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# Application of Information-Sharing for Resilient and Sustainable Food Delivery in Last-Mile Logistics

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**Abstract:** The growing food demand, the tendency for organic food, and the adaptation of the e-commerce business model require new food supply chain management approaches. On the one hand, 30% of the world's produced food is wasted, and $CO_2$ emissions are rapidly growing due to transport. On the other hand, the increasingly complex and dynamic environment is decreasing the effectiveness of food supply chains. Because of these trends, sustainability and resilience are becoming more relevant to food supply chains. Therefore, the objective of this paper is to propose a strategy based on information exchange to improve food quality and decrease the level of $CO_2$ emission in last-mile deliveries of food products. To achieve this goal, an agent-based model of last-mile deliveries was developed. The model simulated traffic flow and traffic accidents as disturbances in the system while measuring the level of $CO_2$ emission and food quality of the network. The simulation compares information sharing between all vehicles in the urban area and without information sharing in four scenarios of the food industry. In practice, information sharing is achieved by using connected vehicle technology. The use of information sharing between vehicles in last-mile delivery processes allows the development of a self-organizing system, which would adapt to disturbances and lead to the development of sustainability in the long run.

**Keywords:** food supply chain; sustainability; resilience; urban logistics; information sharing

**MSC:** C90-10

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## 1. Introduction

The food industry faces challenges due to changing consumer trends and the business environment. On the one hand, the demand for food products is growing due to the growing world population and the increasing life expectancy rate. The world population is expected to reach 9.8 billion by 2050 [1]. The average life expectancy in Europe will be 82 years by 2050 [2]. The demand for organic food products is also growing, which requires reducing lead time in order to maintain better product quality [3]. On the other hand, constant disturbances and a changing business environment decrease the efficiency of the food supply chain. Urbanization will continue at an accelerated pace, and approximately 70% of the world's population will be urban compared to 49% today [4]. The complexity of the food supply chain will increase because the United Nations is promoting the collaboration of SMEs (small-scale farmers produce more than 70% of the world's food needs) [5]. The last mile of the supply chain is less efficient, comprising up to 28% of the total logistics cost [6]. Food losses and waste cost the global economy approximately USD 990 billion annually [7]. Part of the waste is generated in the household stage, and the other part is generated in the storage and delivery stage. "While it is clear that major calamities and disasters can have a considerable effect on traffic and transport systems, there is a knowledge that more minor disturbances in traffic and transport systems can also play an important role in reducing the efficiency of such systems" [8]. "Travel times between customers are not deterministic, but uncertain and differ during the day with respect to traffic volumes and stochastic events such as congestion" [9].

From another perspective, these issues raise concerns about the environmental effect of the reduction of $CO_2$ emissions. "The distribution of goods in urban areas, together with the flow of private traffic, are among the main sources of energy consumption, air pollution and noise" [10]. Most of the research conducted has focused on reducing $CO_2$ emissions from genetically modified products, rather than specifically on food supply chains. Seebauer et al. (2016) found that the use of cars for the final delivery leg, known as the "last mile," significantly affected overall carbon emissions in retail channels [11]. Carling et al. (2015) found that consumers who switch from traditional to e-retail can reduce their transport-related $CO_2$ emissions by an average of 84% [12]. Nabot and Omar (2016) conducted a study comparing the environmental impact of online and in-person retailing and found that online shopping plays a significant role in reducing $CO_2$ emissions due to the efficiency of last-mile deliveries [13]. Kellner (2016) analyzed the impact of traffic congestion on $CO_2$ emissions but did not consider the impact on food quality [14].

These trends influence the sustainability aspect of the food supply chain in terms of environmental and social aspects. From an environmental perspective, disturbances increase $CO_2$ emission levels, and from a social perspective, disturbances increase the duration of delivery and reduce nutritional value. When disturbances are very intense, food waste can even have an economic effect related to lost profits. Therefore, the concept of resilient and sustainable supply chains has gained more recognition in recent years. For example, a research paper focused on how to develop a resilient/sustainability index [15]. The paper analyzed the relationship between resilience and food waste and determined that resilience elements, which help reduce food waste, are anticipation and consideration. These approaches are important because food has a short shelf life, and it loses its value completely if it is not sold. Other research papers have focused more on force majeure and promoting the horizontal collaboration of food supply chains. However, the proposed approaches have several practical problems with regard to collaboration management. For example, research indicated that the effectiveness of collaboration as a supply chain resource has been questioned due to concerns associated with collaborative technologies [16]. Another paper stated that firm strategy and behavior in supply chain collaborations are identified as the main reasons for supply chain failure [17]. Therefore, the research conducted by the authors attempts to analyze the missing gap in the approaches and suggest a management framework for resilient and sustainable food supply chains. A previous publication of the authors analyzed the disturbances with regard to demand fluctuation. The publication proposed a redundancy approach based on collaboration demand forecasting to increase collaboration between supply chain members and increase the effectiveness of redundancy usage [18]. This publication addresses disturbances from the perspective of transport in urban logistics. "Minor disturbances in traffic and transport systems can also play an important role in reducing efficiency" [8]. In this publication, disturbances are defined as traffic accidents that are irregular and cannot be estimated from the usual traffic flow data analysis. The influence of traffic jams and congestion on $CO_2$ emissions has previously been analyzed [19]. However, only a limited number of research papers analyzed food quality and $CO_2$ emission levels in the food supply chain, and essentially no research has examined the relationship of sustainability with disturbances in the food supply chains [20–25].

Therefore, the aim of this article is to propose a system based on information sharing to improve food quality and decrease the level of $CO_2$ emission in last-mile deliveries of food products.

## 2. Perspective on Sustainable and Resilient Food Supply Chains

The trend for healthier food products is changing the competitive environment drastically. "With the world's population rising and expected to reach 9 billion by 2050, a plan for the development of the organic sector is needed to meet this demand" [26]. "Industrial food has changed from being 'scientific' and 'safe' to being 'toxic' and potentially harmful to our long-term health" [27]. Furthermore, the trend for e-commerce and direct delivery to homes is creating even more difficulties in the food industry. "Direct selling of food from producers to consumers is not a new development. The possibility of buying food through regional markets, through catalogues, or directly at the farm existed before. But the Internet improves direct access to the consumer" [28]. The growing trend of directly delivering organic food products to consumers also raises concerns about the levels of $CO_2$ emissions due to the increased travel distance. Therefore, it is necessary to develop new delivery techniques to address this issue [13]. A research paper compared meal-kit deliveries with conventional grocery shopping [29], they stated that meal-kit deliveries can reduce food waste; however, a comparison with conventional groceries requires the comparison of energy demand. Another paper analyzed electronic grocery deliveries in last-mile deliveries and concluded that "a prominent finding is that home delivery of food and groceries is associated with fewer trips to physical grocery stores and reduced car use on these trips" [30]. The market size of internet retail was USD 1.17 trillion in 2016 and is estimated to grow to a size of 2.1 trillion with an AAGR of 13.33% by 2020 [3]. "By 2025, the share of online grocery spending could reach 20%, representing $100 billion in annual consumer sales" [31].

However, currently, there is a great deal of food waste due to ineffective supply chain processes and household behavior. Food losses and waste cost the global economy approximately USD 990 billion annually [7]. The European Commission has launched a project for the development of food systems, focusing on increasing nutrition levels and promoting local production [32,33]. The growing complexity of the food industry further increases the challenges of management. The complexity of the food supply chain will increase because the United Nations is promoting the collaboration of SMEs (small-scale farmers produce more than 70% of the world's food needs) [5]. From the perspective of the supply chain, these changes should consist of more local distribution facilities and local farmer initiatives [34]. Research conducted empirical research regarding the development of short food supply chains, which they considered a novel trend to ensure sustainable agriculture [35]. Due to this growing complexity and the increased demand for healthy food, the concepts of resilient and sustainable food supply chains are growing. "The sustainability of agrifood systems is most often defined with reference to the three pillars of sustainability (environmental, economic and social), in an often static and normative way, while the notion of resilience is defined in reference in a more dynamic way, in terms of the ability to cope with shocks and stresses." [36]. To cope with this growing challenge, a system approach should be adapted to the management of food supply chains. "Complexity economics sees the economy as in motion, perpetually 'computing' itself, perpetually constructing itself anew. Where equilibrium economics emphasises order, determinacy, deduction, and stasis, complexity economics emphasizes contingency, indeterminacy, sense making, and openness to change" [37]. "The key to ensuring a sustainable and resilient supply of essential ecosystem services on which humanity depends is by enhancing the resilience of socioecological systems, instead of optimizing isolated components of the system" [38]. To implement system thinking in food supply chains, collaboration between supply chain members should be promoted and official logistic groups formed. "Collaboration ensures the exchange of information between supply chain partners and reduces uncertainties and complexities. Collaboration through appropriate partnership and information exchange in the early stage of supply chain operations would reduce uncertainties and complexities" [39]. Only by integrating information and innovative technologies can a resilient and sustainable supply chain be achieved. Integration of such approaches can provide self-organizing capabilities to the food supply chain. "The adaptive capacity of a supply chain to reduce the probability of facing sudden disturbances, resist the spread of disturbances by maintaining control over structures and functions, and recover and respond by immediate and effective reactive plans to transcend the disturbance and restore the supply chain to a robust operation state" [40]. Cordes and Hulsmann indicated that from a CAS perspective, supply chains obtain self-healing processes, which is related to robustness for supply chain resilience. In addition, they imply that additional research is needed related to empirical and simulation-based methods [41]. Thus, the proposed application of information sharing provides adaptation abilities to the logistic cluster members, which, in the long run, trends towards sustainable and resilient food supply chains. There may be difficulties in sharing information between all vehicles in the urban environment due to issues of collaboration. These issues from a technical perspective can arise due to large amounts of data flow and latency issues, while from a social perspective, not all companies might agree to share their vehicle data due to competition. However, research by Los et al. (2020) found that sharing full route plans is always beneficial for individual carriers, regardless of the level of route information shared by other carriers [42].

