavirta et al. (2002)	LR	Environmental impact	●	◑	●	◑	●	●
Durand and Gonzalez-Feliu (2012)	CS	Environmental impact	○	●	◑	◑	●	●
Seitz (2013)	MM	Customer behavior	○	◑	○	◑	◑	○
van Loon et al. (2015)	MM	Environmental impact	◑	◑	●	○	◑	●
Emec et al. (2016)	SM	Decision support	●	◑	◑	◑	●	●
Koç et al. (2016)	MM	Environmental impact	◑	●	●	◑	◑	◑
Tadei et a. (2016)	CS	Fulfillment design	◑	◑	◑	◑	◑	●
Pan et al. (2017)	DS/SM	Decision support	●	◑	◑	●	●	●
Evers et al. (2018)	DS/SM	Decision support	◑	○	◑	◑	◑	●
Fikar (2018)	SM	Decision support	◑	●	◑	●	●	●
Waitz et al. (2018)	SU/SM	Decision support	◑	◑	○	○	●	●
Cebollada et al. (2019)	DS	Pricing system	◑	○	◑	●	◑	◑
Davies et al. (2019)	CS	Fulfillment design	●	◑	◑	◑	◑	◑
Hardi and Wagner (2019)	SM	Environmental impact	◑	◑	●	◑	●	◑
Ulrich et al. (2019)	MM	Demand forecast	●	◑	◑	●	◑	●
Caption: ● = full consideration; ◑ = partial consideration; ○ = no consideration								
Abbreviation: SM = Simulation modelling; MM = Mathematical modelling; LR = Literature review; SU = Survey; CS = Case Study; DS = Data screening								

Table 1 provides a granular overview about the status quo of current research related to simulation-based e-grocery assessment. The majority of publications deals with assessing, quantifying, and benchmarking potential impacts of an increasing e-grocery utilization (Siikavirta et al. 2002), analyzing the consumer behavior (van Loon et al. 2015; Pan et al. 2017), providing a status quo on grocery home delivery (Koç et al. 2016; Waitz et al. 2018), or evaluating the environmental impact of diverse fulfillment concepts (Hardi and Wagner 2019). Concerning logistics concepts for grocery deliveries, several studies propose, conceptualize, or examine different concepts, whereby manifold studies are directly related to assessing or comparing the impact of different concepts (Kämäräinen et al. 2001). The publications are classified depending on the individual scope of the research regarding the provision of an explorative research overview (Research Overview), the evaluation of different e-grocery concepts (Concept Evaluation), the assessment of sustainability attributes related to e-grocery (Sustainability), the evaluation of the economic viability und profitability of various e-grocery business models (Profitability), the approach to assess, benchmark and quantify e-grocery by means of simulation (Simulation Approach), as well as the aim to determine logistical influences caused by different delivery models and strategies (Logistical Influence). While the environmental value of e-grocery fulfillment has been assessed in several studies, we could not find any publication dealing with the environmental impacts of both order fulfillment as well as supply chain operations, taking into account individual peculiarities required for e-grocery and stationary grocery.

3 METHODOLOGY

3.1 Research Design

To develop a comprehensive simulation model capable of producing reliable as well as valid results, we have followed an interlaced research process, as shown in Figure 1.

