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Discrete Optimization

The efficacy of exclusive territory assignments to delivery vehicle drivers ☆

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Abstract

A supporting logic for having a vehicle driver exclusively assigned to serve the same territory on every delivery trip is the deepening of the driver's knowledge of the territory and the customers therein. This contributes to the driver's proficiency in serving that territory. However, in situations of randomness in day-to-day customer demands, the choice of exclusive territory assignments entails the sacrifice of sub-optimal route configuration. This study quantifies the extent of that sacrifice in order to depict the cost implications of exclusive territory assignments vis-à-vis tactics that keep pace with day-to-day demand fluctuations by allowing for flexibility in the assignments. The study's analysis of exclusive territory assignments covers those that involve territory sharing among a team of drivers.

Keywords: Routing; Simulation; Transportation; Assignment

1. Introduction

In freight delivery operations involving ground transport from a depot to geographically dispersed customers, the responsibility of ensuring that customers receive their requested deliveries does not end with configuring the routes and determining the intra-route delivery sequences. One of the additional tasks is to decide which driver should serve which route. One might use a tactic, herein labeled *exclusive territory assignment*, that involves configuring the routes once and then exclusively assign each one to a specific driver. The logic of this tactic is that task repetition by delivery vehicle drivers can contribute to their proficiency. That is, repetitively making the deliveries on the same route and, hence, to the same customers and within the same geographic sub-division of the region served by the depot should deepen a driver's knowledge of important specifics: the customers, the road network, the terrain, etc. However, in situations of random daily fluctuations in each customer's demands over time, the resulting proficiency benefits can be canceled out. In particular, the configuration of the routes under exclusive territory assignment might not be optimal for some demand outcomes; i.e., it forfeits the route design efficiencies that are attainable with

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an approach of re-grouping the customers and re-sequencing the deliveries to match each day's actual demand outcomes. Because this approach of completely reoptimizing the routes each day results in the potential for daily changes in the customer groupings, exclusivity in the driver-to-customer assignments cannot be guaranteed. This paper uses the label *non-exclusive assignment* to describe an assignment tactic that is based on daily route reoptimization.

Quantitative analysis of the forfeited route design efficiencies of the exclusive territory assignment tactic (vis-à-vis a non-exclusive assignment tactic) is this paper's primary objective. The analysis involves studying how these efficiencies are affected by three routing factors: customer demand variability, vehicle capacity, and size of the team of drivers assigned to each territory. The thinking behind the third factor is that the pooling effect of exclusively assigning a team of drivers (instead of a single driver) to each territory can reduce the forfeited efficiencies. The pooling benefit comes from partial or intra-territory route reoptimization; i.e., limited customer grouping/sequencing adjustments in response to each day's demand outcome. The paper's second objective is to quantify the impact of team size on a benefit that serves as a rationale for territory-based assignment. That benefit, which contributes to deepening a driver's knowledge of a territory's specifics, is the manageable (relatively small) number of customers a driver is required to learn about. As an aside, this paper acknowledges that learning about a larger number of customers is a desirable *objective*; e.g., drivers so learned give their company a wider range of desirable customer-to-driver assignment options. But as is to be expected, more desirable objectives are likely to call for more effort to achieve so this paper's focus is on the required *effort* (i.e., the driver's learning burden) and not on the objective per se. This effort grows with the size of the team, for as will be elucidated in the next section, a team approach really involves combining multiple single-driver territories. This means that a team member can be called on to serve (learn about) a customer that, prior to the combining of territories, was the exclusive responsibility of another driver.

The study's primary contribution is to the literature on tactics for addressing probabilistic customer demands in vehicle routing problems and particularly on analysis of alternatives to the established benchmark of daily route reoptimization. The basis for the study of alternatives is the long acknowledged concerns about the inherent routing instability of that benchmark; e.g., Bertsimas (1992) and Waters (1989) commented on the potential problem of unpredictable changes in the day-to-day duties of route planning and execution. The alternatives covered in the literature generally focus on the route configuration and recourse decisions of vehicle routing/dispatch employees; e.g., recourse decisions necessitated by significant differences between actual and projected customer demands. Papers on such alternatives can be traced back to early works such as Tillman (1969), Golden and Stewart (1977) and Golden and Yee (1979). Examples of subsequent works include Benton and Rossetti (1992), Gendreau et al. (2001), Laporte et al. (2002), and Secomandia (2001). This paper adds the driver workforce dimension to the analysis of alternatives by focusing on the personnel decisions of how to assign drivers to routes and territories.

To elaborate on the pursuit of this specific research objective, and the findings, the remainder of this paper is organized into four sections. The first of these formally details of the research problem. Section 3 presents the research methodology. Section 4 discusses the findings and their potential ramifications for territory-based driver assignment policies under conditions of probabilistic customer demands. The paper's concluding section summarizes the study's main contributions and identifies some of its possible extensions.

2. Problem specifications

This paper analyzes situations in which N geographically dispersed customers have delivery requirements (demands) that fluctuate each day according to a specified gamma distribution. Demands across customers are uncorrelated and each customer's demand (*iid*) has the same gamma parameters. From a central depot, vehicles, each with capacity Q units, are dispatched daily to serve all N customers, and each trip begins and ends at the depot. The depot is assumed to have (access to) the number of vehicles (fleet size) and drivers (denoted D) required to satisfy the largest realistically attainable value of total demand across all customers on any day. It is assumed that maximizing drivers' knowledge of the customers they serve is an important goal. The practical importance of this goal has been noted in the literature by, e.g., Cheong et al. (2002, p. 18). An instructive commentary on its importance in freight transportation/delivery practice is also reflected in a transportation company CEO's explanation of why his company was among logistics companies to be awarded the title of "One of Canada's 50 Best Managed Companies" in 2004. A part of his explanation was the service improvements customers experienced from being served by a driver who is a familiar face and hence very knowledgeable of their operations in areas such as merchandise receiving: "*One of the biggest advantages our driver retention provides our shipper clients is consistency of service – familiar faces showing up at their facilities*".[1] Under these general features, this study's research problem involves comparison of exclusive territory assignment with a policy (based on complete route reoptimization) of non-exclusive assignments. The comparison criteria are route design/configuration efficiencies and the number of customers a driver is required to learn about.

