Spatial disparities in operator performance and attractiveness of ride-pooling in Amsterdam

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Abstract

Despite its potential benefits of reduced traffic congestion and discounted trips, incorporating ride-pooling in a city comes with a set of challenges that require thorough analysis, optimisation, and planning. Even though, services like *Uber* have existed in Amsterdam for over a decade, city wide ride-pooling has yet to be implemented. This paper uses an algorithm for exact matching of attractive shared rides (ExMAS) and Albatross travel demand data to map and analyse the spatial disparities of key performance indicators of a ride-pooling service in Amsterdam and discover the potential of certain areas in the city. The experiments utilised a set of increasing discounted fares for ride-pooling with increasing travel demand levels. A ride-pooling service with higher discounted fares generally increased the attractiveness of the system and reduced the total vehicle hours, when compared to its non-shared counterpart. It was found that the largest vehicle hour reduction were in areas on the periphery of Amsterdam (namely the West, North, and East areas) where rides of higher degree and longer trips lengths were more likely. However, the user attractiveness of the system tended to be higher in central areas of the city where trip density was higher, trip length shorter, and ride degrees lower. The study also determined that variance of the vehicle hours and user attractiveness decreased and stabilised with increasing demand level. This paper could be a starting point in optimising the possible roll out schemes for a ride-pooling service in Amsterdam.

Keywords— ExMAS, Ride-pooling, Ride-hailing, Spatial discrepancies, Performance, Level of service

1. Introduction

Transport demand is surging in the 21st Century since the majority of the human population now lives in cities.[1] This surge in transport demand allows for a market space in personalised transport services where multiple transport modalities can be combined into one channel, usually referred to as Mobility-as-a-service (MaaS). The idea is to integrate mobility services such as ride-pooling (also known as ride-sharing), ride-sourcing, and bike-sharing with public transport which would ease the planning and paying of travel, thus allowing for lower (personal) car oriented movement.[2]

A key concept for MaaS is ride-pooling, which essentially, permits users to travel at a reduced fee (compared to ride-hailing) with other travellers that are heading approximately in the same direction. The intention is to increase the usage of a vehicle, potentially reducing operator fleet size and traffic congestion, which in turn could reduce travel times for multiple types of road users. However, the extent of these benefits are still unclear and often disputed.[1,3–5] Ride-pooling essentially penalises users' travel times due to the detours created by picking up and dropping passengers.

Research has shown that ride-pooling services are subject to various spatio-temporal patterns and travel characteristics.[6,7] The distribution of demand depends on the built environment and population distribution of a city where certain areas, such as businesses districts and city centres, could generate a much higher demand for mobility.[3] The demographic of certain areas of a city would also influence the use of ride-pooling in a city. Methods such as spatial pricing may assist in controlling the state of supply while also maximising platform revenue.[8]

For the case of Netherlands, *Uber*, available since 2012[a], has grown as a major platform for mobility within Amsterdam and other major Dutch cities. However, many of the platform's innovations led to conflicts with existing Dutch laws where attempts to institutionalise its innovations (*UberPOP*) took place and ultimately failed.[9] Such institutional conflicts could be a partial cause to the non existence of ride-pooling services in Amsterdam (and the rest of the Netherlands), such as *UberPOOL*. Out of 50 countries that *Uber* operates in, the Netherlands was the second highest on the list where a 5 km ride costs $10.07.[b] Such prices could be unattractive by a user due to the country's already extensive (and cheaper) public transport network and transport infrastructure. Lowering the ride price to increase attractiveness could be unprofitable for *Uber* as it could be that the demand is still not there to match the operating costs and thus rolling out a ride-sharing platform still be very costly for the company. Understanding the disparities of performance of ride pooling throughout a city could aid in successfully launching such a platform in Amsterdam.

1.1. Literature review

The benefits and detriments of the implementation ride-pooling systems in cities generates an extensive amount of discussion in the mobility sector. The intentions of a ride-pooling system is to reduce the total vehicle hours and the required fleet size of the operator thus alleviating the traffic congestion by lowering car ownership in a city.[10] Under some scenarios, the total travel and waiting times of both ride-hailing and private car users.[3,5] However, some research shows that successful ride-pooling designs draw patrons from public transportation modes and that private-car users would tend to switch to ride-sourced services due the reliability, comfort, privacy they provide.[4] Usually people with higher income use a personal vehicle more often and therefore finding ride-hailing more attractive. Public transport is most frequently used by people with lower income for which ride-pooling services would be more attractive.[11] In order to decrease traffic congestion, ride-pooling must become a more attractive alternative to private car users.

Extensive research was also conducted on the spatio-temporal disparities of ride-pooling and ride-sourcing along with the public transport and car. Research shows that only a few areas in a city would PT travel time favours that of a car[6] where the former usually has shorter travel durations for shorter distances (i.e. ¡ 3 km) and during peak hours. Furthermore, the use of cars seem to dominate in the night and areas when and where the PT schedule is limited. On the other hand, ride-sourcing has significant increases in usage during peak hours where operational characteristics such as fleet size and utilisation rate with distinct patterns in residential and business areas.[12] Ride-sharing is also seen not to be balanced in different neighbourhoods in a city as service usage is not only limited to gender and income distribution but PT and amenities accessibility.[13] This could lead to spatial pricing of ride-pooling and sourcing systems is also able to control the supply state of the provider in certain areas.[8]

In all, the research thus far analyses the disparities of ride-pooling and hailing with respect to pool-matching probability, matching windows and service-fares. Limited research exists on the spatial disparities of the performance and level of service (LOS) of a ride-pooling system with respect to discount price (when compared to the ride-hailing counterpart). This leads to a research gap where little is known about area specific attractiveness and performance of ride-pooling in a city. Understanding such areas could allow the operator to optimise their service in areas with higher car ownership and poorer PT accessibility. Allowing for a successful roll-out in Amsterdam, for instance.

