The Algorithms that Drive Ride Hailing Services

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***Abstract*— Ride hailing services such as Uber, Careem, and Lyft have been studied extensively in academia in the context of their socioeconomic implications. However, owing in part to opaque, 'black box' Application Programming Interfaces (APIs), there is a dearth of material on the design and analysis of the algorithms which facilitate ride sharing applications. This paper aims to rectify this disparity and is concerned with the matchmaking and price optimization algorithms that drive the popular ride hailing services Uber and Careem. More specifically, the paper first provides a formal definition of each of the aforementioned problems. It then presents a high-level overview of the algorithms that Uber and Careem most likely use to solve these problems and analyses them in light of simulation data. It then discusses specific inefficiencies and pitfalls of the algorithms and suggests ways in which they can be overcome before describing the algorithms' impact on the daily lives of drivers, passengers, and citizens of the modern world.**

***Index Terms*—Algorithms, Uber, Careeem, Ride Hailing, Analysis**

I. Introduction

RIDE hailing services are considered to be amongst the most disruptive innovations of this decade, having spearheaded the rise of the sharing economy, especially in the United States and Europe [1]. As discussed in [2], peer-to-peer transportation services such as Uber were responsible for generating up to 38% of the €3.6bn Euros worth of the UK's sharing economy revenues in 2015. The economic impact of these services is rivalled only by their growth and popularity. Established in the early 2010s, startups like Uber [3], Careem [4], and Lyft [5] have since expanded to become multinational, billion-dollar companies. In this regard, Uber is clearly leading the charge. With its $68bn market valuation in 2015 [6], Uber eclipsed decades-old conglomerates such as General Motors, Ford, and Honda in terms of growth.

Innovative marketing campaigns and business models have indeed played an important role in transforming these startups into household names [7]. However, the real catalysts behind the meteoric growth of ride sharing services are the algorithms which drive these services' smartphone applications.

A. Overview of the Ride Hailing Service Model

Each ride sharing service such as Uber or Careem has its own smartphone application, which allows smartphone users to utilize these services as either drivers or passengers. Passengers are able to enter their destination into the app, which uses geolocation to match the passenger with a driver in the vicinity who is willing to accept the ride. The application also provides an estimated cost of the ride for the passenger and does the calculation and processing of the actual fare after the ride has been completed.

The same app also allows individuals to register as drivers and use their own vehicles to find nearby passengers who have requested a ride, drive them to their destinations, and accept payments for the ride [8]. Ride hailing services earn revenue through a processing fee that is included in the total fare paid by a passenger or, equivalently, deducted from the total payment received by the driver.

B. The Role of Algorithms

Ride hailing services are unique in that the process of matching passengers with drivers and optimizing a price for fares is managed through a set of complex algorithms [9]. This eliminates many of the shortcomings inherent in conventional taxi and chauffeur services. For instance, algorithmic matchmaking is faster and more accurate than a taxi dispatch operator redirecting a vehicle to a passenger who has requested a ride. More importantly, however, the price of the ride is not decided arbitrarily by either the passenger or the driver, but rather by a data-driven algorithm [10].

II. Problem definitions

From a technical point of view, there are two problems which ride hailing services (or rather the algorithms that drive them) have to solve, namely matchmaking and price optimization. Each of these problems

A. Matchmaking

The first problem ride hailing applications have to solve is that of matching an available driver with a passenger who has requested a ride. This is essentially an online taxi dispatching problem.

Managing thousands of such vehicles altogether, to some extent, used to be conditioned by the lack of technical means to coordinate between a fleet of vehicles. This imbalance between taxi supply and demand posed two negative impacts on the taxi service market:

- longer waiting time for the customers.
- longer empty cruising time for taxi drivers.

In essence, a taxi dispatching problem is no different than a vehicle routing problem, whose main goal is to find the best set of routes for a fleet of vehicles to navigate in order to transport a specified set of customers [11]. Whenever a customer calls for a taxi/cab the taxi operator either accepts or rejects the booking request, depending on the available taxis. Once an operator confirms the customer's request, it must be attended. Moreover, it is implicit that passengers desire to be transported from to their destination as soon as possible and are not keen on sharing a taxi with anyone else (although this is not true for UberPool and similar ride hailing applications, which are not the subject of this paper). To handle this workload of customer requests popping at random places the vehicles do not start their journey and end up in one depot but are geographically spread all over a specified area where shifts begin [12]

The aforementioned problem has been considered from two chief viewpoints in taxi research literature.

1) Rule-based Dispatching Systems

Early research focused on the rule-based dispatching systems. A model was set up which would attend the customer's request on a first come, first serve basis [13]. Further research investigated the efficiency of such a system by considering the customer wait time and route lengths in real time traffic [14]. Other than some fractional improvements resulting from these studies, the model was not able to overcome the fundamental limitation of successive assignments worsening the schedule quality over time.

2) Concurrent Dispatch Systems

In response to the failure of the above mentioned model, automatic concurrent taxi dispatching model was proposed. It would handle customer's request more efficiently b assigning them rides while simultaneously monitoring the number of available vehicles in the fleet along with vehicle capacity constraints. But still this system can run out of available taxis so it barriers the new incoming requests and as soon as a taxi is available, it redirects the request to a free driver [15]. This tactic is now commonly used in large cities worldwide, where customers can call a cab from their mobile phones and their request will be handled in the most efficient way [16].

As such, the problem of matchmaking is one of coordinating a fleet of vehicles while simultaneously using a buffer or similar construct to handle requests. It is driven by the constraints of minimizing estimated arrival times (ETA)s, fuel consumption, and time spent by the drivers looking for a fare. For ride sharing applications, this also presents a challenge in terms of the sheer volume of data that needs to be processed.

The next few sections of the paper will discuss various matchmaking algorithms in practice and how they are useful for facilitating driver-rider interactions via ride hailing applications. [17].

