Sketch Planning Tool for Sustainable and Resilient Urban Goods Distribution: User Manual

September 2023

A Research Report from the Pacific Southwest Region University Transportation Center

Miguel Jaller, Associate Professor, Department of Civil and Environmental Engineering, Co-Director Sustainable Freight Research Program, Institute of Transportation Studies, University of California, Davis

Anmol Pahwa, Postdoctoral Scholar, Institute of Transportation Studies, University of California, Davis

Pacific Southwest Region UTC
University Transportation Center

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. PSR-22-48	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle Sketch Planning Tool for Sustainable and Resilience Urban Goods Distribution: User Manual		**5. Report Date** 09/30/2023 **6. Performing Organization Code** N/A
7. Author(s) Miguel Jaller, 0000-0003-4053-750X Anmol Pahwa, 0000-0002-9431-3168		**8. Performing Organization Report No.** UCD-ITS-RR-23-70
9. Performing Organization Name and Address METRANS Transportation Center University of Southern California University Park Campus, RGL 216 Los Angeles, CA 90089-0626		**10. Work Unit No.** N/A **11. Contract or Grant No.** USDOT Grant 69A3551747109
12. Sponsoring Agency Name and Address U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE, Washington, DC 20590		**13. Type of Report and Period Covered** Final report (10/01/22 – 09/30/23) **14. Sponsoring Agency Code** USDOT OST-R
15. Supplementary Notes METRANS project webpage: https://metrans.org/research/sketch-planning-tool-for-sustainable-and-resilient-urban-goods-distribution-user-manual DOI: https://doi.org/10.25554/eqpc-5569 Data DOI: https://doi.org/10.5061/dryad.bk3j9kdjt		
16. Abstract The urban goods distribution system is a critical component of modern society. However, the COVID-19 pandemic exposed significant vulnerabilities in this system as it struggled to cope with an unforeseen surge in demand. This crisis highlighted the urgent necessity of developing a resilient and sustainable urban goods distribution system capable of efficiently recovering from high-severity disruptions. Our research team previously developed a novel analytical model, the Robustness, Redundancy, Resourcefulness, and Rapidity - Last-Mile Distribution - Resilience Triangle (R4-LMD-RT) framework to address this challenge. In line with the previous work, this work aims to create a sketch-planning tool tailored for local jurisdictions based on the R4-LMD-RT model. This tool assists in strategically planning urban goods distribution systems, identifying land use requirements, and proposing sustainable and resilient strategies, such as urban consolidation, micro-hubs, alternative delivery points, and zero-emission vehicles. As part of a case study, the authors validate the effectiveness of this planning tool by applying it to the city of Los Angeles for a COVID-19-like disruption. This research outcome paves the way for more sustainable and resilient urban goods distribution systems in the post-pandemic world.		
17. Key Words Last-mile, Sustainability, Resilience, Crowdsourcing, Collection-points, Micro-hubs	**18. Distribution Statement** No restrictions.	
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 39 / **22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Contents

About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the U.S. Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

U.S. Department of Transportation (USDOT) Disclaimer

Disclosure

Miguel Jaller and Anmol Pahwa conducted the "Sketch Planning Tool for Sustainable and Resilient Urban Goods Distribution" research at the University of California, Davis. The research took place from 10/01/2022 to 09/30/2023 and was funded by a grant from the United States Department of Transportation (USDOT) in the amount of $73,638. The research was conducted in the Pacific Southwest Region University Transportation Center research program.

Acknowledgments

This study was partially or entirely funded by a grant from the Pacific Southwest Region University Transportation Center (UTC), supported by the U.S. Department of Transportation (USDOT) through the University Transportation Centers program. The authors would like to thank the PSR and the USDOT for their support of university-based research in transportation and especially for the funding provided in support of this project.

Abstract

The urban goods distribution system is a critical component of modern society. However, the COVID-19 pandemic exposed significant vulnerabilities in this system as it struggled to cope with an unforeseen surge in demand. This crisis highlighted the urgent necessity of developing a resilient and sustainable urban goods distribution system capable of efficiently recovering from high-severity disruptions. Our research team previously developed a novel analytical model, the Robustness, Redundancy, Resourcefulness, and Rapidity - Last-Mile Distribution - Resilience Triangle (R4-LMD-RT) framework to address this challenge. In line with the previous work, this work aims to create a sketch-planning tool tailored for local jurisdictions based on the R4-LMD-RT model. This tool assists in strategically planning urban goods distribution systems, identifying land use requirements, and proposing sustainable and resilient strategies, such as urban consolidation, micro-hubs, alternative delivery points, and zero-emission vehicles. As part of a case study, the authors validate the effectiveness of this planning tool by applying it to the city of Los Angeles for a COVID-19-like disruption. The outcome of this research paves the way for more sustainable and resilient urban goods distribution systems in the post-pandemic world.

Sketch Planning Tool for Sustainable and Resilient Urban Goods Distribution: User Manual

Executive Summary

In the period leading up to the COVID-19 pandemic, the retail industry experienced a gradual and significant shift towards e-commerce. Yet, traditional in-store shopping remained the primary choice for consumers. However, the outbreak of the COVID-19 pandemic triggered a sudden and significant change in consumer behavior. Due to strict measures to contain the virus, which limited public movement, many consumers, including first-time users, went online shopping for essential items such as groceries, medicine, and healthcare products. Some e-retailers also faced increased demand for personal protective equipment from healthcare workers and hospitals. The pandemic revealed weaknesses in the supply chain, which was typically optimized for cost efficiency and just-in-time delivery, making it vulnerable to major disruptions.

Our research team previously developed a novel analytical model, the Robustness, Redundancy, Resourcefulness, and Rapidity - Last-Mile Distribution - Resilience Triangle (R4-LMD-RT) framework to address this challenge. This study focuses on developing a sketch planning tool to assess the resilience of last-mile distribution in the e-commerce sector using this previously developed R4-LMD-RT framework. The assessment combines three key elements: the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) resilience framework, a continuous approximation-based last-mile distribution model, and the concept of the resilience triangle.

Per prior research, the primary objective of this study is to develop a customized sketch-planning instrument designed for local authorities, utilizing the R4-LMD-RT framework. This tool aids in strategically organizing urban freight distribution systems, pinpointing land usage prerequisites, and suggesting eco-friendly and robust tactics, including urban consolidation, micro-distribution hubs, alternate delivery points, and emission-free vehicles. In a specific case study, the authors confirm the effectiveness of this planning tool by applying it to Los Angeles in a scenario similar to the disruptions caused by COVID-19. The findings of this research pave the way for more sustainable and resilient urban freight distribution systems in the post-pandemic era.

Introduction

Typically, e-retailers observe steady year-on-year growth in demand with a few high-probability, low-severity fluctuations through the year, such as around the holiday season. To cope with such market dynamics, e-retailers regularly monitor and manage their distribution operations, which can include the redesign of vehicle delivery routes (short-term operational management), procurement or disposal of resources, e.g., staff and equipment (medium-term tactical management), or even reconfiguration of the distribution structure (long-term strategic management).

However, the surge in e-commerce demand after a typical low-probability, high-severity disruption gives e-retailers little time to reassess and reconfigure tactical and, even more so, strategic management decisions. Thus, constrained to a pre-disruption level of resources, the e-retailers must cope with the surge in demand while operating at a much lower level of service than usual by outsourcing last-mile operations in a range of ways: either to crowdsourced fleets for delivery or to customers for pickup at collection-points, or to logistics service providers (LSP) for distribution; as well as by prioritizing the delivery of essential goods at the cost of delayed service for other goods.

Considering the role of e-commerce last-mile distributions in ensuring the supply of essential goods, it is pertinent to assess the resilience of last-mile distribution operations in terms of retailers' ability to maintain and efficiently restore the level of service in the event of such low-probability, high-severity disruptions. To this end, the authors developed Robustness, Redundancy, Resourcefulness, and Rapidity (R4) - Last Mile Distribution - Resilience Triangle (R4-LMD-RT) framework that can 1) model e-retailer's last-mile distribution operations using Continuous Approximation (C.A.) techniques, 2) develop the retailer's operational, tactical, and strategic decision-making to model its behavior pre-, peri-, and post- disruption and 3) evaluate its response to disruptions through. Note, R4-LMD-RT model is founded on the mathematical principles and proofs established in the seminal work of Daganzo (*1-4*).

Based on this novel performance-based qualitative-cum-quantitative domain-agnostic resilience assessment framework, this project seeks to develop a specialized sketch-planning tool for local governments, utilizing the R4-LMD-RT framework. This tool aids in the strategic planning of urban freight distribution systems by identifying land usage requirements and proposing eco-friendly and robust strategies, including urban consolidation, micro-hubs, alternative delivery points, and zero-emission vehicles. Through a case study, the authors substantiate the tool's effectiveness by applying it to Los Angeles during a pandemic-like disruption. This study's findings pave the way for sustainable and resilient urban freight distribution systems in the post-pandemic era.

Getting started

Before using the tool, enable the Solver add-in in the Excel Options dialog box. Click the File tab, and then click Options below the Excel tab. In the Excel Options dialog box, click Add-Ins. In the Manage drop-down box, select Excel Add-ins, and then click Go. In the Add-Ins dialog box, select Solver Add-in, and then click OK. After enabling the Solver add-in, Excel will auto-install the Add-in if it is not already installed, and the Solver command will be added to the Analysis group on the Data tab in the ribbon.

Further, you must establish a reference to the Solver add-in. Click the Developer tab, and then in the Code group, click the Visual Basic command. With a module active in the Visual Basic Editor, click References on the Tools menu, then select Solver under Available References. If Solver does not appear under Available References, click Browse, and then open Solver.xlam in the \Program Files\Microsoft Office\Office14\Library\SOLVER subfolder.

