

# Simulation-based Assessment of Grocery Shopping in Urban Areas

Marvin Auf der Landwehr\*, Maik Trott, Christoph von Viebahn

Faculty IV – Business and Computer Science, Hochschule Hannover, Ricklinger Stadtweg 120, 30459 Hannover, Germany; \*[marvin.auf-der-landwehr@hs-hannover.de](mailto:marvin.auf-der-landwehr@hs-hannover.de)

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**Abstract.** This study proposes a simulation approach for modelling, assessing, and quantifying travel distances caused by stationary grocery shopping activities as well as e-grocery deliveries on the last mile. Utilizing an integrated emission calculation model, the simulated travel values are converted into relevant emission output factors to assess the individual impact of e-grocery deliveries compared to individual shopping trips by private consumers for different scenarios. While e-grocery does not yield an emission saving potential for low penetration rates less than 20 %, up to 41.5 % of the total emission outputs can be economized when home deliveries are employed for a moderate share of the urban population.

## Introduction

Technological advancements as well as the digitalization trend have a major influence on human behavior, interaction, and communication patterns. Especially in the transport sector, new technologies entail alternative business models, strategies, and shopping habits, which have a huge potential to disrupt existing mechanisms and standards. Consistently, urban freight transport has to evolve constantly in order to cope with the adapted shopping habits of (potential) consumers as well as the environmental concerns and objectives of all involved stakeholders [1]. High traffic volumes resulting from commercial as well as private transportation activities account for perseverative congestions and extended travel times as well as environmental contamination caused by vehicle emissions.

Accordingly, the development and implementation of new, emission-free drive concepts as well as the fortification of alternative means and modes of transport have

become a major point of concern, especially in Europe [2]. While commercial traffic is dominated by last-mile delivery operations, a major share of traffic loads and traffic-related emissions arising from private traffic in Germany or the United States of America is related to grocery shopping activities [3, 4]. To exploit the opportunities and overcome the challenges of shifting consumer habits and new digital technologies, the food retail organization has initiated a major transformation within the recent years.

While first approaches to online food retailing, also known as e-grocery, already became evident in the 1990s, the concept has gained increasing popularity in many markets, particularly in the last decade [5]. As the consumer behaviour is changing rapidly, home delivery concepts for grocery and food products are promoted and likely to gain more popularity in the near future [6]. Besides of economic benefits in terms of operational efficiency and economies of scale, an increasing utilization of e-grocery, with delivery tours substituting private shopping errands, can potentially aid in reducing traffic loads. Furthermore, this can yield advantages regarding emissions in urban areas, where last-mile logistics, traffic volumes, and environmental pollution have become major points of concern [7].

However, as the individual environmental benefits of e-grocery directly depend on the infrastructural, behavioural, and operational context, few studies have assessed and quantified its particular effects compared to stationary grocery shopping, yet. To cope with concept-specific peculiarities and behaviour-dependent variables such as individual usage rates, shopping trip proportions, store selection, and basket composition, which are not entirely adaptable to and testable in a real-world setting, a configurable simulation model can serve as a valuable investigation tool for evaluating the environmental impacts of stationary grocery shopping compared to grocery deliveries in terms of emissions.

Moreover, this approach aids in investigating and examining the impact of future mobility trends such as vehicle electrification [8] and convergence of mobility and logistics [9] on the ecological value of e-grocery as well as stationary grocery shopping. Hence, this publication aims to provide a conceptual simulation framework that is capable of comparing stationary shopping and e-grocery, whereby the latter will be examined by means of home-delivery operations from a food fulfilment center, as this is a prevailing and most common business model for online grocery provision on an international scale [10, 11].

While hybrid delivery concepts (e.g., Click and Collect) are increasingly gaining importance on an international scale, they are not (yet) operated by the major German retailer that serves as reference and validation object for our simulation study. Similarly, returns in the simulated operation model are handled in terms of reception checks, meaning that deliveries are checked upon the delivery reception and, if necessary, returned directly with the delivering carrier [10]. Accordingly, return operations do not result in additional transportation activities or traffic loads and will not explicitly be considered in this study.

By developing and employing a sophisticated simulation model for analyzing the individual emissions caused within the context of e-grocery and stationary food retailing, all relevant details (e.g., mileage) and dynamic structures like behavioral influences (e.g., mode of transport choices) within the respective system can be reproduced and quantified. While the model proposed in this paper focuses on an exemplary urban district in the center of Hanover, Germany, the simulation approach can also be adapted for other metropolitan areas, providing a uniform approach to assess the environmental value of e-grocery for different specificities.

## 1 Related Work

Motivated by the growing importance of e-grocery during the last decade, several studies have attempted to assess, quantify, or benchmark the economic, social, and environmental impacts of various grocery fulfilment methods. Hardi and Wagner investigated the CO<sub>2</sub> emission balance caused by grocery deliveries as well as private shopping activities in a given city district in Munich, Germany [12]. By employing a Monte Carlo simulation approach, taking into account real-world geo-data, randomly selected target households, delivery probabilities, and individual routing methods, they calculated and analyzed break-even points for energy consumption and CO<sub>2</sub>

emissions based on simulated vehicle distances and individual power efficiency factors. The results of the study indicate a significant emission savings potential of the e-grocery concept compared to individual stationary grocery shopping activities in the area of investigation. However, the calculation and simulation approach is static and neglects dynamic confounders and influencing factors such as individual shopping behavior (e.g., outlet choice depending on shopping type, chained trips) as well as delivery time windows, ultimately limiting the practical relevance and reliability of the results.