2.1. Route design/configuration efficiencies

For the policy of exclusive territory assignment, with one driver exclusively assigned to each territory, the approach is to subdivide the region served by the depot into D territories, averaging N/D customers per territory. So on any given day, at least D delivery trips are made (a trip is used here to mean the dispatch of one vehicle and driver to serve a set of customers). Extra trips in excess of D are made in territories that have total demand in excess of Q units on that day. While justifiable on grounds that each driver gains the repetition-based learning benefits from visiting the same group of N/D customers daily, the tactic forfeits some of the route design efficiencies that would be attainable if the customer groups (and hence the customer-to-driver match ups) are allowed to change in response to daily demand outcomes. That is, if complete route reoptimization is used as a prior step to the assignment of drivers to routes (customers).

For example, on days when total demand across all customers is unusually low, the complete route reoptimization solution might call for fewer vehicles and lower travel distance. However, because the reconfigured routes (regrouping of customers) might violate the exclusive territory assignment policy – i.e., it might require a driver to go inside a territory that is exclusively assigned to another driver – the route design benefits of lower travel distance and fewer vehicles must be forfeited. Forfeiture of these benefits can also occur on days when total demand is unusually high. On those days, vehicle capacity constraints might mean that a single delivery trip by a driver is insufficient to serve the customers in his assigned territory. Here again, the exclusivity of the territory assignment would mean that if the goods must be delivered on the day under consideration (the assumption in this study) then that driver would have to make a second trip to cover the customers who did not receive all their requirements on the initial trip. Increases in travel distance (and vehicle dispatches) that result from demand surges are likely to be smaller with the completely reconfigured routes, which, through greater flexibility in regrouping customers to minimize the number of separate trips, reflect a more cost-effective response to these surges.

In some cases, management at the depot may elect to exclusively assign each territory to a team of G (>1) drivers rather than to a single driver. With each territory being the shared responsibility of a specified team of drivers, the number of territories would be D/G (one of which could be a fractional territory served by fewer than G drivers) and there would be an average of NG/D customers per full territory. This allows limited (intra-territory) regrouping of customers and makes it possible to save on trips. As an extreme example, if, on a given day the total demand of the NG/D customers in a territory does not exceed Q units then, subject to upper limits on a driver's trip length and duration, one trip (i.e., one dispatched vehicle and one driver) may be sufficient to serve all of that territory's customers. More generally, if the day's territory demand $\leqslant (G - v)Q$ units then as many as v fewer trips can be made to that territory on that day. Fig. 1 is a stylized illustration of how territory sharing works. The map in the right panel of the figure shows the case for $G = 1$ in which drivers Andy and Bobby each have their separate territories but with sharing ($G = 2$), each driver can now serve customers that were previously assigned exclusively to the other driver.

Pooling also reduces the risk of the territory's capacity (GQ) falling short of demand. This risk reduction reduces the required number of trips (and the required travel distance) since there is less need for the recourse activity of dispatching vehicles/drivers to customers who were inconvenienced

[1] The CEO's full ad verbatim explanation appears on p. 49 of the April 2004 issue of *Canadian Transportation and Logistics*.

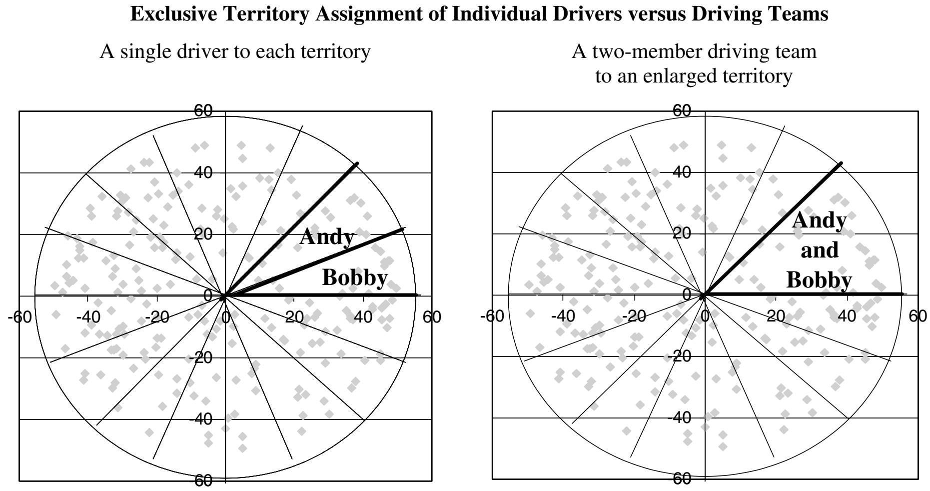

Fig. 1. Exclusive territory assignment of individual drivers versus driving teams.

by the capacity shortfall. Greater territory sharing by enlarging the driving team (increasing G) can therefore be viewed as the use of partial route reconfiguration to progressively reduce the value of metrics that gauge the forfeited route design efficiencies. The metrics used here are $(V_{\mathrm{ET}} - V_{\mathrm{NE}})$ and $(L_{\mathrm{ET}} - L_{\mathrm{NE}})$, where V_{NE} and L_{NE} denote, respectively, the daily average number of trips (vehicle/driver dispatches) and travel distance under non-exclusive assignments, with V_{ET} and L_{ET} being the corresponding parameters for the exclusive territory assignment tactic.

2.2. Required knowledge of customers

Using a team of drivers to reduce the forfeited travel efficiencies means that some of the benefits of exclusivity in the driver assignment must be given up. For example, as Fig. 1 illustrates, each driver has to learn about a larger territory and about the particulars of a larger number of customers in order to continue being effective in his delivery duties. Interestingly, as will be shown in the findings, the additional number of customers (as a proportion of the baseline number) need not be the same as the proportional increase in the team size; e.g., it need not automatically follow that Andy and Bobby will each need to become familiar with twice as many customers as they had before they formed a team. That is because, following each day's intra-territory re-grouping of customers, this research uses an approach of ensuring that each day, every customer has an above average chance of being served by the driver who has to date become most familiar with that customer. That is, dispatch/routing staff's daily activities can be characterized as having two broad elements: a route configuration decision (minimizing intra-territory travel distance and vehicle dispatches) and a personnel assignment decision (maximizing customer-driver familiarity). Under non-exclusive assignment, which is based on daily route reoptimization, territorial boundaries are ignored in the route configuration decision but the same driver-to-customer assignment principle is used. So the essential difference is that with the non-exclusive assignment tactic, the frame of reference in executing the procedure is the entire service region comprising all N customers while for the exclusive territory assignment tactic, the frame of reference is the individual territory comprising approximately NG/D customers, each territory being treated independently of the others as a mini service region.