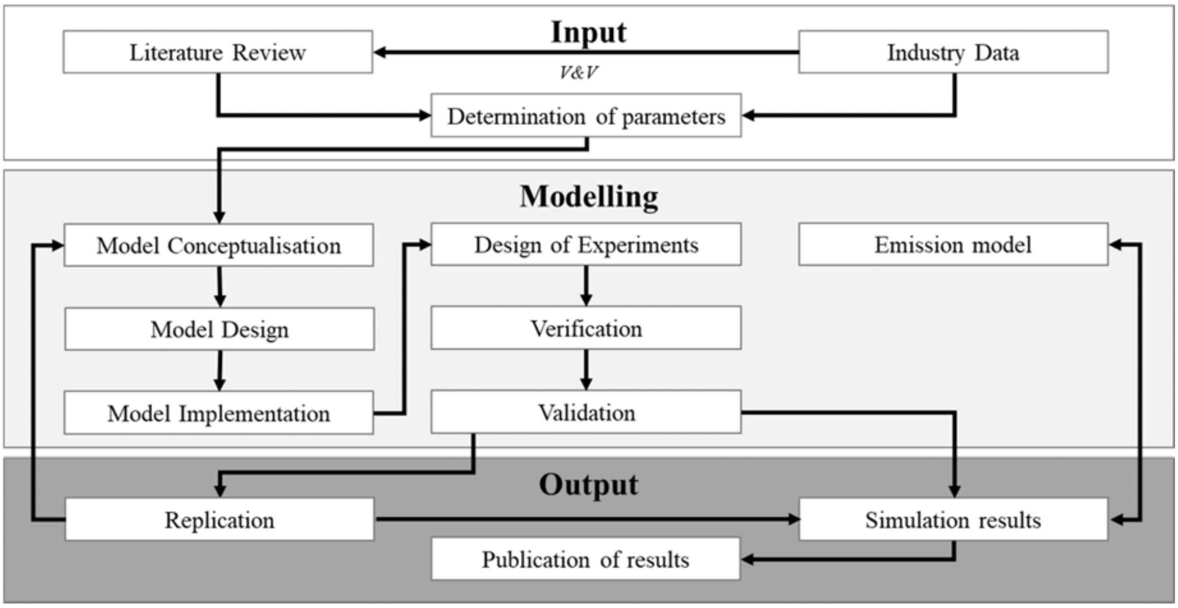


Figure 1: Research approach for the simulation study.

To collect valid input data for the simulation modelling process, we conducted a systematic literature review on relevant parameters based on the rigorous guidelines of Webster and Watson (2002). Therefore, we searched major library catalogues and databases for search terms related to e-grocery fulfillment as well as supply chains and analyzed the resulting literature sources in terms of their title, abstract, and keywords. The review was conducted between March 2019 and January 2020 and comprised five search and analysis iterations. In addition to the direct literature search, we also conducted a backward search by assessing citations from the literature results as well as a forward search, where we identified publications quoting relevant articles descried during the search phase. Ultimately, we also reviewed literature introduced in the related work section. An overview about the structure, content, and outcomes of the literature review is given in Table 2. Moreover, we gathered information on the existing stationary as well as e-grocery supply chain, behavioral patterns of customers, as well as system-relevant influence factors (e.g., provider capabilities) by collecting expert feedback and operational data from our industry partner, a major German bricks and clicks retailer. This information was used to validate the insights from the literature review and collectively act as input parameters for the simulation study. Subsequently, based on the derived parameters, we initiated the modelling process by conceptualizing, designing and implementing the formal simulation model. An overview about the specific data sources influencing model assumptions as well parameters is provided in Section 3.2. While structural data, such as population density, number of registered vehicles, and household composition, were directly obtained from the city of Hanover, additional insights on model input parameters and system assumptions were derived by consulting scientific data sources.

In line with the objectives of this paper, we developed several simulation experiments to investigate and benchmark the role of e-grocery compared to stationary shopping in a holistic supply chain context. Ultimately, we verified and validated (V&V) our simulation model, results, and experiments by calibrating them against information from our industry partner. Replications that did not meet the calibration criteria in the course of the V&V process were employed to adapt the model conceptualization and lead to an iterative design process. Furthermore, we developed an emission model capable of transferring mileage into emission outputs to assess the environmental value of the simulated concepts.

Table 2: Systematic literature review.

Database	*Search Term*	*Search Fields*	*Hits*	*Relevant*
Google Scholar	(“e-grocery” OR “home delivery” OR “online food retailing”) AND (“delivery” OR “fulfillment) AND (“simulation” OR “decision support” OR “supply chain” OR “impact”)	Title, Abstract and Keywords	12.134	112
AISeL			142	8
JSTOR			76	3
IEEExplore			2.012	32
Science Direct			98	5
Taylor & Francis			122	7
		Backward/Forward search/ Related Work		22/14/17
			Total	**220**

3.2 Model Assumptions, Data, and Parameters

To simulate the real environmental impact, changes in consumer behavior and travel need to be assessed holistically (e.g., shopping frequency, trip chaining). Hence, the following assumptions have been made:

- **Model scope:** The scope of the model is restricted to the areas “Mitte”, “Oststadt”, “List” and “Groß-Buchholz” in Hanover, Germany. The entire population in the given pilot area consists of 9,400 households (Landeshauptstadt Hannover 2019). To improve computation times and increase the experimental value of the simulation model, we have selected a 15 % sample (1,410 households).
- **Time windows:** Delivery time windows have been determined by analyzing the mobility and shopping behavior of consumers in the given pilot districts and vary from one to six hours between 8 am and 8 pm (Nobis and Kuhnimhof 2018).
- **Vehicle type:** In line with common grocery industry practices (Hübner et al. 2019), it is assumed that heavy duty trucks (HDT) are employed for deliveries between the central warehouse (CW) and regional warehouse (RW) as well as the RW and the FFC, while medium duty trucks (MDT) are utilized for transportation activities from RW to supermarket outlets (SO) and FFCs to distribution spokes (DS). Ultimately, last-mile deliveries are conducted via light-duty vehicles (LDV).
- **Fleet:** If a delivery vehicle is unable to fulfill an order within a given time window due to time or capacity constraints, additional vehicles are utilized to fulfill the respective orders. In line with information from our partner organization, a maximum of 12 vehicles can be made available.
- **Supermarkets:** As we focus on the operations of one particular grocery chain, we assume that stationary shopping activities are concluded with one SO. In total, the pilot area features 14 SOs.
- **Shopping type:** Stationary shopping trip types are clustered into trips for small and bulk purchases (Nobis and Kuhnimhof 2018). Depending on the shopping type, modal split and SO selection differ. For bulk shopping trips, car utilization is higher (66 %) than for small purchases (56 %) and customers select supermarkets based on a distance-based preference function (e.g., high probability for close-range SOs in the case of small purchases). Moreover, average basket values (€ 22 offline and € 80 online) are included in the shopping frequency by means of an adjustment factor (3,63).
- **Shipment quantities:** Shipment frequencies from CW to RW as well as from RW to FFC and SO have been pre-determined, whereas shipping frequencies from FFC to DS, shopping trip frequencies from household to DS and order fulfillment frequencies from DS to household dynamically depend on the purchase behavior of consumers at simulation runtime.
- **Trip distance:** Trip distances are calculated with a bidirectional A* point-to-point algorithm based on an OpenStreetMap network and validated with actual geographic data for the pilot areas.

Table 3 provides a synopsis on the parameters of the simulation.

Table 3: Simulation parameter values and classification.

Category	*Value*	*Unit/Type*	*Final Source*
Capacity HDT	700	Orders/Fixed	Industry Partner
Capacity LDV (Min/Mean/Max)	16/18/19	Orders/Variable	Industry Partner
Capacity MDT (Min/Mean/Max)	160/180/190	Orders/Stochastic	Industry Partner
Car Utilization Bulk/ Small Purchases	66/56	Percentage/Fixed	Nobis and Kuhnimhof 2018
Daily Delivery Frequency CW-RW	0 - 1	Trucks/Variable	Ge et al. 2019
Daily Delivery Frequency RW-FFC	0 - 1	Trucks/Variable	Ge et al. 2019
Daily Delivery Frequency RW-SO	1 - 3	Trucks/Variable	Ge et al. 2019
Daily Shopping Frequency	50	Percentage/Fixed	Papastefanou and Zajchowski, 2016
Delivery Capacity MDT	3	Supermarkets/Fixed	Hübner et al. 2016
E-grocery utilization (Min/Max)	0/100	Percentage/Discrete	Assumption
Location of CW	50.051605, 8.658582	Coordinates/Fixed	Industry Partner
Location of FFC	52.447304, 9.697542	Coordinates/Fixed	Industry Partner
Location of RW	52.358022, 10.120982	Coordinates/Fixed	Industry Partner
Selection Cluster (Bulk Purchases)	4	Kilometers/Fixed	Nobis and Kuhnimhof 2018
Selection Cluster (Small Purchases)	2	Kilometers/Fixed	Nobis and Kuhnimhof 2018
Service Time HDT (Mean/SD)	60/10	Minutes/Stochastic	Industry Partner
Service Time LDV (Mean/SD)	7/2	Minutes/Stochastic	Industry Partner
Service Time MDT (Mean/SD)	60/10	Minutes/Stochastic	Industry Partner
Share of Bulk/Small Purchases	56/44	Percentage/Fixed	Nobis and Kuhnimhof 2018
Vehicle Speed Inner City (Mean/SD)	30/5	Km/h/Stochastic	Seitz 2013
Vehicle Speed Outer City (Mean/SD)	70/10	Km/h/Stochastic	Seitz 2013
Working Days	6	Days/Fixed	Hübner et al. 2018
Working Hours	7.8	Hours/Fixed	Hübner et al. 2018