ExMAS is an exact, replicable demand driven algorithm that complements trips into shared rides. The algorithm is composed of utility-based formulation where the search is bound to attractive shared rides and graph searches with a sequence of predetermined nodes which then derives an exact solution to the search space. Subsequently, cross-scenario sensitivity analyses such as pricing strategies can be easily conducted where the developments in travel behaviour research can be incorporated into the analyses.[14] Other real-time solutions are mostly supply driven models which deter effective supply-demand feedback loops.[15,16]

1.2. Study objective and research questions

The possibilities of conducting supply driven sensitivity analyses with ExMAS guided this research's study objectives. With that, the prime study objective is to examine the effects that ride-pooling pricing has on

[a] URL: `https://tinyurl.com/y5hlc2gr`[Retrieved on 28/01/2021]
[b] URL: `https://tinyurl.com/y5p35k28` [Retrieved on 28/01/2021]

its vehicle hour reduction (VHR), LOS, and ride degree in Amsterdam (when compared to it ride-hailing counterpart). The term VHR relates the vehicle hours saved when using a pooled ride instead of a private ride. In essence, the spatial disparities of the performance of operator and user costs are investigated in this paper. This study objective would ultimately aid with spatial pricing schemes of such ride-pooling platforms in Amsterdam. Additionally, this research would further increase the knowledge on the operating costs and end user benefits of ride-pooling systems in Amsterdam.

The study objective can also be further elaborated as a set of research questions that aid with obtaining the relevant results. The main research questions (RQ) are as follows:

1. *When subject to a specific discount, what parts of the city are the most promising for the user and operator of a ride-pooling service?*

2. *At what demand levels do the level of service and profitability stabilise across the city?*

An area is deemed promising by quantifying the level of service and profitability of the user operator respectively. This done with the use key performance indicators (KPIs) which are further elaborated in Section 2, along with with the travel demand data used and the design of experiments for this research. The results of the experiments are reported in Section 3. Finally, the results, experiment limitations, and future work are discussed in Section 4.

2. Method

In this section the underlying formulas used to compute the performance indicators for the vehicles hour reduction and LOS are showcased in Section 2.1, these formulas are all based on the ExMAS algorithm.[14] The tools use to generate the network graph and the travel demand are presented in Section 2.2. The experiment outline for this paper is then shown in Section 2.3.

2.1. Identifying the performance indicators from ExMAS

With ExMAS, travellers only choose a pooled ride if they deem it more attractive than a non-shared trip. The algorithm essentially attempts to assign trips to shared rides. The (dis)utilities of the shared (pooled) and non-shared (hailed) trips are $U^s_{i,r}$ and U^{ns}_i respectively, where i indicates the traveller. The attractiveness of a shared ride can be expressed as the difference between these two utilities (also seen in Equation 1). Here, a shared ride r is deemed attractive if $U_{i,r}$ is positive.

$$U_{i,r} = U^s_{i,r} - U^{ns}_i \tag{1}$$

To efficiently compare the traveller utility, ΔU_r will be used. This is essentially the weighted difference of the utilities of the shared and non-shared service, visualised in Equation 2. If $\Delta U_r = 0$ then the traveller will not find the pooled option attractive and thus opting for the non-shared ride. Since, the disutility of an option is measured, a shared ride is chosen if and only $\Delta U_r < 0$ which means that $U^s_r < U^{ns}_r$.

$$\Delta U_r = \frac{U^s_r - U^{ns}_r}{U^{ns}_r} \tag{2}$$

The service fare of a shared & a non-shared ride in this paper is characterised as λ^s & λ^{ns}, respectively and are measured in (€/km). The fare of each ride is the product of the respective service fare and the distance travelled. Furthermore, the discount offered for sharing a ride is computed as $\lambda = \lambda^s - \lambda^{ns}$. In order to create attractive shared rides, $\lambda^s < \lambda^{ns}$ and therefore $\lambda < 0$. This compensates for the downsides of shared rides such as longer travel and the discomfort of sharing a trip. The experiments performed in this study are conducted by varying the relative discount where, $\lambda = -(\lambda^s - \lambda^{ns})/\lambda_{ns}$. As an example, $\lambda = 0.15$ represents a shared fare 15% lower than the non-shared alternative.

On the operator side, determining whether a shared ride generates a higher profit than non-shared rides can be calculated with Equation 3. The revenues generated by a shared ride are the sum of trip lengths l_i multiplied with λ^s while the costs are proportional to the ride length l_r. The revenue of a non-shared trip is similar, however here costs are not proportional to the sum of the trip lengths. In Equation 3, Q_r represents the sequence of served trips.

$$\sum_{i \in Q_r} \lambda^s l_i - l_r > \sum_{i \in \mathrm{Q}_r} \lambda^{ns} l_i - \sum_{i \in \mathrm{Q}_r} l_i \tag{3}$$

Rearranging Equation 3 would allow for the shared ride profitability to be expressed as:

$$\lambda_r = 1 - \frac{l_r}{\sum_{i \in Q_j} l_i} \tag{4}$$

A selected shared ride is seen as profitable if $\lambda_r > \lambda$. It is important to note that a profitable ride of a high degree may be composed of multiple non-profitable lower degree rides.

However, the term 'profit' will not be used to quantify the performance of the operator as it does not account for multiple factors such as: drivers operating with an empty vehicle (i.e. driving to a passenger or idle) and drivers waiting for the traveller. Moreover, numerous conditions influence the break-even point which go beyond the scope of this report. For these reasons, the operator performance indicator will be referred to as the average VHR which is represented in Equation 3 with λ_r. More travellers using the sharing service (thus also allowing a higher degree of travellers per ride) should yield a higher reduction in total vehicle hours than a non-sharing service. A positive λ_r indicates that vehicle hours of the shared ride are reduced.

2.2. Generation of the travel behaviour and demand

The travel behaviour data was obtained from Albatross: A Learning Based Transportation Oriented Simulation System.[17] This activity based model of travel behaviour described which activities are conducted and where, along with the transport mode involved.

The network graph of Amsterdam is generated using OSMnx.[18] This allows Amsterdam's complex street network to be decomposed into nodes and thus generating a skim matrix. For this paper, 2019 PC4 of the Netherlands is used to assign locations of the activities from the Albatross data which is then converted to the nodal locations using OSMnx, facilitating map visualisations.

Furthermore, it is important to note that even though Albatross assigns a mode to a traveller, some agents are given very long bike rides (i.e. longer than 10 km) or very short car car rides (i.e. less than a kilometre). For such reasons, the data was filtered for trips longer than 1000 m. Regardless of the chosen model stated in Albatross, all agents are assumed as potential ride pooling or hailing users.

The resulting trip requests Albatross file contained a total of 178651 potential trips that spanned over the course of a full day. Only a sample of these trips is used for the experiments conducted as described in following subsection.