Given this distinction, this study's analysis of exclusive territory assignment as a possible alternative to non-exclusive assignment is tantamount to an analysis of the efficacy of rigid territorial boundaries. In the immediately forthcoming description of the assignment principle, specific and relevant distinctions between the two tactics are noted. The description requires the following definitions:

$X_{rj}^{(T)}$ 1 if route r is served by driver j on day T, 0 otherwise; for complete route optimization, the number of routes can be as large as D (i.e., $\max[r] \leqslant D$) and for exclusive territory assignment, each territory's number of routes for a day can be as low (i.e., at least one route is run) and (save for recourse trips made to customers inconvenienced by a capacity shortfall) as high as G

$x_{ij}^{(T)}$ 1 if customer i is served by driver j on day T (i.e., if customer i is on the route served by driver j: route r), 0 otherwise

$c_{ij}^{(T-1)} = \sum_{t=1}^{T-1} x_{ij}^{(t-1)}$ cumulative number of visits to customer i by driver j up to day $T-1$. With the exclusive territory assignment tactic, $c_{ij}^{(T-1)} \equiv 0$ for drivers or customers not assigned to the territory under current consideration

$C_{rj}^{(T-1)} = \sum_{i \in n_r} c_{ij}^{(T-1)}$ cumulative number of visits to all customers on route r by driver j up to day $T-1$; n_r defines the set of customers on route r. That is, from the total of all N customers, the summation for each route (r) in the case of non-exclusive assignment considers only the smaller subset of customers on that route ($i \in n_r$); in the case of fixed territory assignment, the subset of relevance is taken from the set of customers within the territory under current consideration.

Since the problem on the current day (T) is to maximize the familiarity between customer and driver by assigning each route to the driver who is most familiar with (has made the most previous visits to) the set of customers on that route, it can be formulated as

$$\text{Maximize} \sum_r \sum_j C_{rj}^{(T-1)} X_{rj}^{(T)} \tag{1}$$

$$\sum_r X_{rj}^{(T)} \leqslant 1 \quad \forall j, \tag{2a}$$

$$\sum_j X_{rj}^{(T)} = 1 \quad \forall r. \tag{2b}$$

In this integer programming formulation, the constraints in (2a) and (2b) ensure that, respectively, each driver serves no more than one route, and that each route is served by exactly one driver. This assignment problem would be formulated and solved after the day's routes (customer groupings) have been determined by application of some route reoptimization algorithm. In this formulation, the coefficient $C_{rj}^{(T-1)}$ is *endogenous*. That is, while the formulation follows the standard single-period structure in the workforce scheduling literature, this paper deals with a multi-period problem. As a result, the assignment solutions in all previous periods $(X_{rj}^{(1)}, X_{rj}^{(2)}, \ldots, X_{rj}^{(T-1)})$ are explicitly used to quantify the driver's current level of familiarity with each customer on each route formed on day T. In the workforce scheduling literature, this endogenous nature of the criterion coefficient has been acknowledged as relevant though seemingly only as a matter for future research; e.g., Quintana and Ortiz (2002). This paper's approach of explicitly treating an endogenous criterion coefficient builds on this acknowledgment.

Note that since there is no value of the criterion coefficient for use in $t = 1$ (i.e., $C_{rj}^{(0)}$does not exist) the solution for $t = 1$ is to randomly match the day's routes with the drivers. From the T solutions over a period of T days, the number of different customers that driver j encounters would be given by the number of non-zero values for $c_{ij}^{(T)}$ across all N customers; i.e., the number of customers that driver j has visited at least once. The parameter for the average of these numbers across all D drivers will be denoted as n_{ET} for the exclusive territory assignment tactic and n_{NE} for non-exclusive assignment. So the margin by which the learning burden on drivers (i.e., number of customers they need to be knowledgeable of) is smaller under the former tactic is $(n_{\text{NE}} - n_{\text{ET}})$.

3. Research methodology

Probabilistic simulation was the data collection methodology, so this necessitated the standard tasks of selecting main effect factors, designing the experiments, running the simulation, and analyzing the simulated data. The three chosen factors were the variance of customer demand (using the gamma distribution, so variance $= \alpha\beta^2$), the capacity of each delivery vehicle (Q units), and the size of the team of drivers exclusively responsible for each territory (G drivers). Following works noting the broad applicability of the gamma distribution in representing demand (e.g., Keaton, 1995), that distribution was chosen as a very flexible and convenient means of studying a wide range of values for demand variability. Alternative distributions such as the Poisson distribution, a special case of the gamma distribution where the mean and variance are related, would be less effective as it would cause analysis of variability to be confounded by simultaneous changes in the mean. Similarly, because of the increased risk of negative values of simulated demand when large variances are being studied (and the resulting need for truncation), the normal distribution is not as convenient and was therefore not considered a viable option. Along with the three main effects factors, two factors were held fixed at one level throughout the experiments. These were the number of customers ($N = 500$) and the service region: an actual 100×100 km^2 road network covering several cities in southwestern area of Ontario, Canada (Fig. 2 shows the map of the region with the depot at the centre). The 500 customer addresses in the simulations were selected from a set of 1000 actual addresses that had an approximately uniform spatial distribution throughout the service region.

Intuition as well as the results of preliminary experiments concerning the direction of the impacts of the three main effects factors provided the rationale for their selection. For example, one should expect larger vehicle capacities to yield shorter travel distances for both the exclusive territory assignment tactic and non-exclusive assignment. Similarly, the travel efficiencies forfeited by the former tactic vis-à-vis the latter should fall as either the size of the driving team increases or demand variability decreases. Given these expected impacts, this study's application of analysis of variance (ANOVA) techniques to the research data was largely a matter of simulation verification via confirmation of the statistical significance and *direction* of the factor effects. As such, the more important insights were not from the ANOVA findings per se but from related analysis depicting the *magnitude* of the factor effects. Table 1 shows the experimental levels for each of the factors. In specifying the factor levels for demand variability, the two parameters of the gamma distribution (α and β) were jointly selected to ensure that each customer's mean and variance of demand were always, respectively, $\alpha\beta = 100$ and $\alpha\beta^2 = 100\beta$. The logic of that approach was to keep the mean fixed in order to permit clear discernment of the un-confounded effect of demand variability.

Fig. 2. Map of the service region (depot at the centre in the city of Waterloo).

