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# A Protocol for simulation modeling of Ridesourcing services in Perth Metropolitan Area: optimisation of fleet size in an urban environment

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**Abstract**

Ridesourcing services have emerged as an alternative transit option for commuters in metropolitan areas. Western Australia has exhibited the highest growth of ridesourcing services as compared to the other regions of Australia. Although the ridesourcing services have attracted a considerable number of riders, whether such services meet the demand still remains a major concern. The introduction of a pricing strategy, 'surge pricing', in order to attract drivers during peak hours has led to concerns related to congestion and emissions. Therefore, it is required to devise strategies to determine the optimal distribution of vehicles in order to meet the spatio-temporal demand of the ridesourcing services. Therefore, this study would develop a simulation model to determine the optimal allocation of drivers to converge to demand through simulation through the principles of Cellular Automata (CA) Theory in order to minimise the drivers and riders' waiting time and overall travel distance of drivers. The boundary conditions for the simulation would be updated through the feedbacks of drivers and riders based on the field survey. The model would be validated through the open-sourced historical data provided by the Perth Uber Company.

*Keywords:* Ridesourcing, Agent-based simulation, intelligent transportation

## 1. Introduction

### *1.1 Emergence of Ridesourcing services around the globe: rise in Western Australia*

The last decade witnessed the introduction of an online platform for ridematching between drivers and passengers, which became popular as 'ridesourcing'. The popularity gained by the ridesourcing services in the last five years, have mandated to confirm their position in the formal transport market. The companies such as Lyft, Ola, and Uber (especially UberX, UberXL, UberSelect) which provide ridesourcing services, have emerged through the introduction of smartphone applications to link the riders with their driver partners. The rapid growth witnessed by these services, can be attributed to the attractiveness of the services provided by the companies mentioned above. Such services have compelled the choice riders to choose this mode to commute over the rest of the modes.

The introduction of the concept of ridematching through online platform was started through the initiation of Zimride at Cornell University for longer trips (between cities) in 2007 (L. Blog, 2016; Farr, 2013; Henao, 2017). But, it was unable to generate the revenues as expected which led to the growth of Lyft in 2012 (Carlson, 2013). The ridesourcing service, in its true form, was first launched by Uber in 2010 in San Francisco with its UberBlack platform (McAlone, 2015). Thus, Lyft became the second company to provide ridesourcing services. But soon, there were other players who emerged all across the globe with Uber leading the chart. Uber expanded its network in almost 450 cities around the globe by the end of 2016(Somerville, 2016).

The ridesourcing market was established in Australia with the introduction of UberBlack by the Uber company in 2012(Deloitte, 2016). The most popular ridesourcing service of Uber, UberX, was introduced in Sydney and Melbourne in April 2014 followed by Perth in July of the same year(McNeill, 2016). Since then, Uber has continued to maintain its leading position in terms of ridesourcing service provider. According to the recent data released by Roy Morgan, 18.4% of the total Australian population is using Uber as their travel mode (Morgan, 2017). The highest adoption rate of Uber was observed in the state of Western Australia where 23.9% of its residents used Uber to reach their destination (McNeill, 2016; Morgan, 2017). This summarizes the significance of ridesourcing services in Western Australia and establishes its importance to be selected for this research.

### *1.2 Synonyms for ridesourcing services used in literature*

Various literatures have used different terminologies to address "ridesourcing" services. The first terminology was introduced by the California Public Utilities Commission (CPUC). CPUC intended to address public safety and as a result termed the service providers as 'Transportation Network Companies' (TNC) (Onesimo Flores & Rayle, 2016). They did not define a formal terminology of the services provided by the TNCs. The terms used to describe the services provided by TNCs include ride-booking or ride-hailing (Shaheen et al., 2017), ridesharing and many more. Ridesharing is a colloquial term, but it creates confusion and controversy since it does not cover all the aspects of the services provided by TNCs. There is a fundamental difference between the ridesourcing services and traditional ridesharing ("the grouping of travellers into common trips by car or van, whereby the driver has a common origin and/or destination with the passengers" (Shaheen et al., 2017)). In contrast to ridesharing, the main motivation of the drivers of these services is income. Some policy makers also found a close resemblance of these services to taxi where a ride is offered by the driver in exchange for a fare. Further confusion is propelled when these services are termed as 'e-Hail (app-based dispatch services)' since taxi companies are adopting these services (Rayle et al., 2014). Besides, introduction of services similar to ridesharing, microtransit ("privately owned and operated shared transportation services with fixed, on-demand schedules, or both" (Shaheen et al., 2017)) etc. by the TNCs are creating incorrect perceptions about ridesourcing services. The terminologies used in the literature available to address the ridesourcing services are listed below:

