Dynamic Pricing in One-Sided Autonomous Ride-Sourcing Markets

Renos Karamanis
Centre for Transport Studies
Civil and Environmental Engineering
Imperial College London
Email: renos.karamanis10@imperial.ac.uk

Panagiotis Angeloudis
Centre for Transport Studies
Civil and Environmental Engineering
Imperial College London
Email: p.angeloudis@ic.ac.uk

Aruna Sivakumar
Centre for Transport Studies
Civil and Environmental Engineering
Imperial College London
Email: a.sivakumar@ic.ac.uk

Marc Stettler
Centre for Transport Studies
Civil and Environmental Engineering
Imperial College London
Email: m.stettler@ic.ac.uk

Abstract—Dynamic pricing has been used by Transportation Network Companies (TNCs) to achieve a balance between the volume of ride requests with numbers of available drivers on two-sided TNC markets. Given the desire to reduce operating costs and the emergence of Autonomous Vehicles (AVs), the introduction of TNC-owned AV fleets could convert such services into one-sided markets, where operators have full control of service supply. In this paper we investigate the impact of utility-based dynamic pricing for Autonomous TNCs (ATNCs) in one-sided markets. We test the method using an Agent-Based Model (ABM) of Greater London in conditions of monopoly and competition, focusing on a statically priced ATNC service that offers a mix of private and shared ride services. Public transport is considered as an alternative mode of transportation in both scenarios. Results indicate that in monopoly, dynamic pricing provides higher revenues than static pricing at non-peak hours when average waiting times are low. On the contrary, in competition, dynamic pricing is superior at peak hours where increased waiting times are observed, thus increasing the value of low waiting time rides. Overall, in both market structures, it is found that shared trips are more popular in dynamic pricing compared to static pricing.

Index Terms—Shared Autonomous Vehicles, Public Transport, Agent-Based Modelling and Simulation

I. INTRODUCTION

Recent advances in information technology and the development of gig-economy business models facilitated the emergence of several TNC operators across the world, that seamlessly connect drivers to travellers using online platforms. TNC platforms act as two-sided markets by providing network benefits for two separate user groups, the drivers and the riders. A common characteristic adopted by major TNCs is the use of dynamic pricing during periods of peak travel, typically implemented using pricing rate multipliers [1]. Such mechanisms consider price sensitivities of potential customers [2] and local imbalances in supply and demand, with the objective to increase driver participation and reallocate spare capacity to poorly served regions of the network.

The underlying principles of current dynamic pricing models are based on TNCs operating as two-sided markets. The anticipated introduction of AVs in TNC fleets is expected to reduce or eliminate driver costs [3], with TNC firms eventually owning the vehicles operating in their networks. In such a scenario, ATNCs will have total control over the supply and will directly transact with riders, hence transforming their ride-sourcing service into a one-sided market. As a result, the need for a means to motivate supply labour to balance demand could vanish, thus affecting the underlying principles of current dynamic pricing strategies. In this paper, we focus on how dynamic pricing strategies would apply in a one-sided ATNC market and study their effect on revenue and collective traveller behaviour.

Earlier studies in taxi pricing (e.g. [4] [5]) considered aggregate supply and demand models to capture the dynamics of urban taxi operations using static fare structures. Dynamic pricing has been prominent in more recent studies, such as [1], which employed queuing theory models and approach, to show that it is more robust than static pricing to uncertainties in potential demand or supply in the system. An agent-based simulation approach with discrete time was used in [6], to show that dynamic pricing reduces average wait times but also lowers service mode shares.

Other studies such as [7] and [8], used historical TNC travel data to assess the effectiveness of dynamic pricing strategies. The authors in [7] concluded that an increase in price when using a dynamic pricing method could contribute to a rise in the supply of rides in the system. The study in [8], argues that at times when a TNC platform is over-burdened, it is forced to send vehicles to pick up distant clients. The authors then show that dynamic pricing helps with alleviating this problem by setting temporarily high prices and maintain
a functioning system at a high demand.

Our review of the literature reveals that while there has been extensive analysis of dynamic pricing on two-sided ride sourcing platforms, there is limited understanding of its implications when TNCs stop being two-sided markets (when AVs enter the market). To address this issue, in this paper, we test a utility-based dynamic pricing model in an ATNC market, with private and shared ride services, in competition and monopoly, with an alternative public transport mode using an ABM.

