Food delivery: a model to assess the economic sustainability of geo-localised delivery

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Abstract: On-Demand Food Delivery (i.e., the delivery of prepared meals supported by online platforms) is experiencing a considerable growth, as consumers are ever more aware of the benefits entailed by this service: having access to a wide range of food types delivered at the own place in a short time. However, the potentialities stemming from this service are still not fully exploited. In particular, nowadays meals are typically delivered at customers' address, without considering other locations. The customers could indeed be reached through GPS in their mobile devices. In addition, the literature provides no evidence on the application of GPS in the food delivery segment to track customers in real-time. This paper aims thus at investigating the use of geo-localised deliveries in the on-demand food delivery sector from an economic perspective. The cost to deliver the order to a customer detected through the GPS position is estimated and compared with the delivery cost of delivery in a pre-defined location. Results show the enhanced profitability of this innovative delivery service, as delivery costs are lower than those of traditional delivery. This study contributes to the knowledge in this unexplored field by providing a model that replicates the food delivery process under this new circumstance and evaluates its economical sustainability. Moreover, it is useful to food delivery practitioners evaluating the introduction of geo-localised customers' solution in their offer, thus enlarging the range of potential delivery locations.

Keywords: food delivery, geo-localised delivery, last-mile delivery

1. Introduction

The On-Demand Food Delivery (ODFD), i.e. the purchase and delivery of freshly prepared meals enabled by the use of online platforms, is experiencing remarkable growth all around the world (Seghezzi et al., 2021), emphasized by the context generated by the Covid-19 pandemic (Osservatori Digital Innovation, 2020). On one hand, the purchase frequency by regular customers is growing. On the other hand, the customer base is becoming wider, due to the extension of the geographical coverage of the service, the enhancement of the offer and the development of new initiatives (Osservatori Digital Innovation, 2019). The growth of ready-to-eat meals delivery has been facilitated by the entrance of "new delivery" players in the market (e.g., Deliveroo, Glovo). They allow consumers to select from a wide variety of restaurants' offers, a service that already existed, but their merit is to integrate it with their logistic networks, providing the delivery service as well (McKinsey&Co, 2016).

The ODFD process involves four main actors, each one with their own tasks and expectations (Zambetti et al., 2017; He et al., 2019): (i) *Platforms,* which match the demand with the offer: incomes are from both restaurants' commissions and customers' delivery fees; (ii) *Customers*, who can access a wide range of food types delivered at the own place in a short time; (iii) *Restaurants*, which can increase their visibility and thus their revenues, without expanding their seating capacity; *(iv) Riders*, who deliver the meals, relying on flexible working shifts.

ODFD presents some criticalities. First, the freshness of the meal has to be maintained until it is received by the customer, resulting in tight time constraints (He et al., 2019). Second, the punctuality of the delivery is very challenging, being it a key success factor (Fikar et al., 2018). Third, the high service level to be provided to the customer results in high costs to be managed (Liu and Florkowski, 2018).

To manage the logistics complexity stemming from the process, platform services rely on algorithms exploiting the Global Positioning Systems (GPS). It is currently adopted for the trackability of the riders during the working shift (Alnaggar et al., 2019), to assign them orders on the basis of their relative distances from restaurants. GPS is a source of value also for the clients since it allows them to check the delivery status of their requests. However, the GPS adoption is still limited to the figure of the riders, while there are no studies on customers' trackability, even if this application could open to new opportunities.

Indeed, some pilot experiments aimed at exploiting GPS to spot customer position were recently conducted in different sectors (e.g., Starbucks, Zalando), in order to further improve the performances. This solution is potentially attractive for ODFD sector for both customers and riders. If considering the perspective of the customers, it could improve the service level, increasing the number of potential locations in which they may receive the meals. Concerning riders, knowing the exact location of customers may facilitate the last phase of delivery.

This work aims at investigating the economic sustainability of geo-localised deliveries in the ODFD sector, leveraging on a model that replicates the delivery process under this circumstance.

The paper is organized as follows: section 2 displays the outcomes of the literature review, conducted in the field of ODFD and geo-localised delivery, respectively, section 3 identifies the objectives and the methodology adopted, section 4 describes the model development, section 5 provides the model application and the sensitivity analysis, and section 6 summarizes the evidence found and conclusions of the work.