3.3 Simulation Model and Components

The simulation model has been built with AnyLogic (Version 8.5.2) and combines agent-based simulation (ABS) properties with discrete-event simulation (DES), building upon an event-based time advancing mechanism related to the behavioral state changes of agents and the respective agent networks. Due to the high amount of autonomous and heterogeneous components as well as the dynamic interdependencies between system units, ABS can effectively be used to model environmental uncertainties and the resulting non-linear, discontinuous, and asynchronous agent interactions (Gómez-Cruz et al. 2017). Moreover, in line with the bottom-up approach, the agent-based simulation approach allows for studying both structural as well as functional aspects of complex networks (such as grocery supply chains) and alter simulation properties for experimentation purposes. The simulation time of one run equals one day. To model the probability of different outcomes resulting from probabilistic variables and stochastic demand fluctuations, we have employed a Monte Carlo approach with a total of 1,361 simulation runs. Figure 2 conceptualizes the simulation model and provides a detailed overview about agents, agent networks, and interdependencies.

Within the scope of our simulation system, we take into account the grocery supply chain operations of our industry partner from the central warehouse to the final customer. Accordingly, product sourcing operations like raw material distribution and manufacturing are not considered. HDT agents deliver goods with a given frequency from CW to RW (see Table 3), where they are temporarily stored for future transport operations. The daily delivery frequencies depend on the respective e-grocery utilization rate, whereby frequencies for the e-grocery supply chain increase with rising e-grocery utilization, while delivery frequencies along the supply chain for stationary grocery shopping decrease (and vice versa). Accordingly, in the equilibrium state (50 % e-grocery and 50 % stationary shopping), delivery frequencies for each channel equal 0.5. Subsequently, depending on the sales channel (stationary or online), products are either shipped directly to the supermarket outlets by MDTs or to the FFC by an HDT, whereby the daily delivery frequencies depend on the individual demand.