B. *Price Optimisation*

Uber and Careem's algorithms are also responsible for calculating ride fares that are acceptable for both passengers and drivers alike. Optimizing prices for both parties is important for the success of a ride sharing service, because the primary source of revenue for such services is a 20% processing fees deducted from driver earnings (and, by extensions, charged to passengers) for every ride [18].

Fig. 1. Predicted variations in demand for Uber cabs in NYC, NY, USA on New Year's Eve, demonstrating the volatility of demand and, as such, surge pricing.

The fundamental challenge of price optimization is twofold. Firstly, prices should be affordable for ride hailing companies' clientele, so the companies can continue to expand market share and revenue generated. At the same time, the price must also be enough to **incent** drivers to accept rides, as without drivers actually doing so, ride hailing companies have no source of income.

The second aspect of the price optimization problem is one that has been thoroughly studied in economics and finance: matching supply with demand [19]. The success of a ride sharing company is contingent on drivers being **available** to cater to passengers who have requested a ride. This means that at any given time, the supply of rides available in an area should ideally match the demand for rides.

Matching supply and demand is by no means a new problem. However, the dynamic nature of a ride sharing services mode of operations is what complicates things. Demand for rides in a locale fluctuates too frequently and by too much for ride sharing companies to accurately predict market trends and to cater to the expected demand by preemptively deploying a fleet of rides. Indeed, Fig. 1 shows that variations in demand for Uber (and similar ride sharing services) varies considerably from hour to hour. The price optimization problem therefore also entails implementing a system that can dynamically update prices in a matter of minutes in order to drive supply and decrease demand.

Consequently, the price optimization problem poses a greater technical and economic challenge for ride sharing companies than the matchmaking one. Clearly, there is a need for a dynamic, responsive, data-driven algorithm that can set ride fares that are acceptable to drivers, passengers, and the ride sharing companies themselves. Ideally, this algorithm should also collate demand and supply data and use variations in ride fares to minimize the demand-supply gap.

III. ALGORITHMS – A HIGH LEVEL OVERVIEW

The algorithms used by Careem and Uber for matchmaking and price optimization are proprietary information and, as such, not publicly available. Consequently, this report does not analyze the actual algorithms used by these companies, but instead presents an overview of techniques, models, and algorithms which Uber and Careem have been hypothesized to use for solving the problems discussed in the previous section.

Refer to Fig. 1. in the Appendix for a block diagram of a generic ride-hailing system.

A. Matchmaking

A ride-matching algorithm can be considered as the engine of a ride hailing system which analyses the constraints and conditions and then finds an optimal set of drivers for the incoming requests. In this report we will define three different algorithmic approaches to model a taxi-dispatch system keeping in mind the, vehicle capacity and maximum passenger wait time, constraints. The main goal of these algorithms is to develop a system that will:

- Minimize passengers wait time
- Maximizing profits by route optimization

The three major algorithmic approaches for solving this problem are as follows.

1) Nearest Vehicle Dispatch Approach

This is the most widely used matchmaking technique in today's taxi-dispatch systems. Its working is very simple and straightforward. When a new customer request is generated in the system, the algorithm firstly finds the location of the customer by using a mapping service (like Google Maps). After pinpointing the passenger's location, it finds the closest vehicle to the passenger by examining reasonable time windows. After designating a vehicle to a single request its timing and routes can be individually optimized.

Since the algorithm only aims to minimize estimated arrival times (ETAs) and does not consider other requests after assigning a task to a vehicle, it cannot handle successive assignments coming in at fast pace, worsening its efficiency overtime.

2) Local Trial and Error Approach

Although this approach is based on a first come, first served basis it is still quite different from the previous approach. In this method every incoming customer request is treated individually and the number of available vehicles at that time is given importance. Thus, this algorithm gives due consideration to the task of efficiently assigning the cabs. This algorithm is based on the following simple steps;

i) When a passenger requests a cab the algorithm first finds its starting position and the passenger's destination while also keeping the previous request in consideration.

ii) The algorithm then collects information about the trips of all the cabs in that area. It matches the request to the available vehicles, keeping the constraints of vehicle capacity and waiting time under consideration. The algorithm then inserts the request at an optimal position in the system. It does this for all the incoming requests.

iii) When the best vehicle is determined the algorithm updates the system with new incoming request and repeats the entire process.

This approach performs better the nearest vehicle dispatch approach and shows improved computational efficiency [20]. The only problem with this approach is that it does not reoptimize the schedules of the vehicles dynamically. Also, when there is no vehicle at the system's disposal, it rejects the request. This causes a decrease in net profits.

3) Hybrid Approach

The hybrid approach functions by assigning taxis to many booking requests simultaneously but in a probabilistic way [21]. Hence it is capable of working in a real-world system. When the algorithm is deployed in a working environment it assigns the cabs based on hit-and-trial approach but over time it makes improvement to the vehicle assignment process by monitoring the request trend. This iterative learning method is what really makes it suitable for real world application [22].

The number of iteration is of great importance for a multi vehicle dispatching algorithm because the larger the number of iterations, the higher is its chance to improve. Moreover, in this way the algorithm is allowed to thoroughly explore through the search space as the number of vehicle increases and also helps to find an optimal set of solutions for assigning the vehicles.

In contrast to the aforementioned approaches, it also provides a regular re-optimization outline to assign vehicles to the new incoming requests as well as update the current vehicle schedules in real-time. The three main factors in employing this approach are discussed below:

i) There is a limited time interval in which the dispatched taxi has to reach the passenger. If this time limit is exhausted the passenger will no longer wait for the vehicle and will find other means of transportation. This constraint on passenger's willingness to wait helps in reducing ETAs.

ii) The algorithm assigns vehicles to the new passengers as soon as they complete their previous trip. For this purpose, new requests are generated from the buffered requests at regular intervals and are served whenever a vehicle is available.

iii) The last factor is concerned with the time complexity of the algorithm. The main goal is to increase the number of buffered requests so that they can be assigned simultaneously to the available vehicles. If the algorithm takes too much time to process the information, it will not be able to get back to the new incoming requests which will in turn reduce the number of potential customers. So, the decision epoch has to be as little as possible to maintain the efficiency of the system.