2. Literature review

ODFD process presents some peculiarities that distinguish it from last-mile deliveries in other industries. They can be summed up as follows: the delivery has a *single pick-up point* (Zambetti et al., 2017); it is a *single-batch delivery*: each carrier picks up one order and delivers it to one customer at a time (Zambetti et al., 2017); the *delivery times* are extremely reduced, due to maintain the freshness of the meal until it is received by customer (Huq et al., 2019); it does not require a fixed warehouse to depart from, and usually *transportation vehicle procurement* is up on the employees, reducing in a considerable way the costs compared to the traditional delivery service (Reyes et al., 2018).

Among them, the time constraint can be considered the most critical one, given the perishability of the good and the customer expectations over punctuality (He et al., 2019; Fikar et al., 2018). Therefore, ODFD services require high logistical efforts in order to grant the fresh meal to be delivered on time (Fikar, et al., 2018).

These being the premises, different scholars have been striving to find ways to cope with time challenges introduced by ODFD. Zambetti et al. (2017) conduct a study on the optimal position and number of depots in order to maximize the covered demand. The model introduced by Fikar et al. (2018) focuses instead on improving the service quality by minimizing the total delay of shipments as a primary objective, while minimizing the total travel distance, secondly. The study of He et al. (2019) deals with the optimization problem under the perspective of three actors: customers, who aim at maximising the utility in the selection of restaurants that pursue the maximisation of the received orders, and platforms that optimise the delivery plan.

However, it is manifest that, when dealing with ODFD issue, there are several aspects of the process that must be taken into account. Nonetheless, each of them presents a recurring feature: client satisfaction is the core issue when managing the last-mile delivery of fresh meals. In particular, with regard to this point, Liu and Florkowski (2018) report that meal quality and speed of delivery are the most important attributes. The survey by Vinaik et al. (2019) shows instead how high prices are "the most challenging factor considered by people while ordering food from an application", more than incorrect orders, poor customer service and long delivery time. According to Furunes and Mkono (2019), the convenience given by the technological mediation is the key success factor of the process.

Anyway, few authors investigated the ODFD phenomenon considering potential innovations in the service, like for example Pinto et al. (2020), who introduced the delivery performed by drones, but no one the introduction of the possibility to deliver the meals by reaching customers through GPS in their mobile phone.

Expanding the focus to last-mile delivery in other industries, there are some papers that cite GPS as the key technology to improve the delivery process. For example, Praet and Martens (2019) rely on GPS historical data of customer position to predict that "the user will be at a certain location for a given day of the week and hour of the day of parcel delivery". Wamuyu (2018), instead, introduces a paradigm in which customers share their real-time location through GPS in their mobile phone and maintain the position until the delivery is accomplished, an expedient that is useful in areas where the addresses are absent. Nevertheless, there is hardly any literature examining the idea of a floating target, tracked with real-time GPS data. Even though the concept of roaming delivery is developed quite deeply, and the delivery location can be different from home, it is always a static point.

Based on the above, it is possible to highlight that the literature provides no evidence on the application of GPS in the food delivery segment to track customers in real-time, but it is believed that the use of GPS could generate new use-cases for the customers.

3. Objectives and methodology

Given the identified gap, this paper aims at evaluating the economic sustainability of geo-localised deliveries in the ODFD sector. More specifically, the goal is to compare the cost to deliver an order to a customer whose position is detected through the GPS with the cost of delivering in a pre-defined fixed location.

The work was organized into five main steps. (i) First, the main variables and actors involved in the food delivery process were identified. (ii) Second, a model representing the ODFD process, both at a predefined location and by geo-localising the customer - intercepting him/her on-the-go or delivering outdoors –, was developed. (iii) Third, the analytical model for the estimation of the service profitability was built. (iv) Fourth, the model was applied to a real case scenario of food delivery in an urban context. (v) Fifth, a sensitivity analysis on four relevant parameters was run, in order to test the reliability of the outcomes of the model application, and the robustness of the model itself.

The main methods adopted in the research to support the model development and application are: (1) literature review, in order to investigate ODFD peculiarities and the usage of GPS technology in the last-mile delivery; (2) interviews with the head of operations of one of the main ODFD players operating in Italy. They had a threefold role: collecting information for the model design, gathering data for the model application, and validating the results obtained.

4. Model development

The model can be divided in two parts: the first one consists of a simulation of the delivery process, either for the traditional service and for the innovative one (section 4.1); the second, provides for an analysis of the costs and revenues associated with the delivery (section 4.2).

The elements involved in model building can be summed up according to the following scheme (see figure 1).

- Input data: variables that can be set by the food service provider.
- Context data: parameters that refer to market characteristics.
- Algorithm: all the necessary steps to replicate the ODFD process.
- Output data: profitability analysis.