2.3. Experiment configuration

The experiments in this study pertain to offering various discount prices where each experiment is replicated five times. The trip requests (nP) is sampled from the Albatross demand file. Depending on the attractiveness, trip requests will opt for a shared or a non-shared ride. The experiments are tested with the following parameters:

- λ: 0.15, 0.2, 0.25, 0.3, 0.35
- nP: 400, 600, 800, 1000, 1400, 1800, 2200, 2600, 3000

All experiments assume that each ride maintains a constant speed of 28.8 km/h. Each vehicle is set to have the same maximum capacity of 5 passengers. The distance-based price rate of each ride was held constant at 1.5 €/km. The experiments also look to solve the assignment problem by maximising the vehicles utility (or minimising the vehicle hours) where 'non-profitable' (i.e. $\lambda_r < \lambda$) are considered as well. Also, since this study directly utilises the ExMAS algorithm, all of the assumptions presented in *ExMAS for system-wide strategic evaluations*[14] hold.

The visualisations of the computed KPIs are done with the use of *H3: Uber's Hexagonal Hierarchical Spatial Index.*[c] This decomposes the city of Amsterdam with a particular number of hexagons which is controlled through an aperture size. For the sake of conciseness, this study reports aggregated KPIs per

[c] URL: `https://eng.uber.com/h3/`[Retrieved on 14/01/2021]

origin of a trip or a picked up traveller. With the use of H3. Each hexagon is a representation of average of the KPIs within the bounds of that hexagon.

It is also important to note that this paper assumes that the total number of travellers (and their positions) of an entire shared ride are known before the first traveller is picked up where each trip request consists of only one traveller. So, if a ride were to consist of three different trips (i.e. a shared ride degree of 3) then it is assumed that the following passengers already made their trip requests when the first passenger is picked up. A ride of a single degree represents a private ride while anything larger constitutes as a shared ride. Thus, if a shared ride will consist of three different trips (i.e. a degree of three) then this ride degree will be known and recorded from the origin of the first passenger. As well, the magnitude of λ_r is also recorded from the origin of the first traveller and is constant for the entire ride. On the other hand, the ΔU_r represents the utility of selecting a service for the traveller, thus staying constant for the entirety of the traveller's trip. This KPI is different for each traveller, therefore the ΔU_r of the origin of every traveller is recorded.

The study presents results from the experiments by means of maps and line plots. The maps showcase the spatial disparities and pattern of the KPIs. The line plots utilise the coefficient of variance (CV) to demonstrate the variation of each KPI across all hexagons. The histograms visualise the distribution of each KPI over the hexagons.

3. Results

The results obtained in this study consist of hexagonal decompositions of Amsterdam, for which each hexagon represents the average KPI of that area. These hexagonal decomposition are seen in Section 3.1. The CV of KPIs across the city are further explained in Section 3.2 where the CV of each KPI is plotted in order to explain the stability of each experiment.

The KPIs presented in this section quantify the VHR, LOS and ride degree. The former two are quantified with λ_r and Δ_{U_r}, for which the computations are provided in Section 2.1. The analysis of these KPIs aims to discover the most promising areas for ride-pooling in Amsterdam where areas with the highest VHR of the operator and largest user attractiveness are visualised. As well, the visualisation of ride degree aids with interpretation of locations with specific λ_r or Δ_{U_r}.

3.1. KPI maps

A total of 135 maps visualising the KPIs across the city were created with the experiments illustrated in Section 2. For the sake consistency, only the hexagonal decompositions of three different demand levels are visualised, namely: low demand, medium demand, and high demand. These three demand levels are defined by experiments where $nP : 600, 1400, 2600$. Furthermore, in Appendix A, maps of the trip densities and travel times for the low, medium, and high demand levels are found and are be used to interpretation of the KPIs.

Figures 1 to 3 show the map the hexagonal average λ_r, ΔU_r, and ride degree for the various discount prices from low to high demand level. The value of λ_r in an area is described with a yellow, turquoise, or blue colour. The yellow colours represents a state when $\lambda_r < \lambda$, or when the VHR is at 'unprofitable' level. The turquoise colour indicates a profitable VHR up to $\lambda_r = 0.4$ and a blue colour indicates the highest VHR in an interval of 0.4 to 0.6. The ΔU_r is illustrated with yellow, orange, or red. More negative values of Δ_{U_r} indicate a higher attractiveness of the ride-sharing service which correspond to the yellow and orange areas. The more yellow, the higher the attractiveness for ride-pooling. The red hexagons represent areas where $\Delta U_r \approx 0$ which means that non-shared rides are predominantly chosen. The ride degree is described with white and shades of green. Hexagons depicted in white represent an area where the ride degree is approximately 1, with most rides being non-shared. The lightest shade of green represents areas of 1 to 1.5 degree, followed by an intermediate shade with degree 1.5 to 2.5 while the darkest represents areas with trips mostly consisting of 3.5 degree. Within the ride degree maps, it can be regarded that non-white hexagonal areas, on average, consist of shared trips.

Furthermore, in Figures 1 to 3, a lower number of hexagons is generally seen in the λ_r maps when compared to the ΔU_r and ride degree maps. This occurs as only the pooled rides represent the λ_r. Including private ride data in the λ_r maps would pollute the data as private rides have data as for a private ride $\lambda_r = \lambda$, thus impeding the spatial analysis of ride-pooling VHR. Both ΔU_r and ride degree maps visualise data from both modalities albeit the former utilises all traveller origins while the latter utilises the origin of only the first picked up traveller (both shared and non-shared).