Concerning a holistic view on behavioral as well as concept-specific variables influencing the environmental impacts of online grocery retailing compared to stationary shopping, van Loon *et al.* developed a framework taking into account that individual consumer shopping characteristics directly influence the environmental footprint of the fulfilment concept [13]. Based on the proposed framework, they built a Life Cycle Assessment model to analyze different online retail methods for fast-moving consumer goods (FMCG) in the United Kingdom, indicating that consumer behavior as well as structural conditions such as routing and fulfilment properties are critical success factors for the sustainability of e-commerce when comparing it to stationary shopping. While their study provides a comprehensive overview about the key impact factors influencing the climate change potential of online FMCG retailing on a general basis, their results depend on the individual input parameters and, hence, are exclusively valid for the area under investigation. Their approach, therefore, lacks a general modelling or simulation framework that can be uniformly adapted to various contexts and scenarios.

Other contributions to the specified research area include studies from Coley *et al.*, who have made an empirical analysis of contrasting food distribution systems in terms of carbon emission outputs resulting from local farm shopping as well as a large-scale vegetable box system [14]. Durand and Gonzalez-Feliu, who assessed three e-grocery fulfilment scenarios in terms of mileage reduction, showed the effectiveness of a hybrid concept, combining home deliveries and proximity reception points [15].

Moreover, approaches to solve different routing problems in urban areas have been proposed by Blas *et al.* [16] and Mayer *et al.* [17], whereas Rabe *et al.* provide insights into the use of discrete event simulation in a supply-chain context [18].

Less recent publications on computer simulation for assessing, quantifying, or benchmarking the environmental impacts of home delivery concepts include studies from Cairns, Punakivi and Saranen, Punakivi et al., and Kämäräinen et al., who applied different modelling and simulation approaches such as route mapping in various international contexts in order to virtually compare distances covered in terms of e-grocery and stationary grocery fulfilment [19, 21, 22, 23].

Generally, these studies uniformly indicate potential advantages of e-grocery. However, they again neglect dynamic system properties and interdependencies such as behavioral variables as well as stochastic influences and fail to model the respective fulfilment system on a holistic scope, ultimately diluting the overall validity, significance, and transferability to the real world. Moreover, the utilized modelling and simulation approaches are case-dependent. Therefore, they cannot be transferred to different contexts and cities, implicitly illustrating the value of a uniform, parametrizable simulation model.

Table 1 provides a synopsis on the related work in the field of e-grocery simulation research. A large share of contributions is related to the assessment, evaluation, or quantification of potential economic, social or environmental impacts of an increasing e-grocery utilization [12, 15, 20], the analysis of behavioral influences on operational performance and concept efficiency [13, 22, 24], or the provision of a comprehensive status quo concerning grocery home delivery concepts as well as research [25, 26, 27].

Regarding grocery logistics concepts related to fulfilment or delivery activities, several studies propose, conceptualize, or examine various concepts in different contexts, whereby the majority of publications are concerned with benchmarking or comparing the impact of these concepts on given target variables (e.g., emissions, costs) [15, 22, 23, 28]. To provide a more comprehensive and concise overview, we have classified the studies based on their research scope and main objectives, namely 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 and profitability of various e-grocery business models (Profitability), the approach to assess, benchmark, and quantify e-grocery through simulation (Simulation Approach) as well as the aim to determine logistical influences caused by different delivery models and strategies (Logistical Influence).

Source	Method	Topic	Research Overview	Concept Evaluation	Sustainability	Profitability	Simulation Approach	Logistical Impact
[6]	MM	CB	⊙	●	⊙	●	●	⊙
[7]	LR	CO	●	●	●	●	⊙	●
[10]	LR	CO	●	●	⊙	●	⊙	●
[11]	CS	FD	●	●	●	●	⊙	●
[12]	SM	EI	●	●	●	●	●	●
[13]	MM	EI	●	●	●	⊙	●	●
[15]	CS	EI	⊙	●	●	●	●	●
[20]	LR	EI	●	●	●	●	●	●
[21, 23]	CS/SM	P	⊙	●	●	●	●	●
[23]	SM	FD	⊙	●	●	●	●	●
[24]	DS/SM	DSS	●	●	●	●	●	●
[25]	MM	EI	●	●	●	●	●	●
[26]	SU/SM	DSS	●	●	⊙	⊙	●	●
[27]	LR	CO	●	●	●	●	⊙	●
[28]	SM	EI	●	●	●	⊙	●	●
[29]	MM	DF	●	●	●	●	●	●
[30]	CS	FD	●	●	●	●	⊙	●
[31]	CS	FD	●	●	●	●	●	●
[32]	DS	PS	●	⊙	●	●	●	●
[33]	SM	DSS	●	●	●	●	●	●
[34]	LR	FD	●	●	●	●	⊙	●
[35]	CS	CO	●	●	●	●	⊙	●
[36]	DS/SM	DSS	●	⊙	●	●	●	●
[37]	MM	DSS	●	●	●	●	●	●
[38]	CS	FD	●	●	●	●	●	●
[39]	MM	FD	●	●	⊙	●	●	●
[40]	LR/CS	CO	●	●	●	●	⊙	●

Consideration: ● = full ; ● = partial ; ⊙ = no consideration

**Table 1:** Overview of e-grocery research based on or related to computer simulation and general concept reviews for different methods (SM = Simulation modelling; MM = Mathematical modelling; LR = Literature review; SU = Survey; CS = Case Study; DS = Data screening, LR = Literature Review) and topics (FD = Fulfilment Design; P = Profitability; EI = Environmental impact; CB = Consumer Behaviour; DSS = Decision Support System; PS = Pricing System; DF = Demand Forecast, CO = Conceptual Overview)

## 2 Research Approach

To provide a simulation framework capable of quantifying mileages and emissions caused by e-grocery as well as stationary grocery shopping activities realistically, we adapted a three-stage research design.

The definition of the area under investigation as well as the choice of an appropriate simulation modelling software and the selection of an adequate research approach constitute the conceptual foundation for the simulation modelling approach and have been aligned with the objectives of this study. In turn, the simulation model, including all conceptual and functional components, parameters, as well as development routines, provides concept-specific results on vehicle mileages. Subsequently, these are transferred to a comprehensive emission model to generate insights on the environmental impact of e-grocery and stationary shopping in the given context.

