ENVIRONMENTAL RESEARCH
INFRASTRUCTURE AND SUSTAINABILITY

PAPER

A framework for determining energy use in rural food delivery services: capturing system interdependencies through an agent-based discrete-event approach

Isabella M Gee, Kasey M Faust and Michael E Webber

1 Civil, Architectural, and Environmental Engineering, University of Texas at Austin, 301 E Dean Keeton St C1700, Austin, TX 78712, United States of America
2 Mechanical Engineering, University of Texas at Austin, 1 University Station C2200, Austin, TX 78712, United States of America

Abstract

Food e-commerce has seen significant growth over the past decade that accelerated after the onset of the COVID-19 pandemic. Last-mile transportation and logistics are widely considered the most expensive and least efficient portion of the supply chain and have multiple important energy trade-offs such as cargo capacity and consumer density. Last-mile transportation energy use in rural areas is underrepresented in the literature. This study proposes a hybrid agent-based and discrete event model framework for evaluating the last-mile transportation energy use of van- and car-based food delivery services in a rural community, based on meal-kit and grocery delivery operations, respectively. This framework quantifies last-mile energy use in rural areas, and is demonstrated here using a neighborhood outside of Austin, TX as an analytical testbed. The study focuses on the effects of consumer density, cargo limitations, and vehicle speed. For the conditions examined with this framework, diesel delivery vans use more total energy than passenger cars for the same trip, though a van delivering four orders uses less energy per-order than a car delivering one order. However, there are trade-offs between vehicle type and mileage, cargo capacity, route density, and speed that are particularly important for delivery services operating in rural areas. This framework can be used by service providers to assess route-specific trade-offs for each vehicle and gauge which is preferable for given operating conditions or to evaluate the energy, and thus also cost, impact of expanding their services to rural areas.

1. Introduction

Food delivery services are currently expanding and gaining popularity in the US; in particular, grocery delivery and meal-kit delivery. Meal-kit delivery services have reached $5 billion in sales after entering the US market in 2012 (Meal Kit History [Infographic] 2017, Packaged Facts 2017). Before the COVID-19 pandemic in 2020, online grocery sales were expected to reach $100 billion in the United States as early as 2022 (FMI and Nielsen 2017, The Nielsen Company 2018). The COVID-19 pandemic in 2020 further accelerated the growth in demand for these services. In April 2020, grocery delivery service Instacart saw sales rise 500% year-over-year (Silverstein 2020). Meal-kits are experiencing similar spikes, with one service Sun Basket seeing sales double each week in early 2020 (Kang and Haddon 2020). And though demand for food e-commerce services has grown due to the COVID-19 pandemic, analysts predict that consumer adoption will continue after pandemic-related restrictions are lifted (Magana 2020, Silverstein 2020). As services like these change the way food is purchased and distributed, they also change the way energy is used within the food system. In particular, these services affect last-mile transportation energy use.
Transportation represented almost 35% of US energy use (including electricity) in 2020 and is the largest source of carbon dioxide in the United States (U.S. Energy Information Administration 2021, U.S. Environmental Protection Agency 2021). The expense of last-mile logistics is also a challenge for food delivery services (Phillips and Smith 2018, Smith 2018). Vehicle fuel costs were the second largest operating cost per-mile in 2019 for trucking companies (ATRI 2019). Food delivery services can have a lower environmental impact compared to personal shopping trips (Borggren et al 2011, Gay et al 2005, Matthews et al 2001b, 2001a, Sivaraman et al 2007, Van Loon et al 2015, Weber et al 2010, Williams and Tagami 2003, Wygonik and Goodchild 2012). As such, food delivery services might help reduce energy consumption in rural areas where personal trips tend to be longer. As food delivery services continue to expand, their operational energy use will grow. Understanding the impacts of different food shopping pathways is important for policymakers concerned about achieving environmental and climate goals, for environmentally conscious consumers, and for companies who wish to manage their costs and impacts.

This study develops and presents a framework to evaluate the last-mile transportation energy use of food delivery services in rural areas, a topic largely overlooked in existing literature. The framework combines agent-based and discrete-event techniques to simulate last-mile delivery transportation for delivery cars and vans, tracking energy use. Using the developed framework presented, we (1) demonstrate the framework in rural area outside Austin, Texas, and (2) and quantify the last-mile energy trade-offs vehicle type, speed, and cargo capacity for the given case study area. These trade-offs were chosen for the case study as their impacts are easy to quantify and relatively well-understood so results will be able to show whether the model is accurately capturing delivery behavior.

2. Background

There is extensive literature on the environmental impact of on-road transportation, personal and freight (Albert and Schäfer 2013, Allen et al 2018, ATRI 2019, Chang et al 2017, Ehmke and Mattfeld 2012, Fan et al 2019, Frey 2018, Kaack et al 2018, Nahlík et al 2016, Reinhart 2015, Schoettle et al 2016, Taptich and Horvath 2015, Weber and Matthews 2008). Along the supply chain of goods delivery, last-mile transportation is often considered the most costly and least efficient stage (Elgart et al 2019, Lin et al 2016, Moroz and Polkowski 2016, Pålsson et al 2017, Vakulenko et al 2019, Wang et al 2016, Weber et al 2008). The last-mile also has multiple energy tradeoffs, especially with respect to mode (i.e. personal shopping or delivery) and choice of vehicle. Research has shown that van-based delivery can reduce the environmental impact of last-mile transportation. Edwards et al (2009), (2010) found that home delivery is likely to produce fewer emissions than traditional shopping for non-food items, though the number of items purchased is an important factor (Edwards et al 2009, 2010). Weber et al (2010) compared the environmental impact of traditional shopping for a music album to delivery alternatives and found last-mile delivery via truck to use less energy than personal transportation. In a review of 56 studies surrounding the environmental implications of e-commerce, Mangiaracina et al (2008) found that home delivery tends to reduce emissions compared to personal shopping. However, these studies primarily focus on delivery for non-food items, such as books, CDs, and clothing.