Navigating the tool

This section helps the user navigate the tool through the different worksheets in the Excel file. This tool contains primarily three kinds of worksheets, namely, input-based, output-based, and function-based worksheets. While the input-based worksheets are for the user to view and edit, the output-based worksheets are for view-purpose only. However, the function-based worksheets are protected for functionality, and the user is strongly suggested not to edit them.

Input-based worksheets

input

The *input* worksheet guides the user to input the necessary data and run the tool. These data inputs include service region parameter values, supply parameter values, and demand parameter values. The authors detail this user input process in the section – Running the tool.

service region

The service region worksheet enlists parameter values of the service region, including the service region's characteristics, the population's demographics, and the emissions costs in the service region.

Characteristics

City	:	name of the city
Region	:	region of the United States
Area	:	service area (in sq. mi.)
Population	:	population of the city above 16 years of age
Congestion Factor	:	avg. vehicle speed relative to the free flow speed in the region
Rate Parameter	:	Facility fixed cost rate parameter
Distance Parameter	:	Facility fixed cost distance parameter
Discount Rate	:	discount rate in the service region

Demographics

Sex	:	percentage of *male* and *female* in the service region
Education Level	:	percentage of people that belong to *none*, *primary*, secondary, and *graduate* education level in the service region
Age Group	:	percentage of people that belong to *generation Z*, *millennial*, *generation X*, *baby boomer*, and *silent* age groups in the service region
Income Level	:	percentage of people that belong to *poverty*, *low*, *lower-middle*, *median*, *middle-middle*, *upper-middle*, and high-income level in the service region
Household Characteristics:		household *size*, and *number of children* in the household

Emissions Cost ($/kg)

Emissions cost for
- Carbon Dioxide emissions (CO_2)
- Carbon Monoxide emissions (CO)
- Nitrous Oxide emissions (NO_x)
- Particulate Matter emissions (PM)

vehicle parameters

The vehicle parameters worksheet lists essential parameters of the vehicles deployed in last-mile distribution, including:

Capacity	:	vehicle capacity (number of packages)
Long-haul Speed	:	vehicle speed outside the service region (mph)
Last-mile Speed	:	vehicle speed inside the service region (mph)
(Un)Loading Time	:	time taken to (un)load the vehicle (hours per package)
Parking Time	:	time taken to park at customer stop (hours per θ packages) *
Service Time	:	time taken to service a customer stop (hours per θ packages) *
Purchase Cost	:	vehicle purchase cost ($)
Driver Cost	:	driver wage ($ per hour)
Maintenance Cost	:	vehicle maintenance cost ($ per mile)
Fuel Cost	:	vehicle fuel cost ($ per unit of fuel consumed)
Fuel Consumption Rate	:	rate of fuel consumption (unit of fuel per mile)
Emission Rate	:	rate of emissions (CO_2, CO, NO_x, and PM) (g of emissions/mile)

* θ refers to the consolidation level in the distribution structure. Refer to the Detailed Modeling Framework for more details.

supply

The supply worksheet enlists supply-side parameters, including the distribution environment and those about the primary distribution channel (retailer's distribution structure) and secondary distribution channel (outsourcing distribution structure).

Distribution Environment

Planning Horizon	:	number of years of operation planned for
Working Days	:	number of working days in a year
Working Hours	:	number of working hours in a day
Market Share	:	market share of the e-retailer
Outsourcing Share	:	maximum share of packages outsourced by the e-retailer

Primary Distribution Channel

Facility	:	facility name (e-commerce fulfillment facility) [g]
Number	:	number of facilities (1) [g]
Location	:	location of the facility relative to the center of the service region[o]
Fleet Type	:	primary delivery vehicle (diesel truck) [g]
Fleet Size Limit	:	primary delivery fleet size (none) [g]
Tour Limit	:	maximum number of delivery tours per day per vehicle (9) [g]
Operation	:	vehicle operations (last-mile delivery) [g]

Secondary Distribution Channel

Outsourcing Channel : Secondary distribution channel deployed

Crowdsourced Delivery

Facility : facility name (e-commerce fulfillment facility) [g]
Number : number of facilities (1) [g]
Location : location of the facility relative to the center of the service region[o]
Fleet Type : secondary delivery vehicle type
Fleet Size Limit : secondary delivery fleet size
Tour Limit : maximum number of delivery tours per day per vehicle
Operation : vehicle operations (last-mile delivery) [g]

Customer Pickup

Facility : facility name (collection-point facilities) [g]
Number : number of collection-point facilities
Location : location of collection-points (located uniformly in the region) [g]
Fleet Type : secondary delivery vehicle type
Fleet Size Limit : secondary delivery fleet size (max customer demand observed) [g]
Tour Limit : maximum number of delivery tours per day per vehicle (1) [g]
Operation : vehicle operations (customer pickup) [g]

LSP Distribution

Facility : facility name (micro-hub facilities) [g]
Number : number of collection-point facilities
Location : location of collection-points (located uniformly in the region) [g]
Fleet Type : secondary delivery vehicle type
Fleet Size Limit : secondary delivery fleet size
Tour Limit : max number of delivery tours per day per delivery vehicle (9) [g]
Operation : operations of the secondary delivery vehicle (last-mile delivery) [g]

[g] Given, [o] Optimized; The user must specify all other parameter values as guided by the *input* worksheet.

demand

The demand worksheet enlists pre- and peri-/post- disruption demand parameters.

Pre-Disruption Demand

Daily Customer Demand : daily customer demand observed by the e-retailer before the disruption

Peri-/Post- Disruption Demand

Default scenarios

COVID-19 : e-commerce disruption observed during the COVID-19 pandemic
Sustained : a COVID-19 like disruption but with no recovery
Decayed : a COVID-19 like disruption but with full recovery

Sharp	:	a COVID-19 like disruption but rapid
Blunt	:	a COVID-19 like disruption but slow

Custom Scenarios

Growth Factor	:	percentage increase to peak disruption
Decay Factor	:	percentage decrease from peak disruption
Growth Half-Life	:	number of days towards half the increase to peak disruption
Decay Half-Life	:	number of days towards half the decrease from peak disruption
Growth Rate Inverse	:	inverse of the rate of increase to peak disruption
Decay Rate Inverse	:	inverse of the rate of decrease from peak disruption

Output-based worksheets

output

The output worksheet characterizes and plots the observed demand and service disruption. With this, the output sheet analyzes the retailer's response to disruption, evaluating last-mile distribution resilience in Robustness, Redundancy, Resourcefulness, and Rapidity – Resilience Metrics. The tool also evaluates Operational Metrics wherein Total Delay expresses cumulative delay in terms of the number of package-days of delayed service. In contrast, the Average Delay evaluates the average number of additional packages delayed on any day and the average number of days a package is delayed, assuming that packages are delivered on a first-come-first-served basis. Moreover, the output worksheet evaluates Economic Metrics that evaluate the Direct, Indirect, and Total Loss to the e-retailer from the disruption. Note the Direct Loss evaluates the change in distribution cost relative to the pre-disruption distribution cost. Indirect Loss accounts for the loss from delayed service, penalizing late delivery (unmet demand) at $5 per package for every day of delayed service. At the same time, the Total Loss is the sum of Direct and Indirect loss, thereby reflecting the explicit and implicit costs to the e-retailer.

Function-based worksheets

pre-disruption demand

The pre-disruption demand worksheet employs a multinomial logit model that depicts consumer choice of shopping channel to estimate total pre-disruption e-commerce demand in the service region.

main

The main worksheet enlists parameters and decision variables relevant to the different optimization models and the simulation framework in the tool.

optimize

The optimized worksheet details the retailer's pre- and post-disruption distribution structure optimization model.

mincost-w|o

The *mincost-w|o* worksheet details the retailer's cost minimization model without using a secondary (outsourcing) distribution channel.

maxcap-w|o

The *maxcap-w|o* worksheet details the retailer's capacity maximization model without using a secondary (outsourcing) distribution channel.

mincost-wo

The min-cost-wo worksheet details the retailer's cost minimization model using a secondary (outsourcing) distribution channel.

maxcap-wo

The maxcap-wo worksheet details the retailer's capacity maximization model using a secondary (outsourcing) distribution channel.

miscellaneous

The miscellaneous worksheet includes some data for functional purposes.

results

The results worksheet outputs the simulation results, including daily congestion levels, demand, unserved demand, primary distribution capacity, auxiliary distribution capacity, served demand, cost per package, disruption, and level of service.

Running the tool

This section details the essential steps to run the tool.

Step 0. Start with the input worksheet.

Step 0.1. Reset values

Step 1. Set service region parameter values in the service region worksheet.