The remainder of this paper is structured into four sections. First, we present the formulation of the dynamic pricing model tested within this study. We then show the ABM logic and the data instance to resemble a future Greater London ATNC scenario. Finally, we examine the results following a closing discussion on the conclusions of this study and the focus of any relevant future work.

II. Dynamic Pricing Model

The actors in our model are ATNCs that offer private and shared ride services of identical quality. They receive ride requests from the public and respond with bids that reflect the current state of their fleets, and the expected wait and travel times. Travellers decide whether to accept a bid or chose public transport using a generalised costing mechanism.

In the monopolistic scenario, a single ATNC applies a dynamic or a static pricing model for its bids, whereas, in the competitive scenario, we consider a duopoly with a dynamic pricing ATNC and a static pricing ATNC. The static pricing model sets the static ride price \( p_s \) as the sum of linear terms consisting of a base fare \( f_s \), a time proportional fare to ride time \( t \) with a rate per time \( f_t \), and a distance proportional fare to ride distance \( d \) with a rate per distance \( f_d \):

\[
  p_s = f_s + f_t t + f_d d \tag{1}
\]

The dynamic pricing model determines the price \( p_d \) using the static price \( p_s \) and a dynamic multiplier \( m \).

\[
  p_d = mp_s \tag{2}
\]

ATNCs that utilise dynamic pricing models are expected to set the value of \( m \) with the objective to maximise the expected revenue for each traveller using the utilities of the available travel options as inputs. Each traveller in our model is therefore assumed to evaluate the utility of each option using a nested logit model. Traveller utilities for each option are calculated using (3) for private ATNC rides \( U_{P_i} \) of each firm \( i \), (4) for shared ATNC rides \( U_{S_i} \) of each firm \( i \) and (5) for public transport \( U_{PT} \).

\[
  U_{P_i} = V_{P_i} + \varepsilon_{P_i} = \alpha - \nu(w_{P_i} + t_{P_i}) - p_{P_i} + \varepsilon_{P_i} \quad \forall i \in I \tag{3}
\]

\[
  U_{S_i} = V_{S_i} + \varepsilon_{S_i} = \alpha - \nu(w_{S_i} + t_{S_i}) - p_{S_i} + \varepsilon_{S_i} \quad \forall i \in I \tag{4}
\]

\[
  U_{PT} = V_{PT} + \varepsilon_{PT} = -\nu(w_{PT} + t_{PT}) - p_{PT} + \varepsilon_{PT} \tag{5}
\]

Where \( \nu \) is the value of time for each traveller which is assumed to vary across the traveller population following a gamma distribution with shape factor \( k \) and scale \( \bar{\nu}/k \). The parameter \( \alpha \) is used to represent the inherent preferences for the ATNCs due to unobserved factors such as comfort, brand image and trust and is assumed to vary across the traveller population following a normal distribution with standard error \( \sigma_\alpha \). \( I \) is the set of ATNCs in the model, which is \( \{1\} \) in monopoly and \( \{1, 2\} \) in duopoly. Parameters \( w_{P_i}, w_{S_i} \) and \( w_{PT} \) represent the waiting times for trips using each travel option. In turn, \( t_P, t_S \) and \( t_{PT} \) are the travel times for each mode. Parameters \( p_{P_i} \) and \( p_{S_i} \) represent the price for private and shared rides of each ATNC \( i \) and \( p_{PT} \) is the price of travelling via public transport.

The stochastic error terms \( \varepsilon_{P_i}, \varepsilon_{S_i} \) and \( \varepsilon_{PT} \) are randomly distributed variables following a type 1 extreme value distribution, which is the assumption underlying the nested logit model structure. The latter assumes a heightened correlation between the stochastic error terms for the ATNCs thus allowing for a higher elasticity between the ATNC alternatives. The travel and waiting times for each option vary between travellers and depend on network characteristics and vehicle distributions across the network at the time of the request.

This study adopts a three-level nested logit model [9], illustrated by the tree diagram in Figure 1. The levels used in the model are defined as follows:

- **Level 1**: Choice between ATNC and Public transport
- **Level 2**: Choice between private or shared ATNC rides
- **Level 3**: Choice of ATNC

The choice probabilities between the modes of ATNC \( T \) and public transport \( PT \) are computed as follows:

\[
  P(b) = \frac{e^{\mu T}}{e^{\mu T} + e^{\mu PT}} \quad \forall b = \{T, PT\} \tag{6}
\]

