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Optimization of prices charged by a ride-hailing platform

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Abstract

The objective of this work is to develop a mathematical model that allows a ride-hailing platform to optimize the prices offered to its customers to maximize its revenue. To achieve this, a general model was developed, using Gurobi and Python, incorporating several key aspects of the problem: potential demand, trip duration, trip prices, willingness to pay of customers, the number of drivers, and their positions.

The behavior of potential customers to price was modeled using a linear decreasing function, which stipulates that an increase in price results in a decrease in the number of customers served. After defining and presenting the model, it was implemented using real data to assess the influence of various parameters on the final results.

Particular attention was given to pricing schemes. Six pricing schemes were defined and tested: single pricing, time pricing, origin pricing, origin-time pricing, origin-destination pricing, and origin-destination-time pricing. Each scheme was evaluated through 375 instances, where an instance corresponds to a specific set of parameter values. These instances were designed to analyze and observe the impacts of the parameters on the results. Specifically, the study focused on the number of customers, the number of drivers, the trip duration, and the prices offered by the platform. Additionally, the impact of driver positioning within the city was also examined.

This work demonstrated that the more degrees of freedom a pricing scheme has, the greater the model's flexibility, which can lead to a higher expected revenue while allowing for lower prices for customers. This creates a win-win situation: customers pay less, the platform generates more revenue, and drivers benefit from an increase in the number of customers, thereby earning more as well. Furthermore, it was shown that the tested parameters significantly and directly influence the results obtained. Finally, driver positioning was identified as a key factor in maximizing the platform's revenue.

Préface

This work marks the culmination of my Master’s degree in Management, pursued as an evening course at the Louvain School of Management, UCLouvain, in Louvain-la-Neuve during the academic years 2022-2023 and 2023-2024. With a prior degree in hand, the goal of this Master’s program was to broaden my understanding of the managerial world and explore new horizons, which has been achieved.

For this final thesis, I aimed to conduct research that is meaningful and engaging to me. What could be more stimulating than optimization? Indeed, optimization and strategic decision-making are areas that particularly intrigue and motivate me due to their significant impact. They have the potential to lead to cost savings, increased revenue, or more generally, to make the best use of resources to achieve objectives. Additionally, the ride-hailing sector has always intrigued me, particularly due to its business model, which is sometimes questioned by the media or users themselves. Thus, I was eager to become more familiar with this field.

Finally, I would like to express my gratitude to my supervisor, Mr. Philippe Chevalier, for enabling me to complete this work. I would also like to extend special thanks to Thomas De Munck for the valuable exchanges and discussions throughout the progress of my research.

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List of abbreviation

Notation	Units	Definition
$\alpha_{j,i}$	[/]	Function describing the arrival of a driver from zone j in zone i
$\tau_{i,j}$	[/]	Average duration of a trip from an origin location i to destination j
$c_{i,0}$	[/]	Number of drivers available at the zone i at a period 0
$c_{i,t}$	[/]	Number of drivers available at the zone i at a period t
C	[/]	Total number of drivers
$d_{i,j,t}$	[/]	Served customer completing service from zone i to zone j at a period t
D_i	[/]	Total number of potential customers from zone i
D	[/]	Total number of potential customers
$D_{i,j,t}$	[/]	Number of potential customers requesting service from zone i to zone j at a period t
i	[/]	Index for the zones
j	[/]	Index for the zones
t	[/]	Index for the periods
O-P	[/]	Abbreviation referring to the origin pricing scheme
OD-P	[/]	Abbreviation referring to the origin-destination pricing scheme
ODT-P	[/]	Abbreviation referring to the origin-destination-time pricing scheme
OT-P	[/]	Abbreviation referring to the origin-time pricing scheme
PD-D	[/]	Abbreviation referring to the distribution proportional to the demand in each zone
P_i	[US $]	Price of a journey from zone i in the case of an origin pricing scheme
$P_{i,j}$	[US $]	Price of a journey from zone i to zone j in the case of an origin-destination pricing scheme
$P_{i,j,t}$	[US $]	Price of a journey from zone i to zone j at a period t in the case of an origin-destination-time pricing scheme
$P_{i,t}$	[US $]	Price of a journey from zone i during period t in the case of an origin-time pricing scheme
P_{plat}^{max}	[US $]	Maximum price a platform would charge for a trip
P_{plat}^{min}	[US $]	Minimum price a platform would charge for a trip
P_s	[US $]	Price of a journey in the case of a single pricing scheme
P_t	[US $]	Price of a journey in the case of a time pricing scheme
P_{user}^{max}	[US $]	Maximum price a potential customer would accept to pay
P_{user}^{min}	[US $]	Minimum price a potential customer would accept to pay
S-P	[/]	Abbreviation referring to the single pricing scheme
T-P	[/]	Abbreviation referring to the time pricing scheme
U-D	[/]	Abbreviation referring to the uniform distribution

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1 Introduction

In the rapidly evolving landscape of urban transportation, on-demand ride-hailing services have revolutionized how people commute. A central challenge for these companies is determining optimal pricing strategies to maximize both revenue and customer satisfaction. Pricing in this context refers to setting the fare rates for rides such that they reflect real-time demand and supply conditions, individual customer preferences, and market competition. The complexity of pricing in the ride-hailing industry lies in its dynamic nature, requiring continuous adjustments based on fluctuating variables such as time of day, location, weather conditions, and local events.

Effective pricing strategies are crucial for the sustainability and profitability of ride-hailing platforms. Properly set prices ensure that drivers are adequately compensated while remaining attractive to passengers, thus balancing supply and demand. For companies, optimized pricing can lead to increased revenue, better resource allocation, and improved market share. For consumers, it means fair pricing and reliable service availability. Mispricing, on the other hand, can result in driver shortages, long wait times, customer dissatisfaction, and ultimately, a loss in market competitiveness. Thus, pricing is not merely a technical challenge but a strategic imperative for the success of ride-hailing services.

Pricing on ride-hailing platforms is inherently challenging due to several factors. First, there is the need to account for the heterogeneous nature of both drivers and passengers. Different drivers have varying levels of willingness to work at different times and under different conditions, while passengers have different sensitivities to price changes. Second, the market is influenced by external variables that are often unpredictable, such as sudden weather changes, traffic conditions, and local events that can cause significant fluctuations in demand and supply. Third, ride-hailing companies operate in a competitive environment where pricing decisions must consider the strategies of rival companies. Lastly, ethical and regulatory considerations add a layer of complexity, requiring a balance of profitability, fairness, and compliance with local laws.

To address these challenges, this study aims to develop a model for optimizing pricing and revenue for on-demand ride-hailing services. The research focuses on formulating a model that integrates real-time data on supply and demand. This involves setting up a simulation environment to test various pricing strategies and evaluate their impact on revenue. The goal is to identify pricing mechanisms that balance the number of drivers and passengers while maximizing the overall efficiency and profitability of the ride-hailing platform. Through this research, we aim to provide valuable insights into the design of more effective and adaptive pricing strategies in the dynamic and competitive field of on-demand transportation services.

To achieve our objectives, this work is divided into several parts :

1) *The literature review*: this part consists of a global view of the research topic. To this end, the first focus is on the sharing economy, which includes ride-hailing platforms. This analysis aims to see what else is out there. Then, the focus is put on several articles that have investigated the problems of ride-hailing platforms with a focus on pricing. In this way, it's possible to get an idea of what is already existing and what can brought or changed by this work.
2) *Methodology and model*: this part aims at presenting the general problem and the implications in a more concrete terms. Therefore, the theory and technology used in this work are presented to set the framework. The model is then defined. First, the problem is explained, specifying the implications and difficulties to be considered. Secondly, the problem is presented mathematically.
3) *Numerical experiment*: in this part, the objective is to test the model and to see the results we get. Therefore, the conditions of the experiments are presented before going to the analysis. The latter is divided into 3 sections: pricing scheme analysis, parameter analysis, and initial distribution of drivers analysis. For each analysis, results are first presented and then discussed.
4) *Conclusion*: the conclusion summarizes the work and highlights the main observations made. Finally, we discuss ways of improving and developing the model.

2 Literature review

2.1 Introduction

The literature review of this work aims at having a global look at the sharing economy and more specifically on the platforms offering an on-demand service, such as ride-hailing platforms. Firstly, a general presentation of the sharing economy is presented, with a particular emphasis on the "On-demand service platforms". Secondly, some papers on the problem of setting prices on ride-hailing platforms are reviewed. This second part provides a view of the current level of knowledge on the topic in existing literature and how this paper can bring new elements to the field.

2.2 Sharing Economy

The term "sharing economy"[1] covers a set of practices that have always existed, and consist of sharing or renting assets, in a peer-to-peer transaction. This economy includes housing, transport, clothing, gardening, etc., it can exist everywhere. In the interest of this work, some of these will be described below.

On-demand service platforms are a part of the sharing economy, allowing users to request specific services in real-time. There are many companies, in several other sectors. As this work aims to focus on ride-hailing platforms, a first list of "on-demand platforms" related to transport is presented below:

- Ride-hailing platform: these platforms are widely used nowadays, enabling users to order a vehicle via an application, and connecting passengers to independent drivers. Those drivers usually own their cars. This type of application and service has spread rapidly in recent years. Ride-hailing platforms offer car owners, drivers, and delivery partners flexible work and income opportunities. Among all the companies that exist,

[1] THE INVESTOPEDIA TEAM (2024). *Sharing Economy: Model Defined, Criticisms, and How It's Evolving*. En ligne https://www.investopedia.com/terms/s/sharing-economy.asp

Uber[2] is probably one of the most known. There is also *Lyft*[3], very similar to Uber, that operates in the US and Canada. In addition to personal rides, Lyft emphasizes its offer of professional travel. *Bolt*[4] is another company present all over the world and mainly in Europe. To complete this non-exhaustive list, there is also *Didi*[5], mainly present in the Asia-Pacific region and Latin America.

- Car-sharing platform: those platforms are interesting because they are not a direct competitor to the ride-hailing platform presented above but they are part of the sharing economy, using vehicles. These platforms can take various forms.

  On one hand, some platforms connect drivers on long-distance journeys with passengers heading in the same direction. The driver owns the car, and all the users share travel costs. The approach allows economical trips with a reduced environmental impact. Among the platforms, *Blablacar*[6] is a car-sharing platform, founded in France, and is now present in many countries.

  On the other hand, some companies make vehicles they own available to rent to their users for short periods. By offering a flexible alternative to car ownership, these platforms help to reduce urban congestion and carbon emissions. Users can reserve a car via the mobile app or website, gaining access to a variety of vehicles suited to different needs. The car does not have to be returned to the place where it was picked up, but it must in any case be redeposited at a suitable location defined by the company. Among existing companies, Cambio[7] is present in several European cities.

It is also interesting to have a glimpse of other platforms being part of the "sharing economy". Industries can draw inspiration from other industries and potentially reuse functionalities from these sectors in order to create a competitive advantage.