In this paper, we will focus on the urban logistics context because, currently, it is the least efficient area, comprising up to 28% of the total logistic cost [6]. In addition, last-mile deliveries dramatically contribute to $CO_2$ emission levels [11]. The concept of resilience is mainly analyzed from the perspective of force major; however, Calvert and Snelder indicated that “Minor disturbances in traffic and transport systems can also play an important role in reducing efficiency” [8]. Other researchers also indicated that traffic congestion and road accidents are several aspects of disturbances in the supply chain that decrease the effectiveness of the system [43]. Due to the complex and rapidly changing environment, it is important for a supply chain to have the ability to quickly adapt to disturbances. To achieve flexibility, supply chain processes must be completely visible, and the information should be used to make decisions independently without constant human interference. In 2008, Osvald and Stirn conducted research on a vehicle-routing problem involving perishable products using time-dependent optimization and including the costs of food waste in the goal function [25]. Research focused on optimizing the supply chain from production to retail, making a significant contribution by measuring the loss of food quality based on product flow and quantity [44]. A more recent study examined the impact of food quality loss in urban logistics, with a particular focus on inventory management strategies and delivery time [20,21]. Part of the approach described in the research by Fikar and Waitz will be included in this research, such as the measurement of food quality and inventory management strategy [21]. However, in our research, we expand the model by including traffic flow and accident information and focusing mainly on urban logistics rather than the whole supply chain as in Fikar’s research [20]. One of the possible approaches to reducing the effect of disturbances on food quality and the level of $CO_2$ emissions is to use information sharing between all vehicles in the urban environment, which could adapt in real time to the changing environment. Today, there are solutions in the market that obtain traffic information mainly from mobile phones or sensors in the city. In this publication case, we focus on vehicles collecting information from the environment and sharing it between all vehicles in the urban environment. This approach allows for maintaining information sharing between all vehicles in real time and can gather more information than just traffic flow. In practice, information sharing between vehicles is called a connected vehicle concept. Research paper amplified the benefits of connected vehicle applications for fleet management functions of vehicle routing and scheduling [45]. Chandra and Nguyen (2020) analyzed the benefits of connected vehicle technology to reduce freight truck emissions, while in this publication, we focus on last-mile logistics [46]. Yao et al. (2020) noted that much of the existing research on connected automated vehicles focuses on improving the performance of the transportation system but does not consider the impact on gasoline consumption and transportation emissions [47]. They found that the optimization method can reduce both gasoline consumption and transportation emissions [48]. Heard et al. (2018) noted that the food distribution industry is likely to be an early adopter of connected and autonomous vehicles, which will have significant effects on the environmental and economic profiles of the food supply chain [23]. Haass et al. (2015) conducted research on an autonomous logistics approach for delivering bananas by sea rather than by land transport, which involved measuring initial food quality and optimizing the quality level to determine routes [49]. This research exemplifies the use of information sharing in urban logistics. In a similar approach, information exchange can be used in the context of urban logistics to improve food quality levels.

Therefore, our research focuses on urban logistics and measures food quality and $CO_2$ emission levels in a dynamic environment by considering traffic accidents that cannot be overseen by regular data analysis and are seen as disturbances to the system. We propose increasing information sharing between all vehicles, which can then be used to optimize delivery routes by developing a self-organizing system. In practice, vehicle sensors can gather more information than traffic flow and accidents. Tan et al. (2019) developed a pollution routing algorithm for last-mile deliveries to minimize negative environmental impacts [50]. Velázquez-Martnez et al. (2016) optimized routes based on $CO_2$ levels taking into account altitude, cargo weight, and truck power [49]. Therefore, the information collected can be expanded to include various sources for improved optimization.

## 3. Materials and Methods

The agent-based model is described following the Overview, Design Concepts, and Details (ODD) protocol [51]; however, the design concept is omitted because it is covered in the introduction and literature analysis sections.

### 3.1. Purpose

The purpose of the agent-based model is to simulate the logistic processes of the food industry and test the proposed system to improve food quality and decrease the level of $CO_2$ emissions. In this publication, the resilience of the system is related to disturbances, which are defined as traffic accidents and cannot be supervised by regular data analysis. Meanwhile, sustainability is the quality of food products, food waste, and $CO_2$ emission levels. Therefore, the idea is to provide systems adaptation possibilities, which would provide resilience and maintain a higher level of sustainability. The secondary goal of the model is to perform a sensitivity analysis to identify the relationship between resilience and sustainability in different scenarios of the food industry. The food industry will be distinguished by categories of market type and population density. The general concept of the model is provided in Figure 1.

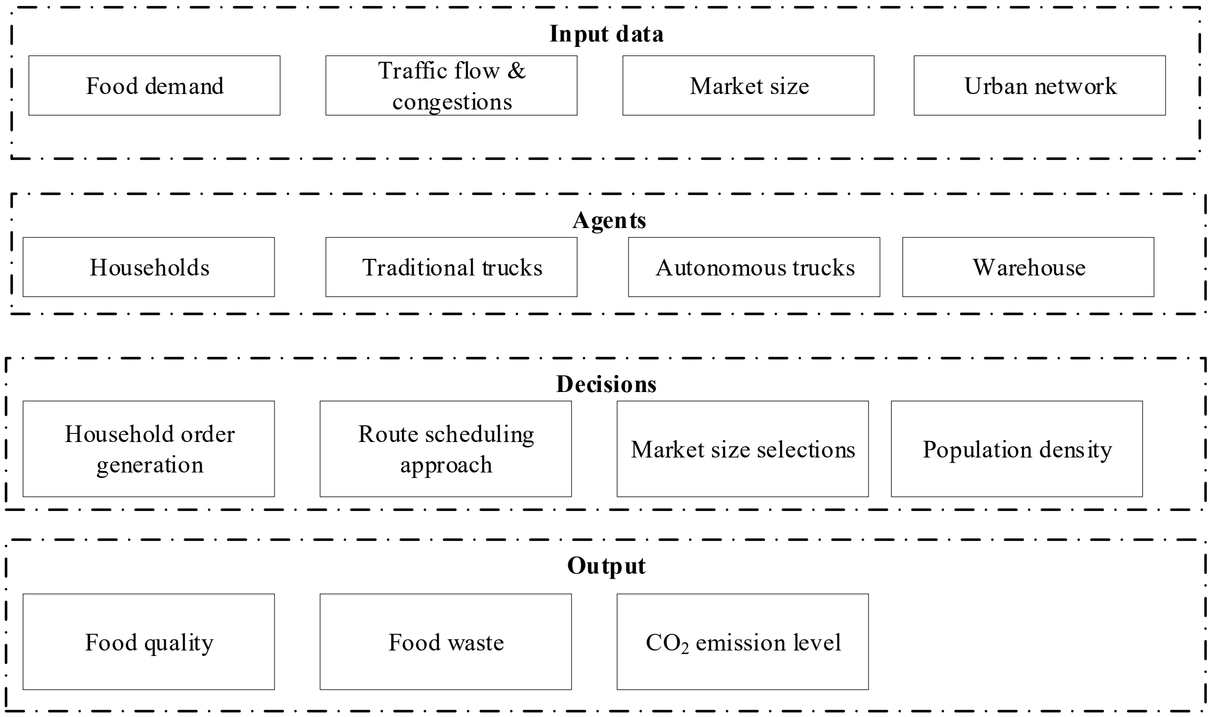


**Figure 1.** Agent-based modelling approach for information sharing analysis for route scheduling and food quality determination.

### 3.2. Main Variables and Scale

Table 1 represents four scenarios in total, which will be used for testing information sharing between all vehicles and no information sharing; therefore, there will be a total of 8 scenarios. The aim of the publication is to identify the relationship between food quality, $CO_2$ emission level, and disruptions; therefore, exact numbers are not necessarily required to represent precise cases; it is important to maintain the relationship between them and change only the analyzed variables, which is defined as ceteris paribus in economics. The number of households in the simulation was set to 400. The distance between consumers was a fixed number of grids, which were used for spatial modelling in NetLogo. The proposition of these indicators was derived from the macro-indicator analysis described above. The average speed of a car is 100%, which represents 60 km per hour with no traffic flow and accidents. In the case of low population density, the speed was set to 90%, while in the case of high population density, it was set to 75%. Then the type of market is based on household interactions. In a small market, it is assumed that the cluster works with 80% of the market, since there are only a few producers, while in the large market type, only 20% of the market share was maintained. The truck number in the large market type was set to 2, while in the small market type, it was set to 4. The number of trucks was set based on the number of households in the market; the purpose was to use as few trucks as possible to fully meet the market demand, otherwise there would be no food waste. More detailed argumentation of the traffic speed is provided in Section 3, "Disturbances".