Table 1: Terminologies used in literature to describe services provided by Transportation Network Companies

| S. No. | Terminology | Description | References |
|---|---|---|---|
| 1 | Car sharing services | Services under which an individual can hire a car on a temporary basis without undertaking the responsibility of ownership | (Akkaya, 2016; Shaheen et al., 2015) |
| 2 | Ride booking services | The vehicle must be pre-booked utilizing the given booking options by the operator | (Government, 2017; Maddocks, 2017; Mandle et al., 2014; Wise, 2017) |
| 3 | Ride hailing services | Transportation services provided by an unlicensed taxi service | (Cohen et al., 2016; LeBeau, 2018; PCMAG, 2018; Zipkin, 2017) |
| 4 | Ridesharing services | Arrangement of a shared ride within a short time span | (Wallsten, 2015) |
| 5 | E-hailing services | Hailing of transportation through an online platform | (Onyango, 2016; Staff, 2017) |
| 6 | Tailored-Taxi services | Taxis which can be reserved through mobile phone at user's convenience | (Zhang et al., 2016) |
| 7 | Ridesourcing services | The ride services offered through app-based platforms, which use personal vehicles in order to maximize the profit. | (Onesimo Flores & Rayle, 2016) |
| 8 | On-Demand ride services | Services which increase reliability as well as promise to bring significant reduction in waiting time | (Chen et al., 2016; Rayle et al., 2014) |
| 9 | For-hire vehicle services | Services where vehicles offer pre-arranged services at the tap of an app. | (Blasio, 2016; Shaheen et al., 2015) |
| 10 | Ride hauling services | Services which have become more popular to the majority of the people as compared to the taxi services | (Blog, 2016) |

Researchers and policy makers have accorded to the fact that these services can definitely be not termed as 'ridesharing' services(O. Flores & L.Rayle, 2017; Henao, 2017). It is required to draw a boundary for the ridesourcing services in order to avoid confusion. Therefore, this study introduces a new term "on-demand en-route ride services" which may be described as, *An online platform which tries to converge to the demand for short distances requires a real-time arrangement of vehicles for a momentary and non-intermittent trip during the course of journey of its participants (riders and drivers) through specific ridematching techniques.*

This study further categorises this section into three groups. This categorisation is done in order to bring the services provided by the TNCs under a single platform. These groups are as follows: 1) Ridesourcing, 2) Ridesplitting/Dynamic Ridesharing and 3) Real-time ad-hoc services. Ridesourcing platforms utilise a driver pool in order to source rides (Ngo, 2015; Rayle et al., 2014). Booking of a ride, fare payment and provision of ratings (drivers and passengers) are conducted through smartphone applications (Shaheen et al., 2016). Ridesplitting, also known as dynamic ridesharing, is a form of service where the ridesourced vehicle and driver is utilized in real-time to match the riders having analogous origins and destinations (Byars, Wei, & Handy, 2017). Real-time ad-hoc services include flexible routing, flexible scheduling, or both. The target groups of these services are commuters and thrive in areas that have prominent connections between residential areas and job centres in downtown (Shaheen et al., 2015). This research would strictly focus on the ridesourcing services for conducting the study.

### *1.3 Rationale for the research*

The demand-supply equilibrium for the ridesourcing services can be attained when the onset of the vacant cabs is equivalent to the onset of passengers from a theoretical perspective with the assumption that the supply is strictly restricted to the ridesourcing vehicles(Lu et al., 2015). It makes it difficult to guarantee the spatio-temporal matching of vehicles with the passenger demand due to the existence of exogenous and heterogeneous factors like asymmetry in information dissemination, short-term variations in existing road network due to occurrence of sudden incidents(Moreira-Matias et al., 2013; Schreieck et al., 2016). Two scenarios can be drawn as a result from the disequilibrium state of supply and demand: a) the state of oversupply (surplus of vacant cabs can lead to inefficient fleet utilisation), b) the state of demand saturation (increment in waiting time of passengers leading to passenger dissatisfaction). Such disequilibrium condition leads to more availability of cabs in areas with low passenger concentration and lesser number of empty cabs in high demand areas. Such disparity results in inefficient service provision.