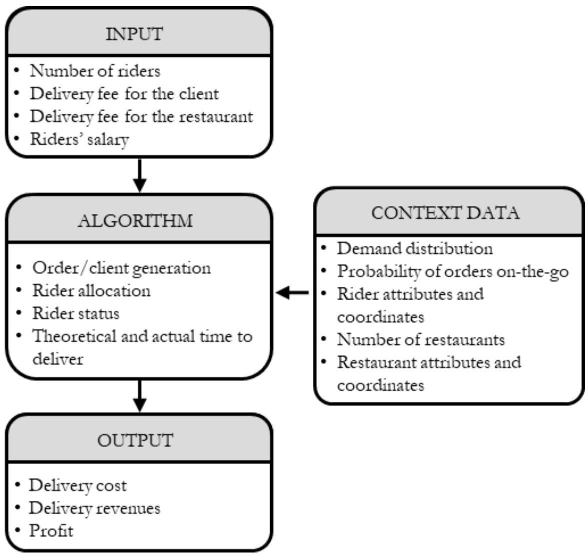

Figure 1: model building blocks

4.1 Simulation model

The simulation model replicates the ODFD process and, in particular, it simulates three different delivery options: (1) delivery at an indoor fixed location, the "traditional" delivery (static indoor); (2) delivery at an outdoor fixed location, e.g., park, square (static outdoor); (3) delivery in the street, by intercepting the customer moving along his path, declared in the moment of the order placement (on-the-go).

The model was designed to adhere as much as possible to reality, but given the significant complexity in dealing with geo-localised delivery, some assumptions were introduced:

- Transportation mode: the delivery is performed through bicycles, due to the advantages provided by the usage of this mean in an urban context, such as the relief of problems associated with traffic congestion, parking, and restricted traffic zones (Zambetti et al., 2017).
- Demand generation: the orders are placed in the system in the minute in which they must be processed. They include both the requests scheduled in advance and the ones issued in "real-time".
- Restaurants' capacity: restaurants can handle multiple orders in parallel, meaning that they can't refuse orders, infinite capacity is thus assumed.

More in detail, the model allocates the orders to the riders who are in charge of the delivery and exploits the geo-localisation of the customers.

The steps of the algorithms, schematised in Figure 2, are the following.

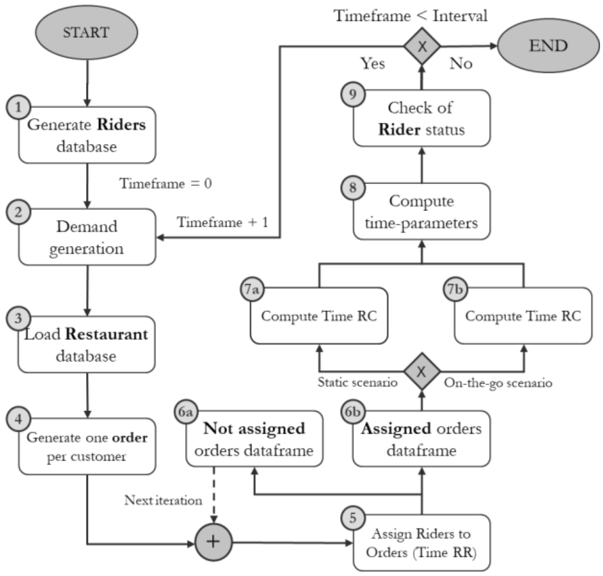

Figure 2: steps of the algorithm

1. Riders database is randomly generated a priori, containing all the relative characteristics (position, experience level, velocity, …).

2. The number of orders requested in a specific timeframe is generated every iteration, according to the demand distribution. Each order is released in the system in the minute it must be processed, in order to be delivered to the customer at the time he scheduled. So, every iteration consists of a timeframe of one minute. Therefore, to cover a wider period of time, such as the one of dinner, the algorithm executes a loop, in which every iteration represents a specific timeframe during the interval of the simulation. For each order is also generated a client with his delivery option and coordinates.

3. Restaurant database, containing real restaurant positions, is acquired by the algorithm.

4. To each client is randomly assigned a restaurant, completing the requirements necessary to fulfil the delivery information.

5. Each order is assigned to a rider. The algorithm minimises the distance between the rider starting position and the restaurant to be reached, taking into consideration both the availability of the rider and his potential rejection of the order. The time and the distance rider – restaurant (RR) are computed through the Distance Matrix API provided by Google Developers. The allocations to each rider are updated in the Riders database.