**Table 1.** Scenario Description.

| Scenario | Market Type | Population Density |
|---|---|---|
| 1 | Small | Low density |
| 2 | Small | High density |
| 3 | Large | Low density |
| 4 | Large | High density |

### 3.3. Process Overview and Scheduling

Firstly, during the initialization of the model, the road network distance was defined based on population density, household number, and fulfilment center. In this simulation case, the harvesting and processing stages were not considered. Distribution centers are placed outside city limits in the suburbs. There were seven types of disturbance levels depending on the level of traffic accidents and the relationship with speed reduction and conjunction time. A more precise description of disturbance types is presented in the input section. The truck scheduling process will depend on whether the information is shared between all vehicles or not. If the information is not shared at all, it essentially represents a simple routing approach only considering the historical speed information. However, in the case of information sharing, traffic flow information is shared in real time between all vehicles.

Figure 2 shows the agent-based model, which is based on the research of Hubner et al. (2016) [52] and Fikar (2018) [20]. First, households make orders, which consist of demand distribution and a 2 h time window for delivery between 8:00 a.m. and 6:00 p.m. based on binominal distribution. Then this order is received at the fulfilment center. With this information, the number of trucks is planned, and depending on the selected truck type, route schedules for individual trucks are generated. Then the deliveries are made, and at 7:00 p.m., the trucks return to the fulfilment center, after which the process is repeated. During deliveries, traffic flow and accidents will be generated, which will disrupt the logistic processes and cause deviations from the planned food quality levels. The speed of the trucks will decrease due to traffic accidents and the influence on food quality will be measured. In practice, companies usually allocate trucks to a particular region for deliveries. However, in this case, the companies need more trucks than necessary. Another difference in practice is that smaller hubs start to be placed within city limits to minimize the distance travelled by trucks. In this simulation, we propose placing a fulfilment center in the suburbs to minimize the costs of land and assets.

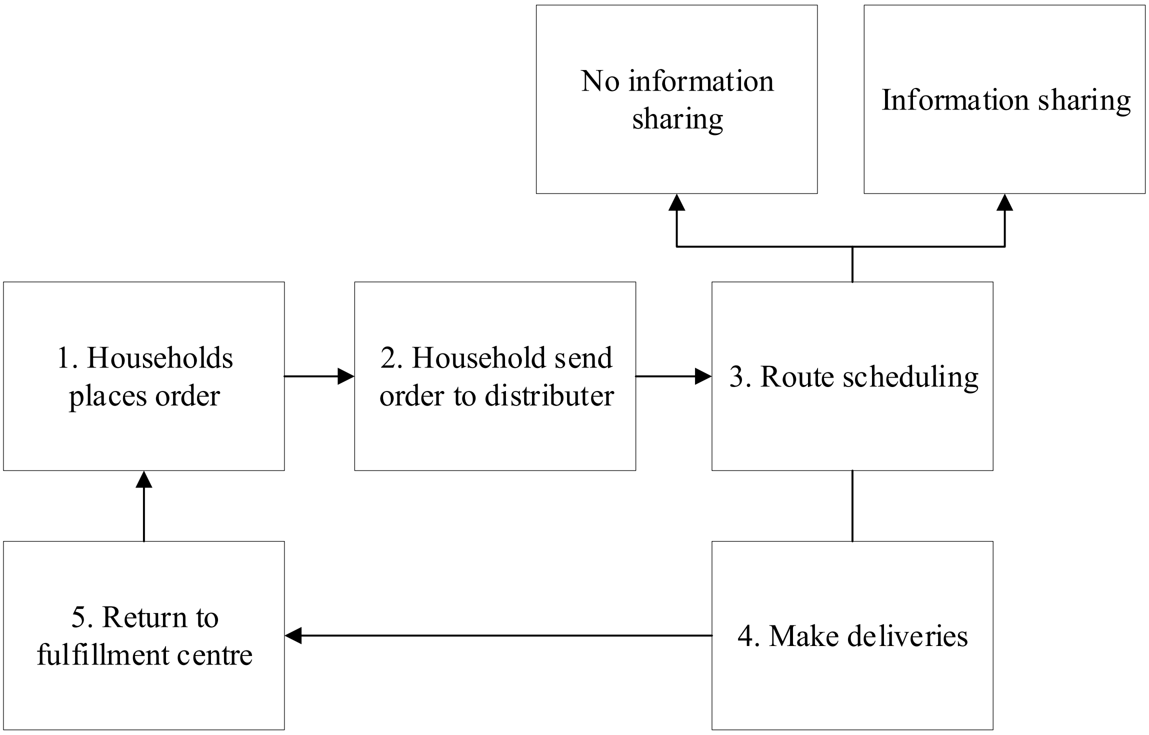


**Figure 2.** The model process.

The main difference in agent behavior is related to the scheduling of the truck route, which is influenced by the information level of the network. In the case of no information sharing, only general information about the traffic flow and speed limits is used. In the case of information sharing, the quantity of information between the vehicles increases. In practice, information can be gathered related to various sources such as pedestrian flow, traffic light malfunctions, road quality, and so on. In this simulation, we limited the disturbance information to only the traffic flow, which is caused by traffic accidents and cannot be foreseen from historical data analysis. Data analysis of traffic flow can provide information about travelling time and speed reduction; however, additional data on traffic accidents in the route-planning process could lead to the system being more resilient.

Figure 3 represents the theoretical and ideal routing case depending on the level of information exchange. In the case of no information sharing, routing is based on ideal conditions and historical speed data; however, in practice, due to disruptions in the system, the delivery takes longer than planned. However, by allowing information to be shared between all vehicles, the routing process can be improved, which will influence the food quality and $CO_2$ emission level.

This concept can be explained as the use of cyber-physical systems in the management of the supply chain. Guo et al. (2020) conducted research focusing on the application of cyber-physical systems for production-logistics systems [53], while in this publication, we amplify the benefits of cyber-physical systems in last-mile logistics. Cyber-physical systems can be defined in 3 layers. The first layer is the physical world, from which information is gathered with sensors and transmitted to the cyber layer. In between them, there is a network that connects the physical layer to the cyber layer. In this case, autonomous trucks have in-built sensors, which gather information. Then, traffic accidents are estimated in the cyber layer from historical data. Afterward, the recommended decision is sent back to the physical layer, and the system adjusts itself.

In this case, the flexibility approach to achieve system resilience is provided, which can be defined as a self-learning system.

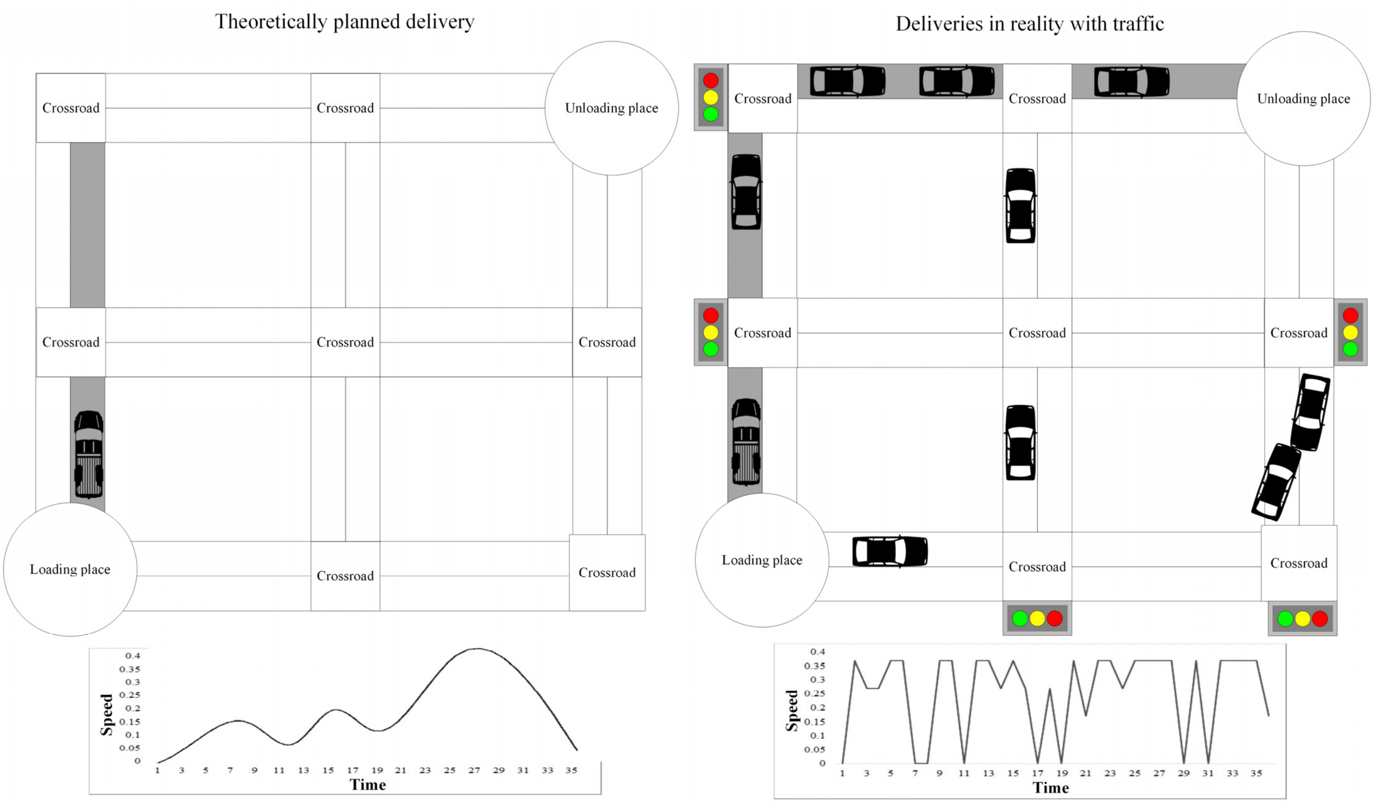


**Figure 3.** Comparison of the planned and actual deliveries.

### *3.4. Design Concept*

The agent-based model attempts to reproduce the process of food delivery to the end consumer. We model the main processes related to last-mile logistics and make some assumptions about agricultural aspects. The second environment that we reproduce is the specifics of the city related to traffic lights, other cars, traffic accidents, congestion, and households (see Figure 4). More specifically, the model primarily has 3 agents involved and 2 types of patches (which is 1 grid representation in Netlogo).