Where \( \mu \) is the scale of the stochastic error terms, assumed to be 1 between the first-level options (ATNCs versus public transport). The probability of choosing between private \( P \) or shared ride \( S \) services is given by:

\[
  P(T_j) = P(T_j | T) P(T) \quad \forall j = \{P, S\} \tag{7}
\]

\[
  P(T) = \frac{e^{\mu T}}{e^{\mu T} + e^{\mu PT}} \tag{8}
\]

\[
  V_T = IV_T \quad \text{is the inclusive value of the ATNC nest and is calculated using equation (9):}
\]

\[
  IV_T = \frac{1}{\mu_T} \ln \left( \sum_j e^{\mu_T \times V_{T_j}} \right) \tag{9}
\]

\[
  \nu = \frac{\mu_T}{\bar{\nu}} \tag{10}
\]
Where \( \mu_T \) is the scale of the error terms for the ATNC options, which captures the heightened correlation between the different ATNC services as shown in equation (10):

\[
c_T = 1 - \left( \frac{1}{\mu_T} \right)^2
\]  

(10)

The value of \( P(T_i|T) \) is calculated using equation (11):

\[
P(T_j|T) = \frac{e^{\mu_T} V_{Pj}}{e^{\mu_T} V_P + e^{\mu_T} V_S} \quad \forall j \in \{P, S\}
\]  

(11)

\( V_P = IV_P \) and \( V_S = IV_S \) are the inclusive values of the private and the shared rides service nests respectively and are calculated using equations (12) and (13):

\[
IV_P = \frac{1}{\mu_P} \ln \left[ \sum_i e^{\mu_P \times V_{Pi}} \right]
\]  

(12)

\[
IV_S = \frac{1}{\mu_S} \ln \left[ \sum_i e^{\mu_S \times V_{Si}} \right]
\]  

(13)

Where \( \mu_P \) and \( \mu_S \) are the scales of the error terms for different ATNCs, capturing the heightened correlations between different options each service type nest as shown in equations (14) and (15):

\[
c_P = 1 - \left( \frac{1}{\mu_P} \right)^2
\]  

(14)

\[
c_S = 1 - \left( \frac{1}{\mu_S} \right)^2
\]  

(15)

The probabilities of choosing a private or a shared ride with firm \( i \) are obtained using equations (16) and (17) respectively:

\[
P(P_i) = P(P_i|P)P(P) \quad \forall i \in I
\]  

(16)

\[
P(S_i) = P(S_i|S)P(S) \quad \forall i \in I
\]  

(17)

The values of \( P(P_i|P) \) and \( P(S_i|S) \) are calculated using equations (18) and (19) respectively and the values of \( P(P) \) and \( P(S) \) are found using equation (7):

\[
P(P_i|P) = \frac{e^{\mu_P V_{Pi}}}{\sum_{i=1}^n e^{\mu_P V_{Pi}}} \quad \forall i \in I
\]  

(18)

\[
P(S_i|S) = \frac{e^{\mu_S V_{Si}}}{\sum_{i=1}^n e^{\mu_S V_{Si}}} \quad \forall i \in I
\]  

(19)

Using the probabilities as estimated by the three-level nested logit model, the expected revenue for the dynamic pricing firm \( i \) from each traveller is defined in equation (20):

\[
E(R_i) = P(P_i)p_d + P(S_i)\beta p_d \quad \forall i \in I_d
\]  

(20)

The value of \( \beta \) corresponds to a reduction factor, assuming shared ride services are priced at a pre-determined discounted rate for the ATNCs. Where \( I_d \subseteq I \) represents the dynamic pricing ATNC in the model. If \( M \) is the set of all possible values of \( m \) defined between \([1, m_{\text{max}}]\), the dynamic pricing firm \( i \) chooses the value \( m^* \) for \( m \) which maximises equation (20), as shown in (21):

\[
m^* = \arg \max_m \{ P(P_i)m p_a + P(S_i)m \beta p_a | m \in M \}
\]  

(21)

III. AGENT-BASED MODEL.

The dynamic pricing method presented in Section II was tested in a city-wide scenario using an ABM. The agents in the ABM are the AVs of each ATNC and travellers. AVs are assumed to exist in the system throughout the whole simulation period, while travellers appear once at the time of their travel request and exit when they are served. Each ATNC in the ABM has a specified fleet size and applies either a dynamic or a static pricing model.

Once a traveller appears is unassigned and sends a travel request to all the ATNCs in the ABM. The ATNCs assign AVs based on their vehicle availability for their private and shared ride services and place their bids for each service as defined by the pricing model in Section II. The traveller, in turn, evaluates the utility of each option using the nested logit model described in Section II and makes a choice. If an ATNC choice is made, the traveller waits for pick-up; otherwise, it exits the system with the choice of public transport.