The three levels for β (demand variability) and Q (vehicle capacity), five levels for G (team size), and ten replications of the experiment yielded 450 observations on the three parameters of interest ($L_{\mathrm{ET}} - L_{\mathrm{NE}}$), ($V_{\mathrm{ET}} - V_{\mathrm{NE}}$), and ($n_{\mathrm{NE}} - n_{\mathrm{ET}}$). The estimate for each of the 450 observations was based on a 300-day simulation, each day representing a separate set of demand outcomes (according to the gamma distribution's parameters) for the set of $N = 500$ customers. Each replicate involved generating a separate stream of uniform random variates to determine which of the 1000 available addresses would be among the selected 500. The simulation run length of 300 days was determined on the basis of the procedures outlined in Law and Kelton (1991). In particular, the run length was incrementally raised until the error margin in estimating the mean for the most erratic of the three output parameters of interest ($n_{\mathrm{NE}} - n_{\mathrm{ET}}$) appeared to settle at a minimum. That apparent minimum – an average standard deviation of 1.27 customers (22.4% of the mean) for the cross-replicate estimates of ($n_{\mathrm{NE}} - n_{\mathrm{ET}}$) over the 45 ($\beta, Q, G$) combinations – was met by the combination of run length (300 days) and number of replicates (10).

For each of the 450 observations, data generation required the input of 150,500 random variates. Of these, 150,000 were for the gamma distributed demands of the 500 customers over 300 days. Determining which of 1000 customers should be among the 500 for the replicate under consideration accounted for the other 500 random variates. Distribution of these was discrete uniform in the range $[1, 1000 - k]$, where k is the number of customers already selected for inclusion in the 500; i.e., sampling without replacement was used. Each customer was uniquely identified by an integer between 1 and 1000. In the sampling frame, customers were listed in ascending order of these numerical identifiers, so after the kth selection, unselected customers with larger integer identifiers than that the most recent selection moved up one position in the list. Assignment of the numerical identifiers was unbiased in that a 1 was arbitrarily assigned to the furthest customer from the depot with subsequent numbers sequentially assigned by making a clockwise sweep

Table 1
Experimental conditions

Factor	Levels/values
Variability of customer demand (β)	Each customer's daily demand is independent and follows an identical gamma distribution with $\alpha\beta = 100$ (to ensure a fixed mean of 100) so variance ($\alpha\beta^2$) = 100β Three (3) levels of $\beta(\alpha)$ examined: 1(100), 50(2), 100(1)
Capacity of delivery vehicles in number of units of the product (Q)	Three (3) levels: 500, 1500, 2500
Number of drivers in the team assigned to each territory (G)	Five (5) levels: 1, 2, 3, 4, 5

(using a radius centered at the depot) until the last of the 1000 customers (assigned #1000) was covered.

The variance reduction principle of common random numbers (CRN) – see, e.g., Law and Kelton (1991) – was used in order to minimize confounding the analysis of factor effects (e.g., the effect of team size) with the effect of different random numbers. So for any given replicate, the same 150,500 random variates were used for all 45 factor combinations. With these random inputs, each simulated day's data generation task involved performing daily reoptimization of the routes (both within individual territories in the case of exclusive territory assignment and across the entire service region for non-exclusive assignment) then obtaining the solutions to the integer programming problems (using Java programming) to determine the assignment of drivers to the routes. Daily route reoptimization was done using Roadshow®, a commercial grade vehicle routing software program. No route reoptimization was necessary for $G = 1$ (one driver to a territory) because once an optimal route has been established for the set of customers exclusively assigned to a single driver, changing the grouping will violate the exclusivity constraint and changing the sequence will not reduce the already optimal travel distance. So at $G = 1$ nothing can be gained by trying to reconfigure the routes in response to day-to-day demand fluctuations.

The partitioning of the service region into territories for each combination of (β, Q, G) started with an approximation for the highest realistically attainable value of total demand across all customers on any day. This was done by generating 10,000 instances of individual customer demand observations for 500 customers and totaling across the 500 customers to estimate the largest 500-customer total. That total (estimated peak demand) divided by the vehicle capacity then rounded up to the next integer yielded an estimate of D: the corresponding number of drivers needed to meet peak demand, or equivalently, the required number of members of the driving staff. So for $G = 1$, D customer groups are required to equitably distribute the territories among all members of that staff. The next step was to solve a standard vehicle routing problem for the specified set of 500 customers with the added constraint that each route must serve between $\lfloor 500/D \rfloor$ and $\lceil 500/D \rceil$ customers, where $\lceil\,\rceil$ and $\lfloor\,\rfloor$ mean, respectively, rounded up and rounded down to the next integer. That solution yielded the D territories for $G = 1$. Exploiting the pie-sliced (petal) shape of the routes, the one containing the furthest customer from the depot was labeled as territory #1 and then the subsequent single-driver territory numbers were sequentially assigned by moving (sweeping) in clockwise direction until all territories were labeled. For $G > 1$ (combining territories to form larger team-served territories), the approach is as suggested in Fig. 1 so if G is, say, three, single-driver territories one through three would become one new territory, four through six would be another, and so on. Fractional territories were used in cases where D was not an integer multiple of G. As an example, $(D, G) = (110, 4)$ would yield 27 full territories (1–4, 5–8, …, 105–108) and a "half-territory" (109–110) served by two (instead of by $D = 4$) drivers.

4. Findings and discussion

Table 2 contains the ANOVA results showing that the three factors and their interactions all have a statistically significant impact on the three relevant differences between exclusive and non-exclusive territory assignment: distance traveled ($L_{ET} - L_{NE}$), trips made ($V_{ET} - V_{NE}$), and customers encountered ($n_{NE} - n_{ET}$). The main effects plots from the ANOVA (Fig. 3) confirm the expected direction of the factor effects and indicate the overall magnitude

Table 2
ANOVA results on the differences between exclusive territory assignment and non-exclusive assignment