Fewer studies have focused on last-mile delivery services for food. Wygonik and Goodchild (2012) found that large reductions in emissions could be obtained from delivery vans compared to personal shopping for groceries in Seattle, WA. Siikavirta et al (2003) compared personal grocery shopping with various home delivery scenarios for groceries in Helsinki, Finland and found that delivery could reduce emissions 18%–87% compared to personal shopping. Rizet et al (2012) compared emissions for yogurt distribution in France between conventional retail and delivery, and found that delivery reduces last-mile emissions compared to all traditional retail options. Most of the studies focusing on food delivery were conducted outside the United States and focus on emissions only. Quantifying energy use has certain advantages over focusing on emissions alone. For example, tracking energy use can help achieve resource conservation goals. In 2019, 37% of total US energy use was for the transportation end-use sector, and 94% of transportation energy came from petroleum or natural gas (USEIA 2020). Energy use can also be easily translated into emissions and fuel costs, including those for other fuels if companies decide to switch fuel sources.

Existing research also tends to focus on van-based delivery and does not disaggregate delivery vehicle type (Rizet et al 2012, Siikavirta et al 2003, Wygonik and Goodchild 2012). With the rise of the gig-economy, many food delivery services now employ drivers using their own vehicles for delivery. Some studies have compared environmental impacts of vans and cars, but through the lens of comparing delivery services to personal shopping. Wygonik and Goodchild (2016) evaluated the impact of urban form on vehicle miles traveled (VMT) and emissions for last-mile transportation using delivery vans and passenger vehicles, focusing on factors such as road density, customer density, and service area. Goodchild et al (2018) developed an analytical model to determine last-mile VMT and emissions for delivery vans and personal travel. They found that customer density and the emissions ratio between vehicles both drive which vehicle produces fewer emissions. Van Loon et al (2015)
compared van-based delivery and parcel delivery services, which use passenger vehicles, for fast-moving consumer goods in the United Kingdom and found that the parcel delivery service has a higher per-item impact. Cars and vans have trade-offs, such as cargo capacity and fuel economy, that will affect which vehicle is most energy efficient for given delivery conditions, warranting individual analysis for direct comparison.

While many studies on the impacts of delivery services focus on urban areas (Ballare and Lin 2020, Borggren et al. 2011, Matthews et al. 2001b, 2001a, Sivaraman et al. 2007), existing literature suggests that energy benefits from delivery services might increase in rural areas. In their literature review, Pålsson et al. (2017) posit that delivery services could save energy in less-dense areas outside of cities compared to personal vehicle use. Similarly, Williams and Tagami (2003) compared delivery to traditional retail for books in urban and rural Japan and found that delivery has more transportation energy benefits in rural areas. Additionally, Wygonik and Goodchild (2012) found that emissions savings from delivery services might be greater in areas with lower population density. However, Goodchild et al. (2018) found that delivery vans can reduce emissions when customers are close in proximity and delivery time, which might not always be possible in rural areas. Capturing last-mile transportation behavior for rural areas in particular can provide insight for food delivery companies that could offer their services in such areas but are concerned about their bottom line. Rural and urban geographies have different characteristics that will impact operating conditions and thus costs for delivery services.

Rural delivery routes have unique characteristics, both route-based and consumer behavior-based. A primary route-based consideration is low consumer density, which increases operation costs for the carriers in that area by increasing delivery distances over fewer customers (Elgart et al. 2019). An urban delivery route might cover 123 stops in 40 mi (Lee et al. 2013), eight stops and 400 packages in about nine miles (Sheth et al. 2019), while one example of a rural grocery-delivery route in Maryland is 173 mi for just 17 stops (Doering 2018). While higher consumer density is a benefit in urban areas, the frequent stops take a toll on fuel economy (Reinhart 2015). Rural routes have fewer stops and less traffic, but their roads can also frequently be in need of service (Mattson and Mistry 2021, TRIP National Transportation Research Group 2020), and pavement quality might impact the environmental footprint of vehicles (Lidicker et al. 2013). Some delivery vehicles, like autonomous models being explored by some grocery delivery companies, might also have trouble getting around rural roads or getting to front doors in zip codes lacking systematic addresses (Ramey 2020, TRIP National Transportation Research Group, 2020, Wells 2020). Besides physical route conditions, rural regions have distinct population, and thus consumer, characteristics as well.

Rural populations tend to be slightly older, with a median age of 44 compared to 37 in urban areas (Mattson and Mistry 2021). And while e-commerce consumers tend to skew younger, the pandemic has prompted consumers of all ages to try grocery delivery, especially those most vulnerable to COVID in their 70s (Hurtig 2021). According to the National Household Travel Survey (NHTS), rural residents, on average, drive more, are less likely to take public transportation, and tend to use older cars with lower fuel economy (National Household Travel Survey 2017). Rural residents also take fewer, longer trips (National Household Travel Survey 2017, Mattson and Mistry 2021) and are more dependent on personal transportation; 4% of rural residents do not own a vehicle compared to 10% of urban residents (Mattson and Mistry 2021). These characteristics will impact shopping habits: how frequently consumers shop, whether they combine activities in one trip (likely for rural residents), how much they buy, what items they buy, and how they choose time windows.