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[2] Uber (2024). *Allez où vous voulez avec Uber.* Available at https://www.uber.com/be/fr/
[3] Lyft (2024). *En route.* Available at https://www.lyft.com/
[4] Bolt (2024). *Aller n'importe où à n'importe quelle heure.* Available at https://bolt.eu/fr-be/
[5] Didi (s.d.). *DiDi Global.* Available at https://web.didiglobal.com/
[6] BlablaCar (2024). *La route des vacances, pas des dépenses.* Available at https://www.fr.blablacar.be/
[7] Cambio (s.d.). *Cambio carsharing. Ma voiture où je veux, quand je veux.* Available at https://www.cambio.be/fr-wal

- Sharing-accommodation platform: A sharing-accommodation platform is a digital service that connects property owners with travellers seeking short-term rentals. It allows users to list, discover, and book various types of accommodations, ranging from apartments to unique stays like treehouses. The most known is *Airbnb*[8]. It is an online platform offering short-term accommodation rentals around the world. The original idea was to rent out one's own home when the owner was away[9]. It offers a flexible and often less expensive alternative to hotels.
- Object-sharing and rental platforms: these platforms are still different from the others. The peer-to-peer rental platform enables users to rent an object to another user. Everyone has things at home that they don't use much, but which could be useful to someone else. Everyone has bought a utensil only to use it once when their neighbor might have had one. These platforms aim at reducing this over-consumption while enabling object owners to earn money and renters to save money. For example, there is *Fat Llama*[10] which is a peer-to-peer rental platform where users can rent out their equipment (e.g., cameras, drones, or musical instruments) to others.

2.3 Ride-Hailing platforms

As mentioned above, ride-hailing platforms connect passengers with drivers for on-demand transportation via a mobile app. The aim of this section is therefore to present works that have carried out research into various operational problems on ride-hailing platforms, such as driver repositioning, driver and customer matching, and demand forecasting, among others. Then, we focus on several articles that have investigated the problem of setting prices on ride-hailing platforms, the subject of this work.

[8] Airbnb (2024). *Airbnb.* Available at https://fr.airbnb.be/
[9] Wikipedia (2024). *Aibnb.* Available at https://fr.wikipedia.org/wiki/Airbnb
[10] Fat Llama (s.d.). *Rent instead of buying.* Available at https://fatllama.com/uk

2.3.1 Operational problems

Before looking at ride-hailing platform pricing, it's worth bearing in mind the complexity and multitude of issues facing such an industry. Some articles dealing with different issues are therefore presented below:

Target market. *F. Alemi, Circella G., Handy S. and Mokhtarian P. (2018)*[11] investigated the factors influencing the adoption of on-demand ride services like Uber and Lyft among millennials and Generation X in California. It finds that higher education, frequent long-distance travel, and technology-oriented attitudes increase the likelihood of using these services, while better land-use mix and regional accessibility also contribute to higher adoption rates.

Choice of passenger transport. *Hwang T-K., Jin B-H, Li Y-M, and Lee S-J (2018)*[12] have investigated how the emergence of ride-sharing platforms like Uber impacts the traditional taxi industry in Taiwan, focusing on factors influencing passenger and driver choices between Uber and Taiwan Taxi. It explores the reasons behind the growth of both platforms from 2013 to 2017 and evaluates the sustainability of Uber's business model in Taiwan's taxi market. Another work realized by *V. Salnikov, R. Lambiotte, A. Noulas, and C. Mascolo (2015)*[13] has compared Uber X and traditional yellow taxis in New York City using detailed fare and movement data, revealing situations where Uber X can be more expensive. It also suggests a mobile app for comparing taxi prices to help consumers make better choices.

Driver profile description. *Jonathan V. Hall and Alan B. Krueger(2017)*[14] analyze Uber's driver-partners, highlighting that they are drawn to the platform primarily for its flexibility, stable

[11] Alemi Farzad, Circella Giovanni, Handy Susan and Mokhtarian Patricia (2018). *What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California.* Available at https://www.sciencedirect.com/science/article/abs/pii/S2214367X17300947

[12] Hwang T-K., Jin B-H, Li Y-M and Lee S-J (2018). *Mobile Sharing Platform Operation Model and System Dynamic analysis : Uber and Taiwan Taxi as Examples.* Available at https://link.springer.com/chapter/10.1007/978-3-319-77703-0_95

[13] Vsevolod Salnikov, Renaud Lambiotte, Anastasios Noulas, Cecilia Mascolo (2015). *OpenStreetCab : Exploiting Taxi Mobility Patterns in New York City to Reduce Commuter Costs.* Available at https://arxiv.org/abs/1503.03021

[14] Jonathan V. Halland Alan B. Krueger (2017). *An analysis of the Labor Market for Uber's Driver-Partners in the United States.* Available at https://journals.sagepub.com/doi/10.1177/0019793917717222

earnings, and competitive compensation. Many drivers use Uber to supplement existing jobs and manage income fluctuations.

2.3.2 Price setting

Pricing is a crucial aspect of ride-hailing platforms. These companies use various methodologies to determine prices based on real-time demand and supply. The tables below summarize some articles, their methodology, data, and main results.

<table>
<tr><th colspan="2">QUEUEING MODEL</th><th>Main result</th></tr>
<tr><td>Authors (year)</td><td>Bai Jiaru, So Kut C., Tang Christopher S., Chen Xiqun, Wang Hai (2018)[15]</td><td rowspan="4">It is optimal to charge a higher price when demand increases.
The optimal price is not always monotonic, e.g. when
- the waiting costs increase
- the provider capacity increase.
The platform should offer a higher payout ratio when:
- Demand increases
- Capacity decreases</td></tr>
<tr><td>Pricing decision</td><td>Optimal price and wage rates that maximize the profit of the platform</td></tr>
<tr><td>Method</td><td>An analytical model with endogenous supply and endogenous demand and a steady-state waiting time performance based on a queueing model in the customer utility function.</td></tr>
<tr><td>Dataset</td><td>Actual data from a large on-demand ride-hailing platform</td></tr>
</table>

<table>
<tr><th colspan="2">TEMPORAL PRICING</th><th>Main result</th></tr>
<tr><td>Authors (year)</td><td>Cachon Gérard P., Daniels Kaitlin M., Lobel Ruben (2017)[16]</td><td rowspan="4">Optimal contract significantly increases platform profit compared to fixed price or fixed wage contracts; surge pricing achieves nearly optimal profit despite not being optimal; surge pricing benefits both providers and consumers by better utilization of providers and balancing prices and access to services.</td></tr>
<tr><td>Pricing decision</td><td>Optimal price and wage rates that maximize the profit of the platform</td></tr>
<tr><td>Method</td><td>With an analytical and numerical model, they studied different pricing schemes with a fixed price, a fixed wage, or both</td></tr>
<tr><td>Dataset</td><td>/</td></tr>
</table>

[15] Bai Jiaru, So Kut C., Tang Christopher S., Chen Xiqun, Wang Hai (2018). *Coordinating supply and demand on an On-Demand Service Platform with Impatient Customers.* Available at https://pubsonline.informs.org/doi/10.1287/msom.2018.0707

[16] Cachon Gérard P., Daniels Kaitlin M., Lobel Ruben (2017). *The role of surge pricing on a service platform with self-scheduling capacity.* Available at https://pubsonline.informs.org/doi/10.1287/msom.2017.0618

TEMPORAL PRICING		Main result
Authors (year)	Hall Jonathan, Kendrick Cory, Nosko Chris (2015)[17]	Surge pricing increases driver supply and allocates rides to those who value them most, improving market efficiency. Without surge pricing, the demand-supply balance deteriorates, causing higher wait times and lower completion rates.
Pricing decision	Surge pricing algorithm; comparison with fixed pricing	
Method	Case studies on a specific event to analyze the supply and the demand.	
Dataset	Data from Uber	

SPATIAL PRICING		Main result
Authors (year)	Bimpikis Kostas, Candogan Ozan, Saban Daniela (2019)[18]	Profits and consumer surplus are maximized when demand is balanced across locations. Both increase with a balanced demand. Pricing differently based on location can benefit the platform if demand is unbalanced.
Pricing decision	Price discrimination and drivers' decision to maximize their earnings with the compensation policy of the platform.	
Method	Use of a network locations	
Dataset	Network of locations	

SPATIAL PRICING		Main result
Authors (year)	Besbes Omar, Castro Franciso, Lobel Ilan (2019)[19]	Optimal prices balance supply and demand in some locations and induce over-congestion in others. Less profitable areas are priced out.
Pricing decision	Pricing for different locations.	
Method	Two-dimensional framework with a spatial decomposition allowing drivers to relocate	
Dataset	In a specific geographic area	

[17] Hall Jonathan, Kendrick cory, Nosko Chris (2015). *The effects of Uber's Surge Pricing : A Case Study.* Available at https://www.uber.com/blog/research/the-effects-of-ubers-surge-pricing-a-case-study/
[18] Bimpikis Kostas, Candogan Ozan, Saban Daniela (2019). *Spatial Pricing in Ride-Sharing Networks*. Available at https://pubsonline.informs.org/doi/epdf/10.1287/opre.2018.1800
[19] Besbes Omar, Castro Francisco, Lobel Ilan (2019). *Surge Pricing and Its Spacial Supply Response.* Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3124571

<table>
<tr><th colspan="2">SPATIO-TEMPORAL PRICING</th><th>Main result</th></tr>
<tr><td>Authors (year)</td><td>Hongyao Ma, Fei Fang, Parkes David C. (2018)[20]</td><td rowspan="4">STP mechanism ensures drivers accept trip dispatches, achieving welfare-optimal, envy-free, individually rational, budget-balanced, and core-selecting outcomes.
It significantly improves social welfare and earning equity compared to myopic mechanisms.</td></tr>
<tr><td>Pricing decision</td><td>Spatio-temporal pricing (STP) mechanism to balance supply and demand across space and time.</td></tr>
<tr><td>Method</td><td>Complete information model, incentive-aligned mechanism, subgame-perfect equilibrium.</td></tr>
<tr><td>Dataset</td><td>/</td></tr>
</table>

[20] Hongyao Ma, Fei Fang, Parkes David C. (2018). *Spatio-Temporal Pricing for Ridesharing Platforms.* Available at https://arxiv.org/abs/1801.04015

3 Methodology and model

3.1 Optimization framework

3.1.1 Introduction

Before getting to the heart of the subject, it is necessary to properly understand what is hidden behind the title of this work. Therefore, it is useful to define the word "optimization". According to the Cambridge Dictionary[21], the definition of this word is given by:

"The process of making something as good or effective as possible"

In a more specific way, "mathematical optimization"[22] has for purpose of finding the best solution between all possible solutions. The objective can be to minimize or to maximize an *objective function*, i.e., a function expressing your final objective in mathematical terms. Given that our world is made up of limited resources, the objective function is optimized, while accounting for several *constraints*. Constraints define the limitations or conditions that the solution must satisfy. These constraints can restrict some values of the problem to be solved or impose relationships among them. The optimization process seeks to find a solution that adheres to these constraints while optimizing the objective function.

In addition to constraints and the objective function, two other important parts of optimization need to be introduced: *parameters* and *decision variables*. Parameters are settings that control aspects of the optimization process. They can be data or settings to test the optimization. They must be clearly defined at the initialization of the problem because they can affect solution quality. In the case of a computer, they can also impact the computational time and the behaviour of the optimization solver. The decision variables represent quantities whose values are to be optimized in the optimization model. They can be discrete or continuous, with lower and upper bounds to guide the optimization process. Indeed, variables may be subject to the constraints. Mathematical optimization is a flexible tool that can be applied to many real-life

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[21] Cambridge Dictionary (s.d.). *Optimization.* Available at https://dictionary.cambridge.org/dictionary/english/optimization
[22] IBM (s.d.). *What is optimization modelling?* Available at https://www.ibm.com/topics/optimization-model

problems occurring: aviation, finance, construction, energy, etc. In the definition of a project and a business process (e.g., production or factory), the use of a mathematical optimization can lead to major savings, better distribution, and use of costs but also to a better organization.