6. At the end of step 5, two different datasets are created:

a. Orders that remain unassigned, due to unavailability or refusal of riders, are saved and re-inserted in the following iteration, having priority over new orders.

b. Orders assigned are saved in a dataset that contains all the orders and riders attributes, necessary to execute the next steps, and the times in which the order was requested and assigned, respectively.

7. The time and the distance restaurant – client (RC) are computed in relation to the order type:

a. Indoor and outdoor static orders: the algorithm employs again the Distance Matrix API, since coordinates of the restaurant and the customer are known.

b. On-the-go orders: customer position R is randomly selected among the points of the customers' path (one point per metre is considered), and it is disclosed to the rider when he picks up the meal from the restaurant. Also, point S, representing the closest one between the customer's route and the restaurant, is found. Then, it is selected the closest point E to the final destination of the client between R and S. The rider moves towards E and enters the client's path. Finally, considering the relative locations and velocities, the meeting point N is found. Distance Matrix API is called two times to compute times and distances, first between the restaurant location and E, and second between E and N (see figure 3).

Figure 3: on-the-go orders resolution

8. The main time-parameters computed during the simulation are:

• Theoretical time: equal to the sum of Time RR and Time RC plus the one required to deliver the meal in the hands of customers. This last value is fixed and it differs depending on whether the delivery is performed indoors or outdoors.

• Actual time: the theoretical time actualised at the actual speed of the rider.

9. Riders' statuses are updated in the related database, checking the remaining time to fulfil the delivery.

Steps 2 – 9 are repeated for every iteration of the algorithm until the last timeframe of the interval.

The final output of the algorithm consists of a dataset containing all the time and distance parameters about the orders assigned during the interval.

4.2 Analytical model

Based on the output of the simulation, the economic analysis is then performed. The overall profit earned during the whole simulation is computed as shown in equation (1):

Profit = (Client delivery fee + Restaurant delivery fee) – (Riders' wage + Riders' forfeit + Cost from order loss) (1)

More in detail, the delivery fees paid by both the customer and the restaurant, which are the two sources of revenues, are considered fixed and they do not vary in relation to the order.

Costs are composed of three components. First, riders' wage, which is based on the time required to accomplish the delivery [h] and a fixed hourly cost [€/h]. Second, riders' forfeit, which is an hourly forfeit assigned to those riders that, at the end of the simulation, rejected and performed none of the deliveries. Third, cost from order loss: each order that at the end of the simulation remains unexecuted is valued as the profit loss.

5. Model application and results

5.1 Base case scenario

The model was applied to a base case scenario, defined through interviews and market analysis. The simulation takes place in a square of about 6,9 km^2 including the "Città studi" district of Milan, the Italian city with the highest number of Food Delivery initiatives (Osservatori Digital Innovation, 2020). It is a small-coverage, level zone, with great viability. The main parameters are presented in Table 1.

Table 1: parameter of the case-base scenario

Parameter	Value
Average number of orders per minute	10 (with a peak in the middle of the interval)
Probability on-the-go orders	20%
Number of restaurants	50
Number of riders	180
Interval of the simulation	2 hours (7.00PM – 9.00PM)

Average order value	25€
Restaurants Fee (on order value)	30%
Delivery Fee for the client	3 €
Riders Salary reference-value	15€/h

At the end of the algorithm implementation, it was possible to compute the Lead time, intended as the sum of the actual time and the waiting time, i.e., the time difference between the timeframes in which the order is requested and assigned. The base case was originated by one simulation (Simulation 1) of the model. The key aggregated outputs are reported in Table 2.

Table 2: outputs of Simulation 1

Output	Value
Number of Requested Orders	1.206
Number of Assigned Orders	1.149
Percentage of Not Assigned orders (NAO)	4,73%
AVG Theoretical Time	17,8 min
AVG Lead Time	23,1 min
AVG Deliveries assigned per rider	3,2 deliv/h

This simulation confirmed that the designed model is a good proxy of the real process. Indeed, the number of requested orders and their distribution meets the system requirements. Moreover, the lead time (23,1 min) and the number of deliveries assigned per rider (3,2 deliveries/h) are realistic according to the interviews with practitioners. However, the results show some inefficiencies related to the sizing of the system. In fact, the number of riders is insufficient to meet the demand, producing some not-assigned orders (4,73% of orders). Moreover, the average lead time is higher than the theoretical time, meaning that the orders had to wait around 5 minutes before being processed, damaging, so, the service level.