Step 1.1. Set service region characteristics → **Step 1.2.** Set service region demographics → **Step 1.3.** Set service region emissions cost

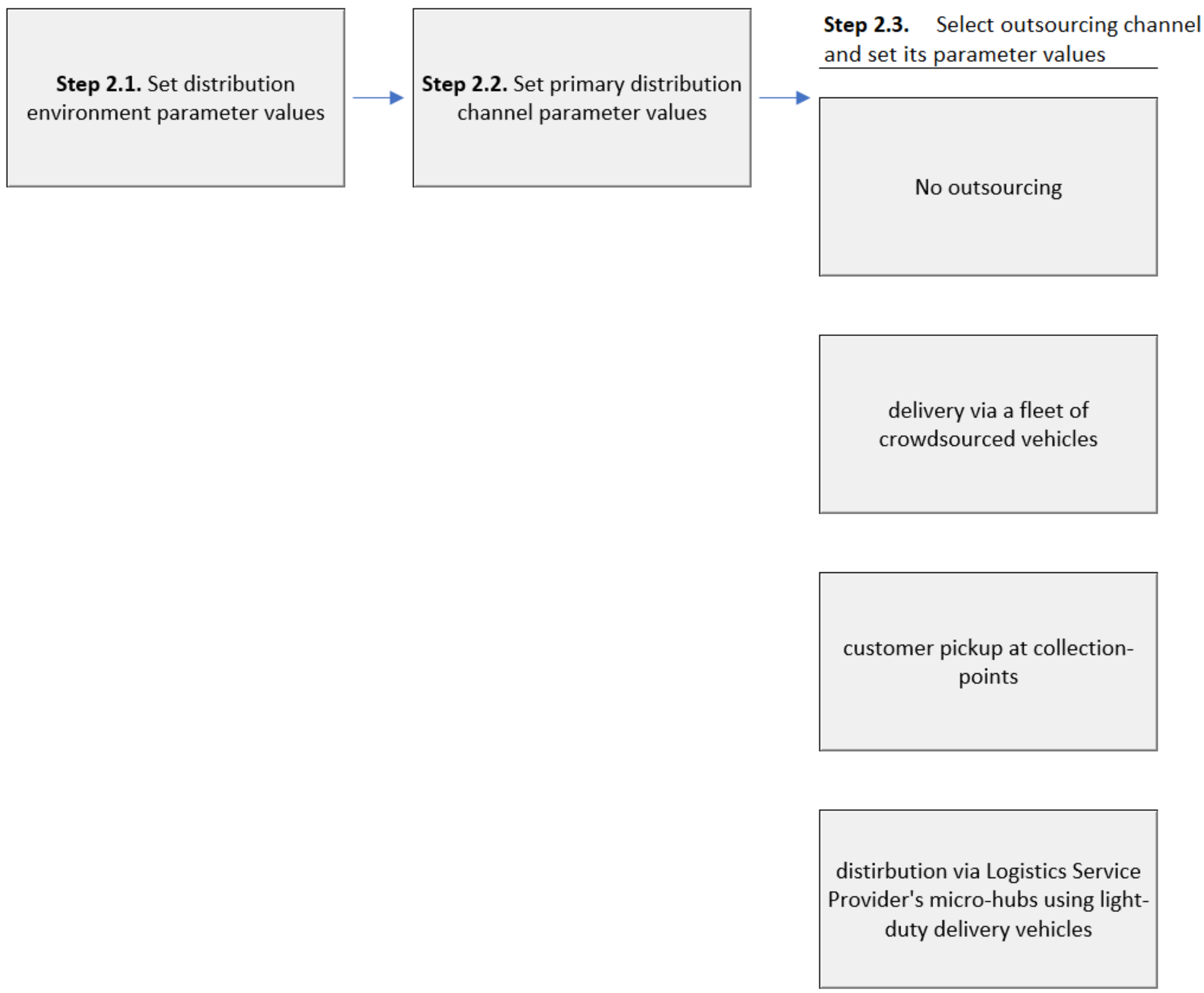
Step 1.1.1. Set service region name in cell B2.
Step 1.1.2. Select the service region location from the drop-down list in cell B3.
Step 1.1.3. Scroll through the bar to set the service region size in cell B4.
Step 1.1.4. Scroll through the bar to set the service region population in cell B5.
Step 1.1.5. Scroll through the bar to set the service region congestion factor in cell B6.
Step 1.1.6. Scroll through the bar to set the service region facility fixed cost rate parameter in cell B7.
Step 1.1.7. Scroll through the bar to set the service region facility fixed cost distance parameter in cell B8.
Step 1.1.8. Scroll through the bar to set the service region discount rate in cell B9.

Step 1.2.1. Scroll through the bar to set the service region gender ratio in cells B15-16.
Step 1.2.2. Scroll through the bar to set service region education levels in cells B19-22.
Step 1.2.3. Scroll through the bar to set service region age groups in cells B25-29.
Step 1.2.4. Scroll through the bar to set service region income levels in cells B32-38.
Step 1.2.5. Scroll through the bar to set the service region household size in cell B41.
Step 1.2.6. Scroll through the bar to set the service region household number of children in cell B41.

Step 1.3.1. Scroll through the bar to set service region CO_2 cost in cell B47.

Step 1.3.2. Scroll through the bar to set service region C.O. cost in cell B48.
Step 1.3.3. Scroll through the bar to set service region NO_x cost in cell B49.
Step 1.3.4. Scroll through the bar to set service region PM cost in cell B50.

Step 2. Set supply parameter values in the supply worksheet.



Step 2.1.1. Scroll through the bar to set the retailer’s planning horizon in cell B2.
Step 2.1.2. Scroll through the bar to set the retailer’s working days in cell B3.
Step 2.1.3. Scroll through the bar to set the retailer’s working hours in cell B4.
Step 2.1.4. Scroll through the bar to set the retailer’s market share in cell B5.
Step 2.1.5. Scroll through the bar to set the retailer’s planning horizon in cell B6.

Step 2.2.1. Select fleet type from the drop-down list in cell B14.

If no outsourcing channel is deployed

Step 2.3.1. Set the outsourcing channel to None from the drop-down list in cell B22.

Else, if the distribution is outsourced with crowdsourced delivery.

Step 2.3.1. Set the outsourcing channel to crowdsourced delivery from the drop-down list in cell B22.

Step 2.3.2. Select fleet type from the drop-down list in cell B28.

Step 2.3.3. Set fleet size limit in cell B29.

Step 2.3.4. Set tour limit in cell B30.

Else, if service is outsourced via collection-points for customer pickup.

Step 2.3.2. Set the number of collection-points in cell B35.

Step 2.3.3. Select fleet type from the drop-down list in cell B37.

Step 2.3.4. Set fleet size limit list in cell B38.

Step 2.3.5. Set tour limit in cell B39.

Else, if distribution is outsourced via the Logistics Service Provider's micro-hubs

Step 2.3.2. Set the number of micro-hubs in cell B44.

Step 2.3.3. Select fleet type from the drop-down list in cell B46.

Step 2.3.4. Set fleet size limit list in cell B47.

Step 2.3.5. Set tour limit in cell B48.

To view/edit vehicle-related parameters, refer to the *vehicle parameters* worksheet.

Step 3. Set demand parameter values in the demand worksheet.

Step 3.1. Set pre-disruption demand → **Step 3.2.** Set peri-/post-disruption demand

Step 3.1.1. Set pre-disruption demand in cell B2.

Step 3.2.1. Select one of the default disruption scenarios or set up a custom scenario.

Step 4. Solve

Step 4.1. Simulate → **Step 4.2.** Analyze

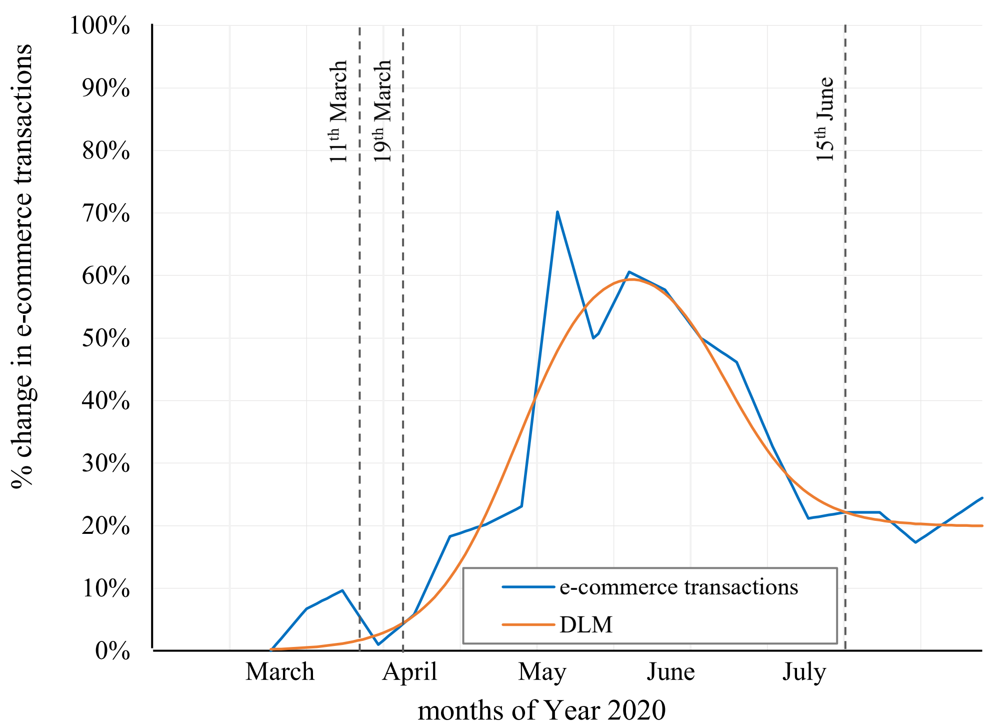
Step 5. Export results

Step 5.1. Export

Case study

Description

The case study here develops analyses for a fairly large-sized e-retailer with a market share of about 30%, serving the city of Los Angeles, a 475 sq. mi. service region with about 100k pre-disruption daily online customers. Further, the authors assume the service region to observe the pandemic-instigated surge in demand (modeled as a double logistic model; Figure 1. Considering such a distribution environment, the e-retailer can organize its distribution structure in the pre-disruption stage for low-cost, just-in-time service. However, to cope with the surge in demand in the peri-/post- disruption stage, the e-retailer must then outsource part of its operations to a crowdsourced fleet for delivery or to customers for pickup at collection-points or to logistics service providers (LSP) for distribution (see Figure 2). In addition to the surge in demand, the authors also model reduced traffic congestion - observed as a consequence of inhibited public movement owing to the various virus containment measures, as a double logistic model similar to the surge in demand. Further, for simplicity, the authors assume no direct impact on the retailer's distribution capacity with the continued availability of resources (staff and drivers) during the disruption.



DLM: Double Logistic Model

$y_t = 0.685/(1 + \exp(-(t - 49.373)/8.447)) - 0.486/(1 + \exp(-(t - 89.512)/7.885))$; $R^2 = 0.937$

Figure 1. Modeling e-commerce demand surge instigated by the COVID-19 pandemic

Table 1 shows the relevant features for each vehicle type deployed in the distribution process. For the analyses, this study assumes a consolidation of 3 deliveries per stop ($\theta = 3$). To evaluate emissions costs, this work accounts for CO2, CO, NOx, and PM emissions from last-mile distribution, valued at $0.066, $0.193, $76.97, and $630.3 per kilogram of emissions, respectively.