3.1.2 Subfield

Optimization can be divided into many subfields, each with their specificities. Indeed, depending on the objective function, the constraints, and the variables, an optimization problem involves a different set of methods and procedures. Therefore, before presenting our specific model, it is important to correctly define the different categories of optimization problems, and their particular features. This does not rule out the possibility of overlapping sub-fields in certain problems (e.g. a problem could be stochastic and non-linear).
Below is an overview of the main types of optimization models, each adapted to specific applications and diverse needs.

1) Linear optimization:
    - This type of optimization is used when both the objective function and the constraints are linear. That is, the variables are continuous and usually nonnegative. The most common algorithm to solve linear optimization models is the Simplex Algorithm, found by Dantzig[23].
2) Integer optimization[24]:
    - This type of optimization is employed when some or all of the decision variables are constrained to take only integer values. It involves solving problems where the objective function and constraints are typically linear. Techniques for solving integer optimization problems include the "cutting plane" method, branch-and-bound or branch-and-cut.

[23] Wikipedia (2024). *Simplex algorithm*. Available at https://en.wikipedia.org/wiki/Simplex_algorithm
[24] Wikipedia (2024). *Integer programming*. Available at https://en.wikipedia.org/wiki/Integer_programming

3) Non-linear optimization[25]:
   - This type of optimization is used when the objective function and/or the constraints are not linear but contain some quadratics terms, for example. This leads to a more complex resolution that can be obtained by using approaches such as Newton's methods, gradients descent, quasi-Newton Methods,…
4) Stochastic optimization[26]:
   - This type of optimization is characterized by the use of uncertainties and/or randomness in the definition of some model parameters. To address such problems, some knowledge about the probability distribution must be integrated (e.g., the Gaussian distribution or Poisson distribution) into the model. The model is then generally decomposed into smaller subproblems that are easier to solve.
5) Heuristic optimization
   - This type of optimization is used when using an exact method is too "expensive" (using too many resources or too much time) to solve a complex problem. Therefore, some approximate methods are used to find solutions that are not optimal but still perform well in practice. Well-known heuristic algorithms[27] include genetic algorithm, tabu search algorithm, or simulated annealing algorithm.

3.1.3 Software

Since solving optimization problems can be highly beneficial, many software has been developed, as shown in Figure 1. This figure shows, for each type of problem (LP = linear programming, QP = quadratic programming, NLP = nonlinear programming, etc), the solvers that could be used. It is impossible to describe all of them and to see which one is the most

[25] Wikipedia (2024). *Optimisation non linéaire*. Available at https://fr.wikipedia.org/wiki/Optimisation_non_lin%C3%A9aire
[26] IBM (s.d.). *what is optimization modelling.* Available at https://www.ibm.com/topics/optimization-model
[27] Anmol Singh (2020). *Heuristic algorithms.* Available at https://optimization.cbe.cornell.edu/index.php?title=Heuristic_algorithms#Popular_Heuristic_Algorithms

accurate or appropriate. However, it seems interesting to have a look at the one that has been used in the case of this work. Therefore, in the next section, Gurobi is described and discussed. In addition, even if it is not included in the table, it is interesting to know that the Solver of Excel can also be used for some categories of problems. However, it is less suitable for heavy and complex resolutions, such as the ones treated in this work.

Solvers	LP, MILP*	APOPT* · ANTIGONE* · Artelys Knitro* · BCP* · CLP · CBC* · CPLEX* · FortMP* · GCG* · GLOP* · GLPK/GLPSOL* · Gurobi Optimizer* · HiGHS* · LINDO* · Lp_solve · LOQO · Mathematica · MINOS · MINTO* · MOSEK* · NAG · SCIP* · SoPlex · Octeract Engine* · SYMPHONY* · Xpress Optimizer*
	QP, MIQP*	APOPT* · ANTIGONE* · Artelys Knitro* · CBC* · CLP · CPLEX* · FortMP* · HiGHS · Gurobi Optimizer* · IPOPT · LINDO* · Mathematica · MINOS · MOSEK* · NAG · Octeract Engine* · SCIP* · Xpress Optimizer*
	QCP, MIQCP*	APOPT* · ANTIGONE* · Artelys Knitro* · CPLEX* · Gurobi Optimizer* · IPOPT · LINDO* · Mathematica · MINOS · MOSEK* · NAG · SCIP* · Octeract Engine* · Xpress Optimizer* · Xpress NonLinear*
	SOCP, MISOCP*	Artelys Knitro* · CPLEX* · Gurobi Optimizer* · LINDO* · LOQO · Mathematica · MOSEK* · NAG · SCIP* · Xpress Optimizer*
	SDP, MISDP*	Mathematica · MOSEK · NAG
	NLP, MINLP*	AOA* · APOPT* · ANTIGONE* · Artelys Knitro* · BARON* · Couenne* · Galahad library · Gurobi Optimizer* · IPOPT · LINDO* · LOQO · MIDACO* · MINOS · NAG · NLPQLP · NPSOL · SCIP* · SNOPT* · Octeract Engine* · WORHP · Xpress NonLinear*
	GO	ANTIGONE* · BARON · Couenne* · Mathematica · LINDO · SCIP · Octeract Engine
	CP	Artelys Kalis · Comet · CPLEX CP Optimizer · Gecode · Mathematica · JaCoP · Xpress Kalis

Figure 1: Classification and listing of several optimization software[28]

3.1.4 Gurobi[29]

Gurobi is praised for its speed and efficiency in solving various types of optimization problems. Among others, the solver can be used to solve linear, mixed integer, quadratic problems, and nonlinear programming. Gurobi offers a user-friendly interface with a comprehensive documentation and seamless integration into several programming languages such as Python, Matlab, R, and Java. Moreover, it offers analysis and diagnostic tools to help users to understand and improve their optimization models. Finally, the wide community of active users provides access to numerous resources, such as open-source packages, and question-answer forums. Of course, this software is not free, even rather expensive, but it offers free academic licenses (which are used in this research).

[28] Wikipedia (2024). *List of optimization software*. Available at https://en.wikipedia.org/wiki/List_of_optimization_software
[29] Gurobi (s.d.). *Decision Intelligence – Across the enterprise.* Available at https://www.gurobi.com/

3.2 Definition of the model

We are now ready to present our pricing problem and its formulation as a linear model. Next, we give an overview of the problem setting. Then, we formulate it in mathematical terms, detailing the objective function and the constraints.

3.2.1 Problem setting and hypothesis

The main objective of this research is to create a model that allows to optimize the revenue of ride-hailing platforms. However, when we talk about such platforms, many objective functions can be used to optimize the revenue. For example, the model could maximize the number of customers having completed their trip with the platform, the model could minimize the number of kilometers traveled by the drivers in order to keep them available as much as possible. In the case of this work, the aim is to examine the impact that pricing can have on overall revenue. Therefore, a model has been implemented using Python and Gurobi. But, before introducing the model, it's important to understand and define the problem, in order to have a global vision of the elements to be considered. That's the aim of the next few paragraphs. After that, in Section 3.2.2, the mathematical formulation is presented. In the fourth part of this work, the model is applied to real-world data to measure the impacts that a decision can have on the results.

Context. Everywhere in the world, the cost of a cab journey is directly proportional to the distance covered by the trip or to the total journey time. However, if there are traffic jams, the trip duration can be much longer. To avoid traffic jams, the driver can decide to use the secondary road network. The duration of the trip and/or the distance can therefore also be affected. In a way, these elements must be taken into account in the price proposed by the platform to the customers. This is not an easy task because, on one hand, you have to be able to anticipate and offer a fair price while remaining competitive and, on the other, you have to allow drivers to earn a decent living. Therefore the company must determine the price range, under certain conditions, within which the price must lie in order to earn enough money and to pay the drivers. In addition to this point, the company must also consider and study the prices that a user would be willing to pay. Indeed, the number of potential customers converted into served customers will directly depend on the prices charged. Of course, this exercise and determination has to be done for each city or country where the company wants to operate.

In addition, it seems logical to assume that, to achieve a high revenue, companies need to make as many journeys as possible. This means that there must be enough drivers available and responsive, but also that these drivers must be at the right place. This leads to several considerations. The first is how many drivers to have on the road network, to have a sufficient presence without having too many, which could result in many drivers leaving the platform because they don't earn enough money. The second is how the company positions these drivers in the various localities and strategic points. For example, having drivers near a train station is certainly more interesting than next to a nursery school. The third is whether it is in the platform's interest to adapt its prices according to the destination. For example, a trip that takes the driver into the city, where there's a lot of demand, could cost less than a trip that takes him out of the city, where there's less demand. These three elements, and certainly others, show the interest that reflection on the position and quantity of drivers available on the platform could have on the revenue.

To sum up, many parameters can be considered to optimize the revenue. In particular, the purpose will be to optimize the prices while ensuring sufficient customer demand and driver availability. Now that the problem has been explained, the next section will present the problem from a mathematical point of view.

3.2.2 Mathematical formulation

Having outlined our problem setting, this section now lists the indexes, parameters, and decision variables to present the mathematical formulation of the problem. Once all the elements have been listed, the optimization model is formulated, and an explanation of its objective function and constraints is provided.

- *Indexes*

$\boldsymbol{i, j = 1, 2, \dots, Z}$	for the zones
$\boldsymbol{t = 1, 2, \dots, T}$	for the periods.

Table 1: Indexes used in the mathematical formulation of the model

- *Parameters*

$\boldsymbol{\tau_{i,j}}$	average duration of a trip from an origin location i to destination j
$\boldsymbol{D_{i,j,t}}$	number of potential customer requesting service from zone i to zone j at a period t
$\boldsymbol{N_i}$	initial number of drivers in location i
$[\boldsymbol{P_{user}^{min}};\ \boldsymbol{P_{user}^{max}}]$	price range within which a potential customer would accept to pay
$[\boldsymbol{P_{plat}^{min}};\ \boldsymbol{P_{plat}^{max}}]$	price range within which a platform would charge for a trip

Table 2: Parameters used in the mathematical formulation of the model

- *Decision variables*

$\boldsymbol{P_{i,j,t}}$	price of a journey from zone i to zone j at a period t
$\boldsymbol{d_{i,j,t}}$	served customer requesting service from zone i to zone j at a period t
$\boldsymbol{c_{i,t}}$	number of drivers available at the zone i at a period t

Table 3: Decision variables used in the mathematical formulation of the model

- *Objective function*

$$\max\left(\sum_t \sum_i \sum_j \left(d_{i,j,t} P_{i,j,t}\right)\right) \ ; \ \forall\, i,j,t \qquad (1)$$

- *Constraints*

$$P_{plat}^{min} \leq P_{i,j,t} \leq P_{plat}^{max} \ ; \ \forall\, i,j,t \qquad (2)$$

$$P_{user}^{min} \leq P_{i,j,t} \leq P_{user}^{max} \ ; \ \forall\, i,j,t \qquad (3)$$

$$d_{i,j,t} = \left(1 - \frac{P_{i,j,t} - P_{user}^{min}}{P_{user}^{max} - P_{user}^{min}}\right) D_{i,j,t} \ ; \ \forall\, i,j,t \qquad (4)$$

$$c_{i,0} = N_i \ ; \ \forall\, i \qquad (5)$$

$$c_{i,t} = c_{i,t-1} - \sum_j d_{i,j,t} + \sum_j \alpha_{j,i} d_{j,i,k} \quad \begin{cases} \alpha_{j,i} = 1 \ if \ k = \left(t - \tau_{j,i}\right) \geq 0 \\ \alpha_{j,i} = 0 \ if \ k = \left(t - \tau_{j,i}\right) < 0 \end{cases} \ ; \ \forall\, i,t \qquad (6)$$

$$c_{i,t} \geq 0 \ \forall\, i,t \qquad (7)$$

The objective function, equation (1), represents the total revenues collected by the platform. The revenues are equal to the sum of the served customers ($d_{i,j,t}$), multiplied by the corresponding prices ($P_{i,j,t}$) for each pair of locations.