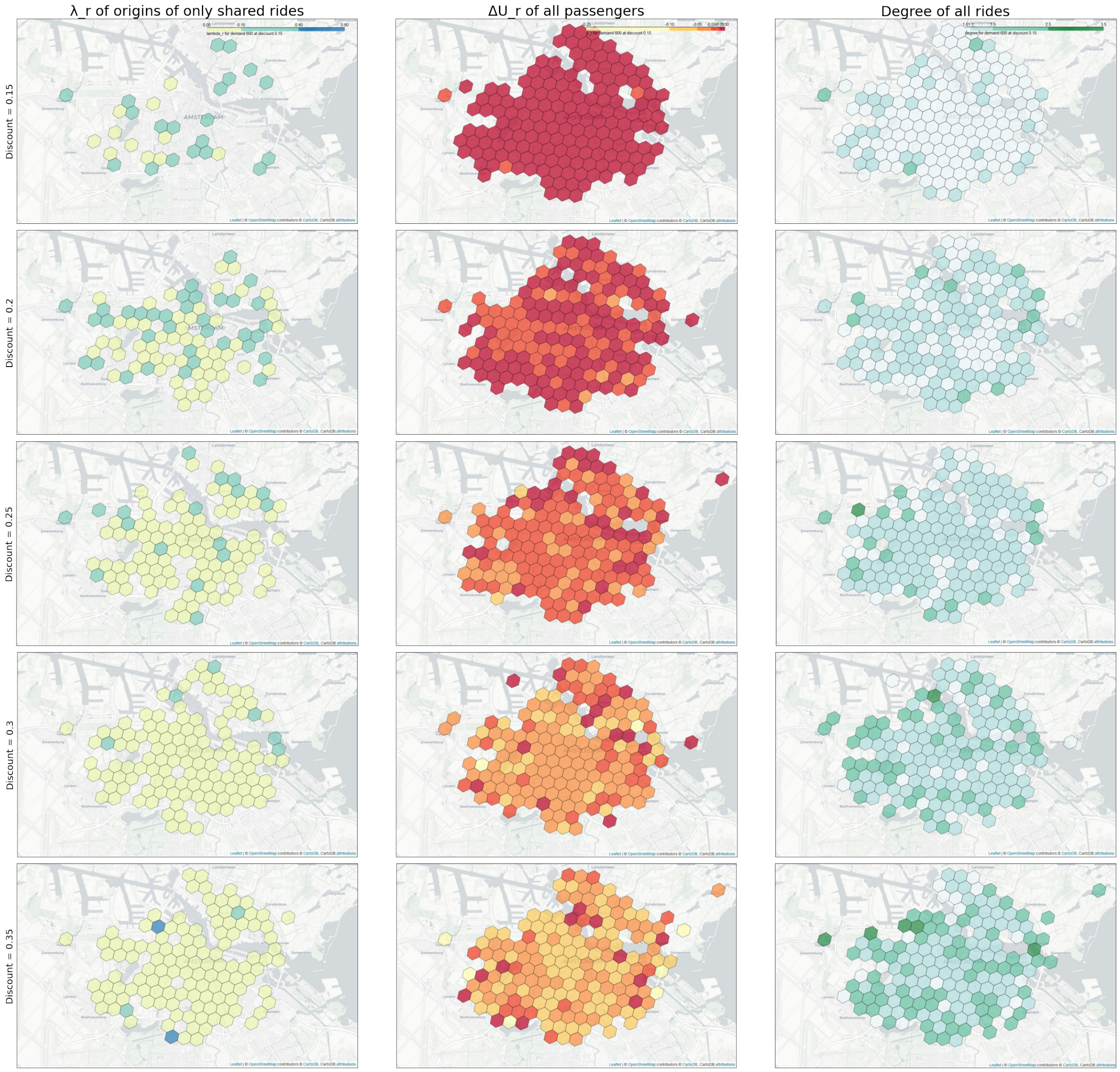


Figure 1: KPI maps generated when $nP = 600$ (low demand level). At low discounts, far fewer hexagons representing λ_r are seen due to a low sample of selected shared rides. More hexagons are seen with Δ_{U_r} and ride degree as they utilise all traveller and ride data (shared and non-shared), respectively. The colour-bar for λ_r alters for every discount level, the interval for yellow is from 0 to λ.

Figure 1 presents maps for a low demand level. At this demand level, the ride-sharing service is likely to have unprofitable VHR for most discount prices. At $\lambda = 0.15$, most of the selected rides are private rides. This is evident in Δ_{U_r} map as almost all of the hexagons are red. However, the ride degree map exhibits a pattern where higher degree rides originate from the city periphery. At $\lambda = 0.2$, ride-pooling becomes an attractive option for travellers where orange hexagons (slightly more negative ΔU_r) are in the Centre-West parts of the city. There is a small increase in areas where $\lambda_r > \lambda$ but a larger proportion of 'unprofitable' areas arise. At $\lambda = 0.25$, most of the city is highlighted as 'unprofitable' while the ΔU_r map shows far more areas with higher preference for ride-pooling. Most of the red hexagons are located in the North and East ends of the city. There is less of a periphery pattern with ride degree as now pooled-rides are seen to originate over the entire city; although only some areas in the East, South, and West have an average degree higher than 1.5. At discounts of 0.3 and 0.35, up to five areas are 'profitable' for the operator. When subject to these discounts, areas with a high VHR are situated in the periphery of the city. In the user's perspective, ride-pooling is far more attractive now with the least negative ΔU_r (and thus least attractive) areas seen in the city periphery. At $\lambda = 0.35$, the highest attractiveness (yellow areas) for ride-pooling is in the central areas of the city, this also corresponds to the areas with 1.1 to 1.5 average ride degree. On the contrary, the periphery has lower attractiveness for ride-pooling which corresponds to the areas with higher ride degree.