For the purpose of this paper, we chose to test the proposed dynamic pricing model on the Greater London road network as obtained from [10]. Using vehicle velocity data from [11] and testing for a weekday between 08:00 to 00:00, we have set the average vehicle velocity to 17.6 km/h between 08:00 to 19:00 and to 32.2 km/h from 19:00 to 00:00. The values of \( t \) and \( d \) in equation (1) are estimated using the average velocity of the system at the time of request and the shortest path via the A* algorithm.

In the absence of a generic trip database for Greater London, the input trip data was created from public transport data (Rolling Origin and Destination (OD) Survey) available from [12]. The database in [12] provides trip counts from and to each London Tube Station at different times of the day and represents a typical weekday in Autumn 2017. Using the trip counts as means of Poisson Distribution for each OD pair and each period in the day, a trip database of 94,816 individual public transport trips was created for a typical weekday which represents a 2% sample of the daily London Tube trip counts.

Each trip in the database was given random origin and destination coordinates within a 20 minute walking distance at 5 km/h from the origin and destination stations of the public transport trip. Consequently, \( t_{PT} \) for each traveller is the sum of the walking time to and from the origin and destination stations respectively and the travel time in the public transport system, allowing for a 2 minute interchange/waiting time which is represented by \( w_{PT} \) in equation (5). The values of \( p_{PT} \) for each traveller were defined using the pay-as-you-go Tube and rail fares for 2017 [13] and depend on the start and finish zones of the public transport network, as well as the time of travel.

The mean value of time \( \bar{v} \) was chosen to be 12.85 GBP/h, which corresponds to the value of time for underground passengers for the year 2035 (assuming ATNC services by 2035) as provided in [14]. The shape factor \( k \) for the gamma distribution of the values of time was chosen to be 3.00 after calibration. To achieve a considerable mode share for ATNCs (since the original database considers public transport trips),
the value of the inherent preference for ATNCs was set to follow a normal distribution \( N(2, 0.5) \).

The correlations of \( c_P \) and \( c_S \) in equations (14) and (15) respectively, were assumed to be equal and set to 0.9. The equality assumption was based on the initial assumption made in Section II that any ATNCs in the simulation offer services of identical quality. However, the correlation between different ATNC services \( c_T \), was set to be 0.6, so as to suggest that price has less weight on the choice between a private and a shared ride than the choice between different firms for the same product. The set \( M \) of the possible dynamic multipliers was set in the interval \([1.0, 3.0]\) in 0.1 increments.

The values of \( f_b, f_t \) and \( f_d \) were chosen so as to reflect the AV rates predicted in the literature. Specifically, the authors in [6], assume shared autonomous electric vehicle (SAEV) prices between $0.75/mi-$1.00/mi, which would generate significant revenues to the operators. Similar studies such as [7], estimate that SAEV services could be offered at approximately $0.66/mi-$0.74 per occupied mile of travel, by performing financial analysis on the anticipated SAEV market.

In our pricing model we price trips on a per time and per distance basis on top of a fixed base fare, therefore, by setting \( f_b = 0.5, f_t = 0.03 \) and \( f_d = 0.15 \), the price per mile depending on the average velocity is as shown in Figure 2. These values converged to a rate of £0.41/mi for the low average velocity scenario (17.6 km/h) and £0.34/mi for the high average velocity scenario (32.2 km/h). A minimum price of £1.00 is set for each trip to avoid low prices for shorter trips. Furthermore, the reduction factor \( \beta \) for shared rides is set to 0.75 between 08:00-19:00 and increased to 0.9 afterwards.

We chose to test our model with both monopolistic and competitive market structures. In the monopoly market structure, we tested different instances of dynamic and static pricing ATNCs, whereas, in the competitive market structure, a dynamic pricing ATNC was operating against a static pricing ATNC at all instances. The different fleet size and market structure scenarios tested with our model are shown in Table I.

IV. RESULTS

The results indicate that the effects of the proposed pricing model vary significantly depending on the market structure. Consequently, we have split the analysis into two parts, focusing on monopoly and competition, respectively.

A. Monopoly

We observe, that in comparison with the static pricing model, dynamic pricing attracts a similar amount of trips in monopoly. This observation can be seen in Figure 3, where although static pricing produces slightly more trips in some scenarios, there are no significant differences in the total trip numbers. This remark appears to be consistent with an increasing number of vehicles.