The price of a trip must lie within a certain range, determined by the company and enabling it to cover its costs, pay its drivers, and make a profit. This range is represented by the constraint (2). In particular, the parameter P_{plat}^{max} represents the maximum price that a platform would be able to charge for a trip from i to j during period t. P_{plat}^{min} stands for the minimum price that a platform could charge. At the same time, for a request to be fulfilled, the price must also be in line with the customer's expectations. This is represented by the constraint (3). Constraints (2) and (3) both represent a number of constraints to be fulfilled equal to: $i * j * t$.

The constraint (4) determines the quantity of served customers as a function of the prices between two locations. The quantity of served customers is directly linked to the price charged in relation to customers' willingness to pay. All associated constraints represent a number of constraints to be fulfilled equal to: $i * j * t$.

The constraints (5) (i constraints) and (6) ($i * t$ constraints) model the evolution of the driver distribution within the network of locations. Each constraint represents the number of drivers available in a zone at the end of the period. Such constraints are useful as they keep track of the repartition of the drivers among the different zones. Specifically, the constraint (5) is related to the initial distribution of the drivers in the first period. The constraints (6) express the evolution of drivers in each zone in the subsequent periods, as served customers arrive and depart in the network. Thus, the number of drivers present in the city i at the end of the period t is made of the three following terms:

1) The number of drivers present in the previous period;
2) The drivers who have left during the current period and;
3) The drivers who have completed service. In order to take trip duration into account, an indicator function $\alpha_{j,i}$ has been added. Indeed, when a driver accepts a potential customer, he is no longer available to meet another request, so it is necessary to consider this aspect to get closer to reality. Once the ride is accomplished, the driver will be available again.

   The function $\alpha_{j,i}$ looks in the past, from all zones j, to see if a driver would have had time to finish his journey to zone i during the period t. If $(t - \tau_{j,i})$ is higher or equal to 0, this means a driver could have started, during the period k $(= t - \tau_{j,i})$, a trip from the zone j to the zone i and arrive during period t. So $\alpha_{j,i}$ is set to 1 to take into account any drivers finishing their journey. Otherwise, $\alpha_{j,i} = 0$ because $t - \tau_{j,i}$ will be smaller than 0, which means the drivers from zone j to zone i are still driving.

Finally, constraint (7), expresses the fact that the number of drivers in a zone is always nonnegative. It represents a total of $i * t$ constraints to be met.

3.2.3 Modelling alterations

Now that the main model has been presented, this section aims at presenting some alterations that can be realized to the model. Those will help to understand how various pricing schemes can impact the revenue. On the other hand, the pricing scheme applied on a ride-hailing platform can depend on many factors, including the time of the day, the origin/destination zone of a service, or the customer demand. It could also be a single and unique price for each ride. Therefore, the decision variables $P_{i,j,t}$ will be defined in several ways to model different types of prices. Here are the different categories and definitions :

- **Single pricing - $\boldsymbol{P_{single}}$ (S-P)**: regardless of the duration, length or type of trip, every customer pays the same price for his or her journey. The expression of the price then becomes:

$$P_{i,j,t} = P_{single} \; ; \; \forall \; i, j, t$$

- **Origin pricing - $\boldsymbol{P_i}$ (O-P)**: the price depends only on the departure zone. This means that it does not depend on any other parameters (time, destination, etc). The expression of the price is:

$$P_{i,j,t} = P_i \; ; \; \forall \; j, t$$

- **Time pricing - $\boldsymbol{P_t}$ (T-P)**: the price will depend only on the period. With this definition, the purpose is to consider that, for example, during lunchtime, the request may be higher. Consequently, the price is mathematically defined as :

$$P_{i,j,t} = P_t \; ; \; \forall \; i, j$$

- **Origin-time pricing - $\boldsymbol{P_{i,t}}$ (OT-P)**: it is a combination of P_i and P_t. The price will vary according to the departure zone and the period time:

$$P_{i,j,t} = P_{i,t} \; ; \; \forall \; j$$

- **Origin-destination pricing - $\boldsymbol{P_{i,j}}$ (OD-P)**: the price will depend on the departure zone and the destination zone but it will be independent of the period time. So, in this case, the price is mathematically defined as:

$$P_{i,j,t} = P_{i,j} \; ; \; \forall \; t$$

- **Origin-destination-time pricing - $\boldsymbol{P_{i,j,t}}$ (ODT-P) :** this alteration is the initial definition of the model. Mathematically, this gives :

$$P_{i,j,t} = P_{i,j,t}$$

Thanks to these different levels of precision, it will be possible to analyze and compare results to see if certain simplifications and/or complexities are really useful.

4 Numerical experiments

In this section, we perform numerical experiments to evaluate the pricing schemes presented in the previous section, under various market conditions. The section begins with a detailed presentation of the experimental setting, describing the data and parameters used during the experiments. Then, multiple results are shown, highlighting the impacts of the different pricing schemes, and parameters on the revenues. For each result, some managerial insights are discussed, to understand the implications for the ride-hailing platform and its customers.

4.1 Experimental setting

Data. It has been decided to run the model on real-world data from the *NYC Taxi & Limousine Commission*[30]*.* These data include pickup time, drop-off time, as well as pickup and drop-off location for every taxi trip that occurred in New York City in February 2019. For the sake of exposition, we restrict the subsequent analysis to trips recorded in Manhattan, on the 6th of February 2019, from 7:00 am to 11:00 am. Yet, provided sufficient computational resources, the model can be extended to larger instances.

For the sake of tractability, we divide Manhattan into 64 discrete zones, and the time horizon (7:00-11:00 am) into 48 periods of 5 minutes. The data are used to derive three groups of parameters:

1) *The demands* of potential customers (64x64x48 tensor) include requests observed by zone of origin (64) and destination (64) between 7:00 am and 11:00 am, over 5-minute intervals (48 intervals).
2) *The average distances* (64x64 matrix) include the average distances observed from one zone to another between 7:00 am and 11:00 am.
3) *The average trip durations* (64x64 matrix) include the average travel times observed from one zone to another, still for the same time horizon.

[30] https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page

Initial distribution of the drivers. As it has been shown in Section 3.2.2, the initial distribution of the driver must be defined by a function. For this work, two distributions are considered, which are described as follows:

1) *Uniform distribution (U-D)*: This is the main distribution used for this work. The number of drivers is evenly distributed at the beginning of the day/shift. This is mathematically written as :

$$c_{i,0} = \frac{C}{\#zone}$$

where C represents the total number of drivers and $\#zone$ the number of zones.

2) *Proportional to the demand distribution (PD-D)*: this distribution is used in order to make some comparison. The quantity of drivers starting in a zone is proportional to the total demand in this zone on the time horizon studied, giving :

$$c_{i,0} = \frac{D_i}{D}\, C$$

where $D_i = \sum_j \sum_t D_{i,j,t}\,, \forall\, i\;, D = \sum_i \sum_j \sum_t D_{i,j,t}$ and C is the total number of drivers.

Model alterations. Once the data are introduced, it seems necessary to remember that tests will be carried out by making several alterations to the base model of Section 3.2. These alterations comprise single pricing (S-P), time pricing (T-P), origin pricing (O-P), origin-time pricing (OT-P), origin-destination pricing (OD-P), and origin-destination-time pricing (ODT-P). By running the model alterations, we can compare the different pricing schemes, and understand their respective effectiveness.

Instances. From the parameters described above, we build several instances to understand how parameter variations impact the pricing schemes described above. As shown in Table 4, our instances, are created by varying the following parameters:

- *The demand of potential customers*: To model various demand conditions, the reference demand, taken from the data, is multiplied by a factor ranging from 0.5 to 1.5 for each matrix component.
- *The number of drivers*: To model various supply conditions, the reference number of drivers is set to 5000 and is multiplied by a factor ranging from 0.5 to 1.5 for each matrix

component. The number of reference drivers has been chosen to reflect the number of cabs in New York, i.e. 13.500,00[31].

- *The average trip duration*: To model traffic congestion, the average trip durations, coming from the data, are multiplied by some factors ranging from 0.5 to 2.
- *The price limits*: As it has been presented in Section 3.2.2, two price ranges need to be defined: the price range a platform could charge for a trip and a price range representing the willingness to pay of a potential customer. But, how can the limits of the potential customer be determined? This determination would deserve a specific research on its own and may change significantly depending on where the study takes place. Therefore, in order to not unnecessarily weigh down the desired approach it has been decided to consider that a user would accept to travel for free (so, $P_{user}^{min} = 0$ €). On the other hand, it was decided to suppose that the maximum price a user would be willing to pay is equal to the maximum price of the platform (so, $P_{user}^{max} = P_{plat}^{max}$).

Factor on the demand	Factor on the drivers	Factor on the trip duration	Price limits $[P_{plat}^{min}; P_{plat}^{max}]$ & $[P_{user}^{min}; P_{user}^{max}]$
0.5	0.5	0.5	[0;10] & [0;10]
0.75	0.75	1	[0;20] & [0;20]
1	1	2	[0;30] & [0;30]
1.25	1.25		[6;20] & [0;20]
1.5	1.5		[12;20] & [0;20]

Table 4: Values of the parameters used in the instances to run the model

Table 4 represents the 375 instances studied. Since there are six model alterations (6 pricing schemes), we executed the model 2250 times.

Experimental setup. The mathematical problem presented in Section 3.2.2 has been implemented using Python as computer language. The model is built with the package Gurobipy, and optimized using the commercial solver Gurobi.

The various instances of the model have been realized on a personal computer *with Intel i7 and 1 GB VRAM*. For each instance, the optimal solution was determined in a limited time (between 30 seconds and 300 seconds) using the Simplex algorithm. It is also important to

[31] Wikipedia (2024). *Taxis de New York.* Available at https://fr.wikipedia.org/wiki/Taxis_de_New_York

point out that, given the large number of instances to be performed, a 5 % optimality gap has also been set in order to limit the model resolution time.

4.2 Result overview

In this section, we analyze and comment our main results. The analysis is divided into three different parts. The first one aims at having an overview of our main results looking only at pricing scheme impact. The second one focuses on the parameters and the influence they can have on the results. In the last part, a comparison is made between the results obtained with the uniform distribution (U-D) of drivers and the distribution proportional to the demand in each zone (PD-D).
In all three parts, the analyses are carried out in the same way: the results are first presented and then they are discussed, underlining some managerial insights.