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Part (a): ANOVA for distance ($L_{ET} - L_{NE}$) using adjusted SS for tests						
Beta (β)	2	6,911,202	6,911,202	3,455,601	1344.58	0.000
Capacity (Q)	2	1.21E+08	1.21E+08	60,551,945	2.40E+04	0.000
Team (G)	4	55,809,622	55,809,622	13,952,405	5428.9	0.000
$\beta * Q$	4	393,020	393,020	98255	38.23	0.000
$\beta * G$	8	401,219	401,219	50,152	19.51	0.000
$Q * T$	8	44,388,131	44,388,131	5,548,516	2158.93	0.000
$\beta * Q * G$	16	548,315	548,315	34270	13.33	0.000
Error	405	1,040,860	1,040,860	2570		
Total	449	2.31E+08				
Part (b): ANOVA for trips ($V_{ET} - V_{NE}$) using adjusted SS for tests						
Beta (β)	2	971.3	971.3	485.6	355.86	0.000
Capacity (Q)	2	37193.8	37193.8	18596.9	1.40E+04	0.000
Team (G)	4	24637	24637	6159.2	4513.29	0.000
$\beta * Q$	4	743.6	743.6	185.9	136.23	0.000
$\beta * G$	8	438.6	438.6	54.8	40.17	0.000
$Q * T$	8	17287.8	17287.8	2161	1583.49	0.000
$\beta * Q * G$	16	200.2	200.2	12.5	9.17	0.000
Error	405	552.7	552.7	1.4		
Total	449	82024.9				
Part (c): ANOVA for customer ($n_{NE} - n_{ET}$) using adjusted SS for tests						
Beta (β)	2	9522.7	9522.7	4761.4	2256.75	0.000
Capacity (Q)	2	15832.9	15832.9	7916.4	3752.17	0.000
Team (G)	4	16227.6	16227.6	4056.9	1922.86	0.000
$\beta * Q$	4	3232.7	3232.7	808.2	383.06	0.000
$\beta * G$	8	5984.6	5984.6	748.1	354.57	0.000
$Q * T$	8	3869.2	3869.2	483.6	229.24	0.000
$\beta * Q * G$	16	1958.3	1958.3	122.4	58.01	0.000
Error	405	854.5	854.5	2.1		
Total	449	57482.5				

of those effects. Figs. 4–6 graph the interactive effects of the factors. The following discussion clarifies the insights from these exhibits, as well as from Tables 3–5.

4.1. Route design/configuration efficiencies

For the travel distance component of route design efficiencies forfeited by exclusive territory assignment vis-à-vis non-exclusive territory assignment ($L_{\mathrm{ET}} - L_{\mathrm{NE}}$), Fig. 3 shows that an increase in β from 1 to 100 (i.e., an increase in customer demand variance from 100 to 100^2) increases the average daily amount forfeited by approximately 300 km (500–800). The effect (reverse) is more dramatic for the other two factors. In the case of the size of the team assigned to a territory, an increase from 1 to 5 produces a drop from approximately 1300 to 350 km. For the dispatched trips component ($V_{\mathrm{ET}} - V_{\mathrm{NE}}$), the corresponding changes are an increase by four trips per day (9–13) for the increase in β, and a decrease by approximately 20 trips per day (25–5) for the increase in team size. The interactive effect of team size and vehicle capacity is noteworthy from a managerial standpoint (Figs. 4 and 5). While the increase in team size when vehicles are small ($Q = 500$ units or an average of five customer stops per vehicle) produces significant drops in travel distance difference, the drops are quite modest for larger vehicles ($Q = 2500$ units or an average of 25 customer stops/vehicle). At the smaller capacity level, the specific drops in the respective differences for travel distance and trips are approximately 2178 km/day ($L_{\mathrm{ET}} - L_{\mathrm{NE}}$) and 44 trips/day for ($V_{\mathrm{ET}} - V_{\mathrm{NE}}$). At $Q = 2500$ units, the corresponding drops are only 178 km/day and 4.6 trips/day.

This result, which can be explained with reference to what occurs under exclusive territory assignment, is strongly influenced by how capacity affects the need for recourse action and is related to the approximate inverse relationship between vehicle

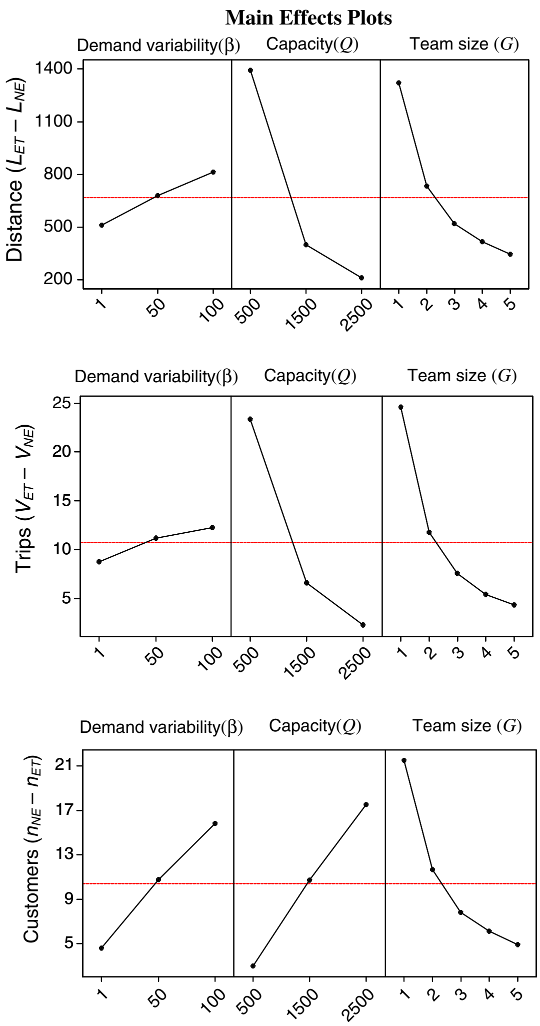

Fig. 3. Main effects plots.

capacity and number of territories. That is, since the required number of territories ≅ (peak total demand)/GQ then, *ceteris paribus*, the required number of territories when individual vehicle capacity is nQ units will be approximately $(1/n)$th the required number when the vehicle capacity is Q units (correspondingly, the number of customers per territory, NG/D, will also be larger when fewer territories are required). The reduced risk of capacity shortfall from pooling a larger number of customers, as well as the sheer reduction in the number of territories within which shortfalls might occur, results in fewer recourse trips (and, hence lower average daily travel distance for those trips).

Table 3 shows that for large vehicles the resulting smallness of the recourse travel (which contributes to the smallness of forfeited route design efficiencies) is such that only small reductions in forfeited efficiencies are achievable by increasing the team size. Case in point is that while at $(\beta, Q, G) = (1, 500, 1)$ the baseline recourse travel distance (2523 km/day) and trips (44.40/day) leave some room for further reductions through increases in G, there is much less room for improvement at $(\beta, Q, G) = (1, 2500, 1)$ since the corresponding daily averages are already low: 20 km and 0.33 trips. Another way of viewing these results on the interaction effect of Q and G is in terms of the inference that large capacity vehicles reduce the importance of increasing the team size as a way to reduce the forfeited efficiencies. Other interaction effects, though statistically significant, are, as depicted in Figs. 4 and 5, relatively slight.