Vehicle sharing appears to be more attractive in monopoly with a decreasing fleet size and seems to converge to a constant value as the fleet size increases. This behaviour could be explained by the expectation that less unoccupied vehicles are available as the fleet size decreases, which results in more cases where travellers are only offered shared trip bids, thus increasing the proportion of shared trips. Furthermore, dynamic pricing appears to produce a higher percentage of shared trips compared to static pricing in monopoly as seen in Figure 4, suggesting that some dynamically priced travellers chose to share but would have preferred private rides in the static pricing case.

When investigating the behaviour of the two models in time, it is observed that most of the dynamically priced trips (\( m > 1.0 \)) occur in non-peak times as seen in Figure 5. It is also evident that dynamic pricing revenue is superior to static pricing overall in non-peak times and especially from shared trips as seen in Figures 6 and 7. The surge of dynamically priced trips in non-peak times can be explained by the fact that, at these periods, ATNCs have an extra margin to price dynamically and still be competitive with public transport
due to the low average waiting times. The observation that dynamically priced trips have a lower than average waiting time as seen in Figure 8 also justifies this argument.

B. Competition

The characteristics of the outputs for dynamic pricing in the competitive market are significantly different than the monopolistic scenarios. Although the total number of ATNC trips appears to be similar to the monopolistic scenarios for the same total vehicle numbers, the static pricing model seems to be vastly superior to the dynamic pricing model in non-peak times, with no significant differences when considering shared rides, as observed in Figures 9 and 10.

Travellers strongly prefer the static alternative when average waiting times are low, suggesting that differences in waiting time at these periods are not particularly significant to justify choosing a more expensive option for a shorter wait. On the contrary, at peak times, when average waiting times are high, dynamically priced trips are attractive if the difference in the wait is significant. These outcomes can be observed in Figure 11, where it can be clearly seen that the percentage difference between the average waiting time of all ATNC trips and the average waiting time of dynamically priced trips is much higher in peak hours. This difference results in competitive revenues for the dynamic pricing ATNC, when compared to the static pricing ATNC.

To further investigate this observation, we considered the relationship between the average waiting time of the system at all different times for all the competitive scenarios with the difference in revenue per vehicle per hour between the dynamic pricing firm and the static pricing firm. Using a custom ABM, we tested the method in the Greater London area road network, with 94,816 individual trips that represent a 2% sample of weekday travel in the London Underground network. Our analysis indicates that dynamic

V. CONCLUSION

This paper presents a dynamic pricing model for ATNC platforms, which estimates bids for private and shared rides based on expected revenue maximisation for each traveller, accounting for alternative travel options. We tested the dynamic pricing model with different fleet size instances in two separate market structures; in ATNC monopoly operating alongside a public transport system, and in competition against a static pricing ATNC and public transport. The dynamic pricing firm maximises its bids by estimating a dynamic multiplier which maximises its expected revenue, with the probability of selection to be an output of a three-level nested logit model.

Using a custom ABM, we tested the method in the Greater London area road network, with 94,816 individual trips that represent a 2% sample of weekday travel in the London Underground network. Our analysis indicates that dynamic
pricing results in increased ratios of shared trips per vehicle than static pricing in both market configurations (monopoly and competition). In monopoly, dynamic pricing produces a higher revenue than static pricing in non-peak hours, whereas in competitive settings, dynamic pricing performs better in peak hours only when system-average waiting times are high. These findings suggest that dynamic pricing could be used as a tool to tackle congestion in future AV-based platforms, with smaller fleet sizes, encouraging more shared rides and increased utilisation of public transport systems.

The potential impact of the proposed dynamic pricing model is bounded by three main limitations which will be explored further in our future work. Firstly, nested-logit models have been extensively applied in transportation [15], but they constitute a simplified approach to choice modelling that cannot adequately capture the effects of dynamic pricing methods. Furthermore, trip datasets in our case study were derived from travel records that pertain to a single mode of public transportation, even if some of the use-cases that we examine involve multiple modes of travel. While this might be an acceptable assumption for the preliminary analysis carried out by this study, further validation is required using datasets from a range of travel modes. Finally, in this study, we did not test competition between many dynamic pricing ATNCs. Testing multiple dynamic pricing ATNCs in competition would result in transforming the model into a game-theoretical one, where ATNC bids are best-responses to competitors. Concluding, future work on dynamic pricing of ATNCs should be focused on more sophisticated choice models, a variety of datasets and multiple dynamic pricing firms.

REFERENCES