4.2.1 Pricing scheme analysis

As introduced earlier, our model is altered to represent six different pricing schemes. For each pricing scheme, the model is solved for 375 different instances. This section aims at having a closer look at the impact of the pricing scheme on revenues. Therefore, several analyses are made before having a discussion based on the results.

PRICING SCHEME - ANALYSIS 1

The first observations are realized based on Figure 2. The figure displays a Boxplot chart representing all the revenues obtained for the 375 instances for each pricing scheme. Several comments can be made:

- As the pricing scheme allows for more flexibility, the collected revenues become higher. For instance, in Figure 2, the median revenue obtained with single pricing (S-P) is lower than with any other pricing scheme. If we rank the pricing schemes type by median revenue in ascending order, we get:

  S-P < T-P < O-P < OT-P < OD-P < ODT-P

  If we were to rank pricing schemes in ascending order of complexity, the chronology would be the same as that obtained with median revenue. Indeed, for each pricing scheme, among the decision variables, there is a certain number of prices to be optimized: single pricing (S-P) = 1; time pricing (T-P) = 48; origin pricing (O-P) = 64; origin-time pricing (OT-P) = 3.072; origin-destination pricing (OD-P) = 4.096; origin-destination-time pricing (ODT-P) = 196.608.

On the other hand, in Figure 2, it is interesting to note that the origin pricing, the origin-time pricing, the origin-destination pricing and the origin-destination-time pricing collect about the same revenues, the maximum, minimum and median revenue presenting minor differences.

- For each pricing scheme, the maximum revenue occurs for the instance:

Factor on the demand	Factor on the drivers	Factor on the trip duration	Price limits $[P_{plat}^{min}; P_{plat}^{max}]$ & $[P_{user}^{min}; P_{user}^{max}]$
1,5	1,5	0.5	[0;30] & [0;30]

Table 5: Instance for which the revenue is maximum - Uniform distribution

- For each pricing scheme, the minimum revenue occurs for the instance:

Factor on the demand	Factor on the drivers	Factor on the trip duration	Price limits $[P_{plat}^{min}; P_{plat}^{max}]$ & $[P_{user}^{min}; P_{user}^{max}]$
0,5	0,5	2	[0;10] & [0;10]

Table 6: Instance for which the revenue is minimum - Uniform distribution

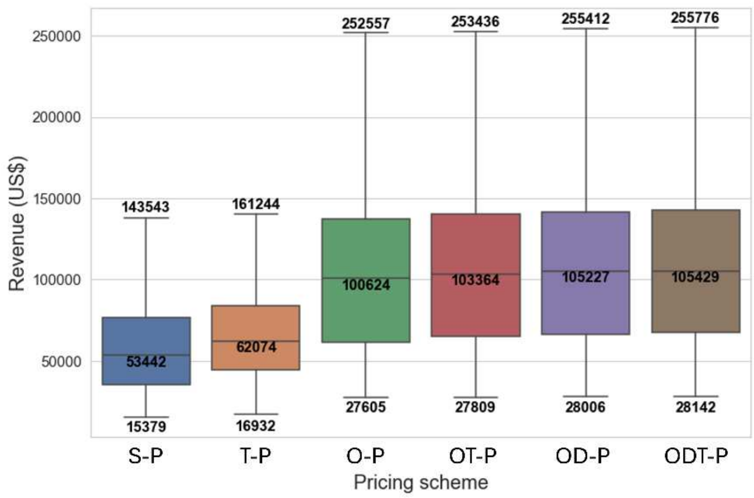

Figure 2: Boxplot of the revenues obtained for each pricing scheme. Each box includes 375 instances – Uniform distribution

Managerial insights and discussion. *First of all*, the observations made for the maximum and the minimum revenue seem logical. Indeed, for each pricing scheme, the maximum revenue is obtained when the potential demand is the highest of all the instances, when the number of drivers available is also the highest, when the trip duration is the lowest and with the bigger prices range. On the other hand, the minimum revenues are obtained with all the "unfavourable" values defined for this work. Based on these observations, companies should try to have as many drivers as possible available, reduce journey time and increase the use of their service.

The second point on which it seems necessary to expand is the proximity of the results obtained for O-P, OT-P, OD-P and ODT-P. What may be surprising at first glance is the closeness of the results between O-Pricing (64 prices to be optimized), OT-Pricing (3.072 prices to be optimized), OD-Pricing (4.096 prices to be optimized) and ODT-Pricing (196.608 prices to be optimized). To dig further into this observation, we are going to make a zoom (Figure 3) on two specific instances that have a demand factor equal to 1,5 and a driver factor equal to 0,5 (on the left) or equal to 1,5 (on the right). These cases are particularly interesting because they highlight situations that are closer to reality, where there are far fewer drivers than there is demand. We can highlight the increase in the median revenue with the use of a more complete pricing scheme. The impact of parameters will be discussed further in Section 4.2.2 but it is interesting to note that with a high demand, when the number of drivers is lower, the pricing scheme has a bigger impact on the revenue. It is also interesting to note that, among O-Pricing, OT-Pricing, OD-Pricing and ODT-Pricing, the boxplots are the smallest when the time is included in the price optimization.

To conclude this first analysis, the higher the precision and the complexity of the pricing scheme, the higher the revenue, and all other parameters held constant.

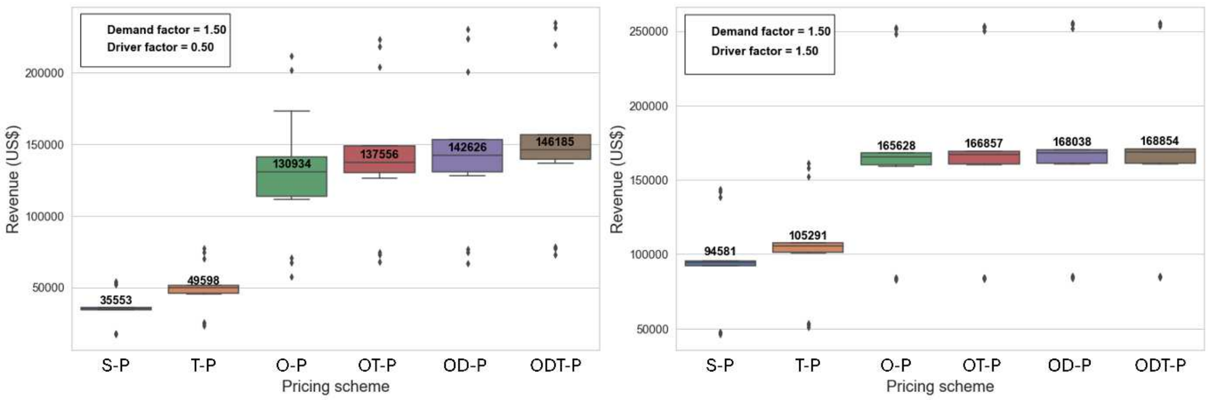

Figure 3: Specific boxplot of the revenue for the different pricing schemes
(Left) Demand factor = 1,5 ; Driver factor = 0,5 – (Right) Demand factor = 1,5 ; Driver factor = 1,5 – Uniform distribution

PRICING SCHEME - ANALYSIS 2

This second analysis is based on Figure 4. The two graphs represent different things, but it's interesting to analyse them in parallel. The graph on the left(right) represents the revenue(served customers) for each pricing scheme normalized with the revenue(served customers) of the single pricing. This normalisation allows us to talk in percentage. Among the observations, we can see :

- All the pricing schemes generate a higher revenue than the single pricing scheme. Moreover, the higher the pricing scheme complexity, the higher the increase of the revenue. Indeed, the results obtained for ODT-Pricing are higher than the results of OD-Pricing, which in turn is higher than OT-Pricing, and so on.
- On the other hand, when looking at the served customers' results, the general trends are the same. The higher the pricing scheme complexity, the higher the increase of the served customers.
- Looking more specifically, we can see that T-Pricing is rather close to the results of single pricing. On the other hand, it is extremely far from the results of the other pricing schemes. When comparing S-P with T-P, O-P with OT-P, and OD-P with ODT-P, the time component doesn't seem to have that much influence on the results.
- It's interesting to note that the gap between results is wider for the served customers. Indeed, for the revenue, the maximum increase is 80% while, for the served customers, without considering T-P, the minimum increase is 181%. When looking at the difference between O-Pricing and ODT-Pricing, the difference for the revenue is equal to 3% while, for the served customers, the difference is equal to 9%. The proportions are not equivalent.

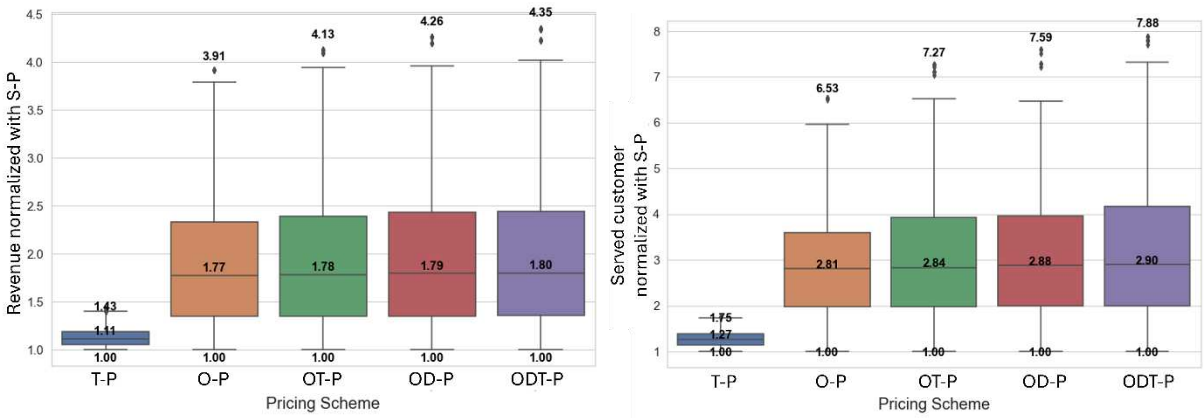

Figure 4: Boxplot of the results of T-Pricing, O-Pricing, OT-Pricing, OD-Pricing and ODT-Pricing normalized with the results of single pricing – (Left) Revenue – (Right) Served customers – Uniform distribution

Managerial insights and discussion. *The first comment* will be based on the comparison between the results of the served customers and the revenue. Indeed, we have observed that, for example, for the ODT-Pricing, the increase of the median revenue is 80% while, for the served customers, the median increase over S-P is equal to 190%. This means that the number of potential customers using the platform and becoming served customers increases dramatically without a corresponding increase in prices. On the contrary, prices may even have fallen, since revenue has increased less. If the prices were to evolve in the same way as the served customers, the revenue would be much higher (and the served customers would not be so high). This means that being more agile, by increasing the complexity of the pricing scheme, enables us to respond to a greater number of customer requests while increasing revenue and remaining price-competitive.

The second discussion focuses on the T-Pricing results. Indeed, given the difference in results obtained with the other pricing schemes, it seems essential to take a closer look. On all the graphs presented so far, it has been observed that the T-Pricing results are very close to the single pricing scheme. With a large number of drivers, this can be intuitively explained by the fact that the influence of price optimization during a given period has no real impact on other periods. Each small period t for which the price has to be optimized can be seen as the full period but with fewer trips. Therefore, the optimization will be very similar except that, as there is less data to consider in period t than in the larger period T, each price can be optimized a little better. This results in higher revenues but keeps the final result close to the single pricing scheme. On the other hand, if the supply of drivers were much lower than demand, we'd probably see different results.