Further study on rural online shopping is warranted. Current literature on rural e-commerce in general tends to focus on developing countries, particularly rural China, and little on shopping habits themselves (Kshetri 2018, Liu et al. 2020, Liu 2020, Ma et al. 2020, Tang and Zhu 2020, Zeng 2019). Some recent studies have looked at using public transportation to facilitate rural last-mile delivery of goods (Elgart et al. 2019, Hamre et al. 2021). These partnerships could provide a new source of revenue for public transit in rural areas and build on existing community services, but about 28% of rural counties have limited public transportation service and 40% have none at all (TRIP National Transportation Research Group 2020). (Goodchild and Toy 2018) compared drones to delivery trucks and found that drones were preferable in services areas close to the distribution center and with fewer recipients. (Park et al. 2018) found that drones can save energy in rural Korea compared to motorcycles when delivering pizzas. Still, current drones are unsuitable for grocery delivery unless orders are limited to a handful of items.

Literature has begun to highlight the importance of considering rural areas, in particular the urban-rural interface, in urban planning decisions (Gren and Andersson 2018, López-Goyburu and García-Montero 2018). Rural areas play a large role in the Milan Urban Food Policy Pact (MUFPP), which was launched in 2015 to encourage Mayors to prioritize food policies in their cities (FAO 2018). Supporting food services that connect peri-urban and rural areas is a specific action listed within the MUFPP’s Food Supply and Distribution topic (Filippini et al. 2019). Such a framework as the one presented in this study could help officials assess planning needs in the face of an increasingly interconnected and complex food system.
Using a hybrid agent based modeling (ABM)—discrete event simulation (DES) approach facilitates the simulation of food delivery by capturing both the high-level, centralized processing operations of the delivery companies through DES as well as the detailed transportation behavior of the delivery vehicles themselves through ABM. DES is an apt technique for modeling operational-level behaviors like order processing because it models the behavior of sequential events over time, and each step can be well-characterized (Tako and Robinson 2012). Previous studies have used DES to model various parts of the food supply chain. Mohan et al (2013) used DES to simulate operations for a food reclamation center. Gopakumar et al (2008) used DES to model warehouse operations at a food distribution center, identifying solutions to improve the efficiency of inbound logistics. Van Der Vorst et al (2000) support the use of DES in modeling dynamic food systems because it can more realistically capture logistics considerations such as interactions between supply chain stages and the timing of events along the supply chain. In regard to ABM, the individual-centric behavior captured has been leveraged in literature. Chen and Chankov (2018) used ABM to simulate drivers picking up and delivering packages throughout a service area. Kin et al (2018) modeled the use of spare capacity in company vehicles for last-mile goods delivery, tracking vehicles miles traveled. Krejci and Beamon (2012) highlighted the applicability of agent-based techniques to the food supply chain specifically, including transportation, because of ABM’s ability to capture the behavior of individual autonomous agents and their interactions.

Despite the benefits of each individual method, few supply chain studies have applied hybrid modeling approaches to leverage the strengths of each modeling technique. In an analysis of 127 logistics and supply chain management (LCSM) papers, Tako and Robinson (2012) found that 3% used a hybrid DES and system dynamics (SD) approach while the remaining 97% used only one approach. Scheltes and de Almeida Correia (2017) recently tracked fleet energy use of autonomous electric vehicles through a hybrid SD-ABM approach, but the vehicles were used for increasing the accessibility of public transport. Hybrid AB-DES approaches have been found in fields like transportation evacuation simulation (Zhang et al 2011), emergency medical services (Anagnostou et al 2013, Fakhimi et al 2014), and large-scale disaster responses (Wu et al 2008), but are yet to be used in this context.

3. Methods and model development

This framework for evaluating the last-mile transportation energy use of food delivery services in rural areas captures interdependencies between food delivery services, the transportation system, and the energy system. Figure 1 conceptualizes the model’s physical interdependencies considered in which a system’s state is dependent on material outputs of another system (Rinaldi et al 2001), as well as geographic interdependencies considered, which are related to the co-location of resources and entities (Rinaldi et al 2001).

Here, a hybrid ABM and DES (ABM-DES) approach is used that operates within a GIS environment in AnyLogic (see figure 2). Van- and car-based delivery services are each modeled, using meal-kit and grocery delivery services that represent two distinct delivery configurations. Notably, the framework may be adapted easily to other delivery configurations by changing household, grocery store, and LDPH locations. DES captures the stages of order processing by the delivery services, while ABM captures the delivery vehicle operations. Delivery vehicles start each simulation at their home location—either a grocery store for cars or local parcel delivery hub (LPDH) for vans. Vehicles only leave these locations during the simulation to make a delivery, in which they immediately return to these locations once the order is fulfilled. Vehicles travel along established routes in a GIS space defined using GIS tiles and routing information available within AnyLogic. Each simulation runs for 1 week as grocery shopping habits are often weekly.

3.1. Model implementation

There are five object classes: households, grocery delivery service, meal-kit delivery service, delivery cars, and delivery vans. Each object class holds unique information and interacts with other object classes; these interactions determine vehicle energy use.