Considering the profit, it emerges that orders delivered outdoor are more profitable than the traditional ones, especially the deliveries at a pre-defined outdoor location. What makes the difference in outdoor orders, both considering on-the-go and static delivery points, is the quickest fixed delivery time, assumed two minutes shorter than the indoor one, since the rider is able to find more easily the customer.

Table 3: profitability of the different delivery options

Delivery option	Profit per order
Static Indoor	6,41€
Static Outdoor	7,27€
On-the-go	6,87€

5.2 Sensitivity analysis

After this first application, further simulations were executed to conduct some sensitivity analysis. The main purposes were to investigate the relationship among variables and their optimal values and evaluate the profitability of the process represented by the model, by varying the conditions. The following parameters were varied:

- Number of riders working in the interval, with the purpose of finding the optimal value to balance the maximisation of the number of deliveries assigned to each rider and the minimisation of the percentage of not assigned orders (5.2.1);
- Probability of on-the-go orders, to assess how the firm profitability is affected by this innovative service (5.2.2);
- Client delivery fee and Restaurants fee, to estimate the impact of the economic parameters (5.2.3).

5.2.1 Number of riders working in the interval

Starting from the base value by 180 riders, it was varied of ±60, being equal to 1⁄3 of the capacity, in Simulation 2 and Simulation 3, respectively. The analysis revealed that in Simulation 2 the system was largely undersized and more than 30% of orders were not assigned due to capacity issues. Simulation 3 accomplished the goal of assigning the totality of orders generated, but the average number of deliveries assigned per rider was below 3, which is regarded as the minimum value to maintain an adequate rider's satisfaction level, according to practitioner interview. Therefore, the optimal number of couriers was found linearly interpolating the number of riders and the percentage of not assigned orders (NAO), resulting in equal to 190, corresponding to around 27 riders per km^2.

Simulation 4, performed with this value, confirmed the results and provided the most efficient solution for the aforementioned requirements, assigning on average 3 deliveries/hour per rider and fulfilling the totality of customer requests.

Table 4: riders' number variation impact on delivered orders

Variables	Sim. 2	Sim. 1	Sim. 4	Sim. 3
Number of Riders	120	180	190	240
Percentage of NAO	32,92%	4,73%	0,00%	0,00%
AVG Deliveries assigned per rider	3,37 deliv/h	3,2 deliv/h	3,085 deliv/h	2,51 deliv/h

Moreover, the relation between the number of riders and the assigned orders affects the company profitability, considering the losses caused by not assigned orders. As shown in Figure 4, the profit increases together with the increment of riders' number (and so the decrease of NAO) up to the optimal value of riders, while the growth rate decreases accordingly. Indeed, the marginal increase in profit per order between Simulation 3 and 4 is minimum and attributable to the randomness of the system.

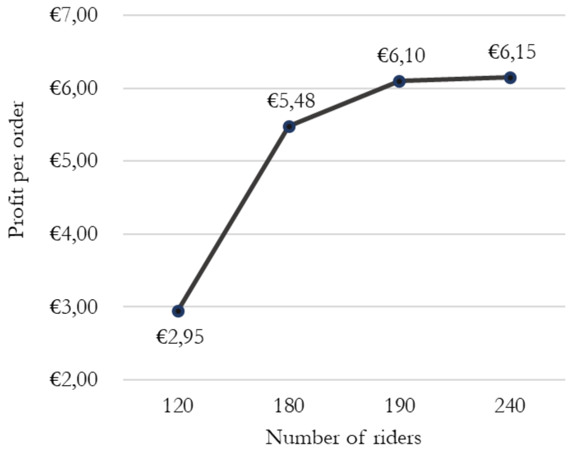

Figure 4: Profit per order related to number of riders

5.2.2 Probability of on-the-go orders

At this point, the probability of generating on-the-go orders was diminished by 10% at a time, in Simulation 5 and Simulation 6 respectively, compared to Simulation 4, assumed now as the base case, in order to test their impact on the overall profitability. The results confirmed the outcomes of the base case scenario. In fact, the introduction of on-the-go orders enhances the overall profitability, as shown in Table 5: Simulation 4, in which the percentage of on-the-go orders is the highest, records the highest average profit among the three. As previously explained, the fixed delivery time of outdoors deliveries, assumed shorter than the indoor one, is the major responsible for the higher profitability of these delivery options.