PRICING SCHEME - ANALYSIS 3

The third analysis aims to take a closer look at the evolution of prices over time for each pricing scheme. The observations will be realized based on Figure 5 and Figure 6. The first represents the average price of a journey over the different periods for S-P and T-P. The second gives the same information but for the other pricing schemes (O-P, OT-P, OD-P and ODT-P). The two graphs have been differentiated to facilitate the comparison and the analysis of the results. The average price has been calculated by averaging all the prices charged for all instances over a given period. To be clear, this is the average price paid by customers for each period. The variation observed in the O-P and OD-P lines are therefore directly linked to the variation in demand served among the periods.

Here are some interesting observations from these graphs :

- The average price charged by period for S-P is just over 16,00US$.
  The average price charged by period for T-P fluctuates around 15,00 US$.
  The average price charged by period for O-P fluctuates around 11,50 US$.
  The average price charged by period for the OT-P fluctuates around 11,35 US$.
  The average price charged by period for the OD-P fluctuates around 11,20 US$.
  The average price charged by period for the ODT-P fluctuates around 11,00 US$.
  To summarize, if the average prices charged by period for the served customers are ordered chronologically from highest to lowest, this gives :

  S-P > T-P > O-P > OT-P > OD-P > ODT-P

  It is clear that the higher the pricing scheme complexity, the lower the price for the same instances and period.
- We'll now take a closer look at the results obtained for each figure, starting with Figure 5. First of all, the average price for the single pricing does not vary between periods. Looking at the T-P curve we can see that values are sometimes greater than for S-P and, more often they are lower.
- In Figure 6, the behavior and the results obtained are completely different from those obtained in Figure 5. An analysis of the curves shown in Figure 6 reveals that they all have a similar appearance. When the average price charged to the served customers increases/decreases over a period, this increase/decrease is observed for all pricing schemes represented. For each period the "proportionality" between the average prices charged to the served customers is the same, i.e.: *O-P > OT-P > OD-P > ODT-P*

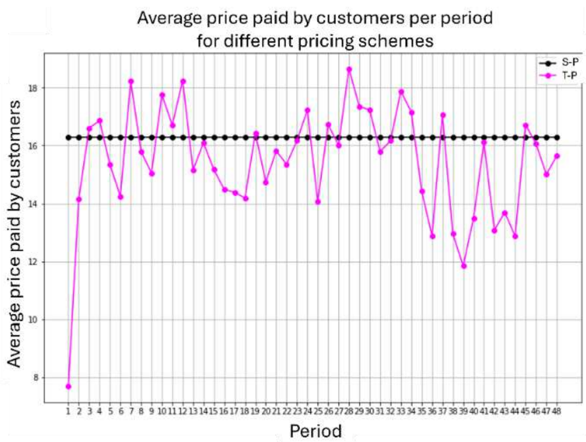

Figure 5: Average price paid by customers per period for the single pricing and the time pricing schemes – Uniform distribution

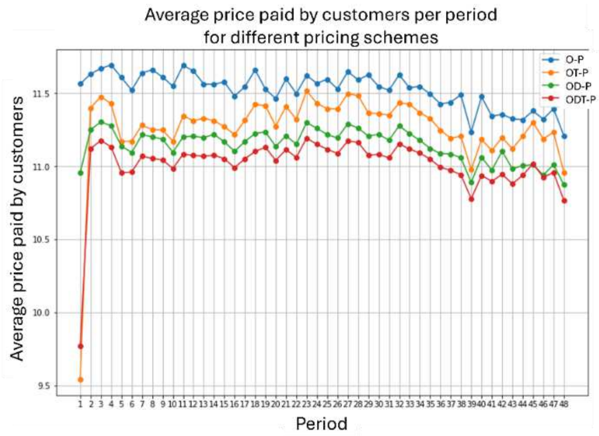

Figure 6: Average price paid by customers per period for the origin pricing, origin-time, origin-destination pricing and the origin-destination-time pricing schemes – Uniform distribution

Managerial insights and discussion. *The first discussion* focus on the results obtain for T-P. It was observed that the average price was closer to that of the single pricing scheme than to that of the other pricing scheme. Moreover, the time pricing curve fluctuates around that of S-P. These observations support the hypothesis made when commenting on the results of analysis 2. The price obtained with the single price scheme corresponds to the "least bad price", but is not, in reality, optimal for any situation. The range of possibilities is greatly reduced. With the time pricing scheme, each price can be optimized more precisely for each period, and the problem is relaxed, which explains why once the average price charged to the served customers of T-Pricing is above the curve of S-P, once the average price is below. On the other hand, the T-Pricing curve is completely different from the other pricing schemes. This suggests that the interactions between periods are not the same. This can likely be explained by the fact that in the majority of the instances, there are many drivers. Moreover, this pricing scheme does not include directly the zones, unlike the other pricing scheme.

The second interesting *aspect* is the influence of the pricing scheme complexity. Indeed, it is clear that the higher the complexity, the lower the mean price charged to the served customer. This can be explained by the fact that there are more and more price variables to be optimized so it's possible to find the best values for each case. This can be explained by the relaxation of the problem. When there are few price decision variables, there are additional constraints to satisfy between all the prices. This greatly reduces the range of possible solutions. This can be seen in the discussion of S-P and T-P. In the end, if there are too many constraints, the global solution won't be the best possible. As the degree of complexity increases, the solutions obtained get closer and closer to the optimal solutions because there is more degree of freedom. And so the global solution also moves towards an increasingly optimal solution.

Based on this discussion, and the observations also made during the first two analyses, it seems clear that for ride-hailing platforms, it will be more interesting to aim for prices for each "individual" demand. Indeed we can see that **the higher the degree of freedom, the lower the prices, while giving a higher total revenue because there are more requests to fulfil. This is a "win-win" situation: the customers pay less, and the platforms and the drivers earn more money.**

4.2.2 Parameters analysis

We now study the impact of specific parameters. The previous analyses of pricing schemes have shown that to maximize the revenue, it would be more interesting to use the ODT-Pricing scheme for a ride-hailing platform. This section will therefore mainly analyse the impact that the parameters have on the results of $P_{i,j,t}$. However, it is worth noting that the analyses and comments made here are equally valid for the other pricing schemes. The results obtained for each parameter (demand factor, price range, driver factors and trip duration factor) will be presented successively. The results will then be discussed.

PARAMETERS - ANALYSIS 1

The first analyses made on the parameters is based on Figure 7. The graph shows the revenue obtained as a function of the demand factor for different price ranges, each colour representing a price limit. The following observations can be made :

- For a given demand factor, when the upper limit of the price is higher, the revenue is also higher. Moreover, all results with an upper limit of 10 are grouped, as are all results with an upper limit of 20 or 30 respectively. It is interesting to note that the price ranges [0, 20] and [6, 20] yield similar results, whereas the price limits [12, 20] generally result in lower revenue. In addition, there seems to be a proportionality factor between the results. In fact, results with an upper limit equal to 20 are more or less 2 times larger than those with an upper limit equal to 10. Similarly, an upper limit of 30 gives results that are more or less 3 times larger.

- Let's take a look at the results obtained for a single price interval, for example [0;30]. It is clear that the higher the factor demand, the higher the revenue.

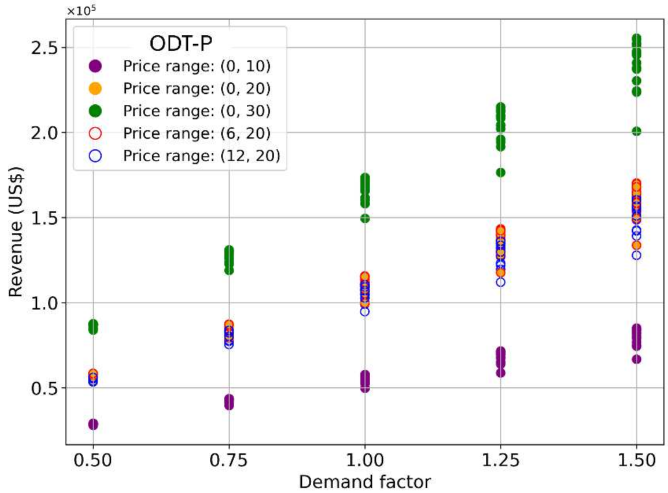

Figure 7: Revenue as a function of the demand factor for different price ranges - Origin-Destination-Time pricing scheme - Uniform distribution

Managerial insights and discussion. *The first discussion* will focus on the demand factor. Having a higher demand factor, and therefore a higher total number of potential customers leads to a higher revenue. This observation can clearly be explained by the number of served customers (see Figure 8). Let's take the price interval [0;30], shown in green, as an example. Each shape represents a different demand factor. So it is clear that the higher the demand factor, the higher is also the served customers and the higher is the revenue. This observation applies to all the price ranges. This is a good reminder that a company must do its utmost to meet as much demand as possible to increase its revenue.

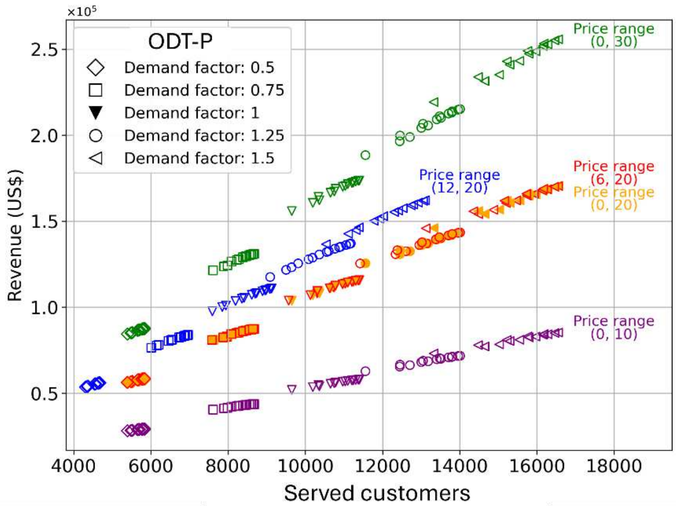

Figure 8: Graph showing revenue as a function of the served customers for several demand factors and price ranges - ODT-Pricing - Uniform distribution

<u>The second comment</u> is about the price ranges. As it has been observed, the higher the upper price limit, the higher the revenue. Before explaining the origin of the observations made, it seems important to recall that several assumptions have been made about customer price ranges:

- Customers are willing to travel for free, so $P_{user}^{min} = 0\ US\$$;
- The maximum prices that customers would be willing to pay are equivalent to the maximum prices that platforms would be willing to charge.

Mathematically, the observation made was to be expected and can be explained. Indeed, in many simulations, we have many drivers who can be assimilated to infinity. In this case, if we assume an infinite number of drivers, and with the hypotheses we made on P_{user}^{min}, the optimal selling price is : $\frac{P_{user}^{max}}{2}$.