Refer to Fig.2. in the Appendix for a block diagram of the matchmaking algorithm.

B. Pricing

This section discusses features of possible pricing algorithms employed by ride hailing companies like Uber and Careem and how these algorithms prove to be beneficial for them in a dynamic environment. These algorithms are modelled using data approximation methods that allows the system to find optimal prices by focusing on the bond between prices and market response [23]. Some of these methods and techniques include:

1) Data Analysis

With the development of data mining algorithms, it has become easier for companies specializing in internet-based services like ride hailing to improve their products. The data acquired by ride hailing apps can be used to predict customer behaviors [24], [25], [26]. This data can also be fed to a dynamic pricing algorithm used by ride sharing companies to enhance customer experience. The algorithms analyzes whether the demand for a particular service has risen in an area or gone down. After analyzing the market response, the system can set an optimal price for that service in that area.

2) Machine Learning

In a real-world situation, the demand and supply for a given resource or service varies constantly, making it impossible to predict market trends from limited amount of available data or by explicitly programming a simulation model. Therefore, computer scientists use machine learning techniques to model complex market environments that enables organizations to forge better pricing policies. These models are made to adapt to the current market conditions without being explicitly programmed to do so and help firms to find optimal pricing solutions for their customers [27].

Similarly, the dynamic pricing algorithms used by Uber and Careem monitor demand variation, competition and buyer behavior to set optimal prices for their passengers. Machine learning techniques can also be used with data driven approaches to better solve dynamic pricing problems [28].

3) Surge Pricing

Popular ride sharing service like Uber and Carrem benefit from a dynamic pricing algorithm called surge pricing, which increases the prices proportionally with demand in a specific area. This algorithm helps to maintain a constant supply of vehicles when demand exceeds supply [8]. The algorithm adjusts the prices by increasing the prices of basic components like base fair, price per kilometer driven, and wait time [29].

Uber and Careem's surge pricing policies have been the subject of much controversy over the last few years.

Consequently, as of 2016, both drivers and passengers are informed whenever a surge multiplier is applied in an area. Drivers are actually incented to look for rides in areas where surge multipliers are in effect so as to meet increased demand for rides

When a passenger requests a vehicle, the algorithms checks the request's origin and destination and then, by calculating the distance that must be traversed, sets a base fair. The algorithms then add a booking fee and other applicable surcharges and displays it to the passenger. With upfront pricing the passenger knows the amount of money that must be paid. But this is not always the case as there are many other variables that need to be accounted for like traffic and other extra stops along the route which can increase the fare.

The algorithm can also detect areas where drivers are scarce in comparison to passengers and thus attempt to match the curves of supply and demand, the algorithms initiate a surge in prices in the area.

This increases the fares of all rides in the area by a factor which is determined by the algorithm after analyzing the gap between the supply and demand. This helps in two ways:

- The surge incents new drivers to look for passengers in the area, hence increasing supply.
- Passengers who are not willing to pay more cancel their requests, reducing demand.

Refer to Fig 3. in the Appendix for a block diagram of the price optimization model and how it links demand and supply with surge pricing.

IV. SIMULATION DATA

This section analyses the efficacy of the Uber and Careem's hypothesized price optimization algorithm. As the source code for the algorithm is not publicly available, it is impossible to present a time and space complexity analysis for it. However, using simulation results for a hypothetical pricing algorithm derived through reverse-engineering Uber's API [30] and actual Uber ride data collected by independent researchers [31], it is possible to gain an insight into the way the algorithm works in practice, which is exactly what this section aims to do.

A. Simulation 1 – "Peeking Beneath the Hood of Uber"

Wilson, Chen, and Mislove attempted an 'algorithm audit' for the Uber app in 2015 and presented their findings in [31]. The researchers tested the surge pricing model by placing 43

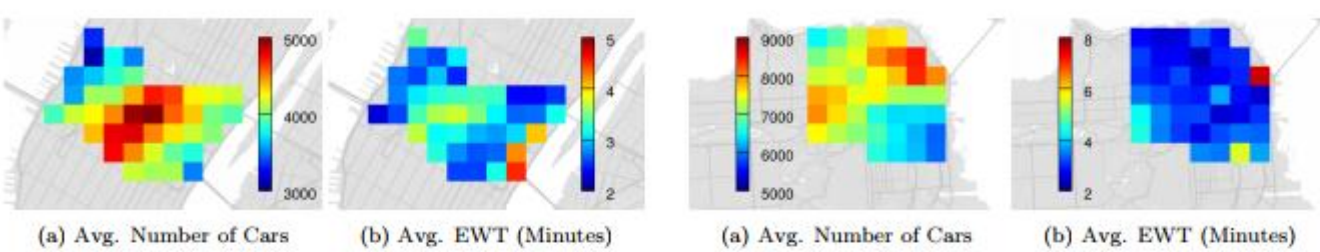

Fig. 2. Heatmaps showing Uber data collected for NYC (L) and SF (R), showing correlation between number of cars and EWT for predefined Uber quadrants.

virtual Uber clients over specific areas of Manhattan, NYC and Downtown San Francisco. By collecting JSON objects from these clients via HTTP requests over a duration of 4 weeks, the researches amassed approximately 1TB of data.

This data included information about surge multipliers, estimated wait times, fulfilled demand, supply, and other parameters hypothesized to be used by Uber's price optimization algorithms.

The simulation results showed that the matchmaking algorithm is clearly effective in minimizing response times, as the average estimated wait time (EWT) for both SF and NYC was around 3 minutes and always less than 6 minutes.

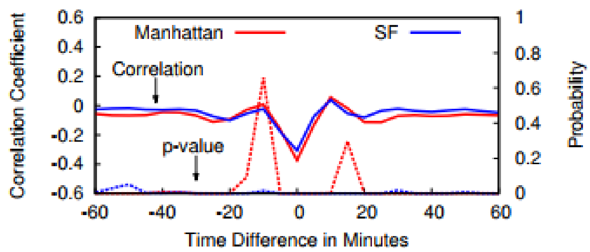

Fig. 3. Diagram showing negative correlation between supply and demand in both Manhattan and San Francisco.