The ridesourcing companies introduced the technique of ‘dynamic pricing’ or ‘surge pricing’ in order to tackle this disparity. ‘Surge Pricing’ was introduced as a platform to offer incentives in order to increase the availability of drivers for under supply conditions, for example, during peak hour, poor weather conditions or gathering at mass events. But, this policy has led to controversies and has resulted into one of the debatable aspects of thebusiness models of the Transportation Network Companies (TNCs)(Rayle et al., 2015; Rayle et al., 2014). Besides, this has created negative impact on both the captive and potential riders who tend to choose other modes. Inclusion of surge pricing during the peak hours also bear a negative impact on the urban road network. Generally, during peak hours, the link volume tends to attain the maximum capacity leading to traffic queueing. The ridesourcing drivers from surrounding areas as well as long-distance areas being attracted to such surge pricing get accumulated in the peak demand zones. Even real-time information about ‘surge pricing’ is provided to the drivers who are not on duty in order to entice them into certain areas with high demand through incentives(Feeney, 2014, 2015; McBride, 2015). This business policy has not been proven successful in achieving solution to disequilibrium condition but has led to the scenarios of oversupply for certain instances. In this regard, this study would focus on the determination of optimum fleet size for ridesourcing services through various strategies based on the driver behaviour.

The regulatory framework for ridesourcing services still remains undefined. Thus, the vehicles under these services thrive on the urban roads unregulated. This research would not focus on defining the platform for regulation of these services. But, it would put forward the directions to sow the seeds of quantity regulation for ridesourcing services. This would provide a tool to the city planners to regulate the number of ridesourcing vehicles thriving on the urban network.

## 2. Aims

The aim of this research is to develop a computer simulation to optimise demand and supply for ridesourcing services in order to minimise the drivers and riders’ waiting time and overall travel distance of drivers. The objectives of the study are:

- Determine and visualise hotspots (pick up locations) of ridesourcing services using Geographic Information Systems (GIS) in order to determine weighted scores of ridesourcing services for Traffic Analysis Zones (TAZ).
- Develop an agent-based simulation model based on the concept of Cellular Automata (CA) to determine the optimal spatio-temporal distribution of supply for demand of ridesourcing services

- Implement and validate the simulation framework through the historical data acquired from Perth Uber Company.

## 3. Methods & Data Analysis

A hotspot analysis would be conducted using Getis-Ord GI* to understand the spatio-temporal pattern of the ridesourcing trips. This would provide us a platform to determine area to define the simulation environment, $A_0$, on which the simulation can be developed. Lattice formation in $A_0$ will be conducted based on the principles of one-dimensional Cellular Automata (CA) neighbourhoods along the street networks. The demand and supply will be synthesised in the cells through the generation of a discrete Random Variable which will be fitted in a Poisson distribution. The initial boundary conditions will be based on the generalised values of the parameters which will be updated through the results obtained from primary survey. The appropriate match for the vehicle and rider would be obtained through the nearest neighbour algorithm. The strategies for transition of vehicles from being empty to receive a passenger would be evaluated based on the driver behaviour. Transition rules for neighbourhood to generate demand and supply based on previous iterations would be formulated. The optimal supply allocation for the synthesised demand would be determined through the evaluation of scenarios based on trips, distance, user and driver waiting time.