Initially, we used the java-based multipurpose software AnyLogic (Version 8.5.1) to design and develop an agent-based simulation model for reflecting shopping-related mileages caused by private as well as commercial traffic in the district *Mitte* of Hanover, Germany. The simulation results served as a basis for the emission calculation, founded on emission factors and structural vehicle data, by the European Environment Agency [41] and the city of Hanover [42].

Overall, this approach allows for a more dynamic, flexible, and thorough comparison, as simulated mileage results can be directly complemented or adapted in order to reflect behavioral and technological scenarios that exceed the actual scope of consideration of the simulation system. Both, simulation model, simulation results as well as emission model and its results were supported and backed up by means of information acquired during an in-depth literature review (i.a., employing data from literature presented in Section 1). Moreover, following an iterative development approach, we constantly verified and validated model components as well as results with data from a major German grocery retailer to ensure a high degree of validity and reliability. In this regard, several test cycles for mileage outputs have yielded a maximum deviation of 5 % of the simulated mileages compared to distances tracked by the retail organization for its real operations. A synopsis on the research approach is given in Figure 1.

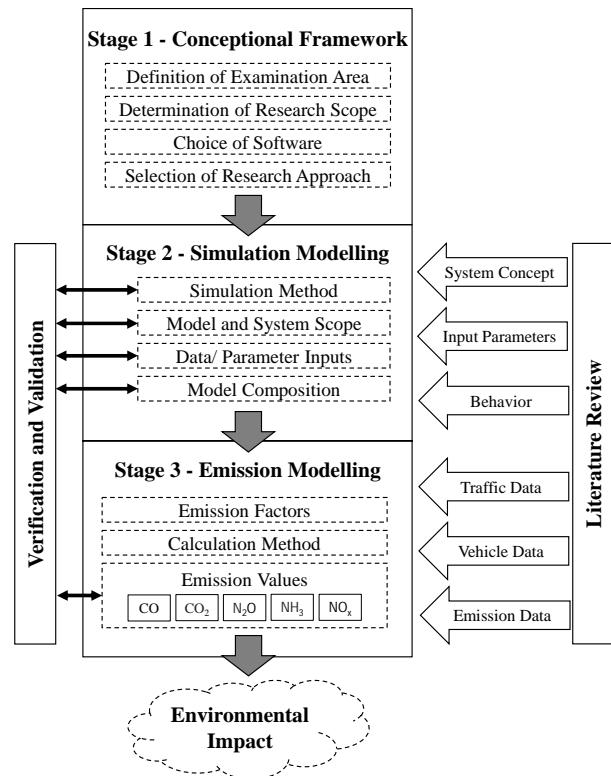


Figure 1: Three-stage research approach.

## 3 Simulation Model and Components

In accordance with the complexity of the problem and the need to model and replicate interdependencies between customers, supermarkets, delivery conditions, and behavioral influences (e.g., supermarket selection, trip chaining), an agent-based modelling (ABM) method was selected to reproduce the real-world system for the area of investigation. In contrast to microscopic simulation techniques such as discrete-event simulation (DES) or macroscopic simulation such as system dynamics (SD), it enables two-direction interactions and can effectively emulate interactions between individuals in a given system, ultimately reproducing global system dynamics by means of networking effects resulting from the modelled agent interactions. This approach appears particularly suitable to reflect behavioral influences and components with geographical reference [43]. The main advantage of ABM in the context of our study is its immanent capability to capture emergent behaviors that are decoupled from the properties of the individual agent (e.g., tour planning and (re-)scheduling) [44].

While other traffic simulation and analytical solution approaches such as SD, DES, Spreadsheet Simulation, or Monte Carlo Simulation are commonly used within the field of supply chain, traffic, and logistics simulation [45, 50], ABS features several benefits within our research. Despite its versatile applicability, Spreadsheet Simulation is rather suitable for models with a simple data structure. Moreover, it limits the data storage capabilities and is less efficient in simulating large or complex systems [45]. Due to the given pro-activeness of the agents, ABS requires a parallel-CPU system or a computer network to avoid sequential state changes across agents leading to reactive agent behaviours similar to entities in a DES [46]. Even though ABS and DES are both Turing complete [49], meaning that their theoretical modelling power is equal when sufficient memory and computational time are given, they are distinctively different regarding their flexibility and efficiency in modelling different types of systems. ABS is not just capable of capturing emergent behaviours resulting from interactions between agents, but generally more efficient in simulating systems with frequently interacting entities [46]. As the focus of our study is placed on the deduction of generic system insights (vehicle mileages) rather than the investigation of detailed interactions (e.g., communication between agents), ABS seems favourable over pure DES-only approaches [51]. Concerning SD modelling, ABS and SD are very similar techniques, whereby ABS takes bottom-up and SD a top-down approach. In fact, “the set of all SD models is a strict subset of the set all ABS models” [52], which is also referred to as the Agency Theorem for System Dynamics [53]. However, due to the given system complexity and the number of involved entities as well as unknown parameters, the bottom-up approach of ABS was likely to support the overall modelling process and, therefore, was more preferential for this study than SD. In line with the ABM approach, in which all relevant entities were modelled as particular active objects, the time-advancing mechanism is discrete and based on the interactions of agents, with each inter- or intra-network-related communication flow element accounting for a time-progression step in the simulation system [54]. In this context, communication flows, including process as well as decision elements outlined in Figure 4, are stored as events and integrated by an event list.

To reduce computing times, enable multiple simulation runs to account for stochastic variances in specific parameter values (Monte-Carlo approach), and increase

the degree of generalizability, credibility, and transferability of the simulation results, the scope of the model is restricted to the district Mitte in the city of Hanover. With 1,604 households, the simulation covers about 22 % of the entire population (7,230 private households) in the area of investigation [42]. The simulation model provides outputs in terms of kilometers covered by private as well as commercial vehicles, allowing to quantify simulation insights and to flexibly convert simulation results into emission outputs to assess and evaluate the environmental impact of given shopping concepts [55].

