

Research Paper on Optimal Allocation of Delivery Partners to Minimize Food Delivery Time

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Abstract- Online food-delivery platforms must decide which vehicles serve which kinds of orders. This paper formulates that decision as a transportation problem and solves it with real operating data. Using 43,641 complete delivery records from the Metropolitan and Urban segments of a Zomato dataset (44 days, 11 February to 6 April 2022), delivery capacity by vehicle type (motorcycle, scooter, electric scooter) is treated as the supply, eight city-by-traffic conditions as the demand, and the historical mean delivery time of each vehicle in each condition as the unit cost. A dummy destination balances the table. The problem is solved with the North-West Corner, Least Cost and Vogel approximation methods, the optimality of the best starting solution is tested with the MODI method, and the result is confirmed in Excel Solver. On a typical day the optimal plan lowers total expected delivery time from 25,680 to 24,357 minutes, a reduction of 5.15% (27.12 to 25.72 minutes per order), by keeping motorcycles on low-traffic orders and giving scooters and electric scooters the congested ones. Over all 44 days the reduction is 5.06%. The saving remains positive under a 25% demand increase combined with a 10% workforce cut (2.87%) and falls to about 1.7% when partner capacity is set close to its observed average. Shadow prices show that an extra order of scooter or electric-scooter capacity saves about 2.3 and 2.8 minutes, while extra motorcycle capacity has no value on a typical day.

Keywords- operations research; transportation problem; Vogel approximation method; MODI method; Excel Solver; food delivery; delivery time; workforce allocation

I. INTRODUCTION

Delivery time is one of the most visible measures of service quality in online food delivery. Customers expect fast delivery, food quality declines with waiting, and slow deliveries tie up partners who could otherwise serve further orders. A platform cannot change traffic, but it can influence who delivers an order and on what vehicle. If some vehicles are consistently quicker in some conditions than others, then the way capacity is matched to orders affects total waiting time even when the number of partners and orders is fixed.

This paper studies that matching problem with operating data from Zomato. The questions it addresses are:

Given different levels of delivery demand and different delivery conditions, how should Zomato allocate its delivery partners so that total expected delivery time is minimized while satisfying demand and workforce constraints?

The research question is how delivery partners can be optimally allocated across different demand and traffic conditions to minimize total delivery time in online food delivery operations.

1. Objectives

To analyze historical food-delivery demand using secondary Zomato data (Sections 3 and 4).

- To examine the relationship between traffic conditions and delivery time (Section 4).
- To estimate delivery-partner capacity from historical operational data (Section 4.3).
- To formulate a delivery-partner allocation model (Section 5), here as a transportation model.
- To determine the optimal allocation using the transportation methods and Excel Solver (Section 6).
- To compare the optimized allocation with the historical allocation (Section 7).
- To evaluate the robustness of the solution under different demand scenarios (Section 8).

2. Contribution

Operational research on delivery platforms often concerns routing and dispatching of individual orders. This study works at a planning level instead: it asks how daily vehicle capacity should be matched to broad operating conditions. The contributions are (i) a transportation model whose costs, supplies and demands are all estimated from the data, (ii) a full hand solution with the three classical starting methods and the MODI test, checked against Excel Solver, (iii) a fair benchmark that uses the same orders and the same workforce as the historical day, and (iv) robustness and shadow-price analysis that shows where extra capacity would be most valuable.

II. INDUSTRY OVERVIEW

The online food delivery industry connects customers, restaurants and delivery partners through digital platforms. Efficient delivery operations are essential to this industry because customers expect timely deliveries, while platforms must coordinate available delivery capacity with incoming orders and varying traffic conditions.

One of the major operational challenges is last-mile delivery, which involves transporting prepared orders from restaurants to customers. Delivery times can vary according to traffic congestion, city conditions and the type of vehicle used. Poor allocation of available delivery capacity may contribute to longer delivery times and inefficient use of delivery resources.

Operations Research provides mathematical techniques for addressing such allocation problems. In particular, the transportation model can be used to determine how limited delivery capacity should be allocated across different operating conditions to minimize estimated delivery time. This study applies the transportation model to a Zomato delivery dataset, using vehicle types as sources and combinations of city and traffic conditions as destinations. The industry context therefore provides the practical motivation for investigating whether an alternative allocation of delivery

capacity can improve expected delivery-time performance.

III. OPERATIONAL CHALLENGES IN THE FOOD DELIVERY INDUSTRY

The online food delivery industry faces several operational challenges that influence delivery efficiency and customer satisfaction. Traffic congestion and delivery-time variability: Traffic conditions can significantly affect travel time, making it difficult to maintain consistent delivery schedules across different locations and periods.