There was a strong correlation between average supply and average demand as well as between average surge pricing and average EWT. There is also a correlation between the supply-demand gap and surge pricing, which has been the focus of earlier sections in this report. Surge pricing has a weak, positive impact on car supply, which means that increased surge pricing in an area resulted in more cars becoming available (a ~3.7% increase). Surge pricing also had a strong, negative impact on the demand in the area, which has been attributed to users wanting to wait for a surge pricing period to elapse before requesting another ride.

As such, the Uber price surging algorithm does mitigate the demand-supply gap, although it does so at the expense of the users and not the drivers. Users have to wait longer for the price surge period to end, which causes demand to fall, while the supply of drivers increases only marginally.

B. *Simulation 2 – Independent Uber Ride Datasets*

Salmon [31] has presented an analysis of Uber ride data for different cities which provides an insight into the factors that Uber's pricing algorithm uses for fare optimization. [31] shows that Uber's prices are indeed tailored to each locale's specific demand and supply conditions, as there is no single price per hour or minutes per mile data that is applicable to every city. In some cities, the price is determined by the total time for the ride whereas in others it is the distance driven that affects the fare.

The dataset also exemplifies how the algorithm favors drivers in some cities, where the price per hour is disproportionately higher than minutes per mile driven, which means Uber considers the time of NYC and Tokyo drivers to be worth more than those of Bangalore or Lagos. This data is summarized in Fig. 4. and shows how the algorithm can favour both drivers and passengers.

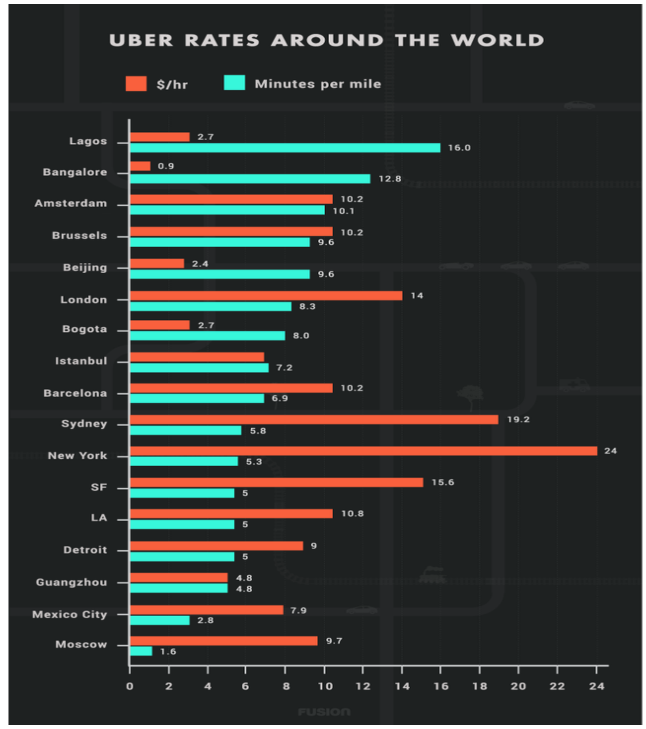

Fig. 4. Bar chart showing Uber rates in different cities of the world, as reported by [31].

C. *Simulation Analysis*

Both the simulation data and the popularity of ride hailing services over their conventional taxi counterparts shows that the algorithms for matchmaking and price optimization are effective, at least to some extent. A 3 to 6 minute response time is impressive, although this figure is likely to be higher in other areas, both inside and outside NYC and SF, where the average number of Uber drivers is at any given time is lower.

Another interesting result is the insight gained into the mechanism of bridging the supply-demand gap. While Uber and Careem both justify surge pricing as a means of meeting increased demand by increasing the supply of drivers, the simulation results demonstrate that the mechanism actually achieves the exact opposite – it drives demand more than it increases supply.

This may be a consequence of the relatively small sample size used by the researchers, as the behaviour of 43 clients is not exactly indicative of that of the 289,000 rides booked through Uber daily in Manhattan alone.

V. PITFALLS AND POTENTIAL IMPROVEMENTS

A. *Price Optimisation Lacks Context*

The price optimization algorithms used by Uber and Careem have been shown to be both responsive and effective in changing prices to meet demand. However, they have also been criticized for lacking a contextual awareness of the market and inadvertently facilitating price gouging [32]. For instance, increased demand for Uber rides in NYC on New Year's Eve resulted in surge multipliers up to 10x and fares upwards of $1,100 for hour-long rides [33]. Also, in NYC, the demand for

Ubers increasing after the 2016 Chelsea explosion resulted in price surging, which was widely criticized as price gouging despite Uber disabling surge pricing following the attack.

B. Surge Pricing is Arbitrary

[34] found that there can be an arbitrarily large difference between Uber surge multipliers in adjacent blocks of a city. Uber (and other ride sharing companies) divide areas into discrete surge units which can result in a substantial difference in fares for passengers who are only a few meters apart. For instance, the simulation found one-fifth of all Uber passengers in Times Square could potentially reduce their rides fares by up to 50% simply by walking to an adjacent surge area.

C. Suggested Improvements

Consequently, the fundamental problem with the price optimization model is a lack of regulation. While Uber has agreed to capping surge multipliers in emergencies and natural disasters [35], there is a need for regulation in its everyday dealings as well. This also applies to other ride sharing companies like Lyft and Careem.

[34] suggests that surge prices should not spike instantaneously but should rather be predicted beforehand and increased gradually over a period of time, perhaps using a weighted moving average to minimize fluctuations in prices.

Another means of combating arbitrary surge pricing is to let drivers, and not algorithms, decide the prices for a given ride, which gives customers the opportunity to accept and decline fares as they please. While this will be closer to the free-market pricing model ride sharing companies have attempted to emulate with their price optimization algorithms, it entails the risk of drivers abusing their power by engaging in price gouging – the exact problem inherent in conventional taxi services which ride sharing companies aim to replace.