3.1.1. Households

Households are agents that generate orders for meal-kit and grocery delivery services. A household can generate one order per delivery service per hour over the course of the simulation. This value was selected to generate sufficient orders over the course of the simulation to extrapolate relevant trends in energy use. The rate of order generation can be changed to reflect demand conditions in future applications.

3.1.2. Grocery delivery service

Grocery delivery services pack and deliver orders from existing grocery stores (e.g. Instacart, Personal Conversation with Instacart Representative 2018). Customers place orders using an online platform, ‘shopper’ employees shop for the items in store, and ‘driver’ employees deliver the complete order using their personal
Figure 1. Schematic of model logic, displaying interdependencies considered between systems. Car- and van-based deliveries are represented by grocery and meal-kit delivery services, respectively. Lines indicate modeled system interactions, with dashed lines indicating interactions where energy use is measured. Reproduced with permission from Gee et al (2019).

Figure 2. Primary interactions between and within DES and ABM components. Order processing—modeled using DES—interacts with agents in the ABM by triggering vehicle deliveries. Reproduced with permission from Gee et al (2019).

vehicle (see figure 3). Grocery delivery services are not explicitly defined agents because the relevant behaviors (e.g. order processing) can be modeled using existing agents (the grocery store). Order processing is done in DES because each relevant step can be isolated and the incoming orders centralized, simplifying the model logic and reducing computational intensity compared to ABM. Individual orders enter the process flowchart and are grouped together through a batch function to be delivered by a single vehicle, as some grocery delivery services fulfill multiple orders in a single trip when they are close in both location and scheduled delivery time. The batch number can be changed to reflect the number of orders to be fulfilled per delivery trip.
3.1.3. Meal-kit delivery service
Customers typically order meal-kits using an online platform, often on a weekly subscription-based plan. The company packs the kits at a company-owned fulfillment center and uses a third-party delivery service to mail them. The meal-kit delivery services captured in this work process and deliver orders from an LPDH as this model focuses on last-mile delivery. Order processing is outlined in figure 3. Similar to grocery delivery service, individual orders can be batched together for delivery. Meal-kit services that contract out their logistics to another provider like the United States Postal Service (USPS) or FedEx, like HelloFresh (HelloFresh 2021), might not have control over whether or not orders can be batched together during local delivery. Batching orders in this case can represent a meal-kit service managing its own logistics or a group of orders that are close enough in distance and time to be batched together. Delivery window constraints were out of scope for this study.

3.1.4. Delivery cars and vans
Delivery cars and vans are modeled as agents, moving grocery orders and meal-kits to consumer households, respectively. Figure 4 provides an overview of the state chart in which these agents interact. Drop-off time at each household is modeled as a triangular distribution with a minimum of one, maximum of three, and most likely of 2 min based on values in the literature (Kämäräinen et al 2001, Punakivi and Saranen 2001). The model tracks the time spent in both the ‘moving to household’ states and the ‘at household’ or drop-off states in separate, internal variables. Delivery vehicle transportation is modeled using ABM to effectively capture communication between vehicles and delivery services as well as vehicles’ complete and individual

---

**Figure 3.** Order processing is modeled using DES. Household-generated orders enter the flowchart at the ‘Source’ stage, move through each action block, exiting at the ‘Sink’ stage post-delivery (delivery vehicle refers to either cars or vans). Reproduced with permission from Gee et al (2019).

**Figure 4.** Order delivery uses ABM, where vehicle-specific state charts define vehicle movement and behavior. Delivery vehicles (i.e. car or van in this study) are modeled as agents, placed at their respective home location at the beginning of each simulation. Vehicles are triggered to begin a delivery by the order-processing flowchart presented in figure 3. During delivery, the vehicle moves throughout the state chart, and thus the GIS space, based on state-specific triggers until delivery is complete and the vehicle can return to the home location. Reproduced with permission from Gee et al (2019).
delivery behaviors. Further explanation of the simulation and vehicle behavior can be found in the Supporting Information (https://stacks.iop.org/ERIS/1/035002/mmedia).

### 3.1.5. Vehicle energy use

Energy use per delivery trip is estimated using the trip duration (in minutes), split between time spent in motion at a set speed (representing average speed) and time spent idle. Conversion factors, in megajoule (MJ) per minute, were calculated for a variety of vehicle speeds using equation (1), where FED is fuel energy density and FE is the fuel economy of the vehicle. Energy intensities used for each vehicle are presented in Table 1.

Variations in fuel economy with speed for gasoline-powered cars were obtained from the U.S. Department of Energy or the Office of Energy Efficiency and Renewable Energy (Speed Kills MPG, USDOE 2018). Fuel economy data for diesel delivery vans used are found in The National Renewable Energy Laboratory (Lamert et al 2012) and from a private industry report (Cummins Inc). Fuel energy density data were obtained from the Alternative Fuels Data Center (2014)

$$\text{Energy intensity } \left( \text{MJ min}^{-1} \right) = \text{FED} \left( \text{MJ gal}^{-1} \right) \times \text{FE} \left( \text{gal mile}^{-1} \right) \times \text{Speed} \left( \text{mile min}^{-1} \right). \quad (1)$$

Total trip time is estimated as the round-trip time, split between time in motion and time at idle, scaled by speed-specific energy intensity, as follows:

$$\text{Trip energy} = (T_m)(E_{I}) + (T_I)(E_{I}) \quad (2)$$

where $T_m$ is the time spent in motion, $T_I$ is time spent in idle, $E_I$ is the energy intensity (MJ min$^{-1}$) at speed ‘i’ for either delivery vehicle, and $E_{I}$ is the energy intensity (MJ min$^{-1}$) of idling for either delivery vehicle. Time spent in motion and idle are tracked within the model, automatically scaled by the associated energy intensity (see Table 1), and summed together at the end of each simulation.