Table 5: On-the-go orders variation – Profitability Analysis

Parameters	Sim. 4	Sim. 5	Sim. 6
Percentage on-the-go orders	19,69%	11,30%	0,00%
Profit per order	6,10 €	6,02 €	5,81 €

5.2.3 Client delivery fee and Restaurants fee

An analysis on the economic parameters (i.e. client delivery fee and restaurants fee) was performed, considering as input data the average value among the ones Simulation 4, Simulation 5 and Simulation 6. Table 6 shows that the impact on the profit of a 10% variation in restaurants fee is 2,5 times higher than a variation of 1 € in the client delivery fee. Considering the client delivery fee as the sole source of revenues, this parameter should be equal to 4,47 €. Moreover, it is worth mentioning that the "free delivery" promotion, a typical marketing operation to increase the penetration rate of platforms, halves the profit per order (3,00 €) compared to the base case highlighted in grey. Furthermore, it is still sustainable even decreasing the restaurants' fee to 20% on ticket value.

Table 6: economic parameters variation matrix

Profit per order		Delivery fee				
		0,00 €	**1,00 €**	**2,00 €**	**3,00 €**	**4,00 €**
Restaurants fee	**0%**	-4,43 €	-3,44 €	-2,45 €	-1,46 €	-0,47 €
	10%	-1,95 €	-0,96 €	0,03 €	1,02 €	2,01 €
	20%	0,53 €	1,52 €	2,51 €	3,50 €	4,49 €
	30%	3,00 €	3,99 €	4,98 €	5,98 €	6,97 €
	40%	5,48 €	6,47 €	7,46 €	8,45 €	9,44 €

6. Conclusion

This paper developed a model that replicates the on-demand food delivery process, both the traditional and the innovative one (using GPS). From its application in different scenarios emerged that the main parameters that affect the profitability are the number of riders, the number of orders delivered outdoor and the economic parameters related to the delivery fee.

According to the results, the introduction of geo-localised delivery in the on-demand food sector is not only economically sustainable, but it also enhances the overall platform profitability, as it may be observed in Table 7, which compares the average profit per assigned order (average of Simulation 4, Simulation 5 and Simulation 6) for each delivery option configuration.

Table 7: AVG profitability of the different delivery options

Delivery option	Profit per order
Static Indoor	5,03€
Static Outdoor	5,73€
On-the-go	5,50€

The contribution of this work is twofold. From the academic perspective, it provides a model that replicates the on-demand food delivery process, including also the innovative geo-localised delivery option. Its application in different scenarios allowed to measure the impact of different variables on the service profitability and to evaluate the benefits stemming from delivering to a customer detected through the GPS position. The merit of the proposed study is, so, the exploration of the potentialities of GPS for the trackability of a floating customer in the urban context. The process represented is clearly simplified, but it allows the comprehension of the complex mechanism between the actors involved. Regarding the managerial contribution, the proposed model is a reliable tool of simulation and can be used by the main players of the market, to evaluate the introduction of geo-localised customers' solution in their system. Moreover, the short timeframe of each iteration allows to well reproduce the time-window constraint typical of this sector, and the reliability of the APIs provider makes the simulations potentially exploitable for different contexts and innovative case scenarios.

Besides, the performed analysis stressed another important issue: the efficient sizing of the system. For the considered application area and the demand distribution, 190 was found to be the optimal number of riders. Further research could deepen this relationship to find a reliable rule for the sizing issue.

However, due to the complexity of this field, increased by the introduction of this innovation, the model presents some limitations. The most relevant are:

- Profit estimation, which only takes into consideration those platform costs directly linked to the delivery process. For a more comprehensive vision of the cost structure, other relevant expenses such as administrative costs, advertising, taxes and legal fees, customer service, riders' assistance, etc. must be taken into account.
- Reliability of data. In the present work the location of customers and riders - as well as the distribution of orders - are randomly generated during the simulation. To overcome this limit, official data could be collected by practitioners through interviews, and the model could be fed with such data.
- Restaurant characteristics. The restaurant's perspective was marginally considered in the algorithm design. Indeed, their capacity was considered infinite, their preparation time fixed as well as the average ticket value. However, each restaurant has its own peculiarities, in terms of capacity, variability in the preparation time and popularity among customers. Further research on their requirements and constraints in the delivery process would enrich the model.
- Orders on-the-go resolution. The on-the-go delivery option provides for the pre-declaration of the path followed by the client. However, this is a strong limitation, and further improvement of the algorithm could enhance the realism of the model, by spotting customer location in real-time and adjusting accordingly the rider's route to reach him. This solution needs a further reduction of the timeframe, up to a value of around 10 seconds.

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