1. Allocation of delivery capacity

Delivery platforms must allocate a limited number of delivery partners and vehicles across areas with varying demand and traffic conditions. Inefficient allocation may result in underutilized resources in some areas and insufficient capacity in others.

2. Vehicle suitability

Different vehicle types may have different delivery-time performance depending on traffic conditions, road accessibility and distance. Selecting an appropriate allocation of vehicle capacity is therefore an important operational decision.

Other challenges include fluctuations in order demand, restaurant preparation delays and route-planning requirements. These factors make food delivery operations complex and create a need for systematic planning methods.

Operations Research techniques, particularly transportation models, can help evaluate alternative allocations of limited delivery capacity. In this study, a transportation model is used to minimize estimated delivery time by allocating vehicle capacity across different city and traffic-condition categories.

IV. BACKGROUND: THE TRANSPORTATION PROBLEM

The transportation problem was formulated by Hitchcock (1941): a homogeneous product available

in fixed amounts at several sources must be shipped to several destinations with fixed requirements, at a known cost per unit on each route, so that total cost is minimized. Dantzig (1951) showed that the simplex method can be specialized to the problem, and Charnes and Cooper (1954) described the stepping-stone method that underlies the u-v (MODI) optimality test used in textbooks. Reinfeld and Vogel (1958) proposed the penalty-based Vogel approximation method, which usually produces a starting solution close to the optimum.

Two structural properties matter here. First, a feasible solution exists only if total supply is at least total demand. When supply exceeds demand, a dummy destination with zero cost and demand equal to the surplus makes the table balanced. Second, when all supplies and demands are whole numbers, the problem has an optimal solution with whole-number shipments, so no integer restriction is needed (Hillier and Lieberman; Taha).

These properties let a problem of delivery capacity, measured in orders, be solved exactly and quickly. In this paper the sources are vehicle types and the destinations are operating conditions. A shipment from source i to destination j is the number of orders in condition j that are delivered by vehicle type i , and its unit cost is the average delivery time in minutes. The problem is therefore one of choosing the vehicle mix for each condition.

V. DATA AND SELECTION OF RECORDS

The source is Zomato_Dataset.csv, which contains 45,584 delivery records. Records were retained when City, Road_traffic_density, Type_of_vehicle, Time_taken (min) and Order_Date were all present, and only the Metropolitan and Urban city segments were used. Delivery_person_ID is complete and is used to count the partners active on each day. Table 1 shows the selection; 43,641 records (95.7% of the file) were retained.

Table 1: Selection of records

Step	Records remaining	Records removed
Raw records	45,584	-
Drop missing City	44,384	1,200
Keep Metropolitan and Urban only	44,220	164
Drop missing Road_traffic_density	43,641	579
Drop missing Type_of_vehicle	43,641	0
Drop missing Time_taken	43,641	0
Drop missing Order_Date	43,641	0

The retained data cover 44 days. On average 992 orders a day were delivered (764 Metropolitan and 228 Urban). Three vehicle types appear: motorcycle (25,509 orders), scooter (14,605) and electric scooter (3,527). Bicycles occur only in the excluded Semi-Urban segment. The mean delivery time is 26.32 minutes (standard deviation 9.29, range 10 to 54).

All records are loaded into the accompanying Excel workbook (sheet Data), and every parameter of the model is computed from them with live formulas, so that the results can be traced and reproduced

VI EXPLORATORY ANALYSIS AND PARAMETER ESTIMATION

1. Traffic and delivery time

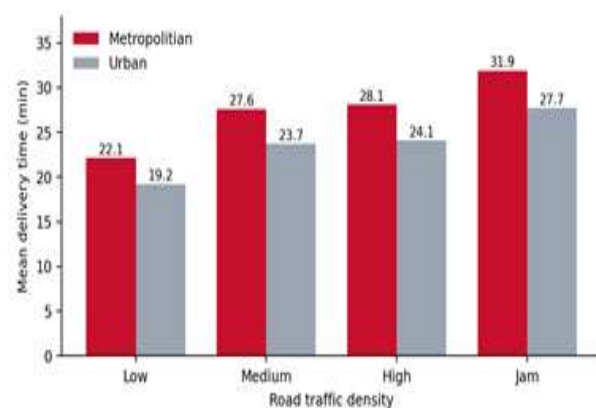


Figure 1: Mean delivery time by road-traffic density and city segmen

Table 2: Delivery time by traffic density

Traffic density	Orders	Mean time (min)	Metropolitan	Urban	Increase vs Low
Low	14,944	21.34	22.13	19.24	-
Medium	10,676	26.75	27.61	23.73	+25.4%
High	4,308	27.24	28.11	24.13	+27.6%
Jam	13,713	31.11	31.91	27.74	+45.8%

Delivery time rises with traffic. A delivery in a traffic jam takes on average 9.8 minutes (46%) longer than one in low traffic. The average delivery time increases from 21.34 minutes in low traffic to 31.11 minutes during traffic jams, showing a clear relationship between traffic conditions and delivery time and the Spearman correlation between traffic level and time is 0.42.