### 3.2. Case study region

The framework is demonstrated with a group of five households located approximately 30 mi outside of Austin, TX. This region was chosen based on both its location and its income. This modeled neighborhood is 17 miles away, through network, from the nearest grocery store and LPDH. Total round-trip distance is approximately 34 mi, including stops (households are about 200 ft apart). The average household goes to a grocery store 3.8 mi away, and those that walk, bike, or use public transit (i.e. are likely to live in more densely populated cities) shop at store only 0.9 mi away (Ploeg et al 2015). The neighborhood had a median household income of over $100 000 in 2014 (PASA 2016), suggesting that residents likely have the means to pay for a food delivery service.

### 3.3. Validation and verification

Four steps (Sargent 1999) were used for model validation and verification throughout its development: conceptual model validation, computerized model verification, operational validation, and data validation. Conceptual validation took place during development of the systems diagram (Figure 1) and model abstraction; both delivery service’s operations were compared to operations reported on company websites and through conversations with customer service representatives. Conceptual validation also involved ensuring that all assumptions and data accurately captured the relevant interdependencies and behaviors. Initial computerized model verification was performed using the model animation to confirm that the vehicles were receiving orders.
and moving within the GIS space as specified. The sensitivity analysis was used to verify that the parameters analyzed did not have a disproportionate impact on model results. Additionally, a trace logic approach was applied to the completed model. Finally, all new model behavior was documented and verified at each stage of development as new complexities were introduced. Operational validation was completed after the model was built. Delivery trip times at various speeds were compared to expected trip durations from an online mapping service. Where data were limited, assumptions were made based on the available data and simulation results were checked for operational validity specifically with regards to the parameters affected by data assumptions.

3.4. Assumptions and limitations
Changes in vehicle fuel efficiency during acceleration and deceleration are not considered. Diesel engines have a higher torque at lower speeds, aiding in acceleration, which could be a benefit in stop-and-go traffic. This advantage could impact the results of overall energy use per-trip as the number of deliveries per-trip increases (U.S. Department of Energy n.d.-c); however, the framework is still valid for capturing trends in rural-delivery energy use because of the low number of households (five) and the rural location, which has less of the stop-and-go traffic that is typical for urban centers.

This study uses fuel economy of traditional diesel delivery vans instead of hybrid or advanced vehicles, which may have improved fuel economy. Some delivery services are also committing to electric-powered fleet additions (Carey 2018). However, diesel is still the dominant fuel of choice for freight vehicles in the US Survey results from the American Transportation Research Institute (ATRI) found that only 11.2% of respondents use a fuel other than diesel or bio-diesel blends within their freight fleets, but vehicles in these fleets represented less than 1% of the total vehicles and mostly used natural gas (Hooper and Murray 2017). Fuel economy can be changed to represent specific vehicles in future iterations, but diesel delivery vans are considered to be a good representation of average conditions. Fuel economy assumptions were also made for delivery cars.

The store-centric grocery delivery services modeled in this work have employees use their own cars for deliveries. There is thus no standard delivery vehicle for this type of service. This lack of standardization means there could be large differences in fuel economy between delivery drivers. Excluding electric vehicles, personal vehicle mileage for 2019 model personal vehicles ranges from 11–58 mpg (USDOE 2019). This framework uses average fuel economy data for all cars in the US.

Finally, energy use and emissions of transportation are often quantified using miles traveled, but duration is used here for computational efficiency. The duration of each simulation is tracked by default within the model, with set start and end times. As vehicle fuel economy changes with speed, fuel (and thus energy) consumption can be easily calculated based on the time spent driving at a certain speed. Additionally, this approach allows for real-time evaluation of temporal considerations in future analysis, such as limited hours of operation for a service, different order rates or times from consumers, or time delays in receiving a delivery (a major factor for consumers) (Joerss et al. 2016). Further, this work is concerned with total and per-order energy use, which is a descriptive metric when considering cargo capacity limitations and consumer density trade-offs and can be converted to a per-mile basis.

4. Results and discussion
The results illustrate how this framework can be used to evaluate trends in last-mile energy use for rural food delivery. As of writing this article, the authors found no similar hybrid AB-DES study of last-mile delivery transportation energy use for comparison, but results are comparable to estimates of last-mile energy use from other e-commerce and transportation studies when applied to the same round-trip distance in this case study (34 mi).