The first type of agent is the household (orange), which is the main actor in the simulation. The household places the orders for food products and selects a time window for delivery; the truck is also assigned to the household. The second type of agent is the truck (yellow), which is responsible for the delivery of the products from the warehouse to the home. The main variables of the truck are related to speed, the type of accident, and other movement variables such as the wait time in the direction near traffic lights. The car agent type (blue) is similar to the truck from the variable perspective; however, cars drive randomly through the city to simulate traffic congestions. When multiple cars and trucks are on the road, it is not possible for the truck to overtake the car, thus deliveries tend to be delayed. This choice was made to limit the complexity of the model and maintain a proper run time. The statement means that when a truck is moving on the road, if the car ahead has been in a traffic accident (that is, speed is reduced), the truck's speed is also reduced, and the truck cannot overtake the car ahead. The Netlogo interface is modelled in grids, which are called patches. In the simulation, we have 2 main types of patches with which agents interact. The first type is the warehouse, which is responsible for loading and unloading cargo from the truck (white). When the truck reaches the warehouse location, the database with the inventory list is updated with the status of the delivery, waste levels, and so on. The second type of patch is an intersection, which is responsible for simulating traffic accidents and traffic lights (red, green, and black). The main patch is the middle of the interaction, which defines the behavior of the side patches to simulate traffic lights. Traffic lights change color at fixed intervals from red to green, and when the red is shown, trucks and cars must stop and wait for the light to change. The middle of the intersection is responsible for the simulation of traffic accidents. Through predefined probabilities, the intersection can change color to black, indicating that a traffic accident occurred; because of this, the average speed of trucks and cars is reduced. Other patches are simply the representation of the industrial location (dark brown), roads (white), and the warehouse (larger area white). The trucks are shown in yellow and the cars in blue. Households are represented in orange.

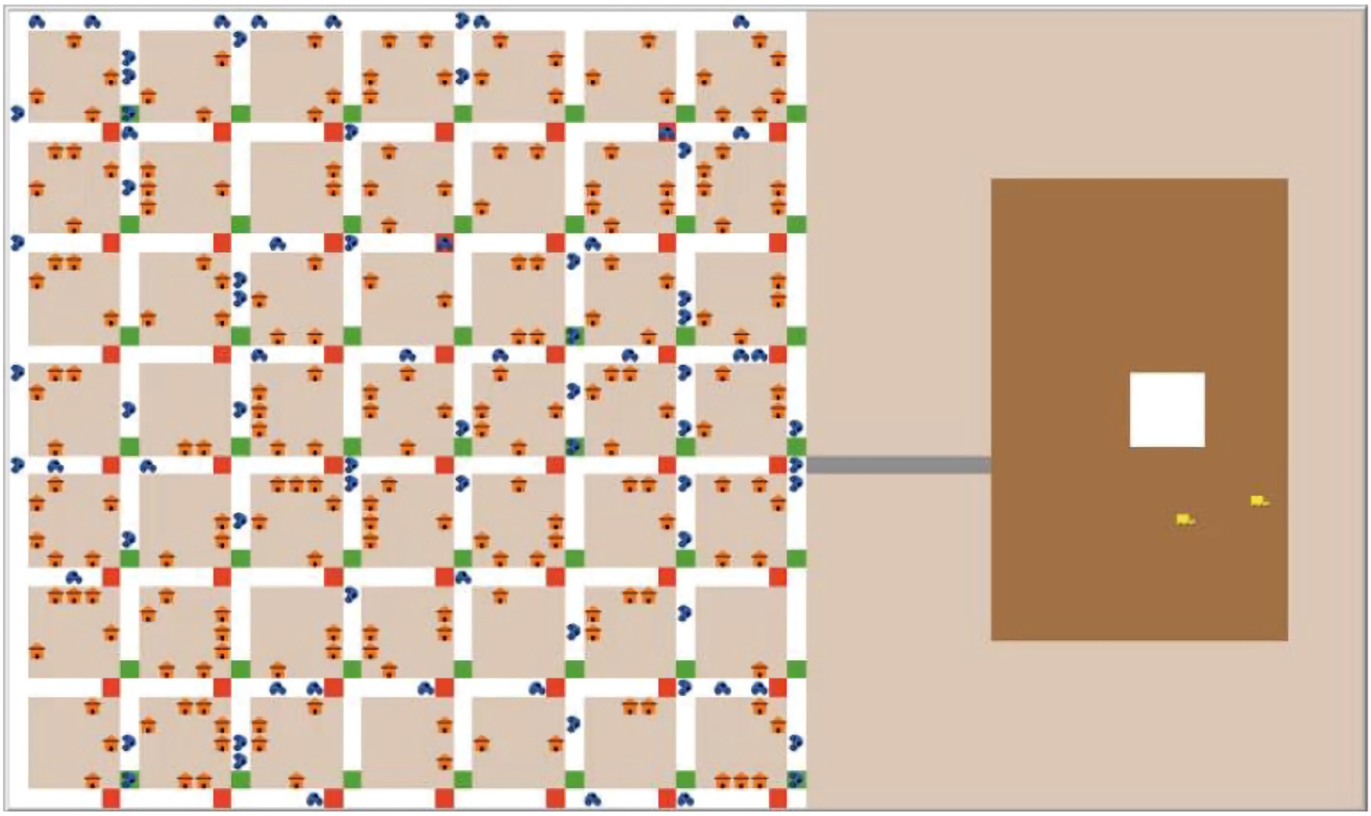

**Figure 4.** Visualization of the agent-based model in Netlogo.

The model might seem too abstract; however, to simulate multi-agent behavior and properly understand the analyzed phenomena, the main trade-off between simple and complex must be solved. If the model is too complex, it might be infeasible to simulate it; however, if the model is too simple, it cannot provide insight into the analyzed phenomena. Thus, in this case, a more abstract approach was chosen to present the initial methodological approach for analysis. In future research, the methodological approach will be applied to an actual case study. However, in this simulation, the proposed model provides information on how the consideration of information sharing between vehicles can improve route planning and allow the development of higher food quality levels and reduction of $CO_2$ emissions.

### 3.5. Initialization, Inputs, and Sub-Models

The simulation of urban logistics focuses on online grocery ordering and aims to determine the relationship between disturbances and food quality. The model uses wholesale data, representing different product categories represented in Table 2. However, the generic food quality model developed by Tijksens and Polderdijk (1996) focuses only on vegetables [54]. The data represent different product categories. A generic approach to products in the simulation will be used, i.e., conclusions for specific product supply chains will not be made, but general conclusions for the food industry will be developed.

**Table 2.** Fitted Distribution Functions Based on empirical data.

| Product Category | Distribution | Coefficient 1 | Coefficient 2 |
|---|---|---|---|
| Frozen products | Pareto | 8.02 | 10.83 |
| Flour products | Log logistics | 0.53 | 1.03 |
| Ice products | Burr | 0.84 | 2.11 |
| Meat products | Burr | 0.89 | 1.81 |
| Milk products | Pareto | 8.02 | 10.83 |
| Pasta products | Log logistics | 0.56 | 0.99 |
| Spices | Log normal | 0.56 | 0.99 |

### *3.6. Demand of Consumers*

Data were collected from 5 food companies, comprising 7 product categories and 838 products [55]. The fitdistrplus package in R (Delignette-muller and Dutang, 2015) was used to fit the distributions [56]. The package analyzes the Pareto, Log Log Logistics, Burr, and Log Normal distributions to the data, and the distributions are chosen based on the goodness of fit statistic. The chosen distributions are presented in Table 2.

During the simulation, the household randomly selects one type of category per order. A fixed random seed is set for all scenarios to maintain validity for comparison.

### *3.7. Food Quality*

Food quality is evaluated following the same approach as Fikar (2018) developed in an agent-based model [18,19]. The approach uses the generic shelf-life model of Tijksens and Polderdijk (1996) [54].

$$k = k_{ref} * e^{\frac{Ea}{R} * \left(\frac{1}{T_{ref}} - \frac{1}{T}\right)} \tag{1}$$

$k$—spoilage rate in days.
$T$—temperature in Kelvin.
$k_{ref}$—spoilage rate at reference temperature $T_{ref}$ and is equal to 1.
$Ea$—energy activation.
$R$—gas constant.

$$KQ = \frac{Q_0 - Q_L}{k} \tag{2}$$

$KQ$—remaining shelf life.
$Q_0$—current quality.
$Q_L$—quality limit.