Metropolitan orders take 4.3 minutes longer than Urban orders on average (Welch $t = 42.5$, $p < 0.0001$). The cost of traffic is therefore real and large, and it is the main reason why the conditions are defined by city and traffic level.

2. Vehicle type and the cost matrix

Vehicle type also matters: mean times are 27.59 minutes for motorcycles, 24.56 for scooters and 24.40 for electric scooters (ANOVA $F = 588.3$, $p < 0.0001$). Crucially, the gap is not uniform. The extra time of a motorcycle compared with a scooter ranges from 1.83 minutes in Metropolitan low traffic to 4.01 minutes in Urban jams, and compared with an electric scooter from 1.94 to 4.63 minutes.

Because vehicles do not rank identically in every condition by the same margin, the way capacity is allocated matters. Figure 2 gives the 3×8 matrix of mean times that serves as the cost matrix of the model; each cell rests on at least 73 observations.

3. Partner capacity and workforce

The unit of workforce is a partner-vehicle-day: one partner riding one vehicle type on one date. The data contain 36,485 such units. A partner handled one order on 29,329 of them and two orders on 7,156; none handled more than 2. The average is 1.196 orders per partner-vehicle-day. Capacity c is

set to the observed maximum of 2 orders per partner per day, since this is the most a partner is known to have delivered; the observed average describes how busy partners were, not how many they could handle. Because this is a judgment, Section 8.3 repeats the analysis for capacities down to 1.2.

The supply of vehicle type i on a given day is $a(i) = c \times P(i)$, where $P(i)$ is the number of partners with that vehicle type who were active on that day. Over the period the mean number of active partners per day was 459.7 on motorcycles, 291.6 on scooters and 77.9 on electric scooters.

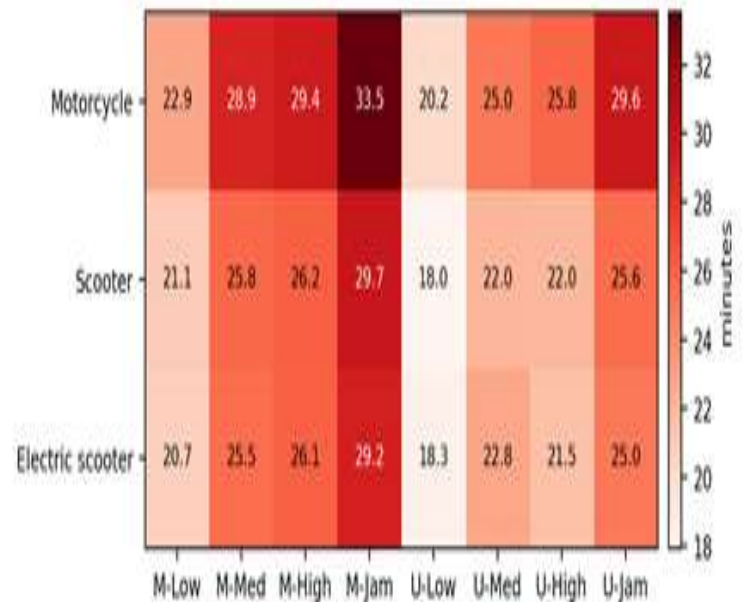


Figure 2: Mean delivery time (minutes) by vehicle type and operating condition (M = Metropolitan, U = Urban)

VII. Model Formulation

1. Sets, parameters and decision variables

Table 3: Notation

Symbol	Meaning
$i = 1, 2, 3$	Sources: vehicle type (motorcycle, scooter, electric scooter)
$j = 1, \dots, n$	Destinations: operating conditions, city (Metropolitan, Urban) x traffic density (Low, Medium, High, Jam), keeping only conditions that have orders on the day
$t(i,j)$	Unit cost: mean delivery time in minutes of an order carried by vehicle i in condition j
$b(j)$	Demand: orders to be delivered in condition j on the day
$a(i)$	Supply: daily order capacity of vehicle type i , $a(i) = c \times P(i)$, with $c = 2$
$x(i,j)$	Decision variable: orders in condition j delivered by vehicle type i