4.2. Required knowledge of customers

The graphs in the bottom panel of Fig. 3 show how the three main effects factors affect the difference between exclusive territory assignment and non-exclusive assignment in terms of the number customers a driver encounters (and must be knowledgeable of in order to perform his delivery duties proficiently). The overall impact of β is that its increase from 1 to 100 results in a 12-customer increase in this difference ($n_{\mathrm{NE}} - n_{\mathrm{ET}}$). Increases in vehicle capacity also increase this quantity: whereas at $Q = 500$, non-exclusive assignment requires drivers to encounter an average of about two (2) customers more than exclusive territory assignment, the average jumps to 19 at $Q = 2500$. Because the size of the driving team increases n_{ET} (without affecting n_{NE}), an increase from $G = 1$ to $G = 5$ reduces the average of ($n_{\mathrm{NE}} - n_{\mathrm{ET}}$) from 22 to 5. From this latter result, it can be argued that as a practical matter, exclusively assigning a team of drivers to a territory does not yield a materially lower learning burden on the drivers. Given that the rounded difference of five resulted from $(n_{\mathrm{NE}} - n_{\mathrm{ET}}) = (35.23, 30.31)$, the thrust of that argument might be that a driver already required to be knowledgeable of 30 customers is unlikely to feel seriously tested by a requirement to be knowledgeable about another five customers.

A test of this argument is beyond the scope of this paper and is a matter for future research since it can only be rigorously examined by research methods involving actual delivery vehicle drivers. Suffice it to note here that if the depot's decision

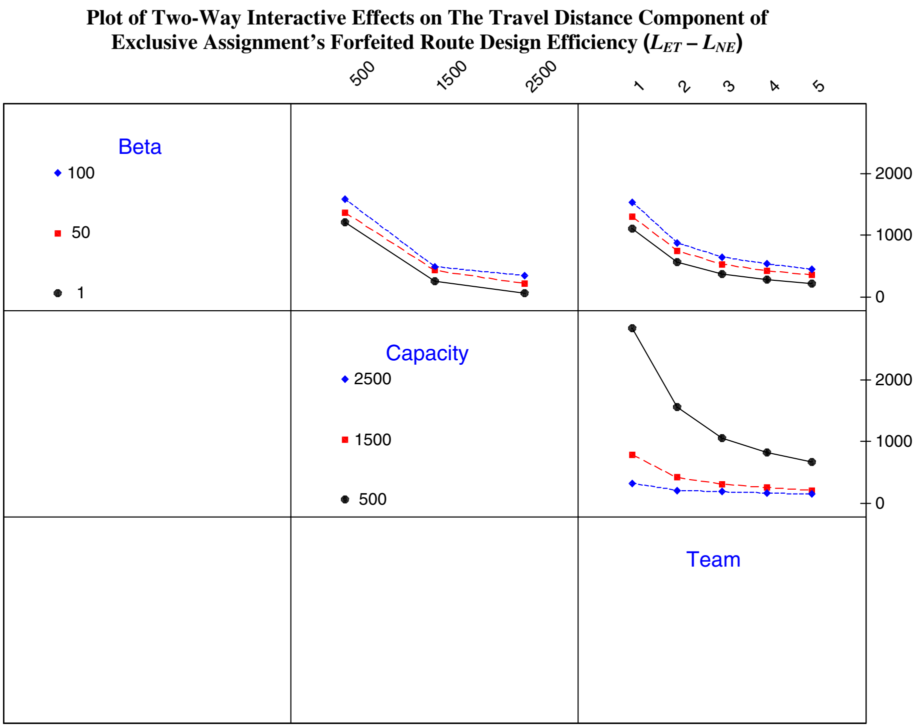

Fig. 4. Plot of two-way interactive effects on the travel distance component of exclusive assignment's forfeited route design efficiency ($L_{\mathrm{ET}} - L_{\mathrm{NE}}$).

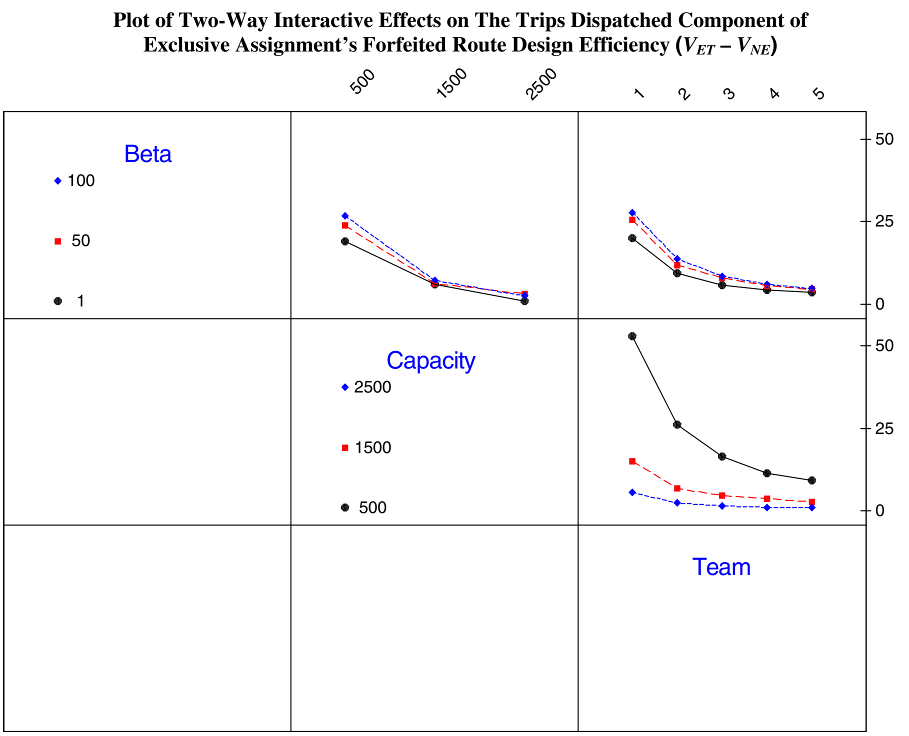

Fig. 5. Plot of two-way interactive effects on the trips dispatched component of exclusive assignment's forfeited route design efficiency ($V_{\mathrm{ET}} - V_{\mathrm{NE}}$).