To increase the quality of the simulation in terms of reusability and transferability [56], the entire model was developed on a parametrizable data basis to enable a context- and scenario-independent adaptation of the modelling framework. Additionally, a configurable behavior model was integrated to specify e-grocery utilization depending on the contextual and structural system condition, ultimately aiding in the simulation of more-realistic scenarios (e.g., due to given constraints like minimum order values, e-grocery will presumably be used more often for bulk purchases). Output-relevant input parameters within the model as well as reference values for the examination area are shown in Table 2.

Parameter	Value	Unit	Type
Shopping Frequency	51	Percentage	Fixed
Car Possession	56	Percentage	Fixed
Bulk Purchases	42	Percentage	Fixed
E-Grocery Utilization	5/20/42	Percentage	Variable
Multi-shop Purchases	Yes	Boolean	Fixed
FFC Location	52.447220, 9.697536	Coordinates	Fixed
Delivery Fleet	5	Vehicles	Fixed
Carrier Capacity	18	Orders	Fixed
Service Time per Order	Mean: 7 SD: 2	Minutes	Stochastic
Loading Time per Order	Mean: 2 SD: 1	Minutes	Stochastic
Trip Chaining Share	26	Percentage	Fixed
Public Transport Share	25	Percentage	Fixed
Vehicle Speed	Mean: 30 SD: 5	Km/h	Stochastic
Working Days	6	Days	Fixed
Working Hours	7.8	Hours	Fixed

Table 2: Simulation model parameter values and classification.

Concerning the conceptual composition of the model, nine agent types have been defined to reflect relevant entities, interactions, and relationships for both shopping concepts. The agents' behaviour is controlled by means of statecharts, defining the decision-making processes within the given agent types and the system environment.

Figure 2 provides an overview of the class diagram for stationary retail and e-grocery. All class elements represent agent types (indicated by the stereotype <<agent>>). The agent type "Main" includes the visualization of the simulation by providing a GIS map (Figure 3), while the "Household" agent type depicts consumers and "Grocery" all super- and hypermarkets in the area under investigation. At runtime, one single instance of the agent type "Main" exists, whereas 1 to *n* agents of the type "Household" and "Grocery" can be instantiated and utilized within the "Main" agent. Each "Household" has access to 0 to 1 "Car" agents for its shopping operations, which are responsible for the actual journey from household to supermarket. The "Purchase" agent represents a data type required for communicational flows. It is assigned to 0 to *n* "Households" to reflect a household's choice to make none up to several purchases at simulation runtime.

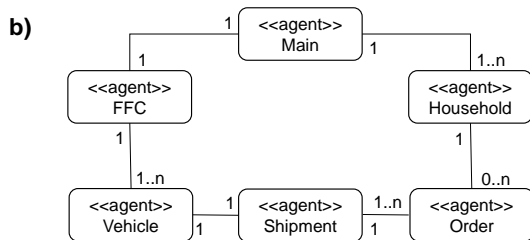
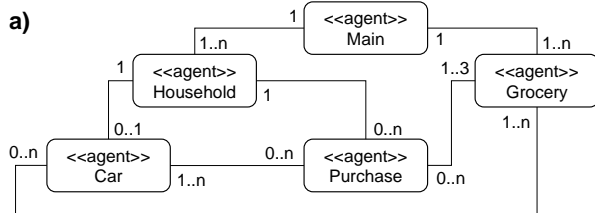


Figure 2: Class diagrams for (a) stationary retail and (b) e-grocery.

In contrast to the class diagram for stationary grocery shopping, the framework for e-grocery contains six agent types. Again, the "Main" agent is responsible for displaying the agent types "Household" and "FFC" (Food Fulfillment Center) at simulation runtime.

Generally, 1 to *n* "Household" agents as well as one "FFC" agent can be instantiated. The "FFC" agent receives orders from the "Household" population, which are depicted as communicational "Order" agents. Subsequently, the "FFC" aggregates all incoming "Order" agents to a "Shipment" agent, which is handed over to the "Vehicle" that is responsible for delivering the orders to the final customer ("Household").

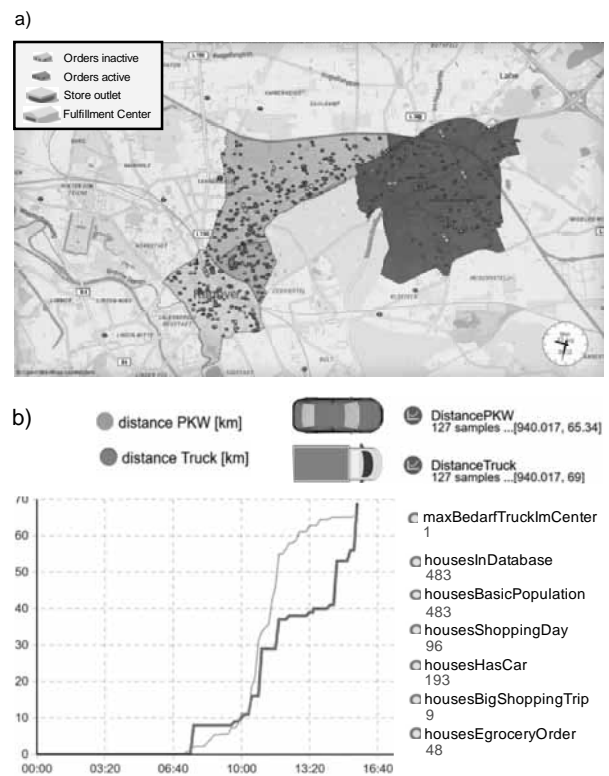


Figure 3: Traffic flow: (a) simulation visualization on GIS map and (b) statistical diagram for vehicle mileages.