2. Model

Minimize $Z = \sum(i) \sum(j) t(i,j) \cdot x(i,j)$ (1)

subject to

$\sum(j) x(i,j) \leq a(i)$ for every vehicle type i (2)

$\sum(i) x(i,j) = b(j)$ for every condition j (3)

$x(i,j) \geq 0$ (4)

Equation (1) is total expected delivery time, (2) says that a vehicle type cannot deliver more orders than its partners can handle, and (3) says that every order is delivered. Feasibility requires that total supply is at least total demand. In all four scenarios of this study it is, with a surplus of at least 211 orders, so the table is balanced by a dummy destination $j = 0$ with $t(i,0) = 0$ and $b(0) = \sum a(i) - \sum b(j)$. Constraint (2) then becomes an equality, and the dummy shipment $x(i,0)$ is the unused capacity of vehicle type i . The number of partners needed is $x(i,j)/c$.

3. Assumptions

- The expected time of an order depends only on the vehicle type and the operating condition, and equals the historical mean of that cell.

- Demand $b(j)$ is the number of orders observed in condition j on the chosen day, and $a(i)$ is based on the partners actually active on that day, so the optimized plan uses no more workforce than the historical one.
- Orders can be assigned to any vehicle type within a day, and time per order does not depend on workload.
- Unused capacity has zero cost. The dataset contain no wage, fuel or vehicle-cost information, so delivery time is the only objective.

VIII. Solution Methodology

The base case is the typical day, 06-03-2022, the day closest to the median number of daily orders. It has 947 orders. No High-traffic orders occurred, so six conditions remain. The workforce was 436 motorcycles, 286 scooters and 72 electric scooters, giving supplies of 872, 572, 144 orders. Total supply is 1,588, so the dummy destination has demand 641.

	M-Low	M-Med	M-Jam	U-Low	U-Med	U-Jam	Dummy	Supply
Motorcycle	22.88	28.93	33.54	20.22	24.96	29.60	0.00	872
Scooter	21.05	25.77	29.71	17.96	22.05	25.60	0.00	572
Electric scooter	20.72	25.55	29.17	18.28	22.77	24.97	0.00	144
Demand	214	223	331	61	54	64	641	1,588

1. Initial basic feasible solutions

Three standard methods were used to obtain a starting solution. The North-West Corner rule fills the table from the top-left corner without looking at costs; the Least Cost method repeatedly fills the cheapest remaining cell; the Vogel approximation

method (VAM) computes for every row and column a penalty equal to the difference between its two smallest costs and fills the cheapest cell of the row or column with the largest penalty. Table 5 gives the VAM solution, which has the lowest cost of the three starting solutions.

Table 5: Vogel approximation solution (cost = 24368.00 minutes)

	M-Low	M-Med	M-Jam	U-Low	U-Med	U-Jam	Dummy	Total
Motorcycle	214	-	-	-	17	-	641	872
Scooter	-	223	251	61	37	-	-	572
Electric scooter	-	-	80	-	-	64	-	144

The VAM iterations were as follows (the dummy column has penalty zero, so the largest penalty in the first step belongs to the motorcycle row, whose

second-cheapest cost is 20.22 minutes above the dummy cost of zero).

Table 6: Vogel approximation iterations

Step	Largest penalty	Cell filled	Orders
1	20.22 (Motorcycle row)	Motorcycle to Dummy	641
2	3.10 (Scooter row)	Scooter to U-Low	61
3	2.08 (Motorcycle row)	Motorcycle to M-Low	214
4	3.97 (Motorcycle row)	Motorcycle to U-Med	17
5	3.55 (Scooter row)	Scooter to U-Med	37
6	0.63 (U-Jam column)	Electric scooter to U-Jam	64
7	3.94 (Scooter row)	Scooter to M-Med	223
8	29.71 (Scooter row)	Scooter to M-Jam	251
9	29.17 (Electric scooter row)	Electric scooter to M-Jam	80

2. Optimality test with the MODI method

In the MODI method each row i receives a number $u(i)$ and each column j a number $v(j)$ such that $u(i) + v(j) = t(i,j)$ for every cell with a shipment (basic cell), starting with $u(1) = 0$. The opportunity cost of an

empty cell is $d(i,j) = t(i,j) - u(i) - v(j)$, the change in total time per order moved into that cell. If all $d(i,j)$ are non-negative the solution is optimal. Table 7 applies the test to the VAM solution.