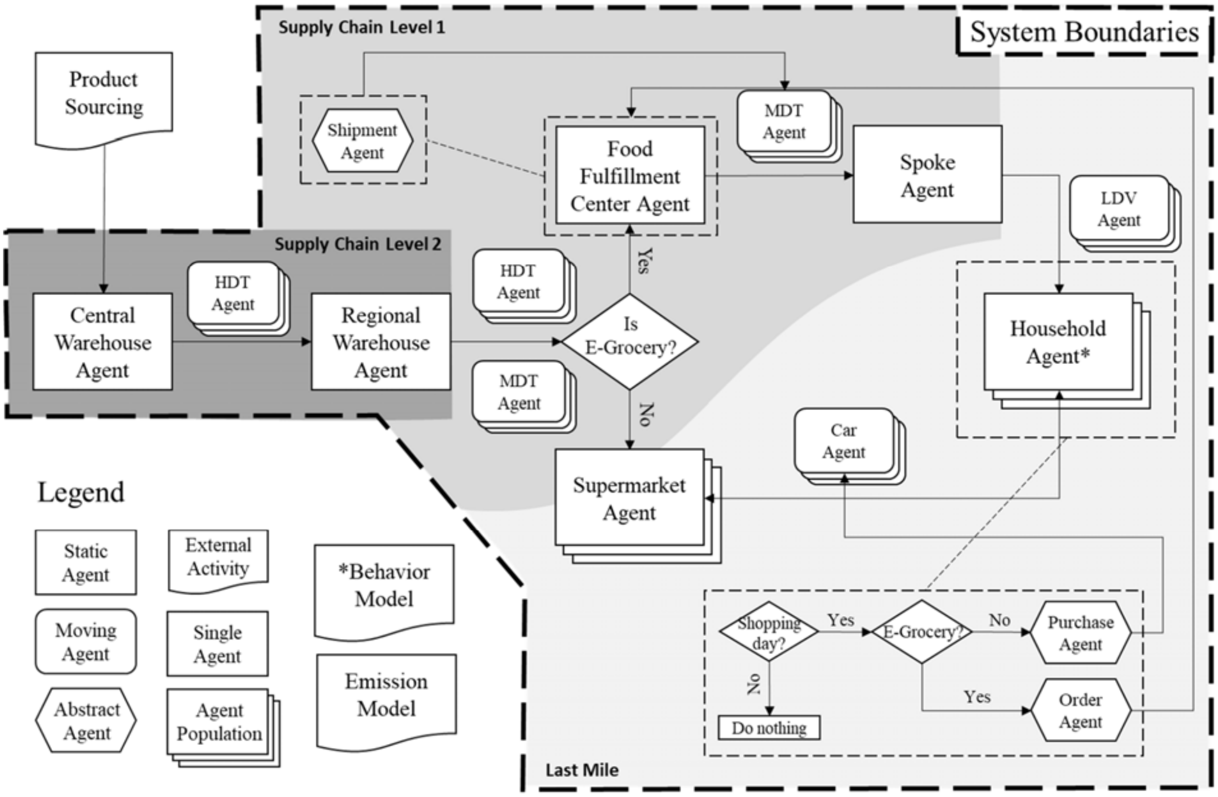


Figure 2: Agent networks and interactions – conceptual model.

In turn, the FFC collects customer orders from the household agents and generates a shipment list for the given vehicle fleet. The shipment agent is passed on to the MDT agent, which transports the ordered items to a DS, where these are cross-docked and finally distributed to the order recipients by LDV agents. Due to the fact that the capacities of MDTs and LDVs in terms of order quantities heavily depend on the respective order contents, based on information from our industry partner, we have stochastically varied the individual capacities. In contrast, supply chain operations requiring HDTs are less sensitive to individual order peculiarities, which is why HDT capacities have been fixed. Concerning stationary grocery shopping, households generate a purchase agent representing a shopping list, which is, depending on the car utilization rate, passed on to a car agent. Based on the individual shopping trip type of each household, the car agent evaluates suitable supermarkets and selects the closest available SO as destination. The behavior model determining the shopping activities of household agents is not instantiated in the simulation model, but integrated by means of behavioral parameter values (e.g., delivery time windows, car utilization).

Physical agents (e.g., HDT, MDT, FFC) are placed in a geospatial environment, where distance-based navigation and routing procedures are conducted in line with an adapted cluster- and time-window-based k Nearest Neighbor (kNN) algorithm (Dudani 1976). Initially, a limited range is determined to assess the availability of customers within the delivery area. The nearest customer (i) from the DS within a given time window is selected as starting point and added to the delivery network. Subsequently, customer (i) is set as starting point for identifying the nearest remaining customer (i) in the given range. If no remaining customer is available in the selected range, the algorithm automatically increases the boundaries until a customer that is still to be delivered in a respective time window has been found or all customers are served within one delivery network. Routes between household agents are chosen by means of a distance-based cost function. CW, RW, FFC, and SOs are considered as unlimited supply and storage sources. Finally, all distances covered by moving agents are recorded in a database and converted into associated emission outputs.

3.4 Emission Model

Our emission model has been designed to convert distance metrics from the simulation study into emissions. Emissions caused by private and commercial traffic ($E_{i,j}$) are calculated by the number of vehicles in a nation's fleet of category *j* and technology *k* ($N_{j,k}$), the average annual distance driven per vehicle of category *j* and technology *k* in kilometers ($M_{j,k}$) and the technology-specific emission factor of pollutant *i* for vehicle category *j* ($EF_{i,j,k}$):