The reference temperature $T_{ref}$ is equal to 283.15 K (or 10 °C). The energy activation and gas constant ratio ($\frac{Ea}{R}$) is set to 12,067.5, based on the average value of the table presented by Tijskens and Polderdijk (1996) [54]. The spoilage rate ($k_{ref}$) is equal to 1. The current quality $Q_0$ of product is equal to 1. The $Q_L$ quality limit is equal to 1 day. The storage temperature of the products in the fulfilment center is equal to 283.15 K, while the storage temperature during delivery is equal to 277.15 K. The remaining shelf life $KQ$ decreases by 1 for each day, assuming linear kinetics.

The simulation does not include the harvesting and food processing stages; therefore, it is assumed that 40% of the food quality is assumed to be lost in the initial stage and only 60% reach the distribution center [57]. Since the simulation uses generic products and does not distinguish categories, we assume that the average shelf life is equal to 5 days. Therefore, once in the distribution center, the shelf life of the product will have already lost 40% of its initial shelf life, therefore the reference shelf life ($KQ_{ref}$) would be equal to 3 days. Therefore, if deliveries are made late and the product reaches the end consumer when the remaining shelf life is 1 day, the product is considered food waste. In an organic food market, the consumer desires high-quality food; therefore, this criterion is met to provide higher consumer satisfaction. When a product is returned to the fulfilment center due to disturbances, the next day, we ignore the products that could not be delivered on time before being assigned as waste and select other products. Shelf life is continuously updated, while the total amounts are calculated before running the next-day simulation. Food quality is expressed as the remaining shelf life; food waste is assigned only when the shelf life reaches 0. The number of food waste is the number of products that have a shelf life of less than 0.

### 3.8. Disturbances

Some researchers might argue that daily disturbances do not influence the efficiency of the system as much as force majeure. However, Calvert and Snelder (2018) indicated that minor disturbances in traffic and transport systems can also play an important role in reducing efficiency [8]. In this simulation, disturbances are defined as traffic accidents and accidents that cannot be controlled by regular data analysis. Traffic flow statistics are used from the traffic grid model, which is included in NetLogo [58]. The number of cars running in the city is set at 60% of the market size. Then the speed of traffic is reduced by 64% between 8:00 a.m. and 9:00 a.m. and reduced by 68% between 5:00 and 6:00 p.m. [59].

Table 3 represents the levels of traffic accidents, which are derived from the UK traffic accident statistics [60]. The higher the intensity, the higher the speed reduction. The probabilities are derived from the analysis of UK traffic accident statistics in the period 2009 to 2014, considering only the London region. Statistics provides an evaluation of traffic severity, the scale of which is a categorical variable from 1 to 3, where 1 is a fatal condition and 3 is slight. In our case, the severities are related to the intensity levels of low, medium, and high. Then the statistics provided the number of vehicles involved in the accident, and the best evaluation interval was estimated to be more than 4 or less. Subsequently, the accident statistics of the London region were clustered using the k-mean algorithm, and using the elbow method, the optimal number of clusters was determined. Then the frequency of events in every cluster group was evaluated. The quantity of conjunction in accident statistics was determined using the DBSCAN algorithm with the haversine metric and a radius of 100 meters. Then the influence of these speed disturbances was evaluated by analyzing the Finnish Transport Agency analysis [61]. Lastly, the probabilities per conjunction increased by 2 because traffic conflict increases with an increase in traffic density [62]. The conjunction is assigned to a cluster with a specific accident probability derived from the statistics used in Table 3.

**Table 3.** The level of traffic accidents.

| Cluster ID | Traffic Accident | Vehicles Involved | Probability Per Conjunction | Reduction to Speed | Accident Duration (min) |
|---|---|---|---|---|---|
| 0 | Low | Less than 4 | 0.000628 | 15% | 60 |
| 1 | Low | Less than 4 | 0.000596 | 15% | 60 |
| 2 | High | Less than 4 | 0.000008 | 70% | 150 |
| 2 | Medium | Less than 4 | 0.000128 | 30% | 90 |
| 3 | High | More than 4 | 0.000004 | 85% | 180 |
| 3 | Medium | More than 4 | 0.000006 | 65% | 120 |
| 3 | Low | More than 4 | 0.000046 | 30% | 90 |

Every tick conjunction will have a probability based on the traffic accident level to change its state to the level, and once it changes state, the next cars driving through the conjunction will be affected by the speed reduction for a fixed amount of time. In reality, all traffic should stop and try to overtake congestion, but in this case, the speed will be reduced, affecting all cars behind and causing a ripple effect across the network. This simplification helps to reduce the complexity of the model and reduce run time.

### *3.9. Measurement of the Environmental Impact*

We assume that in the model, 100% speed is equal to 60 km per hour, and it decreases according to traffic and accidents. The simulation is modelled in seconds, where 1 tick is equal to 6 s.

The modelling approach in NetLogo is a patch, where 1 patch is equal to 0.1 km. Based on these assumptions, the emission level (g/km) can be evaluated by Formula (3) [63].

$$E = 0.0343 * v^2 - 5.1159 * v + 367.86 \tag{3}$$

where $E$ is the emission level (g/km) and $v$ is the speed (km per hour).

Then the $CO_2$ emission level for the refrigerator unit is added to the emission level caused by the fuel consumption of driving. Products are delivered with the temperature controlled at 277.15 K or 4 °C (chilled), and the refrigerator unit consumes 1 liter of diesel per hour, which is obtained from the publication of Navickas et al. (2015) which evaluated fuel consumption by trailer area to fit the type of light vehicle type [64]. In this case, 1 liter of diesel consumed for the refrigerator generates 2900 g of $CO_2$ emissions [65]. Therefore, the total amount of $CO_2$ emission is defined in Formula 4. The generation of the level of $CO_2$ emission from warehousing is not considered in this publication because the change in operations is performed in the stage of product distribution and not inventory management.

$$TEL = \sum_{k}^{K} E_k * TD_k + RUE_k \tag{4}$$

where $TEL$ is the total emission level, $TD$ is the total distance travelled, $RUE$ is the emission level of the refrigerator unit, and $K$ is the maximum truck quantity, $k \subseteq K$.

### *3.10. Route Scheduling Approaches*

The model uses first principal rules to define the main processes of ordering and delivery. Then the environment is reproduced as a city with traffic flow and accidents. Figure 5 provides a brief explanation of the importance of information sharing and the possibility of estimating traffic jams. In this part, the mathematical expression of the route scheduling approach will be elaborated.

In the beginning, two grids representing the suburbs region and the urban region will be generated. In the suburban region, we create a fulfilment center and connect it with a road to the urban region. The size of the urban region is generated based on the selected market size. Currently, there is a tendency to focus on decentralized warehouse networks and place hubs in urban areas, but in our case, we want to show how it is possible to improve effectiveness through information sharing by minimizing costs. Of course, pick-up places can be allocated in the city for increased customer satisfaction. Furthermore, we allowed the traffic to flow freely in the region without disturbances and without any deliveries. We ran this simulation for 5 days and evaluated the average speed per patch per time. By doing this, we obtained a graph (G) with households, fulfilment centers, and intermediate stops with averaged times between neighboring stops at each hour. Afterward, we reevaluated the graph to fit only households and fulfilment centers by time travelled for every hour and obtained a set of RN nodes. Using the initial simulation results, we constructed the graph time travelling matrix as an approximation function set, which represents the travel time between the graph nodes at a specific time (see Formula (5)).

$$RNM = \begin{bmatrix} f(RN_{1,1}, t) & \ldots & f(RN_{1,n}, t) \\ \ldots & \ldots & \ldots \\ f(RN_{n,1}, t) & \ldots & f(RN_{n,n}, t) \end{bmatrix} \quad (5)$$

where function $f\left(RN_{i,j}, t\right)$ represents the travel time from the $i - th$ node to the $j - th$ node at time $t$.