Table 7: MODI test on the VAM solution (basic cells marked; smallest $d = -0.646$)

$d(i,j)$	M-Low	M-Med	M-Jam	U-Low	U-Med	U-Jam	Dummy	$u(i)$
Motorcycle	basic	0.245	0.918	-0.646	basic	1.182	basic	0.000
Scooter	1.080	basic	basic	basic	basic	0.085	2.910	-2.910
Electric scooter	1.289	0.319	basic	0.868	1.266	basic	3.453	-3.453
$v(j)$	22.884	28.683	32.619	20.867	24.959	28.423	0.000	

One cell is negative: $d(\text{Motorcycle}, \text{U-Low}) = -0.646$. Moving orders into this cell improves the plan. The closed loop is (Motorcycle, U-Low) $\rightarrow$ (Motorcycle, U-Med) $\rightarrow$ (Scooter, U-Med) $\rightarrow$ (Scooter, U-Low), and the largest feasible shift is $\theta = 17$ orders. The

new cost is $24368.00 + 17 \times (-0.646) = 24357.03$ minutes. Table 8 repeats the MODI test on the improved solution: every $d(i,j)$ is now strictly positive, so the allocation is optimal and the optimum is unique

Starting from the other two solutions leads to the same optimum: the Least Cost solution needs four MODI iterations and the North-West Corner solution six.

3. Excel Solver implementation and validation

The same problem was built in Excel Solver (sheet TP_S2 of the workbook). The unit costs, supplies and demands are linked by formula to the Data sheet. The changing cells are the 3 x 7 block of shipments $x(i,j)$; the target cell is the total time

=SUMPRODUCT(cost, shipments), to be minimized; the constraints are that row totals equal the supplies, that column totals equal the demands, and that the variables are non-negative. The Simplex method is selected in Solver. No integer constraint is required, because the supplies and demands are whole numbers and the transportation problem then has a whole-number optimum.

Table 8: MODI test on the improved solution (smallest $d = 0.085$, all positive)

$d(i,j)$	M-Low	M-Med	M-Jam	U-Low	U-Med	U-Jam	Dummy	$u(i)$
Motorcycle	basic	0.891	1.564	basic	0.646	1.827	basic	0.000
Scooter	0.434	basic	basic	basic	basic	0.085	2.265	-2.265
Electric scooter	0.644	0.319	basic	0.868	1.266	basic	2.807	-2.807
$v(j)$	22.884	28.037	31.973	20.222	24.313	27.777	0.000	

Table 9: Excel Solver set-up for the typical day

Solver item	Setting
Set objective	Total expected delivery minutes (cell B20), To: Min
Changing variable cells	Shipment block $x(i,j)$ (B14:H16)
Constraints	Row totals = supply (I14:I16 = J14:J16); column totals = demand (B17:H17 = B18:H18)
Options	Make unconstrained variables non-negative; Simplex method
Result	Total time 24357.03 minutes, equal to the MODI optimum

The optimal plan was verified in two independent ways: the MODI test of Table 8 and a numerical optimization routine (HiGHS, through SciPy) gave the same total time of 24357.03 minutes. The workbook contains the optimal plan in the changing cells of each scenario sheet, recalculates

the total time by formula, and checks that supply and demand constraints hold.

IX. RESULTS FOR THE TYPICAL DAY

Table 10: Optimal allocation of orders (last column of the dummy is unused capacity)

Optimal $x(i,j)$	M-Low	M-Med	M-Jam	U-Low	U-Med	U-Jam	Dummy	Total
Motorcycle	214	-	-	17	-	-	641	872
Scooter	-	223	251	44	54	-	-	572
Electric scooter	-	-	80	-	-	64	-	144

The optimal plan has a clear structure:

Electric scooters and scooters are used to their full capacity: 144 orders on electric scooters (supply 144) and 572 on scooters (supply 572). They receive the Metropolitan Medium and Jam orders and the Urban Medium and Jam orders, where a motorcycle

would lose the most time (about 3 to 4.6 minutes per order).

Motorcycles deliver only 231 of the 947 orders, all in low-traffic conditions (214 Metropolitan-Low and 17 Urban-Low), where their time penalty is smallest (1.8 to 2.3 minutes). The remaining 641 units of motorcycle capacity are unused.

Scooters and electric scooters are scarce, motorcycles are not. This is why the plan needs the vehicle types in the opposite proportions from those observed historically.

The optimal plan saves 1,323 minutes of delivery time on this one day (about 22 hours of waiting)

and shortens the average delivery by 1.40 minutes. The comparison is fair: both plans use the same orders, the same workforce and the same cost matrix, so the gain comes only from matching vehicle type to condition.