$$EP_{i,j} = \sum_k (N_{j,k} \times M_{j,k} \times EF_{i,j,k}).$$

Vehicle categories include passenger cars, LDVs, MDVs, and HDVs, while technologies range from Euro 1 to Euro 6. Regarding private traffic, the fleet has been specified by structural data for the given pilot districts (Landeshauptstadt Hannover 2019). The referenced commercial vehicle categories are outlined in Table 4. Ammoniac (NH_3), nitrous oxides (N_2O), and nitrogen oxides (NO_x) are calculated by the given emission factors, whereas carbon dioxide (CO_2) emissions of vehicles *k* combusting fuel *m*, are derived by:

$$E_{CO_2,k,m}^{CALC} = 44.011 \times \frac{FC_{k,m}^{CALC}}{12.011 + 1.008 r_{H:C.m} + 16.000 r_{O:C,m}},$$

where FC^{CALC} is the fuel consumption of the vehicles for the respective time period and $r_{H:C}$ as well as $r_{O:C}$ being the ratios of hydrogen to carbon and oxygen to carbon in the fuel. Input values on emission factors, vehicle categories, pollutants, and technologies have been extracted from Ntziachristos and Samaras (2018).

Table 4: Referenced commercial vehicles.

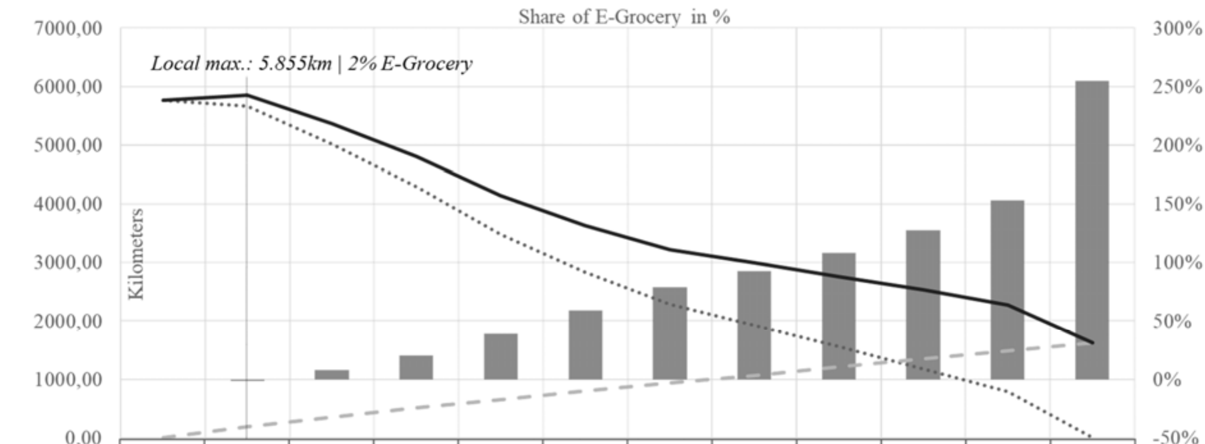
Category	*Abbr.*	*Reference Vehicle*	*Properties*
Light Duty Vehicle	LDV	Renault Master L2H1 with Kiesling Flat Runner Box Body	96 kW / 130 PS; ENERGY dCi 145 engine; Diesel; Euro 6b; 2.29 tons tare weight
Medium Duty Truck	MDT	MAN TGL 7.180 with MAN thermal case	140 kW / 190 PS; MAN D0834 engine; Diesel; Euro 6; 5.3 tons tare weight
Heavy Duty Truck	HDT	MAN TGS 41.330 with Krone Profi Liner SDP 27 eLB4-CS	264 kW / 360 PS; MAN D2066LF80 engine; Diesel; Euro 6; 15.9 + 6.2 tons tare weight

The proposed methods can effectively be used to calculate total emission outputs based on emission factors and driving distances to a good approximation. The factors combine various influencing factors such as driving speeds in different environments (motorway, highway, urban area), acceleration and decaleration, or ambient temperature and, therefore, present average values. Hence, the model is generally better suitable for comparing relative effects of individual scenarios than calculating absolutes with high accuracy.