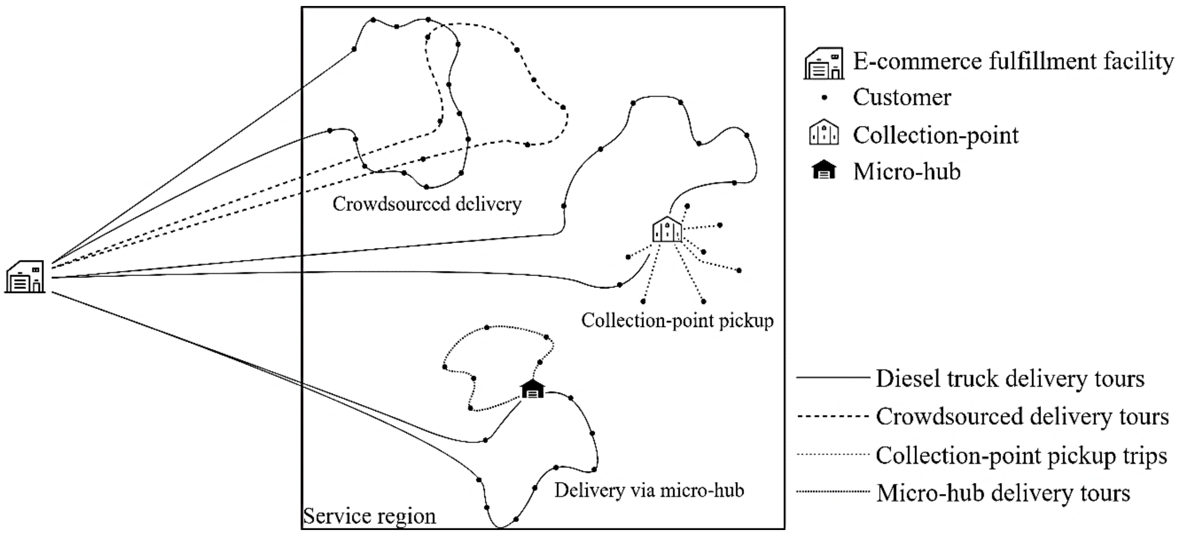


Figure 2. Last-mile distribution with outsourced service

Table 1. Vehicle characteristics

Vehicle characteristics		Diesel Truck	Pickup Truck	Passenger Car	Cargo-Bike
Capacity	number of packages	360	30	1	30
Long-Haul Speed	mph	55	60	60	10
Last-Mile Speed	mph	20	25	25	10
(Un)loading Time	hours per package	0.005	0.0083	0.0083	0.005
Parking Time	hours per θ packages	0.042	0.0208	0.0208	0.0208
Service Time	hours per θ packages	0.050	0.050	0.050	0.050
Purchase Cost [a]	$	80000	0	0	6500
Driver Cost [b]	$ per hour	35	20	0	30
Maintenance Cost [b]	$ per mile	0.200	0.000	0.000	0.120
Fuel Cost [c]	$ per gallon/kWh	3.860	0.000	0.000	0.120
Fuel Cons. Rate [a]	gallon/kWh per mile	0.100	0.050	0.030	0.029
CO_2 Emission Rate [d]	g per mile	1049	386	303	0.000
CO Emission Rate [d]	g per mile	0.767	1.770	1.090	0.000
NO_x Emission Rate [d]	g per mile	4.140	0.170	0.075	0.000
PM Emission Rate [d]	g per mile	0.132	0.003	0.002	0.000

[a] Jaller, Pineda and Ambrose (*5*) [b] Caltrans (*6*) [c] AAA (*7*) [d] California Air Resource Board (*8*)

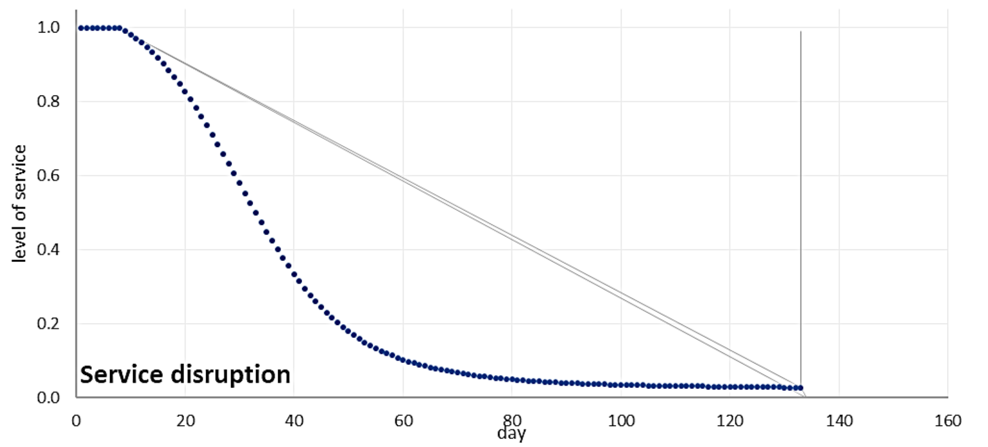


Figure 3. Service disruption with no outsourcing channel deployed

No outsourcing channel deployed

When no outsourcing channel is deployed, the e-retailer cannot maintain and restore functionality (Figure 3), resulting in a total loss of 0.3b$ throughout the disruption (Table 2). Thus, to cope with disruption, the e-retailer must outsource part of its distribution operations to an outsourcing channel.

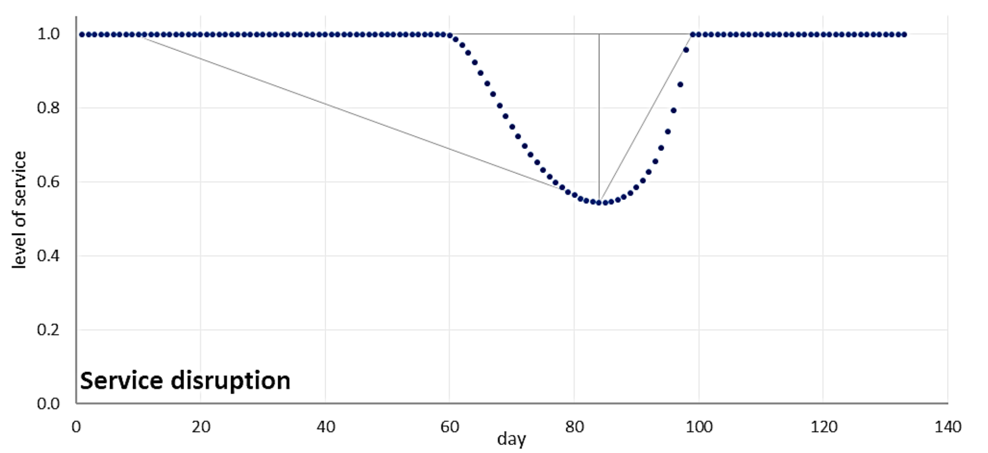


Figure 4. Service disruption with crowdsourced delivery

Delivery via a fleet of crowdsourced vehicles

To begin with, for delivery via a fleet of crowdsourced vehicles, the case study here assumes 500 crowdsourced drivers with their light-duty pickup trucks to be available at the disposal of the e-retailer. Moreover, the analysis here assumes the e-retailer remunerates these crowdsourced drivers hourly only and not for their fuel or vehicle maintenance expenses. Note due to such limited incentives, the analysis assumes the crowdsourced drivers make only one delivery tour for the e-retailer. However, with crowdsourced delivery, the e-retailer can restore last-mile service (Figure 4), albeit with a total delay of 0.863m pkg-days and a total loss of $6.53m (Table 2).

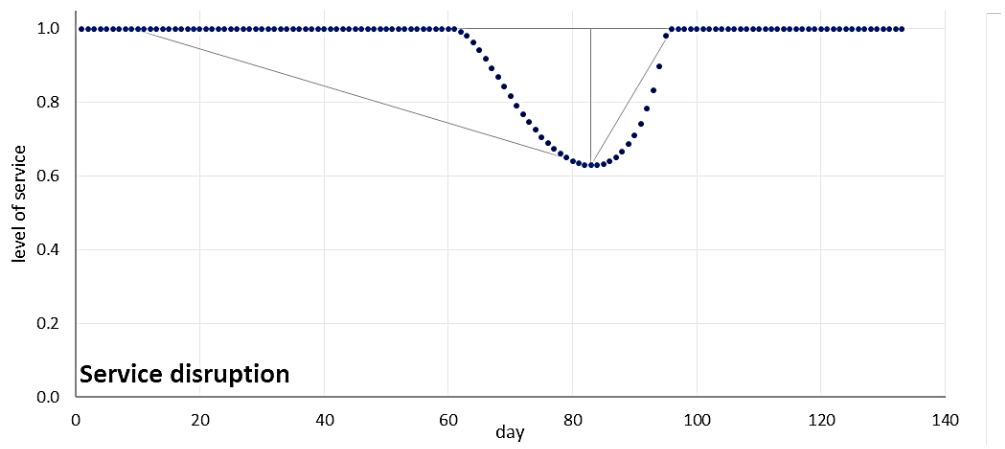


Figure 5. Service disruption with collection-point pickup

Customer pickup at the collection-points

On the other hand, for customer pickup at the collection-points, the case study assumes the e-retailer will ship packages from its e-commerce fulfillment facility to 200 such lockers (located randomly and uniformly in the region), from which the customers finally collect the packages. Note the analysis assumes that at most 45% of the customers would be willing to collect packages from the nearest collection-point. Nonetheless, when outsourcing the last mile to the customer, the e-retailer can restore service (Figure 5), exhibiting a robustness of 0.63, redundancy of 0.65, resourcefulness of 1.0, and rapidity of 0.83 (Table 2).