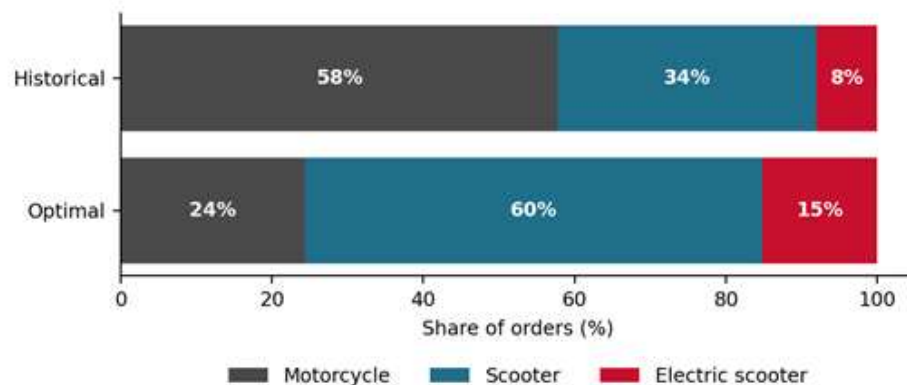


Figure 3: Share of orders by vehicle type, historical versus optimal allocation (typical day)

Table 11: Optimal versus historical allocation, typical day

Measure	Historical	Optimal	Change
Motorcycle orders	547	231	-316
Scooter orders	324	572	+248
Electric-scooter orders	76	144	+68
Total expected delivery time (min)	25,680	24,357	-1,323
Average time per order (min)	27.12	25.72	-1.40
Reduction in total time			5.15%

The optimal plan saves 1,323 minutes of delivery time on this one day (about 22 hours of waiting) and shortens the average delivery by 1.40 minutes. The comparison is fair: both plans use the same orders, the same workforce and the same cost

matrix, so the gain comes only from matching vehicle type to condition.

1.Comparison of solution methods

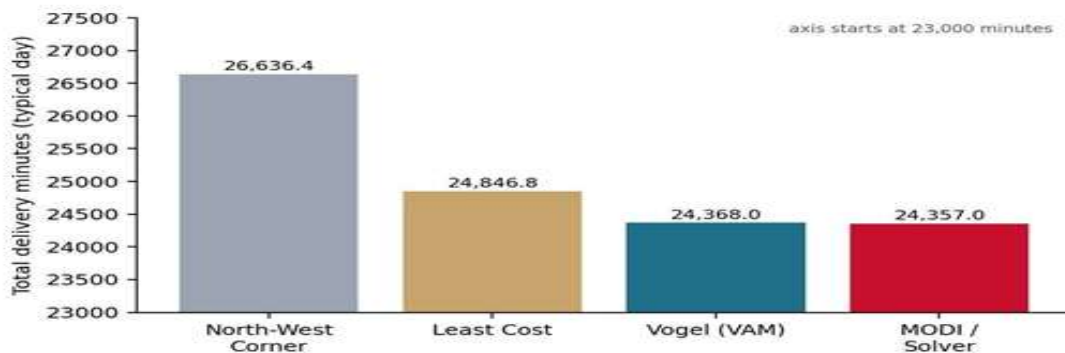


Figure 4: Total delivery minutes obtained by each method (typical day)

The North-West Corner rule, which ignores costs, ends 9.4% above the optimum, and Least Cost 2.0% above. Vogel's method is within 0.05% (10.98 minutes), and a single MODI iteration reaches the optimum. Cost-aware starting methods matter, and penalty-based ones matter most.

2. Shadow prices

The dual (shadow) price of each supply constraint gives the value of one more order of capacity. For the typical day it is 0.00 minutes for motorcycles (capacity is not used up), 2.265 minutes for scooters and 2.807 minutes for electric scooters. Adding

capacity for one more scooter order would therefore remove

2.26 minutes of delivery time, and for one more electric-scooter order 2.81 minutes, because an order moves from a motorcycle to the quicker vehicle at the margin. Under the stress scenario S4 the values rise to 3.16 and 3.70 minutes. A partner who can complete two orders a day on an electric scooter is worth about 5.6 minutes of delivery time a day on the typical day, a figure that could be weighed against the cost of acquiring such vehicles.