4 RESULTS OF THE SIMULATION STUDY

With each simulation run representing one particular day, the evaluation of the results is based on e-grocery utilization rates, showing the potential benefits or drawbacks of grocery home deliveries in terms of traffic influences and emission outputs. Initially, we study the attractiveness of increasing e-grocery utilization in terms of sustainability from a social point of view, which can be related to vehicle mileages and consequently traffic loads in our study. Subsequently, we examine the emission outputs and outline important characteristics.

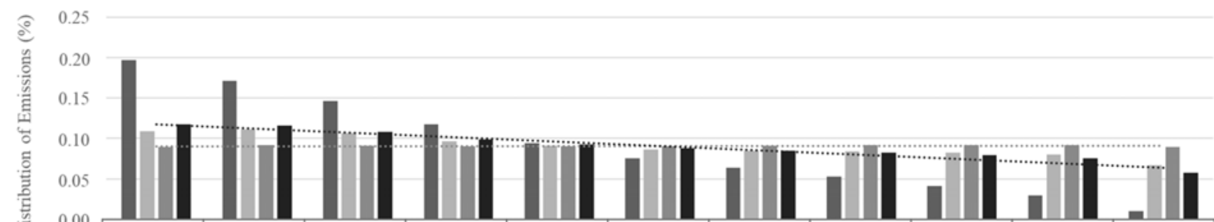
On average, kilometers covered for a single shopping trip equal 3.9 for small and 5.7 for bulk purchases. Overall, 97.60 % of all e-grocery orders could be fulfilled within the required time window. As shown in Figure 3, stationary shopping without e-grocery operations results in a total distance of 5,766 kilometers across the entire supply chain per day. In turn, an increase in e-grocery utilization results in a decrease of total kilometers, ultimately leading to a mileage reduction potential (measured relative to the optimal value) of up to 255 % in the case of 100 % e-grocery. For e-grocery utilization rates of 10 %–90 %, stationary shopping and e-grocery supplement each other, which needs to be noticed when comparing e-grocery scenarios with the baseline scenario (0 % e-grocery utilization). The local maximum for mileages occurs for a an e-grocery utilization rate of 2 %.



	0	0.02	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Deviation	0%	-2%	8%	20%	39%	59%	79%	93%	108%	128%	153%	255%
Stationary	5766	5662	5013	4288	3485	2830	2284	1922	1558	1180	790	0
E-Grocery	0	193	347	515	654	800	937	1070	1208	1352	1486	1626
Combined	5766	5856	5360	4803	4138	3630	3222	2991	2766	2532	2276	1626

Figure 3: Average kilometers per day and deviation (in percent of the optimum value) depending on e-grocery utilization.

In terms of environmental impact, which we outline by means of emissions outputs, our study results show that both CO_2 and NH_3 emissions significantly decrease with an increasing e-grocery utilization. However, contrary to the development of mileages, NO_x emissions only decrease to a minor extent, while nitrous oxide N_2O emissions even add up compared to the baseline scenario (Figure 4).



	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Total NH_3	92.13	80.31	68.32	55.05	44.05	35.30	30.05	24.72	19.51	13.97	4.88
Total NO_x	1175.31	1201.94	1147.33	1045.50	984.10	934.12	919.13	907.32	889.99	863.82	724.87
Total $N2_O$	419.85	432.15	428.70	423.97	424.02	425.11	426.99	429.32	430.99	432.46	420.85
Total CO_2	2007821	1984646	1855205	1689649	1586042	1498093	1448302	1405748	1352089	1291929	981604

Figure 4: Average emissions in grams per day depending on e-grocery utilization

Analyzing mileages and corresponding emissions based on supply chain levels, it becomes obvious that most emission outputs for traditional grocery shopping occur on the last mile, while in the case of e-grocery, emissions occurring between CW and RW constitute the main share of total emission outputs (Figure 5).