Between eight studies and 19 scenarios, delivery van energy use ranges from 160 MJ for an empty, small (3 ton max payload) van (Fan et al 2019) up to 1100 MJ for a class 5 delivery van with fuel economy based on congested, urban operating conditions (Lee et al 2013). Results from this study, over all vehicle speeds, fall well within that range (figure 6). The USPS fleet is still primarily comprised of Northrop Grumman Long Life Vehicles, which average about 10 mpg diesel (Bagoge 2021). This mileage requires about 500 MJ for a 34 mi trip, similar to the case study delivery van at 55 mph with five stops. Reinhart (2015) looked at a box delivery truck operating at 55 mph and 50% payload for the engine options (Reinhart 2015). Energy use for a 34 mi trip ranges between about 510–670 MJ using the given fuel economy (7.4–9.7 mpg), but energy use on a parcel route instead of 55 mph yields energy use between 860–1000 MJ (Reinhart 2015). In this case study, energy for a delivery van at 55 mph falls between 460 and 500 MJ. Car-based findings from this study also align with results from 8 studies and 12 scenarios, which yielded a range of 30–440 MJ. The high of 440 MJ is for a car operating at 10 mpg and is a little over two times the energy required in this study for a car operating at 20 mpg. While representative fuel economy data were used for the vehicles in this case study, individual delivery vehicles and their fuel economies are highly variable. For example, a 2020 Chevrolet Silverado might get
15 mpg, a 2015 Toyota Prius 95 mpg-equivalent electric or 50 mpg gas, and a 2020 Ford Transit Connect 16 mpg (U.S. Department of Energy 2020, n.d.-d, 2015). This variability will have a considerable impact on last-mile energy use.

Within this case study, car-based delivery is generally energetically preferable to van-based (figure 5). These trends are to be expected given relative fuel economies (table 1). Total energy use aligns with the defined relationship between fuel economy and speed; round-trip energy for both vehicles is lowest when fuel economy is at its highest near 50–55 mph (Cummins Inc, Lammert et al. 2012, Speed Kills MPG, USDOE 2018). An 18 months evaluation of UPS delivery vehicles found that conventional diesel vans drove 30.5% of miles under 20 mph and 22% above 50 mph, characteristic of more urban routes (Lammert and Walkowicz 2012). Rural routes might shift this breakdown with less congestion and traffic, but smaller delivery vehicles or cars might be able to drive faster than bulky vans. In practice, lower consumer density and cargo limitations for smaller cars might make vans preferable in certain conditions.

Consumer density can be modeled by changing the number of orders per-trip. Within the model, energy use per-order decreases with additional orders (figure 6). This trend is also expected; the benefits of clustering orders together are well defined (Boyer et al. 2009), but decreasing consumer density limits the impact of order clustering. Different routes will have different densities. Delivery vans might be advantageous in less dense regions because they can carry more orders than cars.

While cars are more energy efficient in this study for the same number of orders, vans generally have a larger cargo capacity. Depending on item number or size, cars might not be capable of carrying multiple orders. Especially large orders might limit cars to one or two households per delivery. Under these limitations, multiple cars would be required to make the same number of deliveries as a single van. In this case study, a van delivering only four orders uses less energy per-order than a car delivering one and slightly more than a car delivering two

---

**Figure 5.** Total per-trip energy use when delivering one and five orders ($N = 1$ and 5) per delivery trip. Trends in total per-trip energy use with speed reflect changes in fuel economy. Vans are more sensitive to changes in speed than cars, indicating that energy use in vans would be impacted to a greater degree by changing traffic conditions in the case study region. Reproduced with permission from Gee et al. (2019).

**Figure 6.** Total per-trip energy use at a vehicle speed of 55 mph, where ‘$N$’ refers to the number of orders fulfilled per delivery trip. Per-trip energy use increases with additional deliveries, but per-item energy use decreases. While cars always use less energy per-order than vans for the same number of orders in the case study region, the larger cargo capacity of vans makes them preferable to cars even when relatively few orders are delivered; a van delivering just four orders uses less energy per-order than a car delivering one. Reproduced with permission from Gee (2019).
(figure 6). However, e-commerce can lead to an increase in smaller, more frequent orders (Mokhtarian 2004). If this holds for the case study region, cars might be better suited for delivering these smaller orders. Rural shoppers might be used to bigger shopping trips if stores are far away, but this habit might change if delivery becomes more readily available. Either way, the break-even point will vary by region as well as by vehicle.

Geographic distribution of households might exacerbate the negative impacts of low consumer density. Vehicles could be able to reach fewer consumers due to time constraints, limiting the benefits of additional orders. The households in the neighborhood modeled here are close together (~200 ft apart), making the energy per-additional order small. Distribution as well as density of households will affect energy use. A service provider might be faced with multiple orders clustered between two areas, necessitating separate trips or vehicles. If four orders are split between two separate neighborhoods, a delivery van might not be energetically preferable to two cars as it is in this case study. Because this framework uses a GIS space, it can capture the impact of different geographies.

Vehicles might also be able to deliver to fewer households because of food safety concerns, regardless of consumer density. The longer food sits unrefrigerated, the bigger the impact to the quality and possibly the safety of the food if ingredients are outside of their optimal temperature zones. Given the longer routes, food safety concerns might be more pressing in rural areas. Many cars and delivery vans are not outfitted with refrigeration units. Present food delivery services account for such considerations in different ways. Meal-kit services pack their kits with ice packs and insulation (Fenton 2017, Gee et al 2019, Heard et al 2019). Peapod uses specialized, refrigerated vans designed to maintain food temperature during delivery (Doering 2018). Specialized vehicles like these were not included in this model due to data limitations, but can easily be incorporated into the framework by changing the vehicle fuel economy used in equation (1).