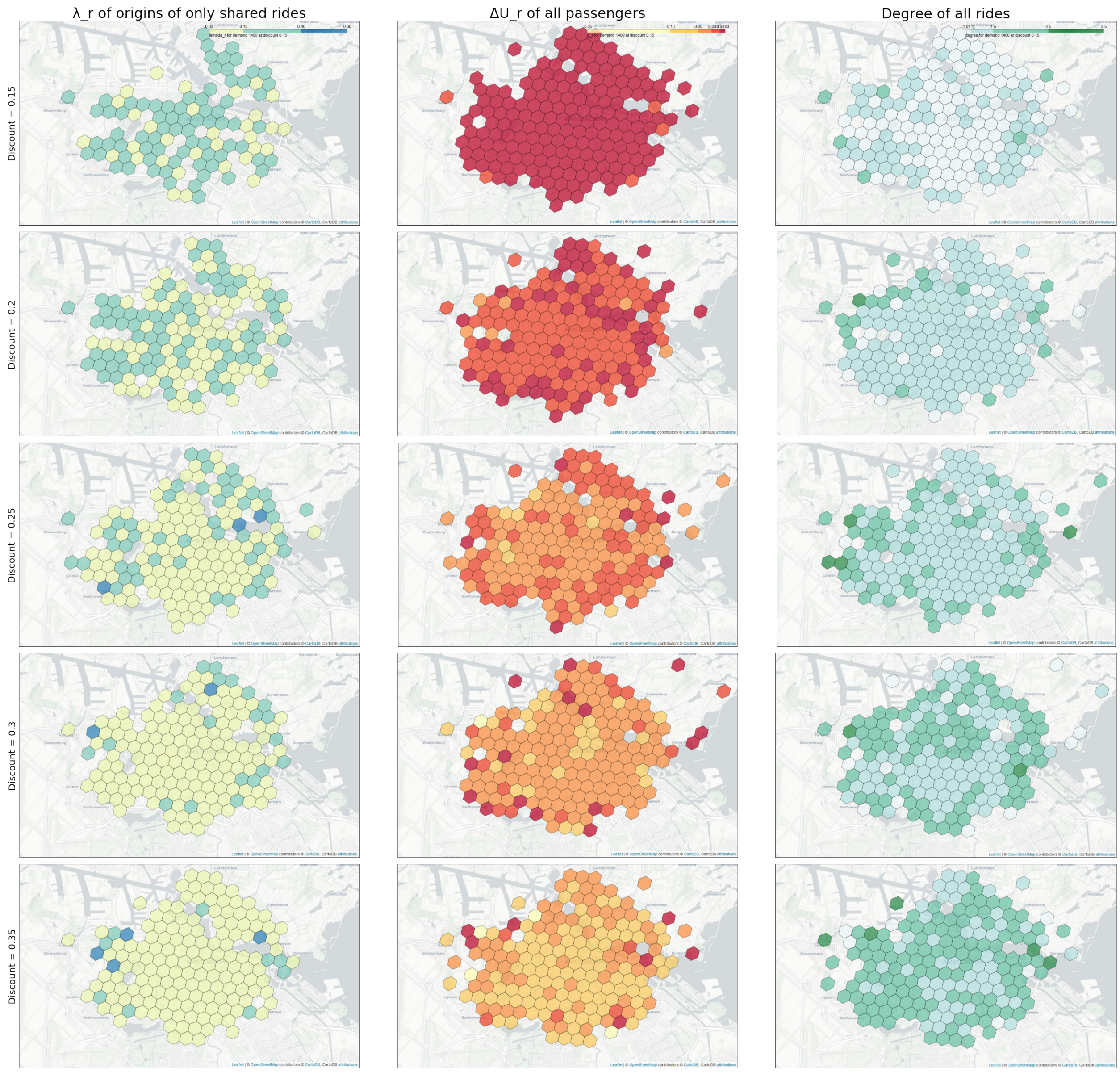


Figure 2: KPI maps generated when $nP = 1400$ (medium demand level). More hexagons visible in λ_r due to the larger number of travellers able to select ride-pooling option.

Figure 1 indicates that the operator is likelier to have more profitable areas at lower discounts when the demand is low. However, no specific area stand out in providing the highest VHR in the city. Users tend to find the ride-pooling service unattractive at these low discount prices, sharing only becomes noticeably attractive when $\lambda = 0.25$ or higher. The peripheral areas of the city are the least attractive for a user to select the ride-pooling. This could be due to the fact that trip travel times are substantially longer in areas just outside the centre, as seen in Figure 6. At low demand levels, ride-pooling does not have specific areas that significantly provide profitable VHR. Only at $\lambda = 0.2$ would there be a number of profitable VHR for the operator wile travellers also find it an attractive option. At this low demand level, it could be possible that travellers are poorly matched for a shared ride (i.e. larger detours needed) and thus insufficiently reducing the vehicle hours for a shared ride.

Figure 2 visualises the disparities of the KPIs when a medium demand level is present in the city. At the lowest discount, most of the city is considered beneficial for the operator where a small number of 'unprofitable' areas exist. When $\lambda = 0.2$, it is immediately clear that attractiveness for ride-pooling slightly increases city wide as the ΔU_r map consists mostly of orange hexagons. The areas with $\Delta \approx 0$ are situated on the city perimeter where are seen in the North, East, and South. The λ_r map shows an 'unprofitable' region in the Central and Southern regions of the city while the region with the largest group of 'profitable' hexagons is visible in the West. The areas with the highest ride degree are also seen in the West at this discount price. With discounts of 0.25 and higher, the number of 'unprofitable' λ_r areas increase. The areas with 'profitable' λ_r tend to remain in the West, North, and East areas of the city. Also at these discount prices, areas with high VHR where $\lambda_r \geq 0.4$ are visible in the West and North. The perimeter of the city generally remains the least attractive for ride-pooling. This similar pattern is also clear within the ride degree maps as rides with degrees higher than 1.5 tend to originate from the city perimeter. Although, at $\lambda = 0.35$, most of the city is seen to operate with rides larger than an average degree of 1.5.