While virtual abstract agents (e.g., Shipment, Order) act as supporting units for communicational flows in the simulation model, physical agents (e.g., Vehicles) are placed in a geospatial environment and feature both, communicational properties as well as process-related characteristics. Navigation and routing procedures are conducted by means of a clustered k-Nearest-Neighbor (kNN) algorithm [57], which is a non-parametric approach utilized for classification and regression, ensuring realistic and efficient delivery operations. Due to their stochastic decision nature, kNN algorithms are generally very robust compared to other routing methods when it comes to solving vehicle routing problems based on noisy training data [47]. Moreover, they allow for solving large problems with high computational complexity.

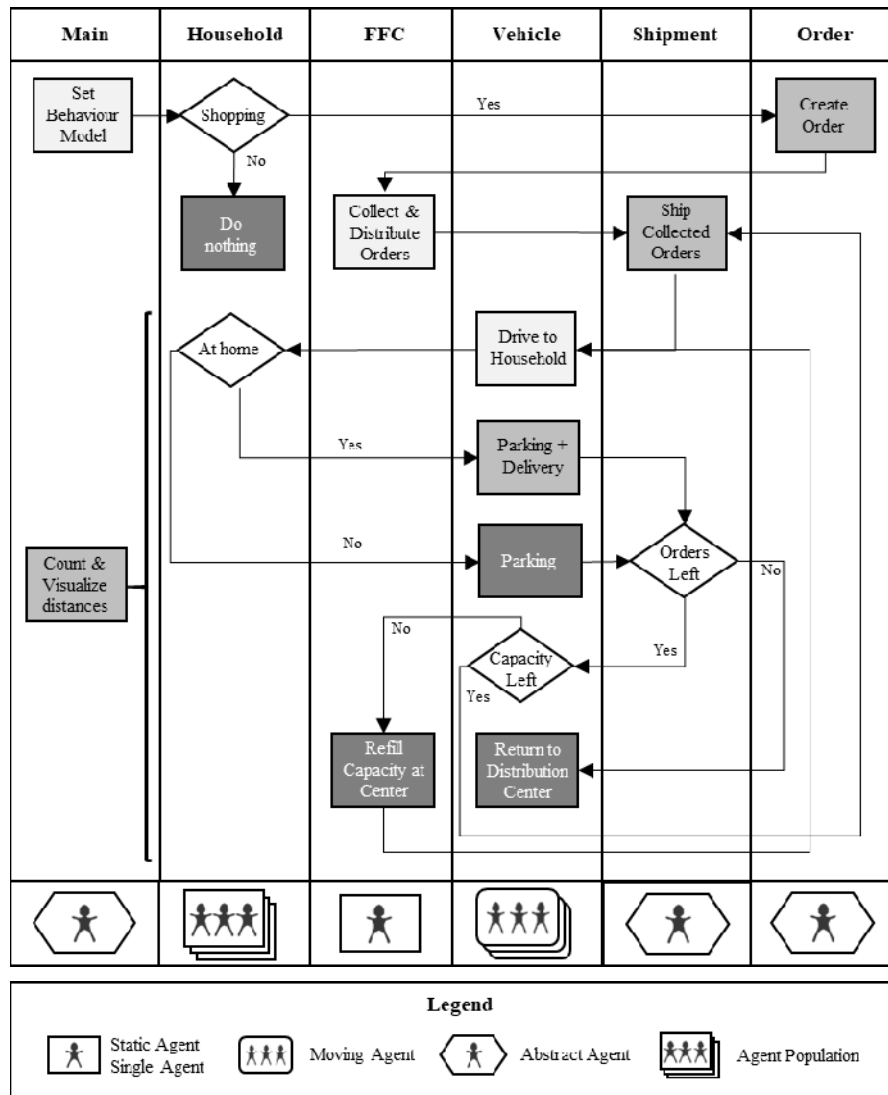


Figure 4: E-grocery simulation process flows.

Besides other routing and classification heuristics such as savings heuristics, insertion heuristics, or sweep heuristics, despite of relatively high computational costs, nearest neighbour heuristics are commonly used to define starting solutions for various routing problems, including the capacitated vehicle routing problem with time windows, as present in our research [48]. As a structure to define spatial relationships, kNN aids in enhancing the model network capacity and features efficient implementation processes [47].

In the context of our adapted kNN algorithm, first, a limited range is specified to assess the availability of customers within a given delivery area. In turn, the nearest customer (i) is set as a starting point for identifying the nearest remaining customer (i) in the given range.

As soon as no remaining customers are available within the set boundaries, the algorithm automatically increases the range until a customer that still has to be delivered in a respective time window has been found or all customers have already been registered in a delivery network. The road network is based on OpenStreetMap (OSM). Routes between household agents are chosen in line with a distance-based cost function, assigning each edge of the routing network with a cost based on the distance between starting point and endpoint.

In terms of process flows, the simulation model comprises two agent networks, representing the concepts of stationary grocery shopping as well as e-grocery. As shown in Figure 4 and Figure 5, for each concept, the simulation model is initiated by setting up a behaviour