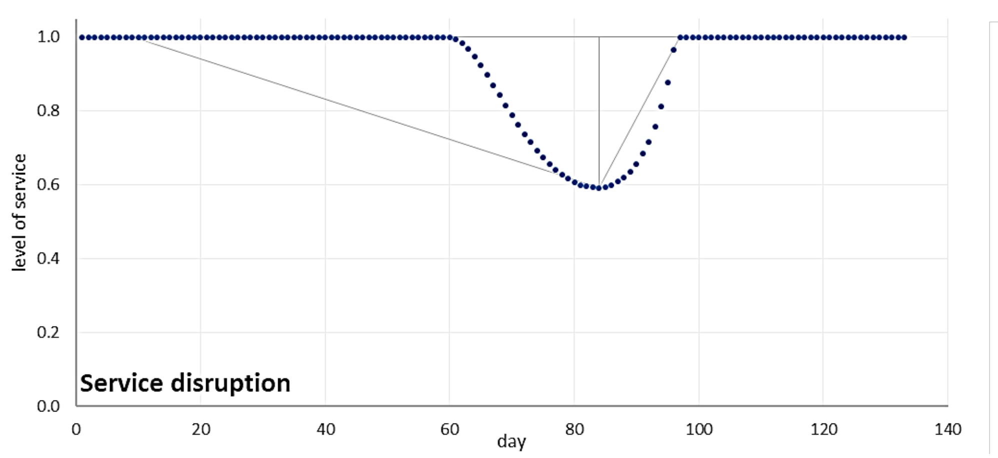


Figure 6. Service disruption with LSP distribution

Distribution via a logistics service provider

For distribution via a logistics service provider, the case study assumes the e-retailer ships packages from its e-commerce fulfillment facility to 20 such micro-hubs (located randomly and uniformly in the region) from where the LSP delivers packages using its 140 electric cargo bikes. Thus, with service outsourced to a logistics service provider, the e-retailer can restore functionality (Figure 6) albeit with a direct loss of $3.65m and an average delay of 7.43k packages per day, resulting in an indirect loss of $3.31m (Table 2).

Table 2. Case study results

Metrics	None	Crowdsourced Delivery	Customer Pickup	LSP Distribution
Resilience Metrics				
Robustness	0.000	0.544	0.629	0.592
Redundancy	0.000	0.593	0.650	0.626
Resourcefulness	0.000	1.000	1.000	1.000
Rapidity	0.000	0.835	0.825	0.840
Operational Metrics				
Total Delay (m pkg-days)	59.64	0.863	0.541	0.661
Average Delay (k pkgs/day)	473.3	9.487	6.145	7.431
Average Delay (days)	14.30	0.164	0.103	0.126
Cost Metrics				
Direct loss (m$)	0.002	2.211	0.623	3.651
Indirect Loss (m$)	298.2	4.317	2.704	3.306
Total Loss (m$)	298.2	6.528	3.327	6.957

Note: Case study results are only illustrative and not for comparison.

Equity impacts

Traditionally dominated by brick-and-mortar stores, the retail sector has witnessed an increasing presence of e-commerce in the past few years. At the turn of the 21st century, e-commerce barely accounted for 1% of total retail sales, yet by the end of the last decade (i.e., 2020), more than a tenth of all retail sales came from online channels. This steady 15% annual growth in e-commerce sales, in contrast to the 4% annual growth in total retail sales in the past decade, came about due to a consistently improving online shopping experience for the consumer (cheaper shipping, expedited deliveries, free returns, etc.) and improved proximity to the market for the e-retailer (digital omnipresence). Yet, despite the ease of online shopping, the wide range of product availability online, and the lucrative offers on e-commerce platforms, traditional in-store shopping continued to be the dominant channel for daily purchases until the COVID-19 pandemic enforced a sudden and significant shift in consumer shopping behaviors.

On March 11, 2020, the World Health Organization (WHO) declared the novel coronavirus (SARSCoV2) outbreak causing the coronavirus disease (COVID-19) as a global pandemic. A level of panic ensued among buyers; the local brick-and-mortar stores witnessed opportunistic purchase behaviors resulting in long queues and hoarding of daily essentials. Governments worldwide enforced aggressive virus containment measures to build the capacity to test, trace, and treat the infected. Following suit, the California State Government issued a stay-at-home order on 19th March 2020, lifted on 15th June 2020. These measures led to a total meltdown of the retail sector. Retailers that primarily relied on physical stores faced the brunt of the crisis.

In contrast, other retailers with some online presence managed through the crunch, though usually at the expense of significant cost-cutting from reduced workforce and operations. The e-retailers, on the other hand, particularly those selling essential goods, daily consumables, groceries, medications, and healthcare products, witnessed an unprecedented surge in demand. The disruption thus instigated a lower level of services, which had negative implications for the efficiency of the distribution system with delayed deliveries or total lack of access to those deliveries, thereby exposing vulnerable and disadvantaged communities to increased risk.

This is particularly evident as the case study here establishes this loss in level of service for a reasonably large-sized e-retailer with a market share of about 30%, serving the city of Los Angeles, a 475 sq. mi. service region with about 100k pre-disruption daily online customers. In particular, the e-retailer observes an average delay of 473k packages per day owing to the disruption, resulting in a total loss of $298m. Thus, it is pertinent that the e-retailer outsources last-mile service to maintain and restore its service when exposed to disruption. In particular, an e-retailer offering rush delivery could employ a fleet of crowdsourced drivers, considering the flexible and on-demand nature of crowdshipping. Yet, another e-retailer may want to mitigate the monetary loss from the disruption and could, therefore, plan for the deployment of collection-points for customer pickup. On the other hand, a more traditional retailer may want to ensure reliability and could consequently outsource part of its last-mile distribution via a (or multiple) logistics service provider(s) distributing through micro-hubs.

Nonetheless, the e-retailer must consider equity implications for its staff, workers, and drivers to ensure a safe working environment and prevent any job hazard under business-as-usual conditions, but with unique protocols for each phase of the disruption. Further, collection-points must be sufficiently located throughout the service region, ensuring accessibility for disadvantaged and vulnerable groups. Moreover, since logistics clusters with micro-hubs are located close to disadvantaged communities owing to lower property rates, such communities have a higher exposure to traffic emissions and accidents. Thus, it is pertinent that the regulatory bodies consider the general equity implications of home-based accessibility to last-mile delivery services and last-mile distribution in terms of exposure to freight-related externalities.

Detailed modeling framework

In this section, the authors detail the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) Last Mile Distribution Resilience Triangle Framework developed in Pahwa and Jaller (*9)* to assess retailer's ability to maintain and efficiently restore the level of service in the event of a low-probability high-severity disruptions.

Description

This work evaluates last-mile distribution resilience for an e-retailer making deliveries in a service region using a homogenous fleet of delivery trucks operating from an e-commerce fulfillment facility. The authors assume the e-retailer organizes its distribution structure (primary distribution channel) for low-cost, just-in-time deliveries. While such a distribution structure can cope with minor disruptions, a severe unforeseen disruption can put the e-retailer at risk of operating at a much lower level of service than usual. Coping with market disruption, the e-retailer may outsource some operations via a crowdsourced fleet for delivery, collection-points for customer pickup, or a logistics service provider (LSP) for distribution from micro-hubs using cargo bikes (secondary distribution channel). Thus, to evaluate the ability of the e-retailer to maintain and efficiently restore the level of service in the event of low-probability high-severity disruptions, the authors here 1) model the retailer's last-mile distribution operations using Continuous Approximation (C.A.) techniques, 2) develop the retailer's operational, tactical, and strategic decision-making to model its behavior pre-, peri-, and post- disruption and 3) evaluate its response to disruptions through a novel performance-based qualitative-cum-quantitative domain-agnostic resilience assessment framework. Below is a list of notations employed in this modeling framework. Note, R4-LMD-RT model is founded on the mathematical principles and proofs established in the seminal work of Daganzo (*1-4*).

List of notations

Distribution environment

Parameters

A	:	Size of the service region
t_o	:	Day 1
ϕ_o	:	Pre-disruption congestion factor
N_o	:	Pre-disruption customer demand
α_1	:	Growth factor
α_2	:	Decay factor
μ_1	:	Growth half-life
μ_2	:	Decay half-life
θ_1	:	Growth rate inverse
θ_2	:	Decay rate inverse
t_s	:	Disruption's start day
t_r	:	Recovery day

t_e : Disruption's end day

Distribution service

Parameters

t : Day t

ϕ_t : Congestion factor on day t

N_t : Customer demand on day t

N_{t-1}^u : Unserved customer demand on day $t-1$

$\bar{N}_t$: Distribution capacity on day t

Distribution structure

Primary channel

Decision variables

ρ_x : E-commerce fulfillment facility x-location relative to the center of service region

ρ_y : E-commerce fulfillment facility y-location relative to the center of service region

Parameters

q_d : Distribution facility capacity

π_d^f : Distribution facilities fixed cost

π_d^o : Distribution facilities fixed cost

W : Working hours in a day

p_u : Maximum share of packages that can be outsourced

Secondary channel

Parameters

N^{cp} : Number of collection-points

N^{mh} : Number of micro-hubs

${q_d}'$: Distribution facility capacity

$\pi_d^{f'}$: Distribution facilities fixed cost

$\pi_d^{o'}$: Distribution facilities fixed cost

W' : Working hours in a day

Distribution fleet

Primary channel

$\bar{m}$: Delivery tour limit

q_v : Vehicle capacity

v_{out} : Vehicle free-flow speed outside the service region

v_{in} : Vehicle free-flow speed inside the service region

τ_{sd} : Service time loading/unloading packages at the distribution facility (per package)