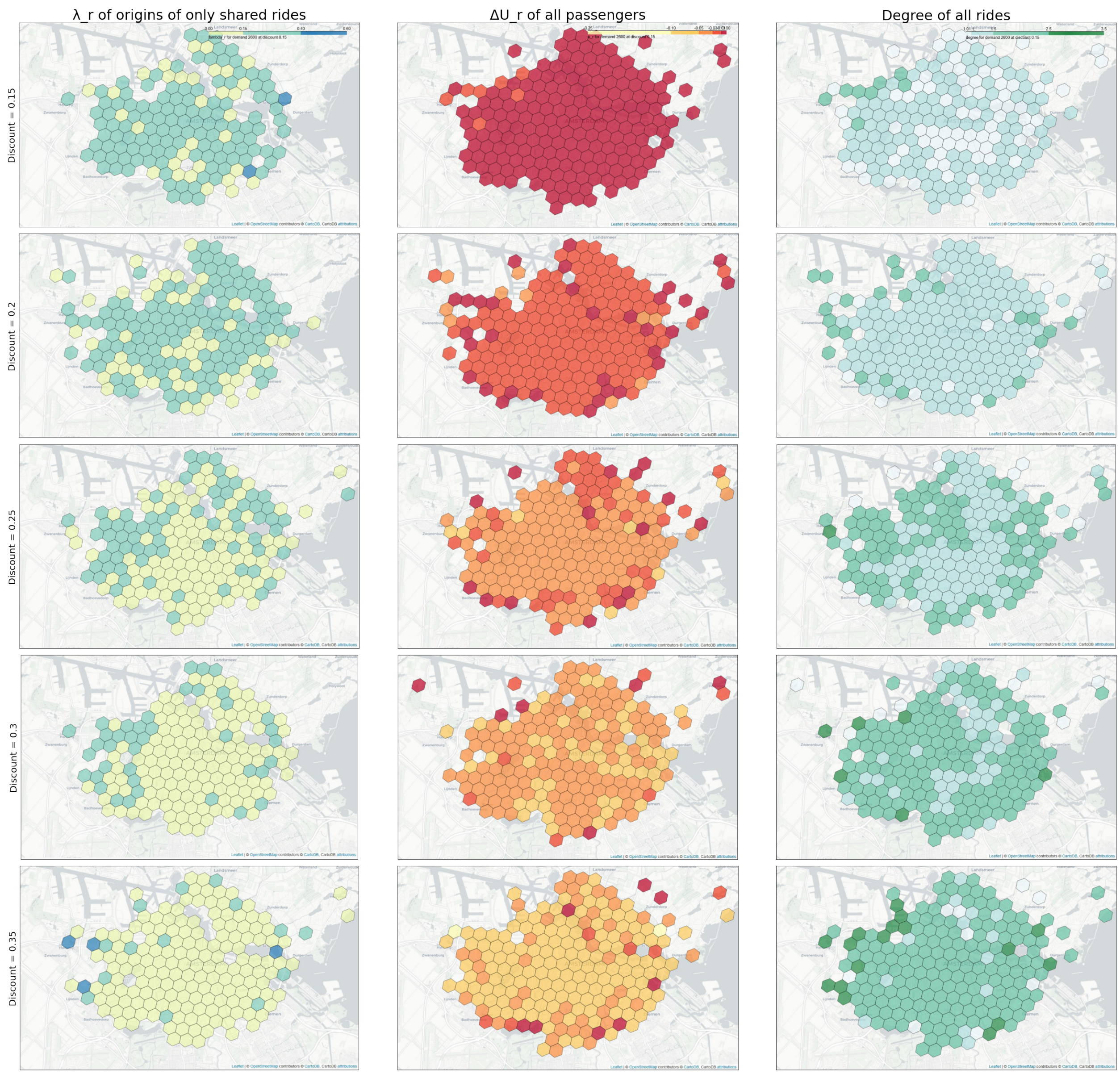


Figure 3: KPI maps generated when $nP = 2600$ (medium demand level).

Figure 2 shows that increasing the discount price of ride-pooling greatly affects the number of profitable areas in the city. Eventually, with $\lambda \geq 0.3$, ride-pooling becomes almost completely unprofitable while when $\lambda = 0.25$, most of the central and southern areas are unprofitable. Even though most of the city finds ride-pooling a very attractive alternative at these high discount prices, it does not seem to pay off for the operator. Regions with areas with higher ride degree usually corresponded to the lowest attractiveness while VHR for the operator was higher. In Figure 6, the largest trip lengths originate from the city perimeter and the highest trip density is seen in the central areas. A correlation emerges between areas with higher VHR and regions with lower trip requests and higher trip lengths. This could also be a reason to why higher ride degrees originate from the city perimeter as it could be easier for a shared vehicle to pick up passengers if driving inwards to the city. However, these higher degree rides in the city perimeter could have higher travel times than the non-shared counterpart. It could be that travellers prefer ride-pooling when the ride degree is lower and travel time shorter.

At high demand level, Figure 3 visualises the spatial disparities of ride-pooling of the KPIs where a similar pattern is seen to that of a medium demand level. With $\lambda = 0.15$ at high demand, ride-pooling is able to serve a lot more travellers where its operations are profitable city-wide. This is seen in the degree map as average degrees higher than 1.1 are seen more in the central and not just the perimeter. However, higher demand level does not seem to alter the attractiveness off ride-pooling at low discounts as $\Delta \approx 0$ for across the city. At $\lambda = 0.2$, groups of 'unprofitable' λ_r areas become slightly more prominent with the groups in the central and southern parts of the city. Most of the city remains in a profitable VHR interval as the average ride degree is at least 1.1 across the entire city. This means that a much larger portion of travellers chooses ride-pooling at this high demand. This is evident in the ΔU_r map almost the all of the travellers find ride-pooling the more attractive option. A much smaller portion of areas have $\Delta U_r \approx 0$ when comparing to the low and medium demand levels, yet still located on the perimeter of the city. At $\lambda = 0.25$, it becomes clear that the Centre and South are unprofitable for ride-pooling in the city. The West and North have the highest VHR fro ride-pooling, however the ride degree is larger in the West than in the North. Areas with $\Delta U_r \approx 0$ become more sporadic but still the lowest attractiveness is seen on the periphery. For discounts of 0.3 and higher, the number of profitable hexagons decrease but the West remains as the most profitable area for ride-pooling. At these discount, ride-pooling is seen as a very attractive, when $\lambda = 0.35$ option as $\Delta_{U_r} \leq 0.3$ and the average ride degree at least 1.5. However, at this highest discount, almost all of the hexagons in the city represent unprofitable VHR.

At this high demand level, Figure 3 that the ride-pooling service can generate sufficient attractiveness at $\lambda = 0.2$. This is beneficial for the operator as most of the city still allows for profitable VHR. At $\lambda = 0.25$, the Southern areas of the city become significantly unprofitable while most of travellers across the city find ride-pooling attractive increases. This is the trade-off that a provider should examine, offering a slightly higher discount price will undoubtedly increase the attractiveness, but a large portion of the city loses its profitability. In Figure 6, the trip density is much higher in the centre while the highest trip lengths are are most common on the West and North peripheral areas. Ride-pooling seems to be the most suitable option for the operator when travel times are longer and trip density lower. At discounts of 0.25 and 0.3, the 'profitable' λ_r areas are most prominent in North, and Wast. However, the ΔU_r maps show that that central areas areas are more attractive for ride-pooling as the city perimeter At this discount price there is no evidence that a higher ride degree is less attractive for travellers. This could be due to the fact that highest trip density seen in the central regions of Amsterdam where the travel time is lowest. Travellers could prefer higher degree pooled rides for travel with short duration. On the other hand, these short trips could be unprofitable for operator as the detour for each trip would be relatively high and thus not allowing for high VHR.