While not strictly relevant to the implementation of the pricing algorithm, making ride sharing algorithms available to researchers for audit and inspection may improve their performance and facilitate debugging. For instance, [34]'s authors identified a bug in Uber's price surging algorithm which was causing some customers to receive inconsistent surge multipliers.

This bug was subsequently fixed when Uber was informed of the same. As such, eliminating the 'black box' model and replacing it with algorithmic transparency may actually improve ride sharing services.

VI. EFFECTS ON DAILY LIFE

A. Making Travel Easier

Ride hailing services have made travelling in cities less of an ordeal. With the proliferation of smartphones, internet access, and the resulting popularity of ride sharing applications, a ride to one's destination is only a few swipes away. Ride sharing applications are especially convenient for people who do not have access to vehicles of their own. This includes young adults, senior citizens, tourists, and working professionals on business trips [36]. Both Uber and Careem have price categories for their rides based on the quality, space, and relative comfort of the driver's vehicle, which means passengers can choose a ride that best suits their budget [37], [38].

In Pakistan, applications like Careem and Uber have been especially useful for women, many of whom prefer to travel using rides booked through these apps over those available through public transport [36]. This is largely due to the relative privacy and safety of rides booked through Uber and Careem, both of which not only conduct background checks [39], [40] for all drivers but also have in-built driver rating systems as incentive structures for drivers to be on their best behavior.

Many businesses are partnering with ride sharing services to augment their own day-to-day travel operations. For instance, United Airlines now allows passengers to arrange Uber rides to and from airports while booking their tickets for a streamlined travel experience [41]. Other ventures, such as Uber for Business, aim to replace conventional corporate transportation services with scheduled Uber rides [42]. As such, ride sharing services have made a foray into the corporate world as well and are no longer simply a service for retail/individual customers

B. Part-time Income

One of the reasons why applications such as Uber and Careem have grown in popularity is because they offer a source of part-time income to almost anyone with a vehicle and a driver's license. While both services do incent drivers to work at specific times or in specific locations through surge pricing [43], drivers are more or less free to decide their own schedule. This has made a new source of part-time or full-time income available to many citizens, both in Pakistan [44] and abroad [45]. While the amount earned by drivers working for ride hailing applications suffers from the same unreliability as any other form of self-employment or similar SME venture [46], it is a feasible option for many to earn money to supplement their income, especially if they decide to drive full-time.

VII. CONCLUSION

There is clearly more to ride hailing applications than meets the eye. Behind the seemingly simple swipes on a smartphone screen that precede every Uber or Careem ride lies a complex system of algorithms that collates location, demand, and supply data to facilitate a streamlined user experience. While matchmaking has been more or less perfected over several decades of public transport research, there is evidently room for improvement as far as price optimization is concerned. The lack of contextual awareness in algorithmic price optimization methods continues to be a challenge, and needs to be resolved through regulation to safeguard against price gouging, accidental or otherwise.

APPENDIX

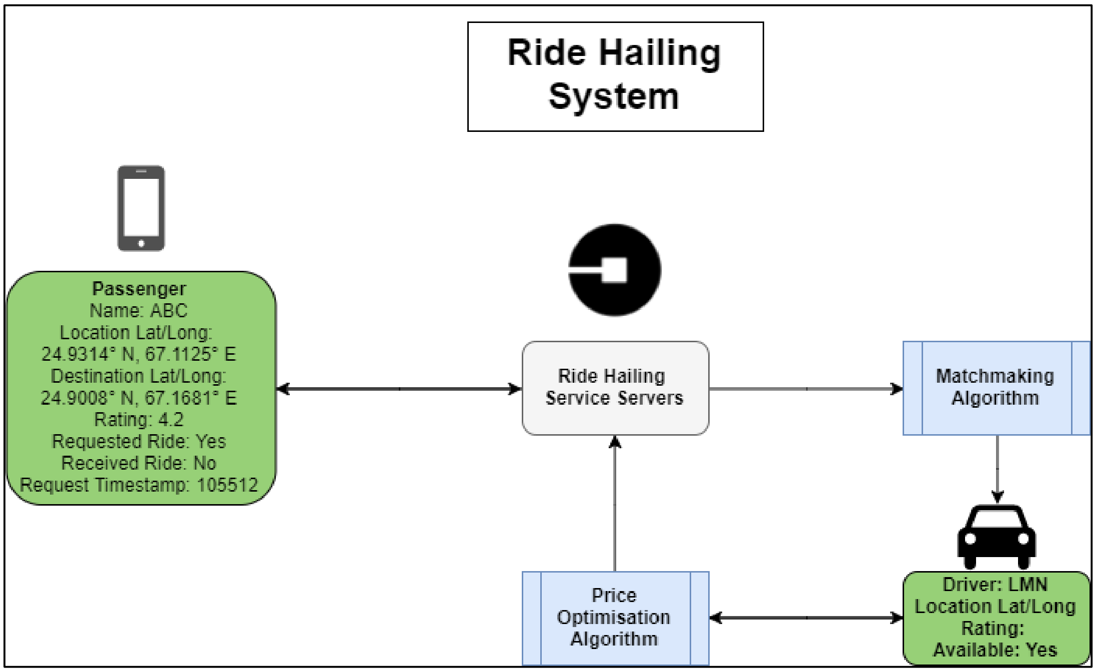

Fig. 1. Block diagram of a generic Ride Hailing system, providing an abstracted overview of all building blocks.