τ_{sc} : Service time delivering packages at a customer stop (per package)

f_o : Fleet size limit

π_v^f : Vehicle fixed cost

π_v^{ol} : Vehicle distance-based operational cost

π_v^{ot} : Vehicle time-based operational cost

Secondary channel

$\bar{m}'$	:	Delivery tour limit
q'_v	:	Vehicle capacity
v'_{out}	:	Vehicle free-flow speed outside the service region
v'_{in}	:	Vehicle free-flow speed inside the service region
τ'_{sd}	:	Service time loading/unloading packages at the distribution facility
τ'_{sc}	:	Service time delivering packages at a customer stop
$\bar{f}'$	:	Fleet size limit
$\pi_v^{f'}$	:	Vehicle fixed cost
$\pi_v^{ol'}$	:	Vehicle distance-based operational cost
$\pi_v^{ot'}$	:	Vehicle time-based operational cost

Distribution operations

Primary channel

Decision variables

C_t^c	:	Number of customer stops per delivery tour on day t
C_t^{cp}	:	Number of collection-point stops per delivery tour on day t
C_t^{mh}	:	Number of micro-hub stops per delivery tour on day t
m_t	:	Delivery tours per delivery vehicle on day t
f_t	:	Delivery fleet size on day t
p_t	:	Share of packages outsourced on day t

Parameters

ρ	:	Long-haul length (distance)
Λ_t	:	Long-haul length (time)
L_t	:	Delivery tour length (distance) on day t
T_t	:	Delivery tour length (time) on day t

Secondary channel

Decision variables

$C_t^{c'}$	:	Number of customer stops per delivery tour on day t
m'_t	:	Delivery tours per delivery vehicle on day t
f'_t	:	Delivery fleet size on day t

Parameters

ρ'	:	Long-haul length (distance)
Λ'_t	:	Long-haul length (time)
L'_t	:	Delivery tour length (distance) on day t
T'_t	:	Delivery tour length (time) on day t

Distribution cost

Γ	:	Facility fixed cost rate parameter
λ	:	Facility fixed cost distance parameter

Π_t^f	:	Fixed cost of distribution on day t
Π_t^o	:	Operational cost of distribution on day t
Π_t	:	Total cost of distribution on day t

Distribution resilience

R_1	:	Robustness
R_2	:	Redundancy
R_3	:	Resourcefulness
R_4	:	Rapidity

Other

ψ^{cs}	:	Binary variable depicting the use of crowdsourced delivery
ψ^{cp}	:	Binary variable depicting the use of collection-points for customer pickup
ψ^{mh}	:	Binary variable depicting the use of micro-hubs via logistics service provider
η	:	Amortization factor
θ	:	Consolidation per stop
k	:	Continuous Approximation parameter

Modeling last-mile operations

To model the distribution and outsourcing operations, this work builds on a continuous approximation (C.A.)-based last-mile delivery model, which, unlike conventional discrete formulation methods, enables long-term strategic decision-making, primarily when operating costs may be needed. Still, the precise plan cannot be established. The equations here detail this last-mile delivery model in the context of this work and how the different phases of the disruption are considered.

Pre-disruption $\left(t \in [t_o, t_s)\right)$ distribution operations

Before the surge in demand ($t \in [t_o, t_s)$), this work assumes the e-retailer operates independently with its fleet of delivery trucks, making all the delivery tours. This delivery tour comprises the long haul, the journey from the e-commerce fulfillment facility to the first customer stop, from the last customer stop back to the facility, and the last mile, the journey between the first and last customer stops. Hence, the length of this delivery tour is the sum of the back-and-forth long-haul distance (ρ) and the last-mile distance, represented by each term in the equation, respectively. The delivery tour time is the sum of the service time loading packages at the facility (τ_{sF} per package), the long-haul travel time (Λ_t), the last-mile travel time, and the service time delivering packages at customer stops (τ_{sC} per customer), represented by each term in the equation, respectively. Note, the long haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility, while the last mile is continuously approximated proportional to the number of stops in the delivery tour - $[C_t^c/\theta]^+$, and inversely proportional to the square root of stop density (δ_t/θ).

Here, θ represents the number of customers consolidated per stop. Note in typical last-mile delivery environments, these distribution operations are constrained by vehicle capacity, working hours, and service constraints affecting delivery tour length and tour time.

$$L_t = 2\rho + \frac{k[C_t^c/\theta]^+}{\sqrt{N_t/A\theta}}$$

$$T_t = C_t^c\tau_{sd} + 2\Lambda_t + \frac{k[C_t^c/\theta]^+}{v_{in}\phi_t\sqrt{N_t/A\theta}} + C_t^c\tau_{sc}$$

Peri-disruption ($t \in [t_s, t_e]$)/Post-disruption ($t \in (t_e, t_r]$) distribution operations

To cope with a low-probability, high-severity surge in demand ($t \in [t_s, t_r]$), this work assumes that the e-retailer will choose to outsource p_t share of its operations via a crowdsourced delivery fleet, collection-points for customer pickup, or via an LSP for distribution from its micro-hubs using cargo bikes (Figure 2). The equations here model the distribution operations for the e-retailer and outsourcing channel combined distribution structure.

Crowdsourced delivery - The crowdsourced operations in this study are inspired by the Amazon Flex program. Much like the retailer's delivery trucks, the crowdsourced drivers collect packages at the e-commerce fulfillment facility before embarking on e-retailer-designed tours. The length of this delivery tour is the sum of long-haul and last-mile distances, represented by each term in the equations, respectively. The delivery tour time is the sum of the service time loading packages at the facility, the long-haul travel time, the last-mile travel time, and the service time delivering packages to the customers, represented by each term in the equations, respectively. As described previously, the long haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility, while the last mile is continuously approximated proportional to the number of stops in the delivery tour (delivery truck delivery tour - $[C_t^c/\theta]^+$, crowdsourced vehicle delivery tour - $\left[C_t^{c'}/\theta\right]^+$), and inversely proportional to the square root of stop density (delivery truck delivery tour - $\delta_t(1-p_t)/\theta$, crowdsourced vehicle delivery tour - $\delta_t p_t/\theta$). Note these distribution operations are constrained by vehicle capacity, working hours, and service constraints affecting delivery tour length and tour time.

Customer pickup at collection-points – Unlike crowdsourcing, where the outsourcing channel operates independently, the e-retailer must fulfill the collection-points using its fleet of delivery trucks before customers can travel to one of the collection-points to collect their packages. Note the model assumes that the e-retailer is located. N^{cp} collection-points randomly and uniformly in the service region, each with a capacity to hold V packages. Thus, the retailer's delivery truck tour comprises long-haul and last-mile, including visits to the customers and collection-points. Therefore, the delivery tour length is the sum of the long-haul and last-mile distances, represented by each term in the equation. The delivery tour time is the sum of the service time loading packages at the e-commerce fulfillment facility, the long-haul travel time, the last-mile travel time, the service time delivering packages at customer stops, and the service time unloading packages at the collection-points, represented by each term in the equation, respectively. Again, the long haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility, while the last mile is continuously approximated proportional to the number of stops in the delivery tour - $[C_t^c/\theta]^+ + \left[C_t^{cp}\right]^+$, and inversely proportional to the square root of stop density - $\delta_t(1-p_t)/\theta + \delta^{cp}$. On the other hand, the customer's collection-point visit (trip) is estimated by the average distance from customer-stop to the nearest collection-point. Note that these distribution operations are constrained by vehicle capacity, working-hours, and service constraints affecting delivery tour length and time.

Distribution via micro-hubs operated by a logistics service provider (LSP) - The authors assume this LSP to operate from N^{mh} identical micro-hubs located randomly and uniformly in the service region, each with a fleet of cargo bikes or other small/light delivery vehicles. The e-retailer must fulfill the LSP's micro-hubs using its fleet of delivery trucks before the cargo bikes from these micro-hubs can embark on last-mile deliveries. Thus, the delivery truck's tour comprises long-haul and last-mile, including customer visits and micro-hubs. The delivery truck's tour length is therefore the sum of the long-haul and the last-mile distances, represented by each term in the equation. The delivery truck's delivery tour time is the sum of the service time loading packages at the e-commerce fulfillment facility, the long-haul travel time, the last-mile travel time, the service time delivering packages at the customer stops, and the service time unloading packages at the micro-hubs, represented by each term in the equation, respectively. As described previously, the long haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility, while the last mile is continuously approximated proportional to the number of stops in the delivery tour - $[C_t^c/\theta]^+ + [C_t^{mh}]^+$, and inversely proportional to the square root of stop density - $\delta_t(1-p_t)/\theta + \delta^{mh}$. On the other hand, a cargo bike's delivery tour is comprised of a long haul, the journey from the micro-hub to the first customer stop and likewise from the last customer stop back to the micro-hub, and the last mile, the journey between the first and last customer-stops. The cargo bike's delivery tour length is the sum of the long-haul and the last-mile distances, represented by each term in the equation. The cargo bike's delivery tour time is the sum of the service time loading packages at the micro-hub, the long-haul travel time, the last-mile travel time, and the service time delivering packages at the customer stops, represented by each term in the equation, respectively. Again, the long haul is estimated by the average distance between the micro-hubs and the customers, while the last mile is continuously approximated proportional to the number of stops in the delivery tour - $[C_t^c/\theta]^+$, and inversely proportional to the square root of stop density - $\delta_t p_t/\theta$. Note these distribution operations are constrained by vehicle capacity, working hours, and service constraints affecting delivery tour length and tour time.