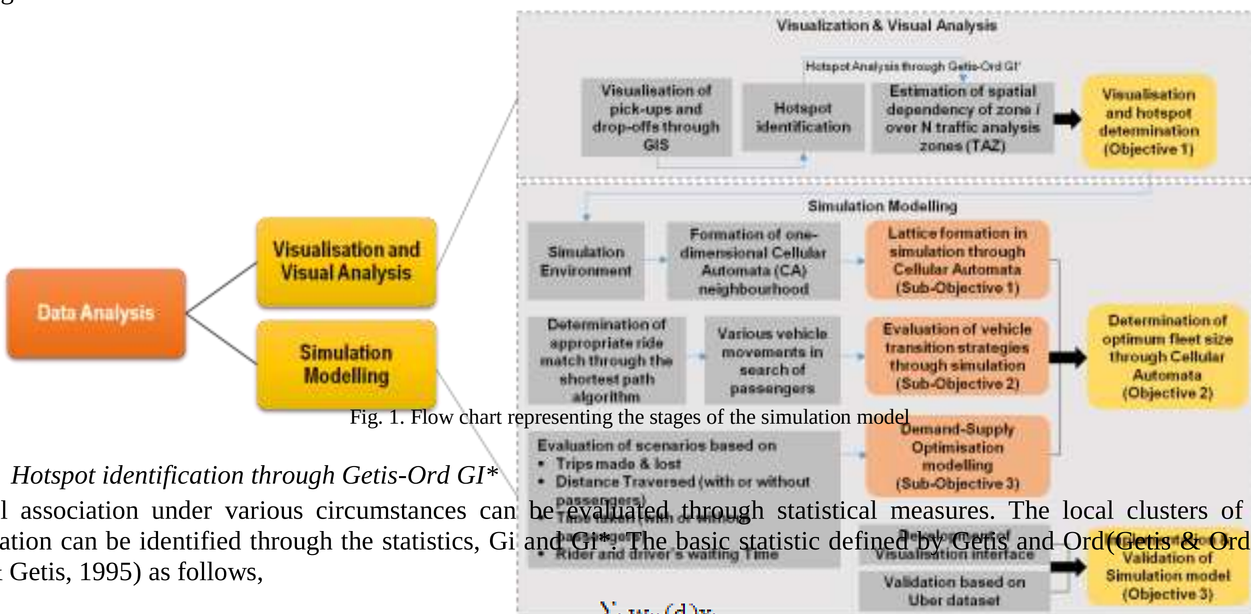


Fig. 1. Flow chart representing the stages of the simulation model

### 1.4 *Hotspot identification through Getis-Ord GI**

Spatial association under various circumstances can be evaluated through statistical measures. The local clusters of spatial association can be identified through the statistics, Gi and Gi*. The basic statistic defined by Getis and Ord(Getis & Ord, 1992; Ord & Getis, 1995) as follows,

$$G_i(d) = \frac{\sum_j w_{ij}(d)x_j}{\sum_j x_j} \; ; j \neq i \tag{1}$$

where, $\{w_{ij}\ (d)\}$is a weight matrix based on spatial association bearing a value of 1 for all features within a specified distance, d. In order to achieve normality the statistical measure was redefined by subtracting the expectation, $E(G_i)$ from the statistic in equation 1. The resultant statistical measure is(Pro, 2017),

$$G_i^*(d) = \frac{\sum_j w_{ij}(d)x_j \;-W_i\bar{x}(i)}{S\sqrt{\{[(nS_{1i}^*) - W_i^2]/(n-1)\}}} \; ; \forall\, j;\, j \neq i \tag{2}$$

where, $$W_i = \sum_{j\neq i} w_{ij}(d),\ \bar{x}(i) = \frac{\sum_j x_j}{(n-1)},\ S = \sqrt{\{\frac{\sum_j x_j^2}{(n-1)} - [\bar{x}(i)]^2\}},\ \text{and}\ S_{1i}^* = \sum_j w_{ij}^2 \tag{3}$$

where, $x_j$ denotes the attribute value of all features, $w_{ij}$ is given by the spatial weight assigned to features $i$ and $j$, $n$ is denoted by the total number of features (Pro, 2017). The resultant high or low z-scores and p-values determine the spatial clusters of the features. The statistic runs a proportional comparison between the summation values of a feature and its neighbours with all the features in the dataset. A statistically significant z-score is derived for each feature given that the probability of random chance for a large difference tends to zero. The positive z-scores for TAZs will determine the high demand locations in contrast to the negative z-scores.

*1.5 Formulation of the simulation environment*

The main focus of this research is to develop and implement the simulation in order to optimise the demand and supply for ridesourcing services. The simulation will be developed based on certain components and agents. The simulation will comprise of three agents which are, a) Rider agent, b) Vehicle agent and c) Ridematching agent. The significant area, $A_0$, identified from the hotspot analysis, will serve as the environment for the simulation. The neighbourhood would be created through the lattice formation based on an array of cells along the street network. In this research we intend to replicate the rider and vehicular movement of ridesourcing services along the street network. In this regard, the appropriate layout with individual cells is formulation of one-dimensional lattice. Cellular automata models for road traffic flow have replicated the road network as the physical environment for traffic simulation (K. Nagel & Schreckenberg, 1992; Nagel, 1996). The simulation intends to replicate the movement of vehicles from one cell to another in conjunction with the principles of the traffic CA models (Nagel, 1996; Sven Maerivoet & Moor, 2005).