While food delivery services are popular among urbanites, about 20% of the US population lives in rural areas, and 8% of these consumers live over 10 mi from the nearest grocery store (Kuhns and Sakse na 2017, Mattson and Mistry 2021, Ver Ploeg et al 2009). Rural consumers with limited grocery access face greater transportation and time costs in order to reach the store than urban counterparts with limited access (Ver Ploeg et al 2009). A national analysis found that populations more rural counties had a greater share of individuals 65 or older, with a disability, and living below the poverty line, all factors indicating a greater need for transportation services (Mattson and Mistry 2021). Rural areas can benefit from delivery services that increase food access and save time, and are therefore a potential market for delivery services (Jilcott Pitts et al 2018). Furthermore, the USDA is piloting the use of federal assistance programs like Supplemental Nutrition Assistance Program (SNAP) and Electronic Benefits Transfer (EBT) for online grocery purchases in 8 states; as almost 30% of the rural population is classified as low-income, the successful demonstration of these programs might help expand the possible reach of food delivery services in rural areas (Jilcott Pitts et al 2018, Ver Ploeg et al 2009). Initial results from the study found that almost 70% of rural food desert census tracts have no grocery delivery service coverage, and 61% of SNAP households in rural food desert tracts have no delivery coverage (Brandt et al 2019). While the pilot program allows SNAP benefits to be used for the purchase of groceries online, it does not cover delivery fees, which might prevent low-income users from using these services. However, a 2017 survey of SNAP recipients found that, if the option existed, half of respondents would be ‘completely likely’ to buy groceries online regardless of an extra delivery fee (Sarmiento 2020). There is thus room for substantial expansion in rural areas, and some services are already expanding in the wake of the novel coronavirus pandemic. Delivery service Favor doubled its delivery area coverage in Texas in April 2020 and expanded into rural zones (García 2020). In some rural areas, farms have started offering delivery services to local residents (Polansek and Oxford 2020). Analysts expect an overall increase in adoption of online grocery services from all generations (Magana 2020).

5. Conclusions and future work

This study contributes a new method for evaluating last-mile transportation energy use of food delivery services in rural areas. By simulating delivery operations, the framework can elucidate how changing operating conditions will affect energy use for individual routes and vehicles and capture trade-offs. Trade-offs exist between vehicle type, speed, cargo capacity, fuel economy, and energy use that might be especially important in rural areas with lower consumer density, longer delivery distances, and unique consumer demographics. The framework is applied here to a case study of two services operating in a neighborhood outside of Austin, TX. For this geographic study region, cars are more energetically preferable than vans for the same number of orders. However, a van delivering four orders uses less energy per-order than a car delivering one. This break-even point will differ between regions, and vehicle choice is an important consideration for delivery services and energy use. Because the households are close together in the study region, incremental energy per-order is minimal, maximizing the benefits or order clustering. Order clustering might not always be possible, however, either due to different customer distributions, vehicle cargo capacity, or the timing of orders.
The framework developed here can be used to quantify these different trade-offs across multiple rural routes, which are likely to proliferate (Garcia 2020, Hurtig 2021, Magana 2020).

Because the framework uses GIS mapping tools, the framework can be customized to multiple geographies and consumer densities. The impact of cargo limitations can be evaluated by changing the number of orders that can be delivered by one vehicle, and the impact of vehicle type and speed by changing fuel efficiencies. Future studies could look at the trade-offs of mixed fleets and electric or alternative vehicles. Deliveries can be made via bikes, scooters, or walking, but these options might be prohibitively time-intensive in rural areas with lower densities or lack of suitable sidewalk access. A recent study comparing electric-assist bikes found that conventional delivery vans were preferable in areas with increasing distance between the distribution center and delivery neighborhood (Sheth et al 2019). Another future study could use empirical data on rural consumer ordering habits or logistics operations to look at the impact of order frequency and timing throughout the day/week on order batching and energy use. Future work could also apply the framework to different regions and cities, which will have their own unique considerations, as a step toward making generalized conclusions. Finally, while the study here compares store-centric grocery delivery and meal-kit delivery, the framework itself is service-agnostic and can be adapted to multiple different types of delivery operations such as warehouse-centric grocery delivery with in-house logistics and refrigerated vans.

Changes in energy use can be translated into costs, which may determine when and how services expand into rural areas. Characterizing vehicle and energy trade-offs can be especially helpful for new services to help inform fleet decisions in the beginning and then as they begin to scale, such as when it makes sense to move from light-duty or personal vehicles to a delivery van. Given the accelerated adoption and the variety of delivery vehicle types between services, it is increasingly important to capture the vehicle-, region-, and route-specific energy trade-offs of food delivery services, particularly in rural areas that are presently understudied. This framework is a first step toward accounting for these trade-offs.

Acknowledgments

This work was funded by the Cynthia and George Mitchell Foundation.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

ORCID iDs

Isabella M Gee https://orcid.org/0000-0002-8778-6733
Kasey M Faust https://orcid.org/0000-0001-7986-4757