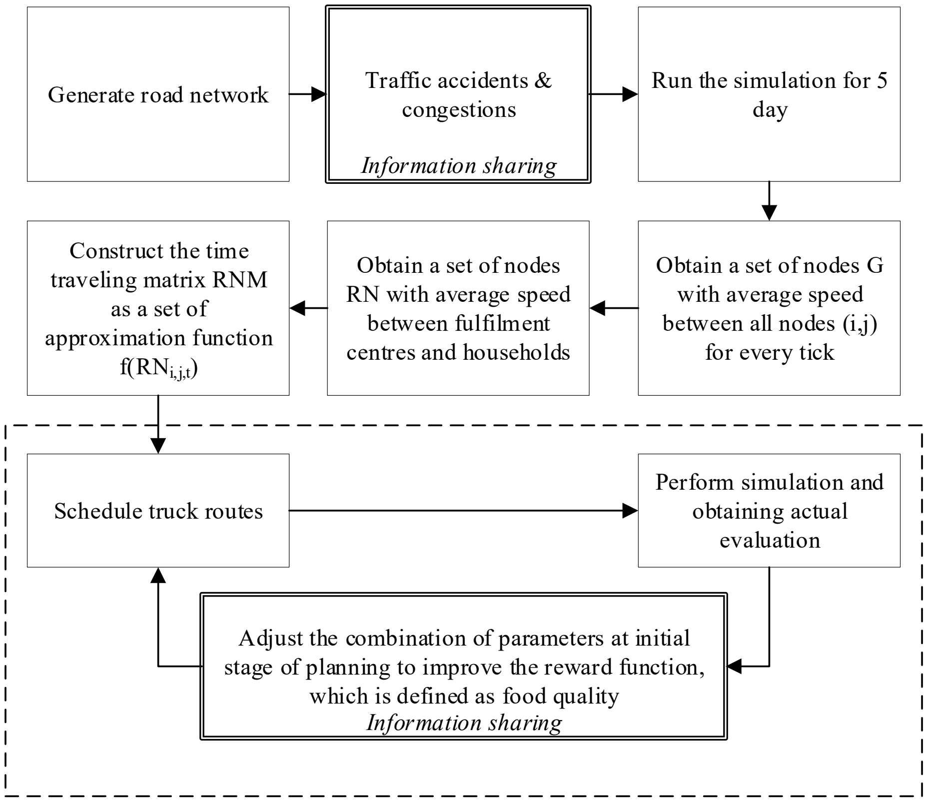


**Figure 5.** Route-scheduling process of information sharing and no information sharing.

In this way, we represent the practice that is currently being used: Companies analyze historical traffic data and plan their routes based on that. Then we receive the orders from the households, which consist of the order size and selected 2 h delivery time window between 8:00 a.m. and 6:00 p.m. based on multimodal distribution. We determine the truck number considering the maximum number of customers served per truck (the maximum number of customers is 25) and order information and obtain the travelled time. In this case, we are not specifying capacity constraints based on weight or product quantity but rather on customers served since the online grocery industry does not have large weights. Then, by considering the truck quantity, delivery time window, and the obtained graph, we formulate the final schedules (*SH*) for every truck. The algorithmic approach is based on the large neighborhood search for the pickup and delivery problem with time windows [22,24,25]. The final schedule evaluation E for the traditional truck approach is described as the remaining shelf life of household orders, which depends on the storage duration and the delivery duration (see Formula (6)).

$$\mathrm{E} = \sum_{i=1}^{|\mathrm{HO}|} KQ_{HO_i} \quad (6)$$

where |HO| is the amount of the set of scheduled household orders HO and $KQ_{HO_i}$ represents the value of the remaining shelf line indicator (see Formula (2)).

When the routes are planned, we evaluate the food quality, food waste, and emission levels and save them as planned indicators. The deliveries in our situation must be made from 8:00 a.m. to 6:00 p.m.; afterward, the trucks are returned to the fulfilment center and the products that were not delivered on time are sent back to the fulfilment center. The quality of the products decreases with the passage of time, while the level of $CO_2$ emission is evaluated only during deliveries. This assumption is made because the inventory management strategy is always the same and the optimization approach changes only for deliveries. During the next day, products that expire before the start of the delivery time window are ignored during this selection, and others are selected based on the first-expiration-first-out (FEFO) rule [21].

During this process, we also evaluate the number of trucks and their utilization, i.e., the percentage of customers served per truck, and save the food quality, food waste, and $CO_2$ emission levels as actual indicators, while the final actual evaluation $E_a$ of the traditional truck approach is expressed as

$$E_a = \sum_{i=1}^{|AHO|} KQ_{AHO_i} \tag{7}$$

Here, |AHO| is the amount of the set of actually served household orders AHOHO.

## 4. Results

A constant random seed is set to maintain variability in the model, and only different scenarios influence the output of the model. In this way, the main environmental variables are constant, and only the analyzed variables are changed (ceteris paribus). One simulation scenario was run for 67,500 ticks or 10 days considering that all deliveries can be made from 8:00 a.m. until 7:00 p.m. The results of the model output are presented in Tables 4–7.

**Table 4.** Model output of planned and actual values obtained of the model (numbers represent day average of the simulated period).

| Scenario | No Information Sharing | | | | Information Sharing | | | |
|---|---|---|---|---|---|---|---|---|
| | Food Quality | | Food Waste | | Food Quality | | Food Waste | |
| | Planned | Actual | Planned | Actual | Planned | Actual | Planned | Actual |
| 1 | 84,413 | 77,474 | 15,257 | 19,047 | 81,417 | 80,163 | 18,158 | 18,975 |
| 2 | 86,666 | 79,356 | 14,975 | 19,181 | 79,270 | 77,956 | 18,156 | 18,997 |
| 3 | 31,046 | 29,544 | 507 | 1154 | 30,827 | 30,687 | 782 | 829 |
| 4 | 31,568 | 30,475 | 514 | 909 | 30,876 | 30,519 | 772 | 953 |

**Table 5.** MAPE by main model scenarios, food quality, and waste of actual and planned.

| Scenario | No Information Sharing | | Information Sharing | |
|---|---|---|---|---|
| | Food Quality | Food Waste | Food Quality | Food Waste |
| 1 | 10.04 | 25.50 | 1.78 | 4.82 |
| 2 | 10.46 | 28.20 | 2.33 | 3.61 |
| 3 | 4.69 | 115.61 | 0.46 | 6.09 |
| 4 | 3.38 | 81.02 | 1.17 | 37.59 |

**Table 6.** Model output of the planned $CO_2$ emission level and actual values obtained by the model (numbers represent the average simulated period).

| Scenario | No Information Sharing | | Information Sharing | |
|---|---|---|---|---|
| | $CO_2$ Emission Level | | | |
| | Planned | Actual | Planned | Actual |
| 1 | 224,142 | 189,524 | 175,261 | 171,425 |
| 2 | 224,100 | 189,466 | 173,125 | 167,777 |
| 3 | 127,403 | 129,370 | 119,003 | 115,219 |
| 4 | 128,883 | 129,250 | 118,516 | 115,016 |

**Table 7.** MAPE by main model scenarios and $CO_2$ emission level of actual and planned.

| Scenario | No Information Sharing | Information Sharing |
|---|---|---|
| | $CO_2$ Emission Level | $CO_2$ Emission Level |
| 1 | 15.40 | 2.16 |
| 2 | 15.41 | 3.09 |
| 3 | 1.87 | 3.20 |
| 4 | 2.65 | 2.95 |

Table 4 represents the actual and planned food quality and food waste. The planned variables are obtained by creating a theoretical schedule based on the orders and available trucks, while the actual is the execution of the schedule in the environment with disruptions. It can be seen that the largest difference between the planned and actual values is in Scenarios 1 and 2. These scenarios represent a small market size; the difference with no information sharing is 8.96% for a low population density and 9.21% for a high population density. Meanwhile, with information sharing, the difference is 1.56% and 1.69%. A similar improvement can be seen when comparing food waste with Scenarios 1 and 2; the difference is 19.90% and 21.93%, while with information sharing it is 4.31% and 4.43%. In some scenarios, the actual food quality of noninformation sharing is better than the actual food quality with information sharing (e.g., scenario 2). The reason behind these results is that, essentially, when using information sharing, we are estimating possible traffic accidents and distributions during the delivery process. It may be the case that we expect to encounter a disruption during the process, but during the actual delivery, it might be that no disruptions occurred.

Table 5 shows the absolute percentage error (MAPE) of information sharing and non-information sharing. It can be seen that in the levels of the majority of cases, the food quality and waste are lower in the case of information sharing.

Table 6 represents the average level of $CO_2$ emissions per day. Scenarios 1 and 2 with no information sharing showed a difference of 18.27% and 18.28% between planned and actual information sharing, while with information sharing, the difference was 2.24% and 3.19%.

When comparing the MAPE of $CO_2$ levels between information sharing and no information sharing, it can be seen that in the majority of cases, information sharing is more effective.

## 5. Discussion

Food systems have gained more recognition in recent years due to the trend of consumers requiring more local and healthier products [66]. Most research conducted on food systems focused on horizontal collaboration and attempts to integrate agents involved in the decision-making process from farms to government institutions [36,67]. Mulcahy (2017) conducted research regarding the analysis of food systems, indicating several important questions, which are addressed in this paper. The first question is related to methods to increase collaboration between small and large food companies to provide more sustainable and local production. The second question amplifies the fact that there is a limited number of practices with which to implement food systems in large population centers (urban areas) [68]. Our research fills the gap from this perspective. On the other hand, we focus on distribution to end-consumers. One of the key practices to increase food access in urban regions and maintain higher food quality levels is to shorten the supply chain. Aubry and Kebir (2013) indicated the importance of shortening the food supply chain. There is a tendency to promote the e-commerce channel for the food industry to decrease the length of the system even more [35]. Collison et al. (2019) analyzed fresh food product delivery and emphasized the need to shorten the supply chain to reduce food waste [69]. On the other hand, we provide a collaborative approach, which involves information sharing and the application of cyber-physical systems in the management of the food supply chain. Ambulkar (2015) analyzed supply chain disturbances from the perspective of a strategic focus on innovations and indicated that although they may be committed to innovation, firms may differ in the degree to which they actively support the innovation efforts taking place across the network on its behalf [70]. If suppliers are not well integrated or if there are alignment issues with the firm's strategy, innovation focus can lead to less coordinated actions within the supplier network and, thus, greater disturbances in fulfilling market demand."