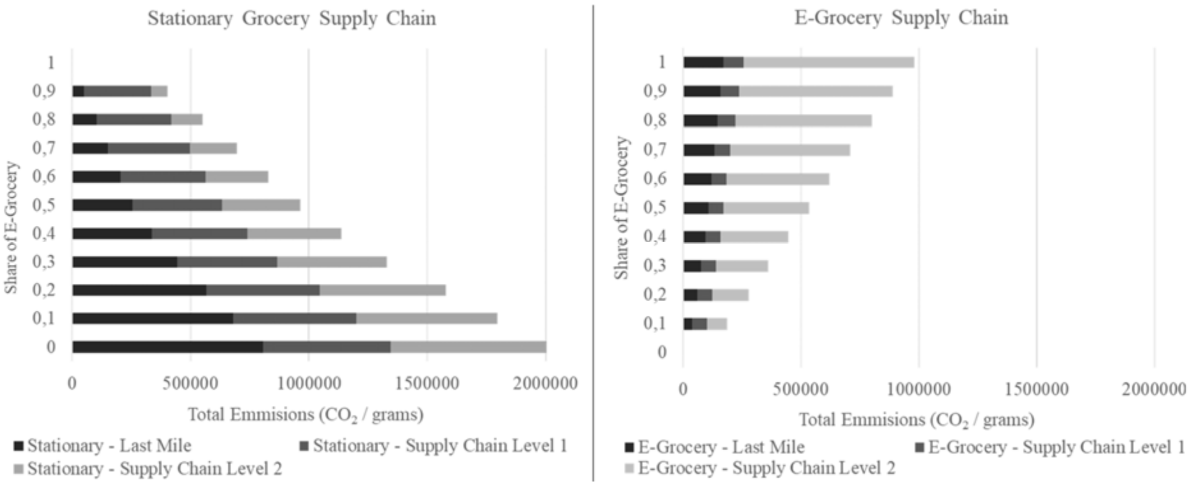


Figure 5: Average emissions in grams of CO_2 per day based on supply chain level.

5 DISCUSSION AND CONCLUSIONS

In this paper, we presented a simulation model capable of reproducing supply chain operations within the context of grocery shopping. The model was designed to investigate the impact of increasing e-grocery utilization on sustainability metrics such as mileage and emission outputs and consequently judge e-grocery in terms of its potential environmental and social benefits within a holistic supply chain context. Applied to the operational case of a major retail organization in Hanover, Germany, we showed that an increasing use of e-grocery offers a huge potential to decrease both mileage- as well as traffic-related emissions. Especially utilization rates starting from 20 % seem to have a very high impact across the entire supply chain compared to the scenario exclusively including stationary grocery shopping. However, despite of the given potential of e-grocery in terms of sustainable value, e-grocery utilization rates fall far below the indicated 20 % rate in many countries. For instance, in Germany, e-grocery utilization currently equals about 1.1 %, whereas even in countries with comparably high utilization rates like the USA or France, e-grocery is not employed regularly by more than 5 % of the population (Hübner et al. 2019). Hence, to make the benefits of e-grocery more feasible in terms of mileage and emission reduction, e-grocery utilization needs to be fostered and promoted in the near future, especially when considering the local maximum at 2 %, indicating that minor e-grocery operations as they are given in many countries even result in increased mileages and emission outputs. Moreover, our analysis illustrated that emissions are not reduced in accordance with the reduced mileages, as fleet compositions and transporter types feature different emission outputs per kilometer driven. Hence, while e-grocery can aid in reducing CO_2 and NH_3 emissions, it has a minor impact on NO_x emissions and even results in increased N_2O emissions. Nevertheless, due to its high emission reduction potential on the last mile, e-grocery can be suggested to reliably aid in traffic and emission reductions in urban areas, as it results in a shift of mileages and emissions across the supply chain.

Besides of the fact that this simulation study has been conducted to realistically model grocery supply chain operations and shopping effects, taking into account various peculiarities such as the impact of chained trips, shopping trip types, average shopping baskets, as well as delivery time windows, still some limitations and opportunities for future research can be identified. First, we did not assess product sourcing processes and operations, which may be influenced by prior supply chain levels and even affect the overall comparison results between stationary grocery and e-grocery supply chain. Moreover, as delineated by our industry partner, we assumed one particular central warehouse and one regional warehouse to be responsible for the entire operations within the given area of investigation. Future research should, therefore, conduct further (sensitivity) analyses to verify our results in different contexts and identify the impact of warehouse locations and different supply chain structures in various countries. Additionally, different cases with other supermarket outlets, geographical structures (e.g., rural delivery areas), or even purchase behaviors influences such as the impact of seasonal demand could be investigated.

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