References

Albert A and Schäfer A 2013 Demand for freight transportation in the U.S.: a high-level view 54th Annual Transportation Research Forum, TRF 2013
Allen J et al 2018 Understanding the impact of e-commerce on last-mile light goods vehicle activity in urban areas: the case of London Transport. Res. D 61 325–38
Alternative Fuels Data Center 2014 Fuel Properties Comparison Department of Energy https://afdc.energy.gov/fuels/fuel_comparison_chart.pdf
Anagnostou A, Nouman A and Taylor S J E 2013 Distributed hybrid agent-based discrete event emergency medical services simulation Proc. 2013 Winter Simulation Conf.: Simulation: Making Decisions in a Complex World pp 1625–36 http://dl.acm.org/citation.cfm?id=2676128.2676186
ATRI 2019 An Analysis of the Operational Costs of Trucking: 2019 Update (American Transportation Research Institute)
Ballare S and Lin J 2020 Investigating the use of microhubs and crowdshipping for last mile delivery Transport. Res. Procedia 46 277–84
Bogage J 2021 Push to Electrify Mail Trucks Gains Wide Support, an Unlikely Win for Both DeJoy and Biden (The Washington Post) https://washingtonpost.com/business/2021/05/09/usps-trucks-electric-biden/
Borggren C, Moberg Å and Finnveden G 2011 Books from an environmental perspective-part 1: environmental impacts of paper books sold in traditional and internet bookshops Int. J. Life Cycle Assess. 16 130–47
Boyer K K, Prud’homme A M and Chung W 2009 The last mile challenge: evaluating the effects of customer density and delivery window patterns J. Bus. Logist. 30 185–201
Brandt E J, Silvestri D M, Mande J R, Holland M L and Ross J S 2019 Availability of grocery delivery to food deserts in states participating in the online purchase pilot JAMA Netw. Open. 2 e1916444
Carey N 2018 UPS Partners with Workhorse to Build Electric Delivery Vans (Reuters) https://reuters.com/article/us-ups-workhorse-group-ups-partners-with-workhorse-to-build-electric-delivery-vans-idUSKCN1G61S7
Chang W-R, Hwang J-J and Wu W 2017 Environmental impact and sustainability study on biofuels for transportation applications Renew. Sustain. Energy Rev. 67 277–88
Lee D-Y, Thomas V M and Brown M 2013 Electric urban delivery trucks: energy use, greenhouse gas emissions, and cost-effectiveness Environ. Res. Technol. 47 8022–30
Lidicker J, Sathaye N, Madanat S and Horvath A 2013 Pavement resurfacing policy for minimization of life-cycle costs and greenhouse gas emissions J. Infrastruct. Syst. 19 129–37
Lin J, Chen Q, Kawamura K, Lin J, Chen Q and Kawamura K 2016 Sustainability SI: logistics cost and environmental impact analyses of urban delivery consolidation strategies Netw. Spat. Econ. 16 227–53
Liu M, Zhang Q, Gao S and Huang J 2020 The spatial aggregation of rural e-commerce in China: an empirical investigation into Taobao villages J. Rural Stud. 80 403–17
Liu W 2020 Route optimization for last-mile distribution of rural e-commerce logistics based on any colony optimization IEEE Access 8 12179–87
López-Goyburu P and García-Montero L G 2018 The urban-rural interface as an area with characteristics of its own in urban planning: a review Sustain. Cities Soc. 43 157–65
Ma W, Zhou X and Liu M 2020 What drives farmers’ willingness to adopt e-commerce in rural China? The role of internet use Agribusiness 36 159–63
Magana G 2020 Online Grocery Shopping Report 2020: Market Stats and Delivery Trends for Ecommerce Groceries Business Insider https://businessinsider.com/online-grocery-report
Mangiaracina R, Marchet G, Perotti S and Tumino A 2008 A review of the environmental implications of B2C e-commerce: a logistics perspective Int. J. Phys. Distrib. Logist. Manage. 45 565–91
Matthews H S, Hendrickson C T and Soh D L 2001b Environmental and economic effects of e-commerce: a case study of book publishing and retail logistics Transport. Res. Record J. Transport. Res. Board 1763 6–12
Matthews H S, Hendrickson C T and Soh D 2001a The net effect: environmental implications of e-commerce and logistics Proc. 2001 IEEE Int. Symp. Electronics and the Environment pp 191–3
Mattsson J and Mistry D 2021 Rural Transit Fact Book (North Dakota State University Upper Great Plains Transportation Institute)
Meal Kit History [Infographic] 2017 The meal-kit industry https://themealkitreview.com/meal-kit-history-infographic/
Mohan S, Gopalakrishnan M and Mizzi P 2013 Improving the efficiency of a non-profit supply chain for the food insecure Int. J. Prod. Econ. 143 248
Mohktarian P L 2004 A conceptual analysis of the transportation impacts of R,C e-commerce Transportation 31 257–84
Moroz M and Polkowski Z 2016 The last mile issue and urban logistics: choosing parcel machines in the context of the ecological attitudes of the Y generation consumers purchasing online Transport. Res. Procedia 16 378–93
Nahlik M J, Kaehr A T, Chester M V, Horvath A and Taptich M N 2016 Goods movement Life cycle assessment for greenhouse gas reduction goals J. Ind. Ecol. 20 317–28
National Household Travel Survey 2017 National Household Travel Survey (Federal Highway Administration)
Packaged Facts 2017 Meal kit market delivers sales of $5 billion—and disrupts industry https://packagedfacts.com/
Punakivi M and Saranen J 2003 Effects of e-commerce on greenhouse gas emissions: a case study of grocery home delivery in Finland Sustain. Cities Soc. 7 77–91
Rizet C, Browne M, Cornelis E and Leonardi J 2012 Assessing carbon footprint of the Y generation consumers purchasing online J. Ind. Ecol. 16 4185
Sarmiento I G 2020 Online Grocery Reaches New Heights in April Grocery Dive https://grocerydive.com/news/online-grocery-reaches-new-heights-in-april/576993/Dive
Silverstein S 2020 Online Grocery Reaches New Heights in April Grocery Dive https://grocerydive.com/news/online-grocery-reaches-new-heights-in-april/576993/Dive
Sivaraman D, Pacca S, Mueller K and Lin J 2007 Comparative energy, environmental, and economic analysis of traditional and E-tail DVD rental networks J. Ind. Ecol. 11 77–91