Table 12: Methods compared

Method	Total minutes	Above optimum	Above optimum (%)
North-West Corner	26636.43	2279.41	9.36%
Least Cost	24846.84	489.81	2.01%
Vogel approximation	24368.00	10.98	0.05%
MODI / Solver (optimal)	24357.03	0.00	0.00%

X. ROBUSTNESS

Table 13: Scenario Results, Each Solved As A Transportation Problem. S1 To S3 Are Real Days (Lowest, Median And Highest Demand); S4 Raises The Peak-Day Demand By 25% And Cuts Its Workforce By 10%

ID	Scenario	Orders	Supply	Historical (min)	Optimal (min)	Reduction	Moto orders
S1	Low-demand day	816	1,370	22,284	21,143	5.12%	186
S2	Typical day	947	1,588	25,680	24,357	5.15%	231
S3	Peak day	1,146	1,828	29,219	27,856	4.66%	348
S4	Stress: peak day, demand +25%, workforce -10%	1,433	1,644	36,644	35,591	2.87%	715



Figure 5: Average delivery time per order by

scenarioThe optimal allocation reduces delivery time in every scenario: 5.12% on the low day, 5.15% on the typical day and 4.66% on the peak day. In the stress test the reduction falls to 2.87% because demand of 1,433 orders leaves only 211 orders of spare capacity, so fewer orders can be moved to quicker vehicles, but the problem remains feasible and the plan still beats the scaled historical mix.

2. All 44 days

The model was solved for every day of the data (workbook sheet All_Days). Total expected delivery time over the period falls from 1,148,489 to 1,090,426 minutes, a reduction of 5.06%, equal to 58,063 minutes or about 968 hours. The daily reduction ranges from 4.66% to 5.36%, and it is

positive on every day, so the result does not depend on a particular day.

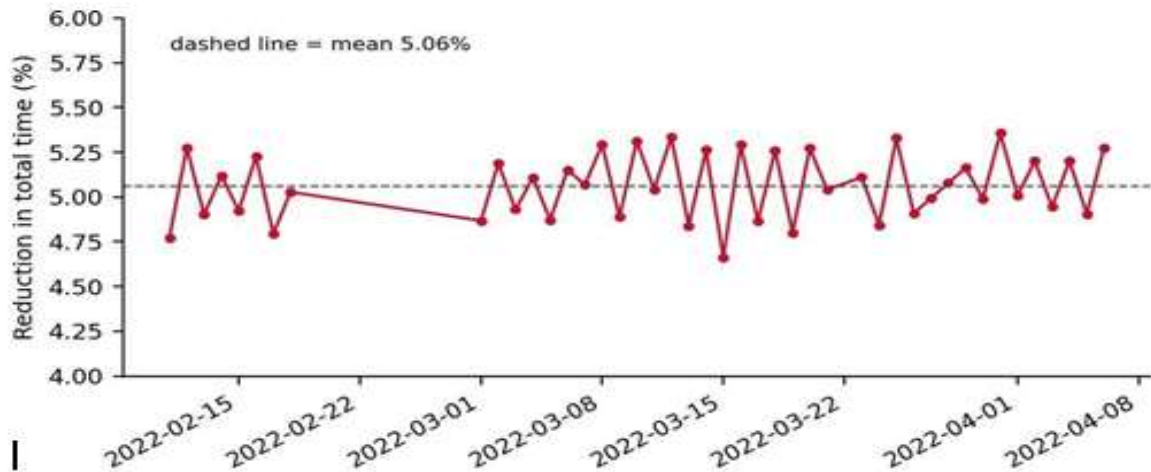


Figure 6: Daily reduction in total delivery time, optimal versus historical

3. Sensitivity to capacity, demand and workforce

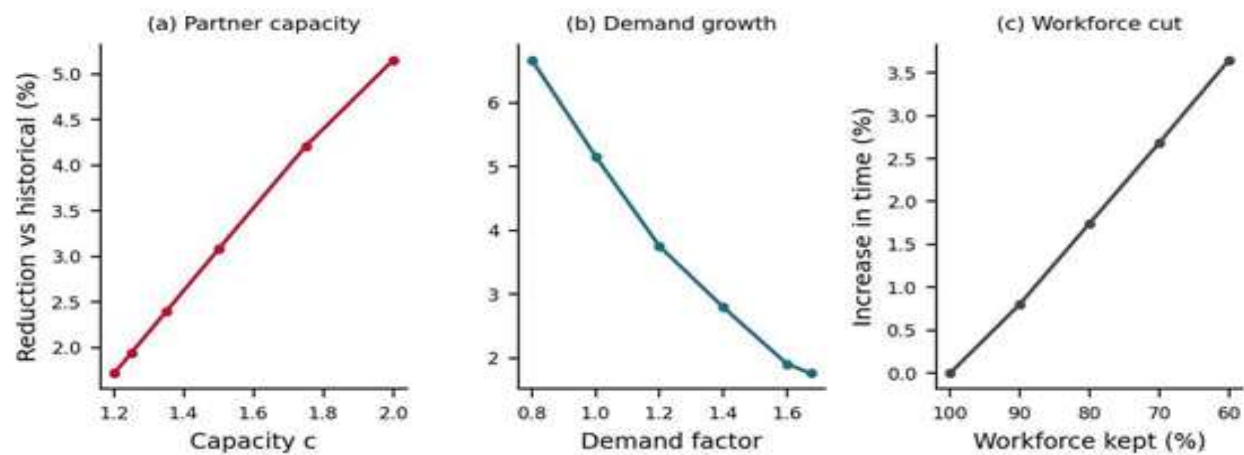


Figure 7: Sensitivity analysis on the typical day: (a) partner capacity, (b) demand growth, (c) workforce reduction