The flexibility approach aimed to optimize the transportation planning process to improve food quality in a dynamic environment. Osvald and Stirn (2008) conducted research on a vehicle routing problem involving perishable products using time-dependent optimization and incorporating the cost of food waste into the goal function [25]. Rong et al. (2011) focused on optimizing the supply chain from production to retail, making a significant contribution through the measurement of food quality loss based on the flow and quantity [45]. A more recent study analyzed the impact of food quality loss in urban logistics, with a particular focus on inventory management strategies and delivery time mboxciteB20-mathematics-2137560,B21-mathematics-2137560. Haass et al. (2015) conducted research on an approach to delivering bananas by sea rather than by land transport, which involved measuring the initial quality of the food and optimizing the quality level to determine the routes [50]. However, no simulation was found that would integrate transportation into the food industry considering traffic jams and accidents [8,71]. Due to this reason, the agent-based model of flexibility provides several contributions. Several limitations of the research can be stated. Firstly, we did not consider different inventory management policies and focused solely on the scheduling process. The limitation of the scheduling process is that it only considers traffic flow and accidents; however, a wider range of information from the environment can be gathered, which would allow for optimizing the routes more effectively. Such integration of information sharing with reinforcement learning can allow adaptation possibilities for members of the logistic cluster members. Another limitation of the scheduling process is that the schedules were generated at the beginning of the day and were not changed during actual delivery, which should be implemented in real-life applications, but at the simulation level, due to model complexity, it would be difficult to implement and validate as the computational resources may be too large to perform a large-scale simulation. The third limitation of the simulation is that validation with actual deliveries is not possible, which is commonly used in discrete event simulations. However, the processes and input data of the simulation are grounded. Additionally, the model was validated by applying 'Animation' [72], where all agent behavior may be tracked graphically during the simulation; therefore, this limitation does not reduce the insight obtained from the simulation. The fourth limitation is that autonomous vehicles (or connected vehicles) can, by themselves, lead to a reduction of the negative environmental impact from a technological view. However, our research focus was mainly on information sharing and route scheduling rather than technological aspects. If both of these aspects were combined, a bigger reduction in $CO_2$ emission could be achieved. The reader is directed to the Autonomous Vehicles overview provided by Wiseman (2020) for details [73].

## 6. Conclusions

In this publication, we proposed a system to increase food quality and decrease the level of $CO_2$ emission during the last-mile delivery of food products. We identify that daily disturbances influence food quality and $CO_2$ emission levels; therefore, it is important to maintain system resilience in order to reduce the negative effect of disturbances on sustainability. The system focuses on applying cyber-physical systems in the food industry. In this case, vehicles with sensors are represented in the physical layer of the cyber-physical systems. In the cyber layer, routing simulations are conducted to decide the most optimal routes. Subsequently, the decisions are executed by the vehicles, thus creating a self-learning system. The described approach explains how, by applying resilience approaches, flexibility and sustainability of the food industry can be achieved, i.e., increased food quality and decreased $CO_2$ emission levels. It is important to note that the proposed system focuses on increasing information sharing without increasing the number of trucks or warehouses. The possibility of increasing system effectiveness with the same number of assets would allow companies to achieve a competitive advantage. To fully utilize the system, it is recommended to form a logistic cluster between the involved members to allow better use of trucks and gathered information. In practice, connected vehicle technology should be applied and integrated with the infrastructure to encourage the variety of data sources even further, which is a promising research area for the future. The present study introduces a route scheduling approach that can be implemented in a range of autonomous vehicles, with a particular emphasis on trucks in the simulation case. This approach may be particularly applicable to densely populated urban areas. Prior research by Figliozzi (2020) highlighted the potential for the use of drones, autonomous delivery robots, and autonomous road autonomous delivery robots [74]. It is suggested that the proposed approach to information sharing and enhanced route scheduling could be adapted to other types of autonomous vehicles, which represents a promising direction for future research.

The main theoretical novelty of the publication is the evidence provided that traffic accidents and congestions (i.e., resilience) do influence sustainability (i.e., food quality and $CO_2$ emission level). Some researchers argue that minor disruptions do not influence logistics processes; however, the identified relationship between resilience and sustainability provides the grounding that minor disruptions are important in food delivery processes. Thus, the concept of supply chain resilience, which primarily focuses only on macro-level analysis, can be expanded to focus on micro-level disruptions as well.

In future research, the methodological approach developed will be applied to a precise case by considering the actual road infrastructure, warehouse and supermarket locations, and online purchasing behavior.

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## References

1. United Nations. *World Population Prospects*; United Nations: New York, NY, USA, 2015.
2. Conrad, H.; Alan, C.; Katherine, R. *The Future of World Religions: Population Growth Projections, 2010–2050*; Pew Research Center: Washington, DC, USA, 2015.
3. Euromonitor International. *The Global State of Online Grocery*; Euromonitor International: London, UK, 2017.
4. United Nations. *World Urbanization Prospects*; United Nations: New York, NY, USA, 2014.

5. Food and Agriculture Organization. *The Future of Food and Agriculture: Trends and Challenges*; FAO: Rome, Italy, 2017; ISBN 978-92-5-109551-5.
6. Ranieri, L.; Digiesi, S.; Silvestri, B.; Roccotelli, M. A review of last mile logistics innovations in an externalities cost reduction vision. *Sustainability* **2018**, *10*, 782. [CrossRef]
7. Council of the European Union. *Food Losses and Food Waste*; Council of the European Union: Brussels, Belgium, 2016; Volume 2016, pp. 1–12.
8. Calvert, S.C.; Snelder, M. A methodology for road traffic resilience analysis and review of related concepts. *Transp. A Transp. Sci.* **2018**, *14*, 130–154. [CrossRef]
9. Köster, F.; Ulmer, M.W.; Mattfeld, D.C. Cooperative traffic control management for city logistic routing. *Transp. Res. Procedia* **2015**, *10*, 673–682. [CrossRef]
10. Faccio, M.; Gamberi, M. New city logistics paradigm: From the 'Last Mile' to the 'Last 50 Miles' sustainable distribution. *Sustainability* **2015**, *7*, 14873–14894. [CrossRef]
11. Seebauer, S.; Kulmer, V.; Bruckner, M.; Winkler, E. Carbon emissions of retail channels: The limits of available policy instruments to achieve absolute reductions. *J. Clean. Prod.* **2016**, *132*, 192–203. [CrossRef]
12. Carling, K.; Han, M.; Håkansson, J.; Meng, X.; Rudholm, N. Measuring transport related $CO_2$ emissions induced by online and brick-and-mortar retailing. *Transp. Res. Part D Transp. Environ.* **2015**, *40*, 28–42. [CrossRef]
13. Nabot, A.; Omar, F. Comparative Study of the Impacts of Conventional and Online Retailing on the Environment: A Last Mile Perspective. *Int. J. Comput. Appl.* **2016**, *138*, 6–12. [CrossRef]
14. Kellner, F. Insights into the effect of traffic congestion on distribution network characteristics—A numerical analysis based on navigation service data. *Int. J. Logist. Res. Appl.* **2016**, *19*, 395–423. [CrossRef]
15. Green, J.J.; Worstell, J.; Canarios, C. The Local Agrifood System Sustainability/Resilience Index (SRI): Constructing a data tool applied to counties in the southern United States. *Commun. Dev.* **2017**, *48*, 697–710. [CrossRef]
16. Adams, F.; Richey, R.; Autry, C.; Morgan, T.; Gabler, C. Supply chain collaboration, integration, and relational technology: How complex operant resources increase performance outcomes. *J. Bus. Logist.* **2014**, *35*, 299–317. [CrossRef]
17. Arvitrida, N.; Robinson, S.; Tako, A.; Robertson, D. An agent-based model of supply chain collaboration: Investigating manufacturer loyalty. In Proceedings of the Operational Research Society Simulation Workshop 2016, SW 2016, Ettington, UK, 11–13 April 2016; pp. 35–44.
18. Gružauskas, V.; Gimžauskienė, E.; Navickas, V. Forecasting accuracy influence on logistics clusters activities: The case of the food industry. *J. Clean. Prod.* **2019**, *240*, 118225. [CrossRef]
19. Boriboonsomsin, B.; Barth, M. Real-World $CO_2$ Impacts of Traffic Congestion. *Transp. Res. Rec.* **2008**, *951*, 1–23.
20. Fikar, C. A decision support system to investigate food losses in e-grocery deliveries. *Comput. Ind. Eng.* **2018**, *117*, 282–290. [CrossRef]
21. Waitz, M.; Andreas, M.; Fikar, C. A Decision Support System for Efficient Last-Mile Distribution of Fresh Fruits and Vegetables as Part of E-Grocery Operations. In Proceedings of the 51st Hawaii International Conference on System Sciences, Hilton Waikoloa Village, HI, USA, 3–6 January 2018; Volume 9, p. 9.
22. Emeç, U.; Çatay, B.; Bozkaya, B. An Adaptive Large Neighborhood Search for an E-grocery Delivery Routing Problem. *Comput. Oper. Res.* **2016**, *69*, 109–125. [CrossRef]
23. Haass, R.; Dittmer, P.; Veigt, M.; Lütjen, M. Reducing food losses and carbon emission by using autonomous control—A simulation study of the intelligent container. *Int. J. Prod. Econ.* **2015**, *164*, 400–408. [CrossRef]
24. Rong, A.; Akkerman, R.; Grunow, M. An optimization approach for managing fresh food quality throughout the supply chain. *Int. J. Prod. Econ.* **2011**, *131*, 421–429. [CrossRef]
25. Osvald, A.; Stirn, L.Z. A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. *J. Food Eng.* **2008**, *85*, 285–295. [CrossRef]
26. Kearney, J. Food consumption trends and drivers. *Philos. Trans. R. Soc. B Biol. Sci.* **2010**, *365*, 2793–2807. [CrossRef]
27. Campbell, H. Breaking new ground in food regime theory: Corporate environmentalism, ecological feedbacks and the 'food from somewhere' regime? *Agric. Hum. Values* **2009**, *26*, 309–319. [CrossRef]
28. Saskia, S.; Mareï, N.; Blanquart, C. Innovations in e-grocery and Logistics Solutions for Cities. *Transp. Res. Procedia* **2016**, *12*, 825–835. [CrossRef]
29. IGee, M.; Davidson, F.; Speetles, B.; Webber, M. Deliver Me from food waste: Model framework for comparing the energy use of meal-kit delivery and groceries. *J. Clean. Prod.* **2019**, *236*, 117587. [CrossRef]
30. Bjørgen, A.; Bjerkan, K.; Hjelkrem, O. E-groceries: Sustainable last mile distribution in city planning. *Res. Transp. Econ.* **2021**, *87*, 100805. [CrossRef]
31. Nielsen, Food Marketing Institute. 2017. Available online: https://www.fmi.org/digital-shopper (accessed on 17 December 2022).
32. Commission European. *Harnessing Research and Innovation for FOOD 2030: A Science Policy Dialogue*; Commission European: Brussels, Belgium, 2017.
33. European Commission. *Food 2030—Future-Proofing Our Food Systems through Research and Innovation*; Commission European: Brussels, Belgium, 2017. [CrossRef]
34. Radar, D.L.T. DHL Customer Solutions & Innovation, Logistics trend radar. *DHL Trend Res.* **2016**, *20*, 1–48.