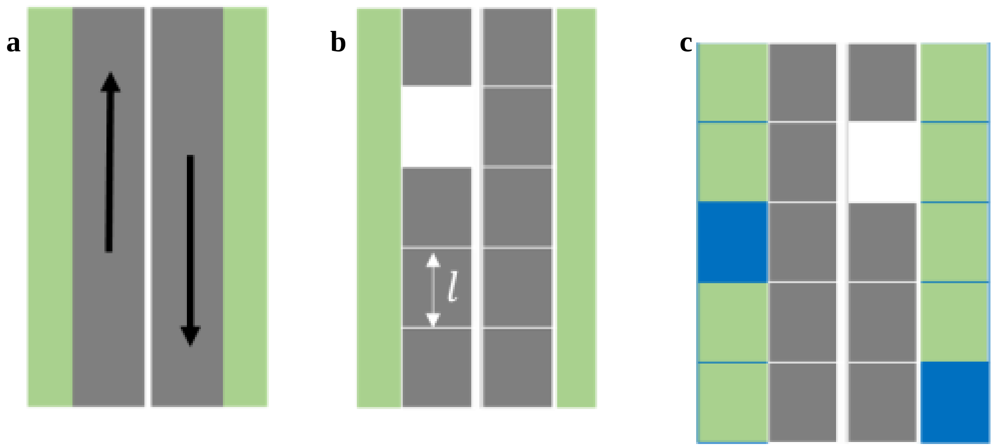


Fig. 1. (a) Representation of Street Network; (b) Lattice formation for vehicle agents over the streets; (c) Blue cells represent the rider agents.

*1.6 Synthesis of Demand and Supply*

This simulation would synthesise demand and supply through the generation of a discrete Random Variable (RV). A discrete RV for demand, $X$ for each TAZ, will be generated for each time period in such a way that, $\sum_{n=1}^{N} X_n = D \leq D_0$, where $D$ denotes the total demand in the area of simulation at time *t*, *n* refers to the TAZ index and $D_0$ is the threshold limit for demand at any time as given by the research conducted by the Roy Morgan Company (Morgan, 2017). The similar procedure will be followed in order to synthesize the supply for each TAZ which will be represented through another discrete RV, *Y* for each TAZ. The total supply would be given by, $\sum_{n=1}^{N} Y_n = S \leq S_0$, where *S* refers to the total demand in the area of simulation at time *t* and *n* denotes the TAZ index and $S_0$ is the total available supply of the Uber drivers. The discrete RV so generated would be fitted in a Poisson distribution since it is used to model the number of events in a given time interval. The demand and supply for this simulation follow the similar pattern. The Poisson distribution that the discrete RV will follow with parameter $\lambda$ will be given by(Boon, 2013),

$$P(X = i) = \frac{\lambda^i}{i!} e^{-\lambda}, \; i = 0,1,2,..; \tag{4}$$

where X is the number of ride requests in a TAZ within a specified time interval which are independently distributed with parameter $\lambda$. The number of vehicles in a TAZ will be represented through the discrete RV, Y.

*1.7 Ridematching between riders and drivers*

The synthesis of demand and supply is followed by initiation of vehicle search based on demand locations. This stage will be conducted through two steps: a) Specification of search radius, and b) Identification of shortest path driver. The search radius is initiated for all origins of the synthesised demand. A certain radius, $r_0$ is specified for the simulation. The algorithm then looks for available vehicles within the specified radius. If the search procedure locates vehicles it updates the number of available vehicles found. The system updates the radius if no vehicles are identified in the initial specification. Once the vehicles are identified the average travel of all available vehicles is estimated, given by, $t_{av} = avg\{t_1, t_2, ..., t_n\}$. The rider is notified about the time required by the vehicle to arrive. The rider waits for the vehicle until the threshold value, $T_0$ is attained. The threshold value is provided in the simulation based on user tolerance. The zone of tolerance for the waiting time of the user is determined through the survey conducted and T0 will be updated accordingly. After the vehicles have been identified within the search radius, the distance from the rider to all the vehicles is calculated. The distance is calculated on the basis of number of cells between the rider and the vehicle (occupied cell). The shortest path driver is selected based on $D_R = \min\{d_1, d_2, \ldots, d_n\}$, where $D_R$ denotes the shortest path between rider and driver, and $d_i$ refers to the distances between the riders and vehicles within search radius. If the number of shortest path driver is more than one, random vehicle selection is carried out.