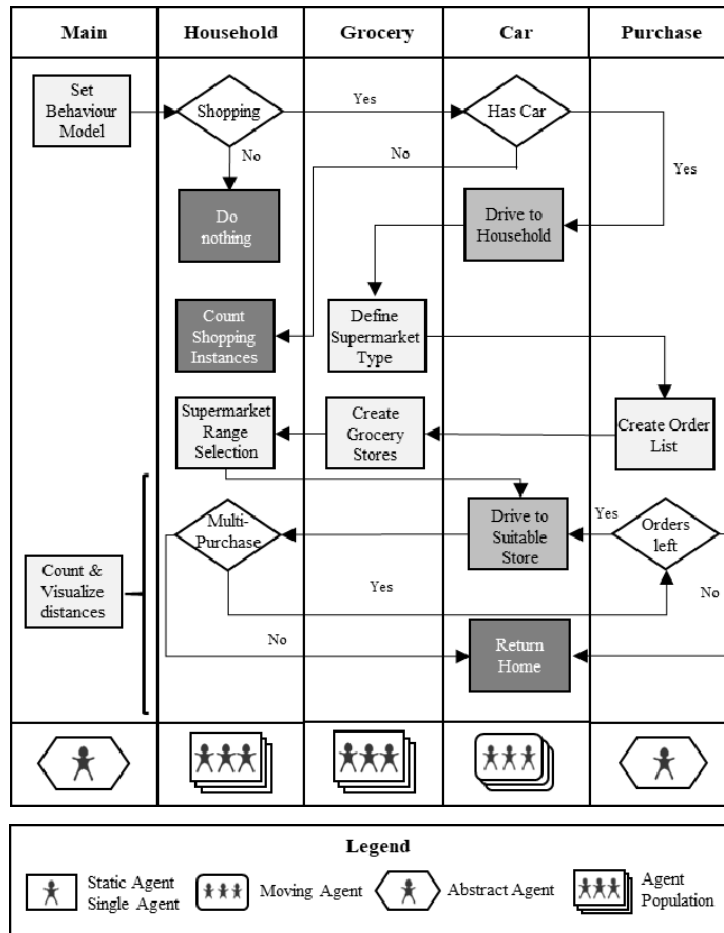


Figure 5: Stationary grocery shopping simulation process flows.

model, which in turn is responsible for the implementation of general rules according to the parameters described above. In the case of e-grocery operations (Figure 4), “Household” agents evaluate their shopping options individually and eventually create e-grocery orders. These orders are collected within the “FFC” and distributed across the given vehicle fleet. Afterwards, a shipment list is collected and the delivery process is initiated by the “Vehicle” agents. Based on a random distribution, a minor likelihood is given for order recipients not being present when a delivery attempt is made. If this condition evaluates to be true, the delivery “Vehicle” parks at the designated location for a specified time and subsequently continues with delivering the remaining orders. In contrast, if the condition returns false, the parking time is extended in order to reflect the actual delivery activity. After each delivery attempt, the “Vehicle” agent reviews the shipment list and checks the “Shipment” agent for remaining orders.

If the remaining order condition returns true, the “Vehicle” agent assesses its remaining order capacities required to complete outstanding orders from the shipment list. If that expression also evaluates true, the “Vehicle” drives to the next customer determined by the kNN routing algorithm and restarts the delivery process. In case the expression returns false, the Vehicle drives to the “FCC” to refill missing order capacities before continuing to fulfil remaining orders.

Households engaging in stationary grocery retail evaluate their individual shopping activities based on a probability distribution, taking into account average shopping frequencies as well as shopping type shares (bulk or small purchases) of German consumers [3]. If the shopping activity expression returns true, the modal split for the shopping trip is determined by the model, randomly assigning cars to the respective households based on structural data for as well as statistical information on car admissions and distribution in the investigated area [42].



For “Households” that have been assigned a car, a “Car” agent is created. Moreover, “Grocery” agents are classified into supermarkets suitable for small or bulk purchases and an order list for the given “Household” agent is created. Finally, “Households” select suitable supermarkets depending on their shopping trip type and drive to the designated destination, following a routing algorithm based on a distance-based cost function. In case several supermarkets are required to complete a bulk purchasing activity (multi-purchase), “Households” head for several supermarkets until all purchases from the order list have been made.

Ultimately, distances are tracked for both agent networks and transferred into a statistical diagram as well as a joint database. Both, stationary retail activities as well as e-grocery deliveries complement each other within a given agent network, providing a complete overview of total distances resulting from different e-grocery utilization rates and shopping behaviours. To account for chained trips (i.e., trips carried out for a different primary purpose than grocery shopping: 74 %) as well as the fraction of individuals employing public transport for their grocery shopping activities (25 %), the respective share of households engaging in these concepts is distributed randomly across all “Household” agents for each simulation run. This was based upon a comprehensive mobility survey in various cities [3].

### 3.1 Encountered challenges

In the course of the outlined model development and the adjacent test and validation iterations, several challenges regarding the quality and availability of data as well as the computational performance of the simulation were encountered. Due to the complexity of the system and a lack of publicly available data sources, the acquisition and choice of model input parameters was a major challenge within the modelling phase. To address this issue and select appropriate input values as well as behavior scenarios, we cooperated with a major German retail chain and acquired missing information by means of expert feedback. Furthermore, the use of a modified kNN algorithm resulted in major computational requirements, which we addressed by defining population samples for each simulation run as well as parallelization of the simulation. Nevertheless, we aim to refine the routing algorithm in future research in terms of its computational efficiency and, therefore, enable larger sample sizes as well as shorter simulation cycles.

## 4 Emission Model

While the simulation model has been designed to simulate and export driving distances in terms of kilometers, we have developed a separate emission model to transfer mileages into specific emissions. Traffic emissions ( $E_{ij}$ ) are derived based on the number of vehicles in a nation’s fleet of category  $j$  and technology  $k$  ( $N_{j,k}$ ), the average annual distance covered per vehicle of category  $j$  and technology  $k$  in kilometers ( $M_{j,k}$ ) as well as the technology-specific emission factor of pollutant  $i$  for each vehicle category  $j$  ( $EF_{i,j,k}$ ). The respective emission calculation equation is denoted as:

$$EP_{i,j} = \sum (N_{j,k} \times M_{j,k} \times EF_{i,j,k}) \quad (1)$$

Vehicle categories include passenger cars (private traffic) as well as light-duty vehicles (commercial traffic), required for delivery operations on the last mile, while vehicle technologies range from Euro 1 to Euro 6. The fleet composition of passenger cars in terms of technologies, combustion engine, and cubic capacity has been determined in accordance with structural data of the city of Hanover [42]. The referenced light-duty vehicle employed for e-grocery delivery operations is a Renault Master L2H1 with Kiesling Flat Runner Box Body and features an ENERGY dCi 145 engine with an output of 107 kW (145 hp) as well as a tare weight of 2.29 tons. Moreover, the given light-duty vehicle combusts diesel fuel and is classified as Euro 6b.