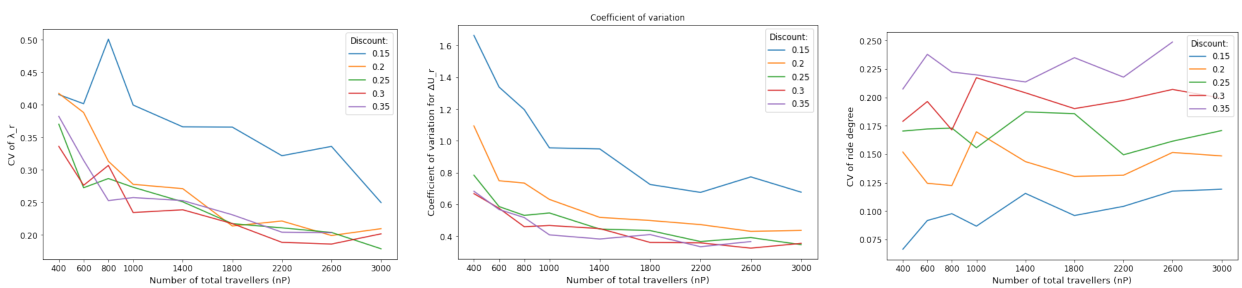
3.2. Coefficient of variance of each map

This section examines the stability of each KPI across all the hexagons of each map. CV is used to quantify the stability as it reports the relative precision of each experiment by taking the ratio of experiments' standard deviation with its mean. Knowing the CV of each experiment would allow a provider to expect a specific variation of VHR or LOS when a certain demand level is projected. **??** visualises the CV of each experiment. The mean KPI of each experiment is plotted in **??**. Additionally when $nP = 3000$, ExMAS tends to crash when the discount is set to 0.35 and was therefore not considered in the analysis as five replications were not obtainable. It is likely that this high demand level and high discount, all travellers opt for using the ride-pooling service for which the algorithm might not be able to handle.

Figure 4a shows plots the λ_r CV across all hexagons of a map with increasing demand level. An exponential trend is visible for discounts of 0.2 and higher while a discount of 0.15 has more of a proportionally negative trend. A discount of 0.15 provides the highest variation across the hexagons while discounts of 0.2 and higher have a generally lower coefficient of variation. For low ($nP = 800$) and high ($nP = 2600$) demand levels, $\lambda = 0.15$ has up to 73% higher CV than that of discounts 0.2 and higher. For all discount prices, the CV is highest when demand is low. This is due to the low number of available travellers to select ride-sharing; for each replication, the change in traveller origins is more significant than at medium or high demand levels. For discounts of 0.2 and higher, CV converges to a value around 0.2. This shows that at high demand levels, the variation of λ_r throughout the city stabilises where discounts of 0.2 and higher generate the same level of precision.

Figure 5a shows that the mean λ_r increases with λ. Only the line representing $\lambda = 0.15$ consistently provides 'profitable' VHR. For $\lambda = 0.2$, ride-pooling only becomes profitable for $nP > 1400$. The mean λ_r of higher discounts never surpasses λ. However, only lines of $\lambda \geq 0.2$ follow a logarithmic trend while $\lambda = 0.15$ follows a slight positive trend. With respect to the CV of each discount, since experiments of λ of 0.2 and higher have similar values, their trends of mean λ_r will always be around the same. The mean trend of $\lambda = 0.15$ is the most unstable and the largest variance of λ_r is expected at this discount price, relative to the larger discounts.

Figure 4b represents the CV for ΔU_r where an exponential trend similar to that of Figure 4a is seen. With this KPI, all discounts follow a similar exponential trend, however the trend of $\lambda = 0.15$ is still noticeably higher than the trends of the higher discounts. The trends of discounts 0.2 to 0.35 follow similar CV, albeit the trend of $\lambda = 0.2$ contains slightly higher CV values. If the average CV values of discounts 0.2 to 0.35 are taken, then CV of $\lambda = 0.15$ is around 80% larger at all low, medium, and high demand levels. Furthermore, the CV is three to four times larger than that of λ_r. This is most likely due to the ΔU_r utilising results from both shared and non-shared rides whereas λ_r only utilised shared ride results.

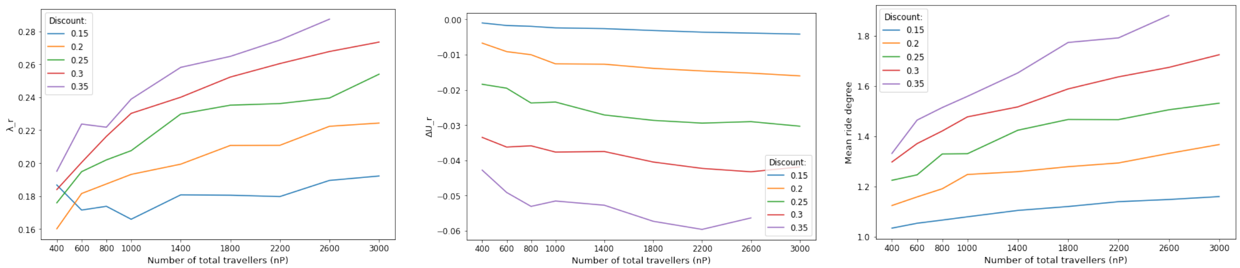


(a) λ_r *(b) ΔU_r* *(c) Ride degree*

Figure 4: Figures representing the CV across all hexagons of each discount under a certain demand level (nP). CV is unit-less while nP is the number of travellers.

The mean values of ΔU_r for every λ are plotted in Figure 5b. Evidently, the KPI becomes more negative with increasing discount, the general attractiveness for ride-pooling increases with larger discounts. However, the CV of $\lambda = 0.15$ is higher for ΔU_r than λ_r due to its mean being close to zero. A pitfall of utilising CV to describe precision is that means close to zero will cause CV to approach infinity. The mean would be closest to zero when $\lambda = 0.15$ because all travellers (both shared and non-shared) are considered while λ_r only considers a ride shared. Thus, the reasons for ΔU_r CV being larger is not strictly due to larger variations across the map but rather ΔU_r being closer to zero, a traveller that selects a non-shared ride has a $\Delta U_r = 0$. In essence, the CV converges to 0.4 for discounts of 0.25 and higher with increasing nP.

Figure 4c represents the CV for the average degree for all the rides. Unlike the the Figures 4a and 2, there is only a slight positive trend for the different discounts. The average CV increases with larger discount prices, however this is expected as Figure 5c shows that the mean ride degree increases with higher discounts. Essentially, if the average ride degree increases, the variation of ride degree also increases. When $\lambda = 0.15$, CV is lowest due to most of the rides being either one or two degree. With higher discounts, travellers opt for using higher degree rides which increases the variation of the results. Even though the mean ride degree increases with nP (where this positive trend increases with discount), CV exhibits only a slight positive trend. It can be concluded that The increase of nP has a minimal effect on the CV for larger discounts and average degree proves to have the lowest variation out of the three KPIs.



(a) λ_r *(b) ΔU_r* *(c) Ride degree*

Figure 5: Figures representing the mean KPI of all hexagons of each discount under a certain demand level (nP).

4. Conclusions and recommendations

This study utilises the recently developed ExMAS algorithm to examine the disparities in performance of a ride-sharing service in Amsterdam. The VHR and LOS were spatially analysed in relation to trip origins.