Capacity. The assumption of two orders per partner is the most influential. If partners could handle only 1.5 orders a day, the saving falls to 3.1%; at 1.2 orders, close to the observed average of 1.196, it is 1.7%, and at 1.19 total supply (945 orders) is below demand (947), so no plan can deliver every order. The direction of the result does not change, but the size of the gain depends on how much spare capacity the platform really has.

Demand. Holding the typical-day workforce fixed, demand can grow by a factor of 1.675 (1,585 orders

against a total supply of 1,588) before the problem becomes infeasible. Within that range the saving over the scaled historical mix declines from 5.2% to 1.8%, as spare capacity is used up.

Workforce. Keeping 90% of the workforce raises optimal delivery time by only 0.8%, and keeping 60% raises it by 3.6% (total supply 950 orders, just above demand). With 55% of the workforce, supply of 870 orders is below demand and the problem is infeasible. The optimized plan could therefore deliver the typical day's orders with a substantially smaller workforce than was active, which the

platform may or may not wish to use, since it also affects partner earnings and service reliability.

XI. DISCUSSION

1. Managerial implications

- Reserve scooters and electric scooters for medium-traffic and jam-traffic orders and use motorcycles mainly on low-traffic orders. This ordering matches vehicles to the conditions in which they have the largest advantage.
- The binding resource is quick-vehicle capacity. The shadow prices show that an additional order of scooter or electric-scooter capacity is worth 2.3 to 2.8 minutes in a typical day, whereas additional motorcycle capacity has no value in this range of demand.
- Because the plan needs far fewer partners than were active, the gain can be taken either as faster delivery or, if time targets are already met, as a smaller workforce. The model quantifies the trade-off in Section 8.3

2. Limitations

- The vehicle effect on delivery time is estimated from observational data. The faster times of scooters and electric scooters may partly reflect the orders they were given (shorter distances, for example), so the savings are model-based estimates and not guaranteed.
- Capacity of two orders per partner is the observed maximum. Section 8.3 shows that the saving depends on it.
- The dataset has no cost information, so the objective is time only, and idle capacity is treated as free.
- Expected times are cell averages. They ignore distance, weather, order type and the number of simultaneous deliveries.
- The model is a daily planning model. It does not capture real-time matching of partners to orders by location and availability, or variation within the day.
- The data cover 44 days and a sample of partners, and partner identifiers appear with more than one vehicle type, which is why the workforce is counted by partner-vehicle-day.

3. Future work

- Add cost per order or per vehicle and use a model that trades time against cost, for example by minimizing a weighted combination.
- Estimate delivery time with a regression on distance, weather and multiple deliveries, and feed the fitted values to the transportation model as costs.
- Apply the model to hourly periods using the order and pick-up times in the dataset, to separate peaks from off-peak times.
- Combine the planning model with a routing model that assigns partners to individual orders.

XII. CONCLUSION

This study shows how Operations Research can help improve food-delivery operations by optimally allocating delivery capacity across different traffic conditions. Using 43,641 Zomato records, the study formulated a transportation model in which vehicle types were the sources, city-traffic combinations were the destinations, and average delivery times were the costs. The findings show that traffic plays a major role in delivery efficiency, with deliveries in jam conditions taking approximately 46% longer than those in low traffic. The Vogel Approximation Method provided a solution close to the optimum, while the MODI method and Excel Solver confirmed the optimal allocation. For a typical day, the optimized model reduced expected average delivery time from 27.12 to 25.72 minutes per order, representing an improvement of 5.15%. The model also achieved a 5.06% reduction across the 44-day period and a 2.87% reduction under a scenario of 25% higher demand and 10% lower workforce availability. The results suggest that allocating more scooters and electric scooters to congested routes and motorcycles to low-traffic conditions can improve delivery

efficiency. The sensitivity analysis also indicates that increasing the availability of faster vehicles may be beneficial. However, these improvements are estimates based on historical data and assumptions about delivery-partner capacity and the effect of

vehicle type on delivery time, rather than guaranteed real-world savings. Overall, the study demonstrates the usefulness of transportation models in delivery-resource planning and provides a foundation for future research incorporating actual operating costs, delivery distances, and real-world vehicle and workforce constraints.

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