This explains the proportions observed between the results: when the upper limit is 10 US$, 20 US$ or 30 US$, the optimum prices are respectively 5 US$, 10 US$ and 15 US$. On the other hand, it was observed that the behaviour with the platform price range [12;20] was different. Indeed, since the minimum price that would be charged is equal to 12 US$, this has an impact on the served customers. As a reminder, in the numerical experiments carried out for this work, the served customers is calculated as : $d_{i,j,t} = \left(1 - \frac{P_{i,j,t}}{P_{plat}^{max}}\right) D_{i,j,t}\ \ ;\ \forall\ i, j, t$

So clearly, when $P_{i,j,t}$ is higher, the served customers are lower. This is why when the lower limit is 12 US$, the served customers are lower than when the lower limit is equal to 6 US$ or 0 US$. In the first case, the optimal price that could be offered to customers would be around 12 US$. In the other cases, the price will be around 10$.

However, this does not seem to significantly impact the overall revenue. Based on this observation, it seems that a company could increase its prices if it accepts having fewer served customers. This decision could be related, for example, to a desire to upgrade the offered service and thus provide a more unique experience. However, such a decision could have negative impacts. Firstly, drivers who earn their money based on their rides might see their number of trips decrease and thus earn less money. They might then decide to stop using the application in favour of another. On the other hand, users, who usually compare prices between competitors, might decide to stop using this platform where prices are too high.

Such a decision (increase the prices) should therefore be analyzed by the company to ensure that a balance can be achieved without losing everyone.

PARAMETERS - ANALYSIS 2

This second analysis is focused on the drivers and on the trip duration parameters. The observations are realized based on Figure 9. As Analysis 1 has already studied the impact of the demand factor and the price range, it has been decided to present reduced graphics so as not to weigh down the discussion. Therefore, these graphs show the revenue obtained for the different driver factors with price range [0;30] and the demand factor equal to 0,5 (on the right) or 1,5 (on the left). The colors represent the different trip duration factors. The observations and comments that follow are valid for all other instances. Here's what these graphs show:

- For a given driver factor and all other parameters fixed, when the trip duration factor is lower, and thus the journey faster, the revenue is usually bigger. This observation can be seen with the demand factor equal to 1.5. When the demand factor is equal to 0.5 and the driver factor is equal to 1.5, this observation is still valid, but to an almost negligible extent.
- The higher the driver factor, and therefore the number of drivers, the higher the revenue. For the demand factor equal to 0.5 and the price range [0,30], the minimum revenue is $\pm 84.500{,}00\ US\$$, and the maximum revenue is equal $\pm 88.000{,}00\ US\$$. So the delta is $+3.500{,}00\ US\$$, which represents an increase of ±4%. On the other hand for the demand factor equal to 1.5 and the price range [0,30], the minimum revenue is $\pm 220.000{,}00\ US\$$ and the maximum revenue is equal to $\pm 255.000{,}00\ US\$$. So the delta is $\pm 35.000{,}00\ US\$$, which represents an increase of ±16%.

Thus, clearly, in both cases, it is interesting to have more drivers.

Managerial insights and discussion. *<u>As the first comment</u>* it can clearly be said that, since there are no constraints or "penalties" in the model on having more drivers, it is interesting for the platforms to have more drivers available because more customer requests can be answered. Consequently, it generates a higher revenue. As it can be seen in Figure 10, when the driver factor is higher, the served customers are higher and therefore also the revenue. This observation was expected and seems relatively obvious. However, this observation needs to be balanced against reality. Indeed, the number of drivers cannot be infinite and, maybe for each driver, the company must pay something. Taxes or a minimum salary? This has not been considered in the optimization and should probably influence the results.

The second interesting *aspect* to analyse is the impact of the trip duration. As mentioned in the comments, and as can be seen from Figure 10, the shorter trip duration, the higher revenue and served customers, all other parameters being constant. However, the results don't double, and the difference in revenue is not always very significant. This suggests that companies have no interest in putting pressure on their drivers.

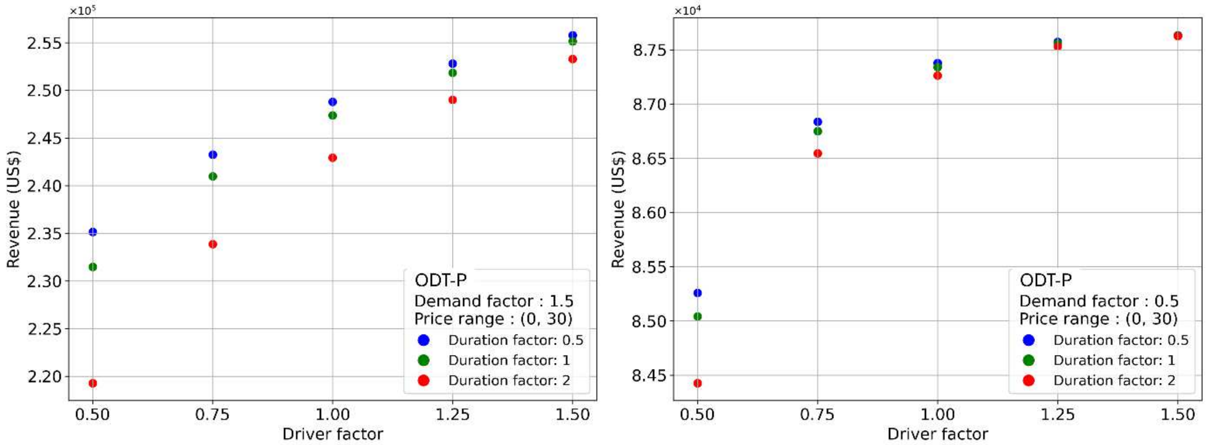

Figure 9: Revenue as a function of the driver factor for different duration factor (ODT-P) - Price range = [0;30] - (Left) Demand factor = 1.5 - (Right) Demand factor = 0.5 - Origin-Destination-Time pricing scheme - Uniform distribution

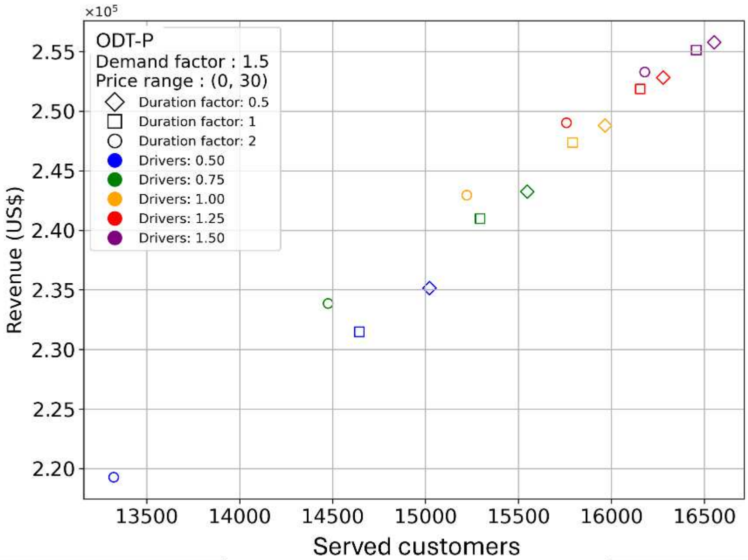

Figure 10: Graph showing revenue as a function of the served customers for several driver factors and duration factors - ODT-Pricing - Uniform distribution

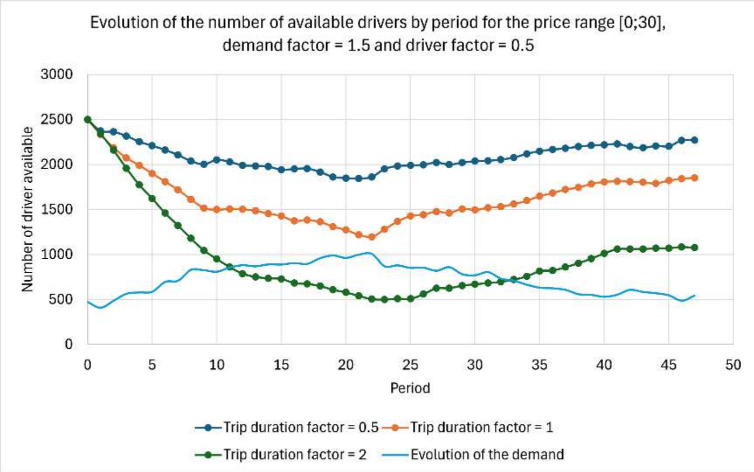

Figure 11: Evolution of the drivers available over the different periods for several trip duration factors – Price range = [0;30] – Demand factor = 1.5 – Driver factor = 0.5 – ODT-Pricing - Uniform distribution

On the other hand, what's interesting to look at, is the evolution of the number of available drivers over time. The situation with the demand factor equal to 1.5, the driver factor equal to 0.5, and the price range equal to [0;30] is represented in Figure 11. Lines with dots represent the evolution of drivers for different trip duration factors (0.5, 1, and 2). The light blue line without dots represents the total potential customers for each period. One of the prerequisites for meeting demand is a sufficient number of drivers. However, in the case of the trip duration factor equal to 2, it is clear that during periods 12 to 32, there are not enough drivers available. Drivers also need to be located in the areas from which the requests originate. That's why it's not certain that for the trip duration factor equal to 1 the requests will be met, even if there seem to be enough drivers. The impact of journey times on drivers' availability is visible.

4.2.3 Driver initial distribution analysis

The purpose of this section is to analyze the impact of the initial distribution of the driver. The objective is to compare some results as the total revenue, the served customers, or the prices charged obtained with a uniform initial distribution (U-D) to an initial distribution proportional to the demand (PD-D) in each zone. Those comparisons will be realized based on three of the six pricing schemes defined earlier. Indeed it was decided not to use the single pricing, the time pricing, and the origin pricing, as these schemes are rather far removed from what is realized in practice.

DRIVER INITIAL DISTRIBUTION – COMPARISON 1

This first comparison looks at the impact of the initial distribution on the revenue and the served customers. Therefore, the results obtained with the initial distribution proportional to the demand in each zone are normalized to the results obtained with a uniform initial distribution. The results obtained are shown in Figure 12. The graph on the left represents the normalization of the revenue and the graph on the right represents the normalization of the served customers. Thanks to these, we can observe that :

- The revenues with a distribution proportional to the demand are bigger than the revenues with a uniform initial distribution since the value is always bigger or equal to 1. Moreover, the median value decreases with the pricing scheme complexity. Indeed, for OT-Pricing, the increase in revenue is equal to 2.2% and for ODT-Pricing, the increase in revenue is 1.6%.
- In parallel, there is the served customers graph which has a similar behavior. Since all the values are bigger than 1, this means there are more served customers with the distribution proportional to the demand. The increase for OT-Pricing is equal to 3.0% and for ODT-pricing it is equal to 2.1%. This means that, in percentage, the increase in the number of journeys made is greater than the increase in revenue.

To sum up, the use of a distribution proportional to demand in each zone makes it possible to increase revenue and served customers. Moreover, in both cases, the more price-decision variables there are, the closer the results of the two initial distributions become.