Returning back to the first RQ of this study, this paper aims at determining the most promising areas of Amsterdam for the user and operator of a ride-pooling service. The spatial disparities in VHR, LOS, and ride degree between ride-pooling with a set discount and its ride-hailing counterpart, these disparities were visualised in a series of maps that ranged from low to high demand with increasing ride-pool discount. The maps of VHR and LOS had inverted patterns, areas where VHR was high and profitable were areas where attractiveness was low. At all demand levels, ride-pooling with a low discount provided the greatest number of profitable VHR areas, however travellers in all areas of the city deemed the service unattractive. With increasing discount, travellers' attractiveness for the service increased while the number of unprofitable VHR areas also increased. For higher demand levels and increasing discount, some areas of the city consistently remained profitable, these areas were located on the city periphery, namely the West, North, and East of Amsterdam. These areas usually consisted of rides with a higher degree, lower trip density, and larger trip travel times. On the other hand, travellers had lower attractiveness for ride-pooling in the city periphery while attractiveness was highest in the central regions where trip density was highest and ride degree generally lower.

The study also examined the stability of VHR and LOS of the operator and user. The variation of each KPI over an entire map was characterised using CV plotted with respect to increasing demand where each data-set was split according to the ride-pool discount. The lowest discount was seen to have the highest CV for both VHR and LOS, around 80% larger than the higher discounts. For VHR, the CV stabilised with increasing demand levels. As well, discounts of 0.2 and almost identical exponential trends which means that ride-pooling at these discounts have a similar level of precision in terms of VHR and LOS. Higher demand levels allow for a more stable performance for ride-pooling, which was also partially seen in the maps as patterns were more profound at these demand levels.

In all, The maps showed that a medium to high demand is required to have a reliable ride-pool service. With discount equal to 0.25, the findings indicate that the West, North, and East regions of Amsterdam are the most promising for the operator; at this discount most of the travellers find the service attractive except on the peripheral areas of the city. The attractiveness of the tide-pooling service decreases services when the discount is set to 0.2 yet almost the entire city is promising for the operator. Low demands are prone to large instabilities in VHR and are seen to consist mostly of unprofitable VHR areas. It is important to know that the service fare was fixed throughout the experimentation, it could be possible that different patterns emerge with higher or lower service fares. This could also lead to further studies the usage of ride-pooling with respect to the demographic in a city.

This research is limited to the uncertainty that low discount prices have on the performance of different areas in a city. The CV plots provided evidence that higher demand levels are able to realise a higher level of precision of the KPIs. It could be possible to obtain a pattern and further insights on the spatial disparities of low demand levels if experiments with a higher number replications are conducted. Furthermore, this paper only examines the performance of the service with respect to the origin of the travellers; future experiments should investigate how this performance differs with respect to the destination of travellers. Future studies could also clarify and formulate an accurate cost model of the sharing and non-sharing service where realistic profitable areas of a city could be discovered. In addition, the objective function used in this report was to maximise the utilities of the vehicle (minimise travel time of vehicles). Such an objective function heavily leans on the operator side and it could be a reason to why the ΔU_r patterns did not match the patterns of the λ_r. Future experiments, should analyse the spatial disparities of the two objective functions as different patterns could arise with respect to an objective functions. Moreover, this research is limited to only two mode choices, future research should incorporate other modes such as public transport and personal vehicles as this would definitely influence the attractiveness of using a ride-pooling service.

In all, the results of the paper could be beneficial to services such as *Uber Express POOL*, which are yet to roll out in Amsterdam. The information provided in this report could be used to help idealise an efficient and reliable platform in the city of Amsterdam. The scripts created for this paper are scalable, which means that results obtained with ExMAS from other cities, with additional and/or different experiment parameters could be easily applied.

Acknowledgements

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Appendix

A. Trip Lengths

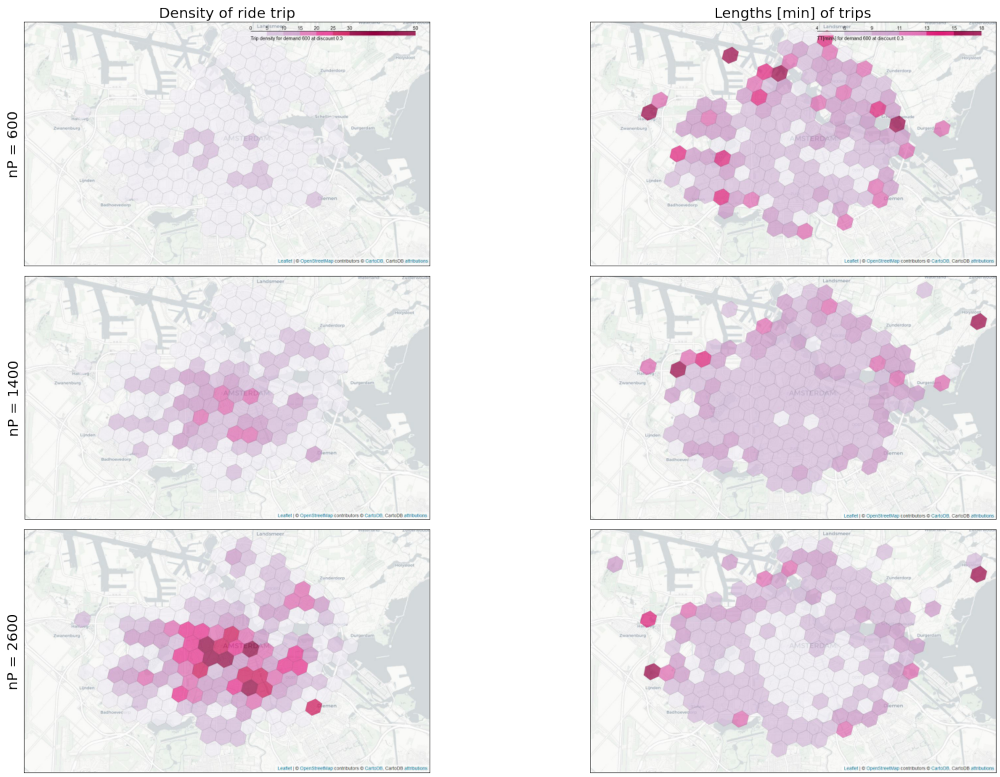

Figure 6: Maps of trip density and trip lengths w.r.t. trip origin for a set of nP at $\lambda = 0.3$.

B. Project Plan

Figure 7: Eight week project plan.