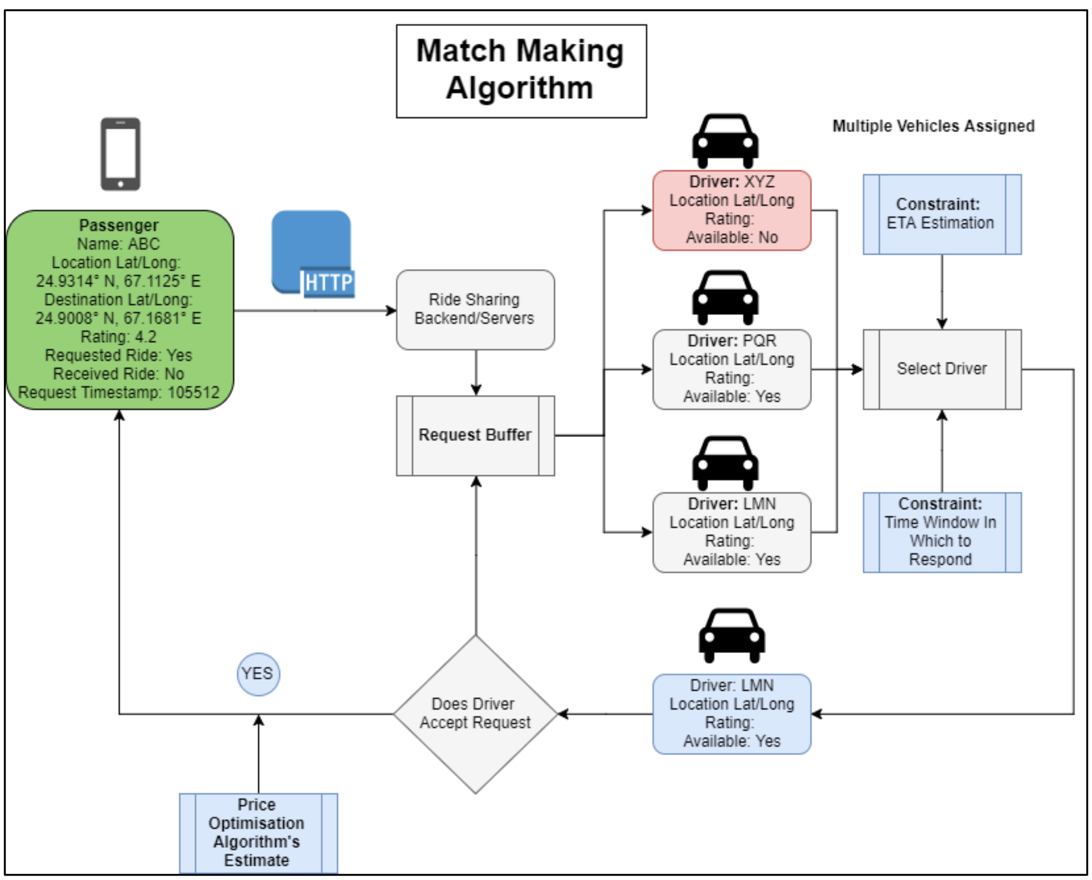

Fig. 2. Block diagram of the Matchmaking algorithm block from Fig. 1, demonstrating hybridized matchmaking strategy using a request buffer and feedback loop.

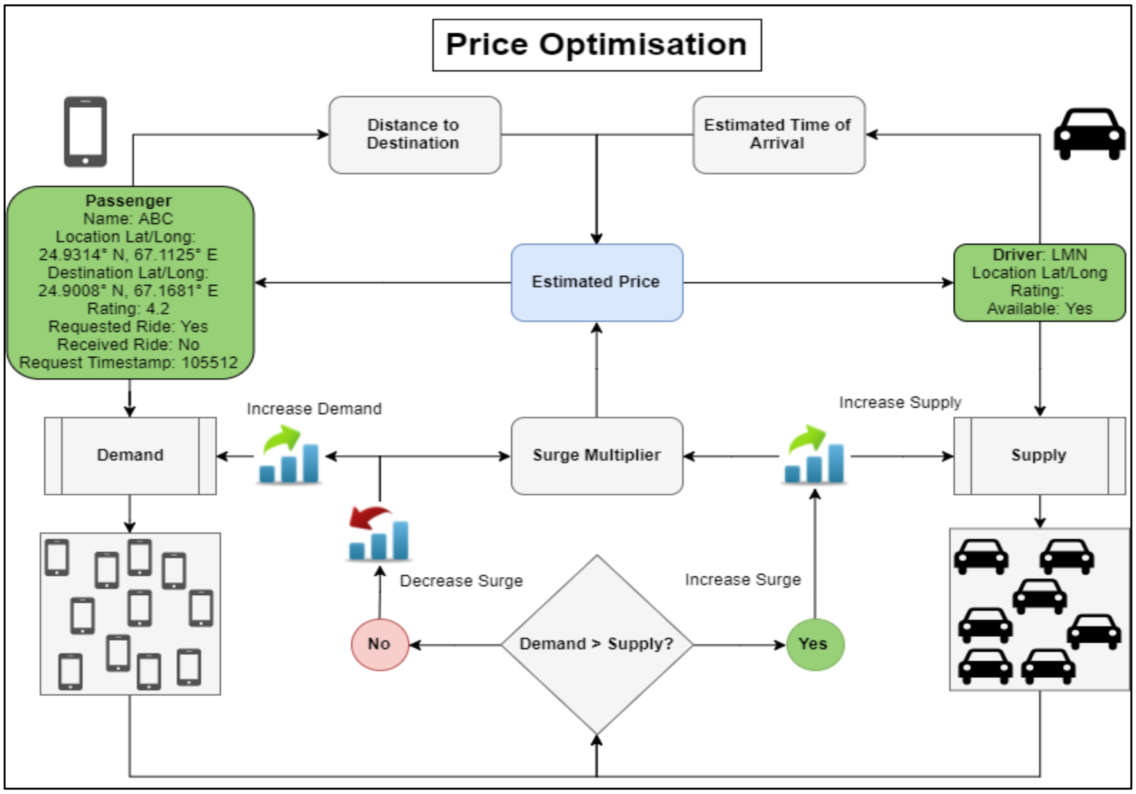

Fig. 3. Block diagram of the Price Optimisation block from Fig. 1, demonstrating relationship between demand, supply, and surge multipliers along with several variables used in fare estimation.