$$L_t = 2\rho + \frac{k([C_t^c/\theta]^+ + [C_t^{cp}]^+ + [C_t^{mh}]^+)}{\sqrt{\frac{N_t(1-p_t)}{A\theta} + \psi^{cp}[p_t]^+\frac{N^{cp}}{A} + \psi^{mh}[p_t]^+\frac{N^{mh}}{A}}}$$

$$T_t = \left(C_t^c + \frac{C_t^{cp}N_t p_t}{N^{cp}} + \frac{C_t^{mh}N_t p_t}{N^{mh}}\right)\tau_{sd} + 2\Lambda_t + \frac{k([C_t^c/\theta]^+ + [C_t^{cp}]^+ + [C_t^{mh}]^+)}{v_{in}\phi_t\sqrt{\frac{N_t(1-p_t)}{A\theta} + \psi^{cp}[p_t]^+\frac{N^{cp}}{A} + \psi^{mh}[p_t]^+\frac{N^{mh}}{A}}} + \left(\frac{C_t^{cp}N_t p_t}{N^{cp}} + \frac{C_t^{mh}N_t p_t}{N^{mh}}\right)\tau_{sd} + C_t^c\tau_{sc}$$

$$L_t' = 2\rho' + (\psi^{cs} + \psi^{mh})\frac{k[C_t^{c\prime}/\theta]^+}{\sqrt{N_t p_t/A\theta}}$$

$$T_t' = C_t^{c\prime}\tau_{sd}' + 2\Lambda_t' + (\psi^{cs} + \psi^{mh})\frac{k[C_t^{c\prime}/\theta]^+}{v_{in}'\phi_t\sqrt{N_t p_t/A\theta}} + C_t^{c\prime}\tau_{sc}'$$

Where,

$$\rho = \begin{cases} |\rho_x| + |\rho_y| & \text{if } |\rho_x| \text{ and } |\rho_y| \geq \sqrt{A}/2 \\ |\rho_x| + \rho_y^2/\sqrt{A} + \sqrt{A}/4 & \text{if } |\rho_x| \geq \sqrt{A}/2, |\rho_y| < \sqrt{A}/2 \\ \rho_x^2/\sqrt{A} + \sqrt{A}/4 + |\rho_y| & \text{if } |\rho_x| < \sqrt{A}/2, |\rho_y| \geq \sqrt{A}/2 \\ \rho_x^2/\sqrt{A} + \rho_y^2/\sqrt{A} + \sqrt{A}/2 & \text{if } |\rho_x| \text{ and } |\rho_y| < \sqrt{A}/2 \end{cases}$$

$$\rho' = \psi^{cs}\rho + \psi^{cp}\frac{2}{3}\sqrt{\frac{A}{N^{cp}}} + \psi^{mh}\frac{2}{3}\sqrt{\frac{A}{N^{mh}}}$$

$$\Lambda_t = \frac{1}{\phi_t}\begin{cases} \frac{\rho}{v_{out}} + \frac{\sqrt{A}}{}\left(\frac{1}{v_{in}} - \frac{1}{v_{out}}\right) & \text{if } |\rho_x| \text{ and } |\rho_y| \geq \sqrt{A}/2 \\ \frac{(|\rho_x| - \sqrt{A}/2)}{v_{out}} + \frac{(\rho_y^2/\sqrt{A} + 3\sqrt{A}/4)}{v_{in}} & \text{if } |\rho_x| \geq \sqrt{A}/2, |\rho_y| < \sqrt{A}/2 \\ \frac{(\rho_x^2/\sqrt{A} + 3\sqrt{A}/4)}{v_{in}} + \frac{(|\rho_y| - \sqrt{A}/2)}{v_{out}} & \text{if } |\rho_x| < \sqrt{A}/2, |\rho_y| \geq \sqrt{A}/2 \\ \frac{\rho}{v_{in}} & \text{if } |\rho_x| \text{ and } |\rho_y| < \sqrt{A}/2 \end{cases}$$

$$\Lambda_t' = \psi^{cs}\Lambda_t + \psi^{cp}\frac{\rho'}{v_{in}'\phi_t} + \psi^{mh}\frac{\rho'}{v_{in}'\phi_t}$$

Developing retailer's decision-making in the pre-, peri-, and post-disruption phase

In the pre-disruption phase ($t \in [t_o, t_s)$), the model assumes that the e-retailer observes a stable daily demand of N_o customers. With the e-retailer having complete knowledge of the delivery environment, the e-retailer organizes its distribution structure to offer low-cost, just-in-time delivery service. Thus, in a static and deterministic pre-disruption phase, the e-retailer minimizes the total distribution cost by considering the location of the e-commerce fulfillment facility, fleet size, number of delivery tours per vehicle, and number of customers served per delivery tour, subject to vehicle capacity, working hours, and service constraints. This total cost includes amortized fixed costs - facility fixed and fleet purchase costs; operational costs - driver, maintenance, and fuel costs; and emission costs. To this end, let (ρ_{x_o}, ρ_{y_o}) denote the optimal e-commerce fulfillment facility location, and let f_o be the optimal retailer's delivery truck fleet size, resulting from minimizing the pre-disruption distribution cost.

Primary distribution channel capacity maximization

$$\max_{\{f_t, m_t, C_t^c\}} \bar{N}_t = C_t^c m_t f_t$$

Subject to,

$$C_t^c \leq q_v$$
$$T_t m_t \leq W$$
$$f_t \leq f_o$$

Primary distribution channel cost maximization

$$\min_{\{\rho_x, \rho_y, f_t, m_t, C_t^c\}} \Pi_t = (\pi_d^f + \pi_v^f f_t)/\eta + m_t f_t (L_t \pi_v^{ol} + T_t \pi_v^{ot}) + \pi_d^o N_t$$

Subject to,

$$C_t^c \leq q_v$$
$$T_t m_t \leq W$$
$$C_t^c m_t f_t = N_o$$

Where,

$$\pi_d^f = \Gamma\left(\left(\rho_x^2 + \rho_y^2\right)^{-\lambda} N_o\right)$$

In the peri-/post- disruption phase ($t \in [t_s, t_r]$), to serve the daily demands of N_t customers ($N_t > N_o$) plus previous unmet demand of N_{t-1}^u customers, the model assumes that the e-retailer will outsource some of its operations via the outsourcing channels. Unlike in the pre-disruption phase, in the peri-/post- disruption phase, the e-retailer has no information on future demand. In particular, at the start of any given day $t \in [t_s, t_r]$, the e-retailer has information only on N_t customers ($N_t > N_o$) received since the start of the previous day, requesting delivery service by the end of this day, and previous unmet demand of N_{t-1}^u customers. To this end, the e-retailer can only optimize for its operational decision variables and not for its strategic or tactical choices. Thus, in a semi-dynamic and deterministic peri-/post- disruption phase, if the combined e-retailer and outsourcing channel distribution structure capacity of $\overline{N}_t$ customers is sufficient to cater to the increased e-commerce demand of $N_t + N_{t-1}^u$ customers, then the e-retailer minimizes the distribution cost of outsourcing deliveries for $(N_t + N_{t-1}^u)p_t$ customers while serving the remaining using its available fleet of delivery trucks, optimizing for the share of operations to outsource, operational parameters of the outsourcing channel, and operational parameters of its delivery tours, subject to vehicle capacity, working hours, service, and resource constraints. However, if the combined distribution capacity of $\overline{N}_t$ customers fall short of the increased e-commerce demand; then the combined distribution structure caters to the $\overline{N}_t$ customers, while delaying delivery for $N_t^u = N_t + N_{t-1}^u - \overline{N}_t$ customers to the next day. Note the distribution cost here includes fixed, operational, and emissions costs for the combined distribution structure.

Combined distribution channel capacity maximization

$$\max_{\{f_t, m_t, C_t^c, f_t', m_t', C_t^{c'}, p_t\}} \overline{N}_t = C_t^c m_t f_o + C_t^{c'} m_t' f_t'$$

Subject to,

$$(C_t^c + \psi^{cp} C_t^{cp}\, N p_t / N^{cp} + \psi^{mh} C_t^{mh}\, N p_t / N^{mh}) \leq q_v$$
$$T_t m_t \leq W$$
$$C_t^c m_t f_t = \overline{N}_t (1 - p_t)$$
$$C_t^{cp} m_t f_t = N^{cp}$$
$$C_t^{mh} m_t f_t = N^{mh}$$
$$f_t \leq f_o$$
$$p_t \leq p_u$$
$$C_t^{c'} \leq q_v'$$
$$T_t' m_t' \leq W'$$
$$C_t^{c'} m_t' f_t' = \overline{N}_t p_t$$
$$f_t' \leq \overline{f}'$$

Combined distribution channel cost minimization

$$\min_{\{m_t, C_t^c, C_t^{cp}, C_t^{mh}\, f_t', m_t', C_t^{c'}, p_t\}} \Pi_t = (\pi_d^f + \pi_v^f f_t)/\eta + m_t f_t (L_t \pi_v^{od} + T_t \pi_v^{ot}) + \pi_d^o N_t$$
$$(\pi_d^{f'} + \pi_v^{f'} f_t')/\eta + m_t' f_t' \left(L_t' \pi_v^{od'} + T_t' \pi_v^{ot'}\right) + +\pi_d^{o'} N_t p_t$$

Subject to,

$$N = \begin{cases} \overline{N}_t & \text{if the objective is to maximize distribution capacity} \\ N_t + N_{t-1}^u & \text{if the objective is to minimize distribution cost} \end{cases}$$
$$(C_t^c + \psi^{cp} C_t^{cp}\, N p_t / N^{cp} + \psi^{mh} C_t^{mh}\, N p_t / N^{mh}) \leq q_v$$
$$C_t^{c'} \leq q_v'$$
$$T_t m_t \leq W$$
$$T_t' m_t' \leq W'$$

$$C_t^c m_t f_t = (N_t + N_{t-1}^u)(1 - p_t)$$
$$C_t^{cp} m_t f_t = N^{cp}$$
$$C_t^{mh} m_t f_t = N^{mh}$$
$$C_t^{c'} m_t' f_t' = (N_t + N_{t-1}^u) p_t$$
$$f_t \leq f_o$$
$$f_t' \leq \bar{f}'$$
$$p_t \leq p_u$$

Where,

$$\pi_d^f = \Gamma\left(\left(\rho_x^2 + \rho_y^2\right)^{-\lambda} N_o\right)$$
$$\pi_d^{f'} = \Gamma \mathrm{A}^{-\lambda} \exp(1.14\lambda) / (1 - \lambda)\, (N_t p_t)$$

To solve the above optimization problems, this work employs Frontline Solver, which first solves a relaxed version of the problem, ignoring the integer constraints, using the Generalized Reduced Gradient (GRG) non-linear method. The Solver then uses the Branch and Bound technique to branch the relaxed problem into subproblems for every integer decision variable in the original problem with appropriate binding constraints, and each is solved using the GRG non-linear method. This process is repeated until the integer decision variables take integer values subject to a tolerance level. Note, the implementation of GRG non-linear method in this tool includes derivatives established centrally for a constraint precision of 1e-7 and convergence threshold of 1e-7.