Concerning specific emission output values, ammoniac ( $\text{NH}_3$ ), nitrous oxides ( $\text{N}_2\text{O}$ ), and nitrogen oxides ( $\text{NO}_x$ ) are calculated by emission factors proposed in [41], whereas carbon dioxide ( $\text{CO}_2$ ) emissions of vehicles  $k$ , combusting fuel  $m$ , are determined by:

$$E_{\text{CO}_2,k,m}^{\text{CALC}} = 44.011 \times \frac{FC_{k,m}^{\text{CALC}}}{12.011 + 1.088r_{\text{H:C},m} + 16.000r_{\text{O:C},m}} \quad (2)$$

Here,  $FC_{\text{CALC}}$  describes the fuel consumption of vehicles for a given period, while  $r_{\text{H:C}}$  as well as  $r_{\text{O:C}}$  account for the ratios of hydrogen to carbon (H/C) and oxygen to carbon (O/C) in the fuel. Overall, the emission model employs emission-, pollutant-, and vehicle-technology-related data inputs from the European Environment Agency [41] and has been designed to assess the relative effects of mobility and logistics concepts based on the driven mileages.

The method can be used to evaluate emission outputs resulting from driving activities to a good approximation and to combine various influencing factors such as driving speeds in different environments (motorway, inner-city), acceleration and deceleration, or ambient temperature. However, the model is primarily based on average values for many influencing factors. Thus, it is more suitable for comparing the relative effects of individual scenarios rather than determining absolute figures with high accuracy.

## 5 Results

Employing the proposed simulation and emission model, we have conducted a sophisticated simulation study on the environmental impacts of e-grocery as well as stationary shopping in the urban area of investigation. With each simulation run representing one particular day, a total of 1,000 simulation runs employing the parameter values referenced in Table 2 have been conducted and analyzed. We assessed three potential behavioral scenarios as well as one benchmarking scenario within the study to reflect current as well as probable future realities concerning the utilization of e-grocery:

1. **0 %-Case:** Sole stationary grocery shopping without any e-grocery activities as benchmarking scenario.
2. **5 %-Case:** 5 % e-grocery utilization rate as present in other European countries such as France or the United Kingdom [58].
3. **20 %-Case:** 20 % e-grocery utilization rate as present in the United States of America [35].
4. **Bulk-Shopping-Case:** E-grocery utilization adjusted to the daily bulk shopping frequency of consumers.

To reproduce reliable outputs, the total results for the entire simulation period have been averaged for each scenario. To enable a holistic assessment and evaluation approach, each e-grocery scenario (1-3) is complemented with stationary shopping activities of the remaining population share. The results of the simulation study in terms of vehicle mileages and the resulting emission outputs per scenario as well as standard deviations (SD) with a 95 % confidence interval for the 1,000 simulation iterations are outlined in Table 3 and Table 4.

Our results indicate that e-grocery can, indeed, contribute to a more sustainable environment in central urban areas as present in the investigated case. Nevertheless, the potential to reduce traffic and emissions in the investigated operational set-up highly depends on behavioural patterns in particular and e-grocery utilization in general.

With low utilization rates as given in Scenario 1, the overall share of traffic-related mileages and emissions exceeds the benchmarking case without any e-grocery operations, proving the e-fulfilment concept to be less efficient from a sustainable point of view than the absence of grocery deliveries. With low e-grocery utilization rates, the delivery fleet features a very low degree of capacity utilization (50 % – 70 %), ultimately resulting in additional mileages and emissions. Moreover, shopping-related behaviour mechanisms such as trip chaining as well as the modal split in the research area reduce the positive effects of order bundling and operational efficiency provided by the proposed home delivery concept.

Scn.	Distance		SD	
	Car	Truck	Car	Truck
0	2428	/	105	/
1	2321	122	102	7
2	1983	359	97	16
3	1354	542	74	28

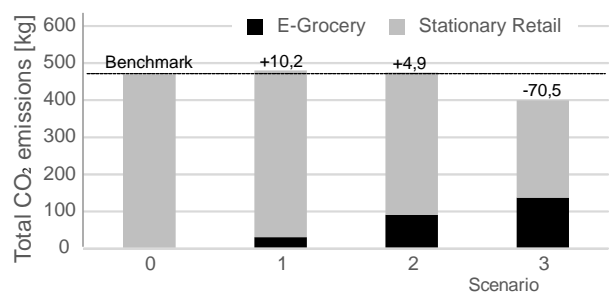
**Table 3:** Distances (in km) and standard deviations per scenario.

Scn.	Emissions				
	CO	CO <sub>2</sub>	N <sub>2</sub> O	NH <sub>3</sub>	NO <sub>x</sub>
0	1.488	469.9	0.007	0.047	0.519
1	1.432	480.1	0.008	0.046	0.614
2	1.243	474.8	0.007	0.040	0.769
3	0.871	399.4	0.006	0.028	0.810

Scn.	Standard Deviations				
	0	0.091	20.818	0.0003	0.002
1	0.098	24.424	0.0004	0.002	0.032
2	0.076	22.184	0.0003	0.002	0.039
3	0.057	21.289	0.0004	0.001	0.048

**Table 4:** Total emission outputs (in kg) and standard deviations per scenario.



**Figure 6:** Total CO<sub>2</sub> emissions resulting from e-grocery and stationary retail per scenario.

Accordingly, also the simulation results of Scenario 2 do not outline a significant mileage or emission saving potential, with some emissions (e.g., CO<sub>2</sub>) still exceeding emission outputs accruing without any e-grocery activities (Figure 6). Concerning high e-grocery usage rates as given in Scenario 3 (42 %), the e-grocery concept can significantly contribute towards reducing CO, CO<sub>2</sub> and NH<sub>3</sub> emissions by up to 41.5 % (CO), 15 % (CO<sub>2</sub>), and 40.4 % (NH<sub>3</sub>) compared to stationary retail in the baseline scenario. In line with the high production of N<sub>2</sub>O and NO<sub>x</sub> emissions by delivery vehicles compared to private vehicles, the former barely change across all scenarios, while the latter even develop contrariwise to CO, CO<sub>2</sub> and NH<sub>3</sub> emissions and increase by up to 56.1 % from Scenario 0 to 3.