REFERENCES

[1] eMarketer, “Uber, Airbnb Lead the Way as Sharing Economy Expands”, eMarketer, June 30, 2017. [Online], Available: https://www.emarketer.com/Article/Uber-Airbnb-Lead-Way-Sharing-Economy-Expands/1016109 [Accessed Feb. 3, 2018]

[2] PwC UK, “The Sharing Economy Grows Up”, PwC, 2016. [Online], Available: https://www.pwc.co.uk/issues/megatrends/collisions/sharingeconomy/outlook-for-the-sharing-economy-in-the-uk-2016.html [Accessed Feb. 3, 2018]

[3] A. Hartman and N. McAlone, “The story of how Travis Kalanick built Uber into the most feared and valuable startup in the world”, Business Insider, August 1, 2016 [Online], Available: http://www.businessinsider.com/ubers-history [Accessed Feb. 3, 2018]

[4] T. Hamid, “In conversation with Junaid Iqbal, CEO, Careem Pakistan”, Aurora (Dawn), April 18, 2017 [Online]. Available: https://aurora.dawn.com/news/1141986 [Accessed Feb. 10, 2018]

[5] B. Gallagher, "Founders John Zimmer & Logan Green Explain How Lyft Was Born Out Of Zimride", TechCrunch, 2018. [Online]. Available: https://techcrunch.com/2013/09/09/zimmer-green-from-zimride-to-lyft/. [Accessed: 10- Feb- 2018].

[6] L. Chen, "At $68 Billion Valuation, Uber Will Be Bigger Than GM, Ford, And Honda", Forbes.com, 2015. [Online]. Available: https://www.forbes.com/sites/liyanchen/2015/12/04/at-68-billion-valuation-uber-will-be-bigger-than-gm-ford-and-honda. [Accessed: 10- Feb- 2018].

[7] R. Bhatia, "How Careem came up with its brilliant campaign", *SME Advisor*, 2016. [Online]. Available: https://smeadvisor.com/featured/behind-the-scenes-heres-how-the-careem-team-came-up-with-that-brilliant-advertising-campaign/. [Accessed: 10- Feb- 2018].

[8] Uber, "How does Uber work?", *Uber*. [Online]. Available: https://help.uber.com/h/738d1ff7-5fe0-4383-b34c-4a2480efd71e. [Accessed: 10- Feb- 2018].

[9] T. Simonite, "When Your Boss Is an Uber Algorithm", *MIT Technology Review*, 2015. [Online]. Available: https://www.technologyreview.com/s/543946/when-your-boss-is-an-uber-algorithm/. [Accessed: 10- Feb- 2018].

[10] M. Jalloh, "Taxi Industry: Pros & Cons Of UBER And Other E-Hail Apps", *Investopedia*, 2014. [Online]. Available: https://www.investopedia.com/articles/investing/110

614/taxi-industry-pros-cons-uber-and-other-ehail-apps.asp. [Accessed: 10- Feb- 2018].

[11] G. Dantzig and J. Ramser, "The Truck Dispatching Problem", *Management Science*, vol. 6, no. 1, pp. 80-91, 1959.

[12] G. Berbeglia, J. Cordeau and G. Laporte, "Dynamic pickup and delivery problems", *European Journal of Operational Research*, vol. 202, no. 1, pp. 8-15, 2010.

[13] Bailey, Clark, J. TD and J. WA, "Taxicab profitability and service quality in the radio despatch mode: The effects of fare structure and fleet size regulation", *Transportation Research Part A: General*, vol. 18, no. 3, p. 259, 1984.

[14] D. Lee, H. Wang, R. Cheu and S. Teo, "Taxi Dispatch System Based on Current Demands and Real-Time Traffic Conditions", *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1882, pp. 193-200, 2004.

[15] V. Pureza and G. Laporte, "Waiting and Buffering Strategies for the Dynamic Pickup and Delivery Problem with Time Windows", *INFOR: Information Systems and Operational Research*, vol. 46, no. 3, pp. 165-175, 2008.

[16] Z. Liao, "Taxi dispatching via Global Positioning Systems", *IEEE Transactions on Engineering Management*, vol. 48, no. 3, pp. 342-347, 2001.

[17] H. Yang, S. Wong and K. Wong, "Demand–supply equilibrium of taxi services in a network under competition and regulation", *Transportation Research Part B: Methodological*, vol. 36, no. 9, pp. 799-819, 2002.

[18] A. Laidre, "What is The Business Model of Uber", *Iplanner.net*, 2018. [Online]. Available: http://www.iplanner.net/business-financial/online/how-to-articles.aspx?article_id=business-model-uber. [Accessed: 13- Feb- 2018].

[19] J. Lee, "How Uber Leverages Supply and Demand: Making You Offers You Can't Refuse | G2 Crowd", *G2 Crowd*, 2018. [Online]. Available: https://blog.g2crowd.com/blog/big-data/uber-leverages-supply-demand-making-offers-cant-refuse/. [Accessed: 13- Feb- 2018].

[20] J. Jung, R. Jayakrishnan and J. Park, "Design and Modeling of Real-time Shared-Taxi Dispatch Algorithms", 2012.

[21] N. Metroplois, A. Rosenbluth, M. Rosenbluth, A. Teller and E. Teller, "Equations of state 33 calculations by fast computing machines", *Journal of Chemical Physics*, vol. 21, no. 6, pp. 1087-1092, 1953.

[22] S. Kirkpatrick, C. Gelatt and M. Vecchi, "Optimization by Simulated Annealing", *Science*, vol. 220, no. 4598, pp. 671-680, 198

[23] N. Diakopoulos, "How Uber surge pricing really works", *Washington Post*, 2018. [Online]. Available: https://www.washingtonpost.com/news/wonk/wp/2015/04/17/how-uber-surge-pricing-really-works/?utm_term=.57ed08c0d7ae. [Accessed: 15- Feb-2018].