35. Aubry, C.; Kebir, L. Shortening food supply chains: A means for maintaining agriculture close to urban areas? The case of the French metropolitan area of Paris. *Food Policy* **2013**, *41*, 85–93. [CrossRef]
36. Lamine, C. Sustainability and resilience in agrifood systems: Reconnecting agriculture, food and the environment. *Sociol. Rural.* **2015**, *55*, 41–61. [CrossRef]
37. Arthur, W.B. Complexity Economics: A Different Framework for Economic Thought. *Complex. Econ.* **2013**, *43*, 1–22.
38. Barrientos, A.H.; De La Mota, I.F. Modeling Sustainable Supply Chain Management as a Complex Adaptive System: The Emergence of Cooperation. In *Sustainable Supply Chain Management*; IntechOpen: London, UK, 2016.
39. Gunasekaran, A.; Subramanian, N.; Rahman, S. Supply chain resilience: Role of complexities and strategies. *Int. J. Prod. Res.* **2015**, *53*, 6809–6819. [CrossRef]
40. Kamalahmadi, M.; Parast, M.M. A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *Int. J. Prod. Econ.* **2016**, *171*, 116–133. [CrossRef]
41. Cordes, P.; Hülsmann, M. Self-healing Supply Networks: A Complex. In *Supply Chain Safety Management*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 217–230.
42. Los, J.; Schulte, F.; Spaan, M.T.J.; Negenborn, R.R. Collaborative Vehicle Routing when Agents have Mixed Information Sharing Attitudes. *Transp. Res. Procedia* **2020**, *44*, 94–101. [CrossRef]
43. Hoffa, P.; Pawlewski, P. Agent Based Approach for Modeling Disturbances in Supply Chain. *Commun. Comput. Inf. Sci.* **2014**, *430*, 144–155. [CrossRef]
44. Ronga, A.; Akkermanc, R.; Grunowc, M. Dielectric properties of a polyethylene-acrylamide blend after plastic flow under high pressure. *Polym. Sci. USSR* **2011**, *31*, 2838–2843.
45. Shladover, S. Connected and automated vehicle systems: Introduction and overview, Journal of Intelligent Transportation Systems: Technology. *Plan. Oper.* **2018**, *22*, 190–200. [CrossRef]
46. Chandra, S.; Nguyen, A. Case Studies on Transport Policy Freight truck emissions reductions with connected vehicle technology: A case study with I-710 in California. *Case Stud. Transp. Policy* **2020**, *8*, 920–927. [CrossRef]
47. Yao, Z.; Zhao, B.; Yuan, T.; Jiang, H.; Jiang, Y. Reducing gasoline consumption in mixed connected automated vehicles environment: A joint optimization framework for traffic signals and vehicle trajectory. *J. Clean. Prod.* **2020**, *265*, 121836. [CrossRef]
48. Heard, B.R.; Taiebat, M.; Xu, M.; Miller, S.A. Sustainability implications of connected and autonomous vehicles for the food supply chain. *Resour. Conserv. Recycl.* **2018**, *128*, 22–24. [CrossRef]
49. Velázquez-Martínez, J.C.; Fransoo, J.C.; Blanco, E.E.; Valenzuela-Ocaña, K.B. A new statistical method of assigning vehicles to delivery areas for $CO_2$ emissions reduction. *Transp. Res. D Transp. Environ.* **2016**, *43*, 133–144. [CrossRef]
50. Tan, Y.; Deng, L.; Li, L.; Yuan, F. The capacitated pollution routing problem with pickup and delivery in the last mile. *Asia Pac. J. Mark. Logist.* **2019**, *31*, 1193–1215. [CrossRef]
51. Grimm, V.; Berger, U.; Bastiansen, F.; Eliassen, S.; Ginot, V.; Giske, J.; Goss-Custard, J.; Grand, T.; Heinz, S.K.; Huse, G.; et al. A standard protocol for describing individual-based and agent-based models. *Ecol. Model.* **2006**, *198*, 115–126. [CrossRef]
52. Hübner, A.; Kuhn, H.; Wollenburg, J. Last mile fulfilment and distribution in omni-channel grocery retailing: A strategic planning framework. *Int. J. Retail. Distrib. Manag.* **2016**, *44*, 228–247. [CrossRef]
53. Guo, Z.; Zhang, Y.; Zhao, X.; Song, X. CPS-Based Self-Adaptive Collaborative Control for Smart Production-Logistics Systems. *IEEE Trans. Cybern.* **2020**, *51*, 188–198. [CrossRef]
54. Tijskens, L.M.M.; Polderdijk, J.J. A generic model for keeping quality of vegetable produce during storage and distribution. *Agric. Syst.* **1996**, *51*, 431–452. [CrossRef]
55. Gruzauskas, V.; Gimzauskiene, E.; Valentinas, N. Forecasting Accuracy Influence to Logistic Clusters Activities: The Case of the Food Industry. *Anim. Genet.* **2018**, *39*, 561–563. [CrossRef]
56. Delignette-muller, M.L.; Dutang, C. Fitdistrplus: An R Package for Fitting Distributions. *J. Stat. Softw.* **2015**, *64*, 1–34. [CrossRef]
57. Food and Agriculture Organization. *Global Food Losses and Food Waste*; FAO: Rome, Italy, 2011.
58. Wilensky, U. *NetLogo Traffic Grid Model*; Center for Connected Learning and Computer-Based Modeling, Northwestern University: Evanston, IL, USA, 2003.
59. Tomtom. *Tomtom Traffic Index 2018*; Tomtom: Amsterdam, The Netherlands, 2018.
60. Department of Transport. *Traffic Counts Statistics*; Department of Transport: Perth, Australia, 2017.
61. Finnish Transport Agency. *Analysis of the Predictability of Traffic during Congestion*; Finnish Transport Agency: Helsinki, Finland, 2014.
62. Wang, X.; Zhou, Q.; Quddus, M.; Fan, T.; Fang, S. Speed, speed variation and crash relationships for urban arterials. *Accid. Anal. Prev.* **2018**, *113*, 236–243. [CrossRef]
63. TRL Ltd. *Assessment and Reliability of Transport Emission Models and Inventory Systems*; TRL Ltd.: Berlin, Germany, 2007; pp. 1–346.
64. Navickas, V.; Baskutis, S.; Gružauskas, V.; Olencevičiūtė, D. The temperature control impact to the food supply chain. In Proceedings of the 20th International Conference, Kaunas, Lithuania, 23–24 April 2015; pp. 42–47.
65. European Chemical Industry Council. *Guidelines for Measuring and Managing $CO_2$ Emission from Freight Transport Operations*; European Chemical Industry Council: Brussels, Belgium, 2011.
66. Wägeli, S.; Hamm, U. Consumers' perception and expectations of local organic food supply chains. *Org. Agric.* **2016**, *6*, 215–224. [CrossRef]
67. Himanen, S.J.; Rikkonen, P.; Kahiluoto, H. Codesigning a resilient food system. *Ecology Soc.* **2016**, *21*, 16. [CrossRef]

68. Mulcahy, J.C. Exploring Scale and Boundaries in Food System Assessments. Ph.D. Thesis, Syracuse University, Syracuse, NY, USA, 2017.
69. Collison, M.; Collison, T.; Myroniuk, I.; Boyko, N.; Pellegrini, G. Transformation Trends in Food Logistics for Short Food Supply Chains—What is New? *Stud. Agric. Econ.* **2019**, *121*, 102–110. [CrossRef]
70. Ambulkar, S. Managing Supply Chain Disruptions: Role of Firm Resilience and Strategic Focus on Innovation. Doctoral Dissertation, Iowa State University, Ames, IA, USA, 2015.
71. Kurihara, S. Traffic-Congestion Forecasting Algorithm Based on Pheromone Communication Model. In Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems (ITSC 2010), Madeira Island, Portugal, 19–22 September 2010; Volume 19, pp. 683–688.
72. Sargent, R.G. Verification and validation of simulation models. *J. Simul.* **2013**, *7*, 12–24. [CrossRef]
73. Wiseman, Y. Autonomous Vehicles. In *Encyclopedia of Information Science and Technology*, 5th ed.; IGI Global: Hershey, PA, USA, 2020; pp. 1–11. [CrossRef]
74. Figliozzi, M.A. Carbon emissions reductions in last mile and grocery deliveries utilizing air and ground autonomous vehicles. *Transp. Res. Part D Transp. Environ.* **2020**, *85*, 102443. [CrossRef]