As shown in Figures 7 and 8, emissions develop in accordance with the share of mileages among private and commercial vehicles in the given scenarios. Per order, each delivery truck covers about 1.0 kilometers in Scenario 1, 0.4 kilometers in Scenario 2, and 0.3 kilometers in Scenario 3, while every passenger vehicle covers a distance of 5.3 kilometers in Scenario 0, 4.8 kilometers in Scenario 1, 3.5 kilometers in Scenario 2, and 1.7 kilometers in Scenario 3, respectively.

The strong decrease in mileage per order for passenger cars in Scenario 3 can be described through the scenario peculiarities, as bulk shopping activities, which often require consumers to select supermarkets in a broader range, are entirely outsourced to e-grocery carriers. Similarly, the kilometers covered per order and delivery vehicle decrease with an increasing e-grocery usage rate, as more-efficient processes in terms of vehicle utilization degree can be achieved.

## 6 Discussion and Conclusion

In this contribution, we presented a simulation approach and model, capable of reproducing shopping activities within the context of grocery retail. Model design and procedure were aligned and delineated to investigate the potential impact of e-grocery on sustainability metrics such as mileage and emissions within an urban context.

The proposed simulation approach and model can be effectively employed to assess the environmental influences of offline and online grocery shopping concepts in urban areas.

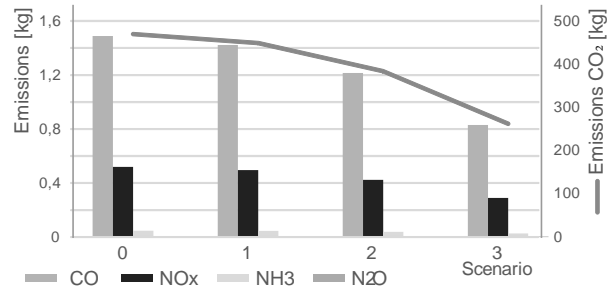


Figure 7: Emission outputs per scenario resulting from private traffic

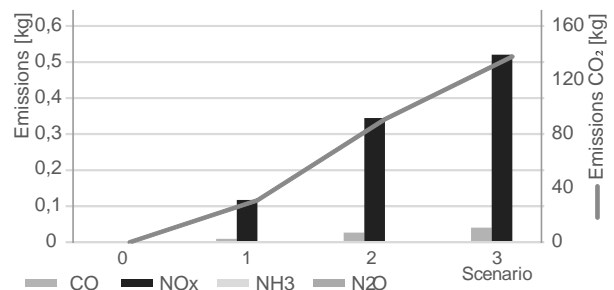


Figure 8: Emission outputs per scenario resulting from commercial traffic

The modelling framework and simulation methodology can be adapted and transferred to other cities as well as contexts and model the impacts of different grocery shopping scenarios based on a prevailing operational delivery model in a dynamic, integrated way. Ultimately, it can be used to quantify both, holistic conceptual interdependencies and system states as well as influences of specific parameters and characteristics.

Applied to the City of Hanover, Germany, we proved that e-grocery can holistically outperform stationary grocery shopping in terms of traffic and emission outputs in the investigated set-up. However, an environmentally beneficial application of e-grocery within central urban areas requires high e-grocery utilization rates to leverage delivery vehicle utilization degrees and overcome influences of behavioral traits such as chained trips. Especially in the latter case, where e-grocery is employed for all bulk purchases across the entire area of investigation, e-grocery yields a very high potential to decrease traffic (by up to 21.9 %) as well as emissions (e.g., CO by up to 41.5 %) compared to a scenario exclusively featuring stationary grocery shopping. Nevertheless, despite its given sustainability potential, currently, e-grocery utilization rates are far below 20 % in many countries, which may result in the fact that the e-grocery operations result in additional traffic and emission outputs [59].

Hence, to tap on the potential benefits of e-grocery within an urban context, the utilization of the concept needs to be fostered and promoted in the near future, especially when considering the high share of mileages and emissions in a scenario with low utilization rates.

While the proposed simulation model and study offer comprehensive insights into grocery shopping impacts, additional constraints and influence factors need to be added and investigated in future research to ensure an integral analysis and evaluation. It can be expected that the location of the respective fulfilment center has a major impact on delivery vehicle mileages in various e-grocery scenarios, which should be examined through simulated sensitivity analyzes. In addition, the simulation approach can be used to analyze the role of different time windows in the operational performance of e-grocery deliveries as well as various national and international fulfilment concepts, as highlighted in [10] (e.g., Click and Collect, grocery deliveries by parcel service providers). Moreover, in line with current and future mobility trends, the role and impact of private and commercial vehicle electrification as well as shared mobility concepts in terms of sustainable operations and emission outputs should be assessed. Future research should employ the basic concepts of our simulation approach and mode, to conduct further analyzes, verify our results in different contexts, and identify the impact of different fulfilment peculiarities in various countries. Ultimately, different cases with other supermarket outlets, geographical structures (e.g., rural delivery areas), or even purchase behavior influences such as the impact of seasonal demands could be investigated.

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