[24] A. den Boer, "Dynamic Pricing and Learning: Historical Origins, Current Research, and New Directions", *SSRN Electronic Journal*, 2013.

[25] N. Srinivasa Raghavan, "Data mining in e-commerce: A survey", *Sadhana*, vol. 30, no. 2-3, pp. 275-289, 2005.

[26] M. Adnan, M. Nagi, K. Kianmehr, R. Tahboub, M. Ridley and J. Rokne, "Promoting where, when and what? An analysis of web logs by integrating data mining and social network techniques to guide ecommerce business promotions", *Social Network Analysis and Mining*, vol. 1, no. 3, pp. 173-185, 2010.

[27] Y. Narahari, C. Raju, K. Ravikumar and S. Shah, "Dynamic pricing models for electronic business", *Sadhana*, vol. 30, no. 2-3, pp. 231-256, 2005.

[28] R. Joshi, "How does Uber's dispatch algorithm work?", *www.Quora.com*, 2018. [Online]. Available: https://www.quora.com/How-does-Ubers-dispatch-algorithm-work. [Accessed: 15- Feb- 2018].

[29] P. Gupta, "How does Uber set its prices? Do prices change a lot?", *www.Quora.com*, 2018. [Online]. Available: https://www.quora.com/How-does-Uber-set-its-prices-Do-prices-change-a-lot. [Accessed: 15- Feb-2018].

[30] L. Chen, A. Mislove and C. Wilson, "Peeking Beneath the Hood of Uber", 2018.

[31] F. Salmon, "The Way Uber Fares Are Calculated Is a Mess", *Fusion*, 2018. [Online]. Available: https://fusion.tv/story/140655/the-way-uber-fares-are-calculated-is-a-mess/?utm_source=twitter&utm_medium=social&utm_campaign=thisisfusion&hootPostID=c6a7c015ae3465d7eb861e125d6ed643. [Accessed: 13- Feb- 2018].

[32] J. David, "Uber cuts surge pricing in NYC's Chelsea amid price gouging accusations", *CNBC*, 2018. [Online]. Available: https://www.cnbc.com/2016/09/18/uber-hammered-by-price-gouging-accusations-during-nycs-explosion.html. [Accessed: 15- Feb- 2018].

[33] C. Smith and Z. Epstein, "New Year's Eve surge pricing enrages Uber users; one man hit with $1,100 fare", *BGR*, 2018. [Online]. Available: http://bgr.com/2016/01/04/new-years-eve-uber-surge-pricing-reactions/. [Accessed: 15- Feb- 2018].

[34] L. Chen, A. Mislove and C. Wilson, "Peeking Beneath the Hood of Uber", 2018.

[35] "Uber Agrees to Limit Surge Pricing During Emergencies, Disasters", *Time*, 2018. [Online]. Available: http://time.com/2967490/uber-agrees-to-limit-surge-pricing-during-emergencies-disasters/. [Accessed: 15- Feb- 2018].

[36] O. Azam, "Fear of ban on ride-hailing apps upsets Karachi - The Express Tribune", *The Express Tribune*, 2017. [Online]. Available: https://tribune.com.pk/story/1312972/fit-operate-fear-ban-ride-hailing-apps-upsets-karachi/. [Accessed: 10- Feb- 2018].

[37] "What is a Car type?", *Careem*, 2018. [Online]. Available: https://help.careem.com/hc/en-us/articles/115008386567-What-is-a-Car-type-. [Accessed: 10- Feb- 2018].

[38] "What’s the difference between UberX, XL, UberSelect, and Black Car?", *Ridesharingdriver.com*, 2016. [Online]. Available: https://www.ridesharingdriver.com/whats-the-difference-between-uberx-xl-uberplus-and-black-car/. [Accessed: 10- Feb- 2018].

[39] F. Zafar and A. Raja, "Year-end review: Uber or Careem, which works better for Pakistan?", *DAWN.COM*, 2016. [Online]. Available: https://www.dawn.com/news/1301230. [Accessed: 10- Feb- 2018].

[40] J. Enverga, "YOUR SAFETY TAKES THE FRONT SEAT", *Careem.com*, 2017. [Online]. Available: https://www.careem.com/karachi/your-safety-takes-front-seat. [Accessed: 10- Feb- 2018].

[41] R. Magazine, "American Airlines and Uber make travel even easier", *Relocate Global*, 2016. [Online]. Available: https://www.relocatemagazine.com/news/reeditor-2016-8429-feb-8431-10-19-8588-american-airlines-and-uber-make-travel-even-easier. [Accessed: 10- Feb- 2018].

[42] V. Vyas, "Uber launches ‘Uber for Business’ to make business travel easier", *Peoplematters.in*, 2017. [Online]. Available: https://www.peoplematters.in/news/technology/uber-launches-uber-for-business-to-make-business-travel-easier-16142?utm_source=peoplematters&utm_medium=interstitial&utm_campaign=learnings-of-the-day. [Accessed: 10- Feb- 2018].

[43] N. Scheiber, "How Uber Uses Psychological Tricks to Push Its Drivers’ Buttons", *Nytimes.com*, 2017. [Online]. Available: https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html. [Accessed: 10- Feb- 2018].

[44] A. Attaa, "Uber Drivers are Making Six Figures a Month in Lahore", *Propakistani.pk*, 2016. [Online]. Available: https://propakistani.pk/2016/04/21/uber-drivers-are-making-six-figures-a-month-in-lahore/. [Accessed: 10- Feb- 2018].

[45] R. Wile, "Here's How Much Uber Drivers Really Make", *Time*, 2017. [Online]. `Available: http://time.com/money/4845407/uber-drivers-really-make-per-hour/. [Accessed: 10- Feb- 2018].

[46] A. Griswold, "When Is Driving for Uber Actually Worth It?", *Slate Magazine*, 2014. [Online]. Available: http://www.slate.com/blogs/moneybox/2014/12/01/what_uber_drivers_make_part_time_earnings_are_a_gamble_but_full_time_more.html. [Accessed: 10- Feb- 2018].