Evaluating retailer's response to disruption

This work further develops the framework to assess the retailer's response to disruption through level of service. Figure 7 presents the use of resilience triangles in this work for an e-retailer witnessing disruption (N_t, ϕ_t; between disruption start and end day) resulting in a loss of service ($r(t)$; until recovery day) which is characterized by the shape and size of triangles pivoted at the pre-disruption peak, peri-disruption nadir, and post-disruption recovered level of service. The level of service is a performance indicator defined as the ratio of demand served to total demand evaluated by solving the optimization models described in the previous subsection. This work then characterizes the drop in level of service as a consequence of the disruption using the proposed Robustness, Redundancy, Resourcefulness, and Rapidity (R4) Last Mile Distribution Resilience Triangle Framework (Figure 7). In particular, this work quantifies Robustness (R1), the ability of the system to withstand disruption, as the gap between the nadir and zero level of the service line. Redundancy (R2), the extent to which the elements of the system are substitutable, is the average downward slope towards the nadir. Resourcefulness (R3), the ability to diagnose and prioritize problems and initiate solutions, is quantified as the ratio of the recovered level of service to the drop in level of service at the nadir. Rapidity (R4), the capability to restore functionality promptly, is the average upward slope towards recovery from nadir.

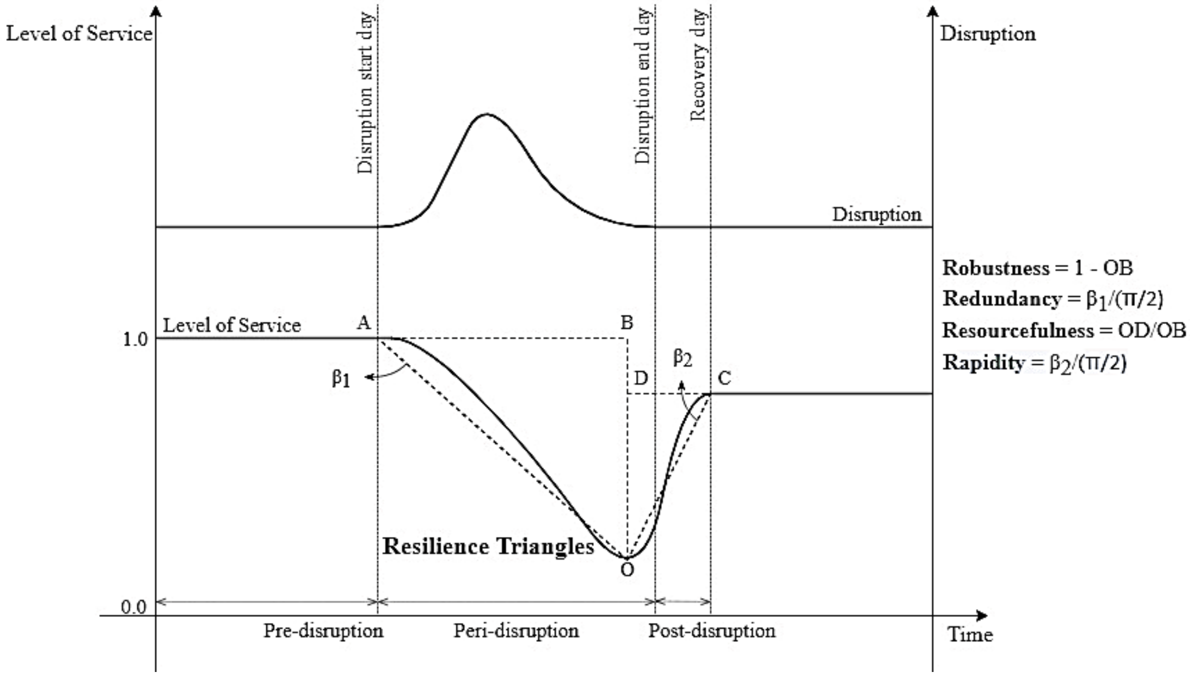


Figure 7. Characterizing the system's level of service under disruption using resilience triangles

$$N_t = N_o\left(1 + \frac{\alpha_1}{1 + \exp\left(\frac{-(t-\mu_1)}{\theta_1}\right)} - \frac{\alpha_2}{1 + \exp\left(\frac{-(t-\mu_2)}{\theta_2}\right)}\right)$$

$$\phi_t = \phi_o\left(1 + \frac{\alpha_1/5}{1 + \exp\left(\frac{-(t-\mu_1)}{\theta_1}\right)} - \frac{\alpha_1/5}{1 + \exp\left(\frac{-(t-\mu_2)}{\theta_2}\right)}\right)$$

$$r(t) = 1 - N_t^u/(N_t + N_{t-1}^u)$$

$$\begin{aligned}
R_1 &= r(t_n);\ t_n = \operatorname{argmin} r(t) \\
R_2 &= \tan^{-1}\Big((t_n - t_s)/\big(r(t_s) - r(t_n)\big)\Big)/(\pi/2) \\
R_3 &= \big(r(t_r) - r(t_n)\big)/\big(r(t_s) - r(t_n)\big) \\
R_4 &= \tan^{-1}\Big((t_r - t_n)/\big(r(t_r) - r(t_n)\big)\Big)/(\pi/2)
\end{aligned}$$

This performance-based qualitative-cum-quantitative framework allows for assessing the resilience of last-mile distribution operations under any disruption. Moreover, this assessment framework's integrated R4 and Resilience Triangle component is not specific to last-mile logistics or transportation systems. It is domain-agnostic and thus can be employed across domains to assess the resilience of any system under disruption.

In addition to Robustness, Redundancy, Resourcefulness, and Rapidity – Resilience Metrics, the authors evaluate the retailer's response with Operational Metrics that quantify the extent of delayed deliveries. In particular, the Total Delay expresses cumulative delay in the number of package days of delayed service. At the same time, the Average Delay evaluates the average number of additional packages delayed on any day and the average number of days a package is delayed, assuming that packages are delivered on a first-come-first-served basis. Moreover, the authors evaluate Economic Metrics that evaluate the Direct, Indirect, and Total Loss to the e-retailer from the disruption. Here, the Direct Loss evaluates the change in distribution cost relative to pre-disruption distribution cost, and Indirect Loss accounts for the loss from delayed service, penalizing late delivery (unmet demand) at $5 per package for every day of delayed service, while the Total Loss is the sum of Direct and Indirect Loss, and thereby reflects the explicit and implicit costs to the e-retailer.

References

[1] Daganzo, C. F. Modeling distribution problems with time windows: Part I. *Transportation Science,* Vol. 21, No. 3, 1987, pp. 171-179.
[2] ---. Modeling distribution problems with time windows. Part II: Two customer types. *Transportation Science,* Vol. 21, No. 3, 1987, pp. 180-187.
[3] ---. The length of tours in zones of different shapes. *Transportation Research Part B: Methodological,* Vol. 18, No. 2, 1984, pp. 135-145.
[4] Daganzo, C. F. The Distance Traveled to Visit N Points with a Maximum of C Stops per Vehicle: An Analytic Model and an Application. *Transportation Science,* Vol. 18, No. 4, 1984, pp. 331-350.
[5] Jaller, M., L. Pineda, and H. Ambrose. Evaluating the Use of Zero-Emission Vehicles in Last Mile Deliveries.In *UC Davis Institute of Transport Studies*, University of California, Davis, Davis, CA, 2018.
[6] Caltrans. *Vehicle Operation Cost Parameters*. https://dot.ca.gov/programs/transportation-planning/economics-data-management/transportation-economics/vehicle-operation-cost-parameters.
[7] AAA. *State Gas Price Averages*. https://gasprices.aaa.com/state-gas-price-averages/.
[8] California Air Resource Board. *EMFAC2017 Web Database*. https://www.arb.ca.gov/emfac/2017/.
[9] Pahwa, A., and M. Jaller. Assessing last-mile distribution resilience under demand disruptions. *Transportation Research Part E: Logistics and Transportation Review,* Vol. 172, 2023, p. 103066.

Data Management Plan

Products of Research

This study develops a Sketch Planning Tool tailored for local jurisdictions based on the Robustness, Redundancy, Resourcefulness, and Rapidity - Last-Mile Distribution - Resilience Triangle (R4-LMD-RT) framework.

Data Format and Content

The Sketch Planning Tool is a Microsoft Excel macro-enabled file in the .xlsm format.

Data Access and Sharing

The project uses publicly available information. Any dataset compiled during the project using the various data sources follows the same access and sharing policies as the original data. The team will make available the datasets used in this work. The research team does not anticipate the use of any data with private or confidential information. Any other user should reference the research team and this project as directed by the National Center for Sustainable Transportation and the Pacific Southwest Region UTC.

Reuse and Redistribution

Any user should follow the copyright guidelines of the original datasets. For other sets produced by the research team, third-party users should cite the work and email the P.I., mjaller@ucdavis.edu, to inform about the use of the data. The data may be cited as follows:

Pahwa, Anmol; Jaller, Miguel (2023). Sketch Planning Tool for Sustainable and Resilient Urban Goods Distribution [Dataset]. Dryad. https://doi.org/10.5061/dryad.bk3j9kdjt