The transition of the state of the cell after the identification of the shortest path driver is described through the introduction of a binary variable, matching component, $\mathcal{M}_0$, in the simulation (where $\mathcal{M}_0 \in \{0,1\}$). The vehicle is withdrawn from the system, i.e. the cell changes its state when the match is established. The state of the cell is transformed from occupied to vacant. The transition of the cell is explained through the following equations (Sven Maerivoet & Moor, 2005),

$$\delta : \mathcal{E}^{|\mathcal{N},\mathcal{M}_0=0|} \longrightarrow \mathcal{E} : \bigcup_{j\in\mathcal{N}} \sigma_j(t) \longmapsto \sigma_j(t+1) \tag{5}$$

$$\delta : \mathcal{E}^{|\mathcal{N},\mathcal{M}_0=1|} \longrightarrow \mathcal{E}_D : \bigcup_{j\in\mathcal{N}} \sigma_j(t) \longmapsto \sigma_i(t+1) \tag{6}$$

$$\longrightarrow \mathcal{E}_R : \bigcup_{k\in\mathcal{N}_r} \sigma_k(t) \longmapsto \sigma_s(t+1) \tag{7}$$

where, $\sigma_j(t)$ refers to the occupied vehicle cell at time t and $\sigma_i(t+1)$ refers to the vacant vehicle cell in the next instant once appropriate match is found. Once the shortest path driver is identified, the binary matching component, $\mathcal{M}_0$, is also introduced to regulate the transition of the rider cells. Once the match is established the rider agent is withdrawn from the system and the origin cell of the rider returns to the empty state from being occupied. Such transition is explained through equation (10) where $\sigma_s(t+1)$ denotes the vacant rider cell in the next instant.

### *1.8 Strategies to define passenger search characteristics*

These strategies are required for the simulation in order to understand the patterns of vehicle movement for different driver behaviour. The initial setup for the simulation will be based on the following strategies which will be updated based on the feedback obtained from survey results. These strategies are formulated for the unoccupied vehicles i.e. for the drivers waiting for passengers based on the theory utilised by Uber for dispatching its vehicles. The strategies are as follows(Voytek, 2014): a) Static, b) Random and c) Movement towards demand gravity. The simulation will also test the combination of these three strategies.

a) Static- In this state, the vehicle will wait for the passenger at a particular location. This location can be specified by the cell where the vehicle became available or the destination location of the trip performed. The simulation will test two strategies under this category, i) Static with threshold limit, ii) Static without threshold limit. The threshold limit, t0, refers to the tolerance level of the driver to receive the next passenger. The zone of tolerance for the driver waiting time would be derived from the survey results. For the first case, the driver starts moving randomly (which will be modelled based on random walk theory) once his waiting time exceeds the threshold limit. For the second scenario, the driver continues to wait for the passenger in the same location until he receives the ride request. The total waiting time for the driver is calculated for both the scenarios and the distance is estimated for the first case. The time and distance so calculated is stored in the database of ridematching agent.