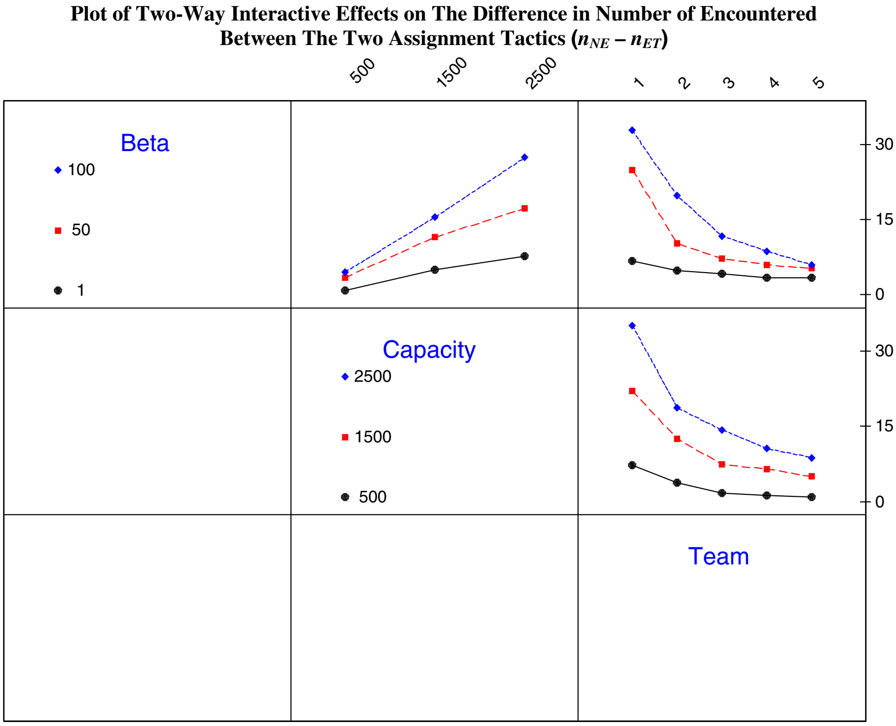

Fig. 6. Plot of two-way interactive effects on the difference in number of encountered between the two assignment tactics ($n_{\mathrm{NE}} - n_{\mathrm{ET}}$).

Table 3
The impact of vehicle capacity on forfeited route design efficiencies of exclusive territory assignment at extreme value combinations of β and G

Main effects factors		Forfeited route design efficiencies			
		Distance traveled		Trips made	
β	G	When $Q = 500$	When $Q = 2500$	When $Q = 500$	When $Q = 2500$
1	1	2553 (2523)	66 (20)	45.36 (44.40)	1.28 (0.33)
1	5	522 (335)	62 (1)	7.04 (6.08)	0.96 (0.01)
100	1	3212 (2379)	542 (314)	59.99 (41.27)	7.33 (5.61)
100	5	829 (307)	234 (30)	10.71 (5.49)	0.56 (0.51)

Notes: In each cell of the table, the parenthetical value of the forfeited route design efficiencies is the amount incurred for recourse travel; e.g., of the average daily quantities of 2553 km and 45.36 trips at $(\beta, Q, G) = (1, 500, 1)$, the corresponding amounts incurred through recourse travel are 2523 km and 44.40 trips.

makers choose exclusive territory over non-exclusive assignment, using a five-driver team, they would, on average, effectively be forfeiting route design efficiencies to the tune of an average of 350 km/day and four trips/day (see the top two panels of Fig. 3) in order to reduce the average driver's learning burden by five customers. While this tradeoff might imply that the lower learning burden is not worth the forfeited travel efficiencies, there are other factor combinations for which the tradeoff may be more supportive of exclusive territory assignment; i.e., a combination of a relatively large value for $(n_{\mathrm{NE}} - n_{\mathrm{ET}})$ and relatively small values for $(L_{\mathrm{ET}} - L_{\mathrm{NE}})$ and $(V_{\mathrm{ET}} - V_{\mathrm{NE}})$. Generally, this occurs for large values of vehicle capacity (Q). For example, in the interaction plot in Fig. 6, the combination of $Q = 2{,}500$ with a single-member team $(G = 1)$ yields an average of 35.2 for $(n_{\mathrm{NE}} - n_{\mathrm{ET}})$ yet, as discussed earlier, for that same combination (see Figs. 4 and 5) the average daily forfeited route design efficiency amounts to 328 km for travel distance $(L_{\mathrm{ET}} - L_{\mathrm{NE}})$ and 5.53 for trips $(V_{\mathrm{ET}} - V_{\mathrm{NE}})$.

Table 4
Travel distance, trips, and customers encountered for exclusive and non-exclusive assignments at extreme values of the main effects factors

Main effects factors			Staff size (D)	Metrics for route design efficiency		Learning burden metric: Customers encountered		Theoretical maximum
β	Q	G		Distance traveled	Trips made	Observed average	Observed maximum	
1	500	1	102	10174	145.92	4.90	5	5
				7621	100.56	7.03	15	$N = 500$
1	500	5	102	8143	107.60	6.66	12	25
				7621	100.56	7.03	15	$N = 500$
1	2500	1	21	3460	21.92	23.81	25	25
				3394	20.64	33.81	64	$N = 500$
1	2500	5	21	3456	21.60	27.37	31	125
				3394	20.64	33.81	64	$N = 500$
100	500	1	117	10821	159.95	4.27	5	5
				7609	99.46	15.31	40	$N = 500$
100	500	5	117	8438	110.67	14.08	21	25
				7609	99.96	15.31	40	$N = 500$
100	2500	1	23	3912	29.22	21.74	25	25
				3370	21.89	77.12	150	$N = 500$
100	2500	5	23	3604	22.45	66.08	109	125
				3370	21.89	77.12	150	$N = 500$

Notes: (i) Travel distance and trips are per day averages and are based on all 10 replicates of the experiment. (ii) The number of different customers each driver encounters over a simulated period of 300 days is averaged across all drivers and across all 10 replicates to get the observed average for "Customers Encountered". Its maximum was observed as the maximum value across all drivers and across all replicates; the theoretical maximum is the number of customers that is *possible* for the driver to be assigned to. (iii) In each cell of the table, the value for the exclusive territory assignment tactic is shown atop the value for the non-exclusive assignment tactic.