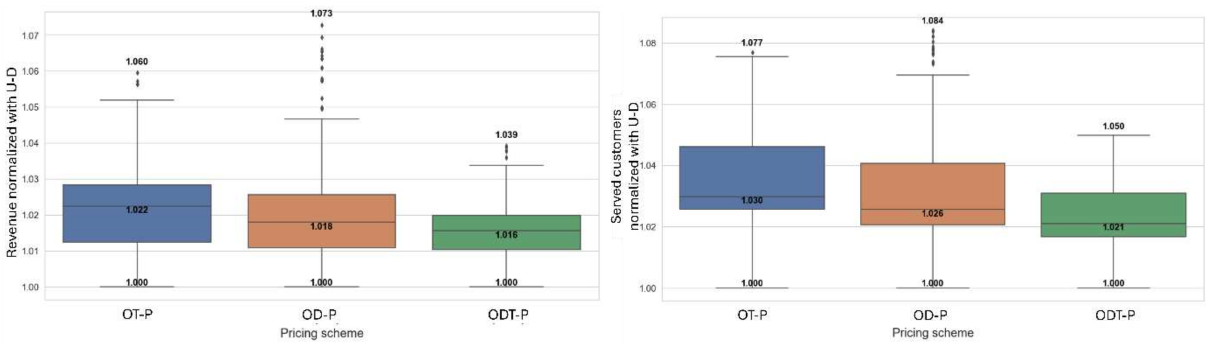

Figure 12: Boxplot of the results of OT-Pricing, OD-Pricing and ODT-Pricing with PD-Distribution normalized with the results of U-Distribution – (Left) Revenue – (Right) Served customers – PD-Distribution

Managerial insights and discussion. *Firstly*, it's interesting to note that while there is an increase in revenue, there is above all a greater increase in served customers. This means that the PD-D can cater to more customers than the uniform distribution. It is therefore very interesting and necessary for a ride-hailing platform to take an interest in the positioning of its drivers.

Secondly, it also appeared that the more price decision variables there were, the more the results between the two initial distributions were "similar". This is explained by the interest of having a lot of decision variables, as this will enable the system to try to find its best balance and to bring drivers where it needs them. It is therefore clear that the initial positioning of the drivers has an impact on the results.

DRIVER INITIAL DISTRIBUTION – COMPARISON 2

This comparison aims to compare the evolution of the price charged to the served customers during the period for the OT-Pricing, the OD-Pricing, and the ODT-Pricing. As a reminder, this is the average price paid by customers for each period. The variation observed in the O-P and OD-P lines are therefore directly linked to the variation in demand served among the periods. Figure 13 shows on the left the evolutions of the prices for the demand distribution and on the right for the uniform distribution. As it was observed for the uniform distribution, the curves of the demand distribution present a similar behavior. Table 7 shows the pricing around which the lines fluctuate for the uniform initial distribution and the demand distribution. For all the pricing schemes compared, this price is lower with the demand distribution.

	OT-Pricing	OD-Pricing	ODT-Pricing
U-Distribution	11,35 US$	11,20 US$	11,00 US$
PD-Distribution	11,05 US$	10,95 US$	10,85 US$

Table 7: Pricing around which the average price paid by the customers per period varies – PD-Distribution

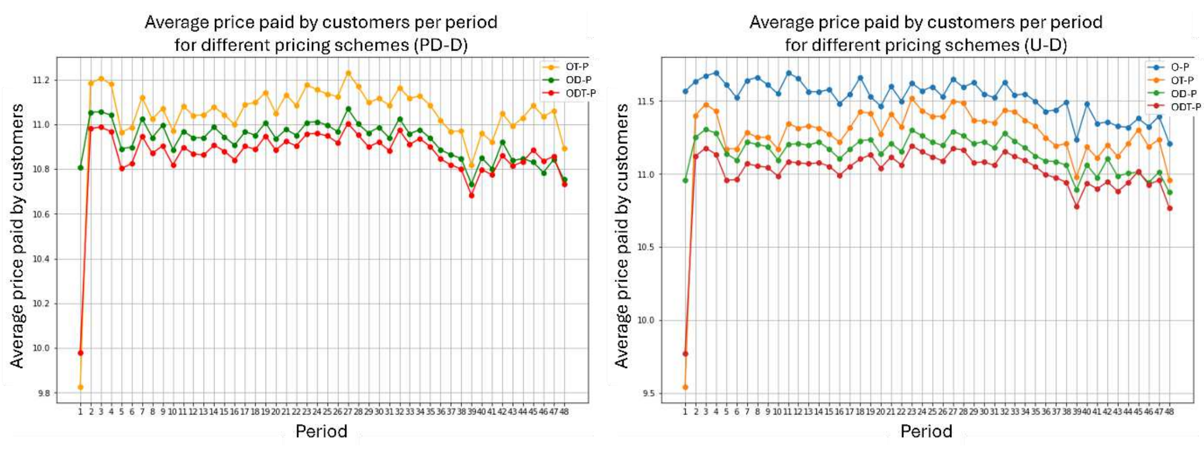

Figure 13: Average price paid by customers per period for the origin pricing, origin-time, origin-destination pricing and the origin-destination-time pricing schemes – (Left) PD-Distribution – (Right) Uniform distribution – PD-Distribution

Managerial insights and discussion. The observation made means that the prices are lower with the demand distribution. This explains the results observed in the first comparison. Reducing prices will bring in more customers. Revenues do not increase by the same proportion because the price is lower, but having more customers leads to a bigger revenue.

DRIVER INITIAL DISTRIBUTION – COMPARISON 3

The last observation to be made is a comparison between the evolution in available drivers, see Figure 14. We can observe that, with the demand distribution, the number of drivers used is higher since there are fewer drivers available in comparison to the uniform distribution. This can clearly be seen with the green lines.

Managerial insights and discussion. This observation simply means that, since the drivers are better positioned initially, there are fewer drivers 'idling' and doing nothing. On the other hand, because they were better positioned from the start, it is possible to respond to more customer demand. This aligns with the observation made during the first comparison.

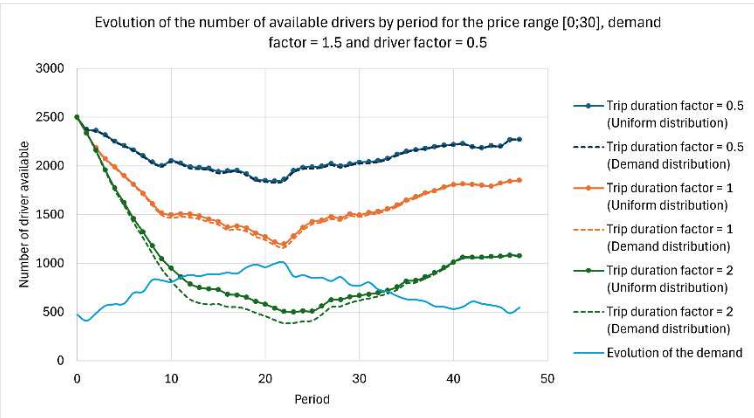

Figure 14: Evolution of the drivers available over the different periods for several trip duration factors – Price range = [0;30] – Demand factor = 1.5 – Driver factor = 0.5 – ODT-Pricing – U-Distribution and PD-Distribution

5 Conclusion

5.1 Research summary and main findings

This work aimed to model the problem of optimizing the prices offered by a ride-hailing platform to its users to maximize its revenues. This was achieved by formulating a linear optimization model, which was then solved using the Gurobi solver in the Python programming language. The mathematical model was executed with 6 different pricing schemes, on real-world data from Manhattan. In particular, the model was applied on 375 instances of parameters, and 2 different initial distributions of the drivers. The analysis was then divided into three parts: the impact of the pricing schemes, the influence of some parameters, and a comparison between the initial distributions of the drivers. In the following paragraphs, we review the main findings gathered during our numerical experiments.

Firstly, focussing on the pricing schemes, it has been shown that the more complex the pricing scheme (with more price decision variables), the higher the revenue. This observation is directly linked to the relaxation of the problem. Indeed, when the number of decision variables is low, the number of implicit constraints in the problem increases, reducing the range of optimal solutions. Using origin-destination-time pricing means lower prices, which is very convenient for customers, who are more likely to use the platform. This directly benefits the platform and drivers, which makes more money, leading to a win-win situation.

Secondly, it has been observed that having more drivers brings bigger revenues and more served customers. Similarly, as the number of potential customers increases, the number of served customers grows, and the collected revenues become higher. The bounds on the price willing to pay by potential customers, or set by the platform, also have a significant influence on the results: the higher the upper limit, the higher the price charged. Lastly, the difference in trip duration showed that the faster the trip, the higher the revenue. This result is intuitive since drivers can serve more customer demand as the trip durations decrease. Nevertheless, this increase was not so significant. This result may suggest that ride-hailing platforms could still offer convenient services to customers during congestion periods. This statement, however, needs to be qualified by the fact that in the experiments conducted, the number of available drivers was often high. As a result, drivers were often waiting for a request.

Finally, the initial distribution of drivers has a significant impact on results. Using the distribution proportional to the total demand in each zone, we noted a growth in the number of served customers, which translated into higher revenues, while enabling lower prices at the same time. This result is interesting because it means that drivers can be strategically positioned by the platform beforehand (e.g., through the form of recommendation) to satisfy more customer demand.

5.2 Research limitations and future avenues

During the analysis of the results obtained with the model defined for this work, several areas for development have emerged. It seems worthwhile to explore them to provide suggestions for making this model more robust and closer to reality. **Among these**, there is the definition of the parameters used, particularly the number of drivers. It would be interesting to test the model with a very low number of drivers relative to the potential customers and observe how the optimal solution would evolve. Indeed, in many instances, it has been observed that the number of drivers was too high. **There is also** the initial distribution of drivers among locations. Indeed, we have observed that the initial positioning of drivers has a real impact on the results. Therefore, it would be interesting to test other distributions. Another promising avenue would be to integrate driver repositioning over time. For example, if a driver stays in an area for too long, the driver could be moved to another location with higher demand. Alternatively, it could be decided that at a certain time, all drivers are repositioned according to some pre-defined function. All these mechanisms could, in some way, reflect reality where drivers are free to relocate to other locations. **Finally**, the definition of price bounds, especially the price thresholds for users, could be explored further. Indeed, significant simplifications have been made regarding these bounds. It would be interesting to conduct more in-depth market studies on customer behavior and their (ir)rational thinking process. In the same vein, it would be interesting to test and define other distributions for the customer's willingness to pay.

In summary, the research field is full of possibilities and insights that deserve attention. Optimization models are certainly interesting for the platforms and the drivers, but can also be beneficial for customers, who could obtain high-quality services, under more favorable prices.

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Abstract :

[FR] Ce travail présente un modèle mathématique linéaire permettant d'optimiser les prix proposés par une plateforme de ride-hailing à ses clients. Des expériences numériques basées sur des données réelles sont réalisées pour examiner l'impact de diverses décisions sur le chiffre d'affaires. Plusieurs schémas de tarification sont testés : tarification unique, tarification temporelle, tarification par origine, tarification origine-temporelle, tarification origine-destination et tarification origine-destination-temporelle. Pour chaque schéma, des expériences varient des paramètres tels que le nombre de chauffeurs, la demande totale, la durée des trajets et les gammes de prix. L'impact de la position des chauffeurs est également évalué. Des discussions permettent ensuite d'identifier les stratégies permettant aux plateformes d'optimiser leurs revenus en utilisant le modèle proposé.

[EN] This work presents a mathematical linear model to optimize the prices offered by a ride-hailing platform to its customers. Numerical experiments based on real data are conducted to examine the impact of various decisions on revenue. Several pricing schemes are tested: single pricing, time pricing, origin pricing, origin-time pricing, origin-destination pricing, and origin-destination-time pricing. For each scheme, experiments vary parameters such as the number of drivers, total demand, trip duration, and price ranges. The impact of the driver position is also assessed. Discussions are then held to identify strategies by which platforms can optimize their revenue using the proposed model.

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