Table 5
Distribution of a driver's visits across encountered customers for $(\beta, Q) = (100, 2500)$ under exclusive assignment (Team size = 5) and non-exclusive assignment

Number (%) of each driver's 300 visits	Number (%) of encountered customers receiving that many of the driver's visits under the tactic of:	
	Exclusive territory assignment	Non-exclusive assignment
256–300 (86–100%)	0 (0.00%)	0 (0.00%)
241–255 (81–85%)	7 (6.42%)	2 (1.33%)
226–240 (76–80%)	16 (14.68%)	13 (8.67%)
211–225 (71–75%)	4 (3.67%)	0 (0.00%)
196–210 (66–70%)	0 (0.00%)	3 (2.00%)
181–195 (61–65%)	0 (0.00%)	0 (0.00%)
166–180 (56–60%)	0 (0.00%)	1 (0.67%)
151–165 (51–55%)	2 (1.83%)	4 (2.67%)
136–150 (46–50%)	1 (0.92%)	0 (0.00%)
121–135 (41–45%)	0 (0.00%)	8 (5.33%)
106–120 (36–40%)	0 (0.00%)	3 (2.00%)
91–105 (31–35%)	5 (4.59%)	1 (0.67%)
76–90 (26–30%)	0 (0.00%)	2 (1.33%)
61–75 (21–25%)	0 (0.00%)	4 (2.67%)
46–60 (16–20%)	4 (3.67%)	4 (2.67%)
31–45 (11–15%)	23 (21.10%)	17 (11.33%)
16–30 (5.33–10%)	4 (3.67%)	25 (16.67%)
13–15 (4.33–5%)	11 (10.09%)	9 (6.00%)
10–12 (3.33–4%)	10 (9.17%)	11 (7.33%)
7–9 (2.33–3%)	9 (8.26%)	12 (8.00%)
4–6 (1.33–2%)	6 (5.51%)	0 (0.00%)
1–3 (0.33–1%)	7 (6.42%)	31 (20.67%)
Totals	109 (100%)	150 (100%)

Notes: This table's data for each tactic, is based on one driver that encountered the largest number of different customers within a 300-day period (across all 10 replicated simulations of 300 days).

Table 4 summarizes the tradeoffs that would be relevant to the choice between the two assignment tactics; i.e., tradeoffs between route design efficiencies and a tolerable learning burden on drivers. The table covers the eight extreme value combinations of the three main effects factors and shows the estimates for L_{ET}, L_{NE}, V_{ET}, V_{NE}, n_{ET}, and n_{NE} for each combination. For each combination, the estimate for exclusive territory assignment is shown atop the corresponding estimate for non-exclusive territory assignment. The table also shows the maximum number of customers (across all ten replicates of the experiment) that any driver encountered for each tactic; e.g., at $(\beta, Q, G) = (1, 500, 5)$ as many as 12 customers were encountered by a single driver under exclusive territory assignment ($n_{\mathrm{ET}} = 6.66$ was the average across all 102 drivers). Note that even these maxima are all less than the number that a driver could, in theory, encounter. For example, at the aforementioned combination of $(\beta, Q, G) = (1, 500, 5)$, a full territory contained a maximum (across all replicates) of 25 customers yet no driver encountered more than 12 customers. Similarly, for non-exclusive territory assignment, a driver could, theoretically, encounter all $N = 500$ customers but the observed maximum is far less than that in every case.

The cause of these results is twofold. First, is the driver-to-customer assignment procedure's emphasis on giving each driver an above average chance of continuing to visit previously encountered customers: this restricts visits to fewer than the theoretically possible number of customers. Second is the fact that some customer groupings are unlikely to be cost-effective enough to ever be used – e.g., a grouping that contains the two customers with the largest customer-to-customer travel distance within a territory – so it is highly improbable for some customers to be in any of the groups that a driver has ever served or will ever serve.

As noted in the paper's introduction, while a driver's deep knowledge of a large number of customers is beneficial, acquisition of that knowledge can be especially burdensome in probabilistic demand settings. As such, the paper views encountering a larger number of customers as a heavier learning burden on drivers. Table 5 elaborates the point by disaggregating the visits of the drivers who encountered the largest number of customers at $(\beta, Q) = (100, 2500)$ for both assignment tactics (with team size $G = 5$ for exclusive territory assignment). For a driver that encountered the observed maximum of 109 customers under the exclusive territory assignment tactic, the second column shows a breakdown in terms of the number of encountered customers receiving different percentages of the driver's 300 visits. The table shows that 32 (26.89%) of the 109 different customer the driver encountered were visited no more than 12 times (4% of the visits), with 13 of these customers being visited on no more than only 6 of the 300 days; i.e., an average of one visit every 50 days.

Such a low frequency of visits to a sizable percentage of encountered customers might not provide the driver with sufficient knowledge of these customers in order to serve them well. So in the driver's efforts to be highly effective in his duties across all customers encountered, his burden may be viewed as the limited number of opportunities (visits) he has to deepen his knowledge of a not insubstantial number of those customers. The third column of Table 5 shows, as expected, that the burden, when characterized this way, is greater for non-exclusive territory assignment: 54 (36%) of the 150 encountered customers were visited no more than 12 times, with 31 of these customers being visited on no more than only three of the 300 days; i.e., an average of no more than one visit every 100 days. This disaggregated analysis reinforces the results obtained from viewing the difference in learning burden between the two tactics as the difference in overall means: $(n_{\mathrm{NE}} - n_{\mathrm{ET}})$.

5. Conclusion

Using simulation experiments as the data collection methodology, this study provides estimates to aid the decision of whether territories comprising sub-groups of spatially dispersed customers should be exclusively assigned (e.g., to small teams of drivers) or whether exclusivity should be eschewed in favour of flexibility to mix the groups. The estimates highlight the decision tradeoff between a more tolerable burden on drivers to deepen their knowledge of customers (with exclusive assignment) and high efficiency in route design (when there is flexibility). The study quantifies how the metrics involved in the tradeoff are affected by three factors: demand variability, vehicle capacity, and the size of the team exclusively assigned to a territory. A key observation from the study is that preference for exclusive territory assignment might be more likely when the depot has large capacity vehicles. Because non-exclusive assignment is based on complete daily route reoptimization, the paper's study of exclusive territory assignment represents an extension of the literature on competing alternatives to complete route reoptimization in probabilistic demand settings.

Reflection on the study's insights suggests that a field-based study would be a potentially useful piece of follow-up work. Such a study could seek to gauge the magnitude of the learning burden that actual delivery drivers experience based on those drivers' perceptions. This would help to examine a conjecture raised in discussing the results: i.e., a driver with deep knowledge of, say, 30 customers, may perceive the burden of learning about a handful of additional customers as light. Such a study could extend the research by adding another perspective to an earlier cited assertion by a transportation company CEO that his company's success is influenced by the drivers' deep familiarity with customers. Specifically, the study could ascertain drivers' perception of what number of customers represents the threshold beyond which acquiring knowledge of more customers might make the drivers' learning burden too challenging to assure the kind of service consistency that this CEO spoke of.

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