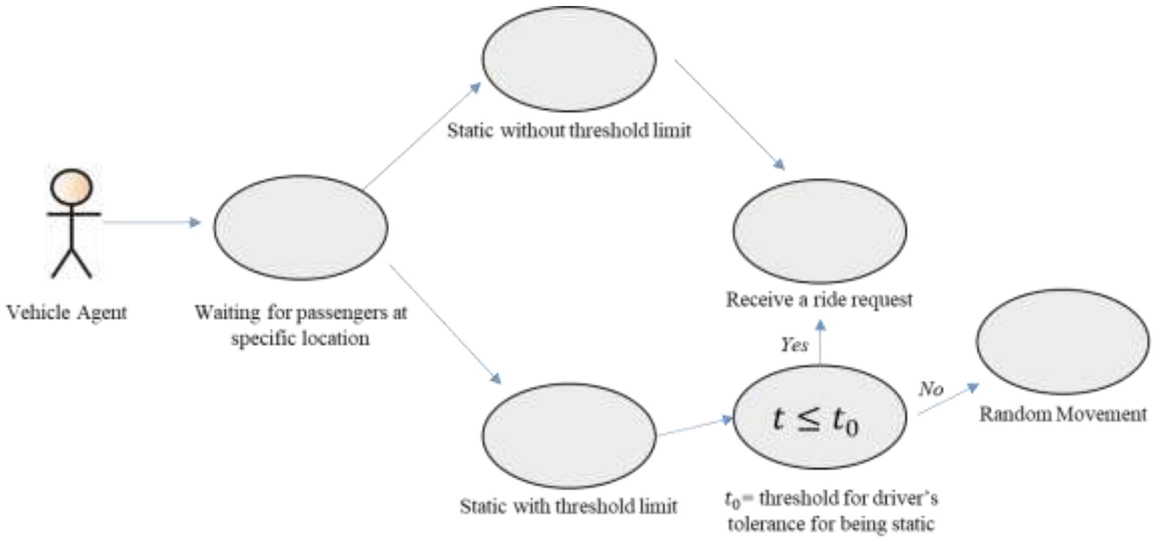


Fig. 2. Use-case diagram to test the stationary strategy for passenger search

b) Random- This state refers to the movement of the vehicles across the system in search of a passenger. This type of randomness is observed in two cases, firstly when vehicle starts looking for passengers once the threshold time limit is exceeded and secondly the vehicles which move around randomly to get a ride without being static. This behaviour can be tested in simulation through random walk theory (RWT). The random movement is terminated as soon as a match is established. The distance and time is estimated through the model and stored in the database of the simulation.

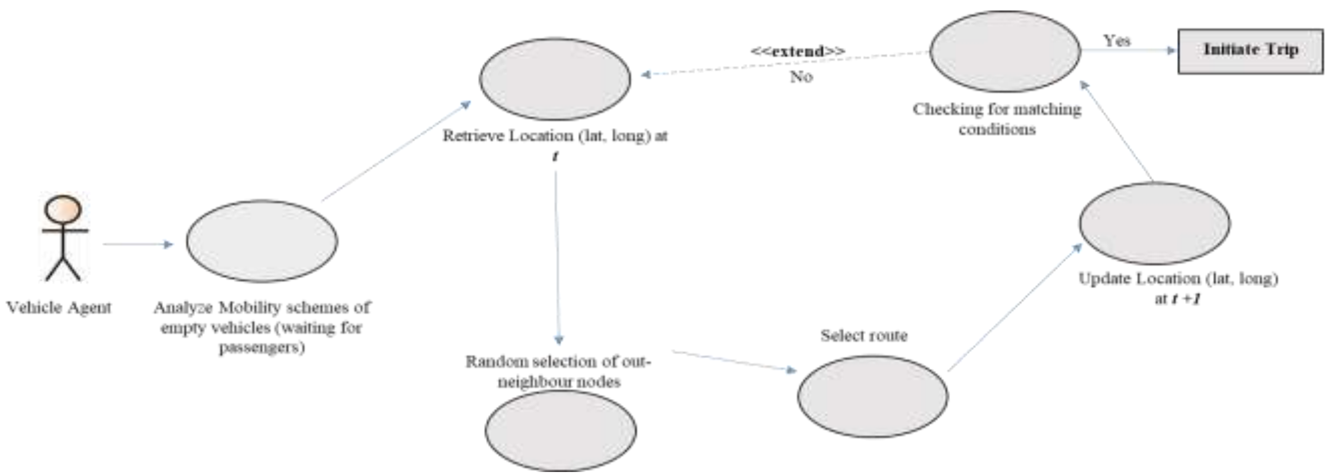


Fig. 3. Use-case diagram of Random Walk Theory to test the random movement strategy

c) Movement towards demand gravity-This state refers to the controlled movement of the vehicles in the neighbourhood. The movement is channelized based on the demand attraction points. The drivers usually drive to certain locations where they expect to get a ride. These locations are the high-demand locations derived from the weighted scores, $W_i$, where, $i \in \{1,2,...,N\}$ and $i$ refers to the index of the TAZ. The cells in the $i$ th TAZ will have the same attraction value. These attraction values will be calculated for certain time intervals. The vehicles will move towards the attraction centroids, $c_0$, within the specified time interval. The attraction centroids will be updated based on the time intervals. An attraction-based algorithm is engaged in the system to estimate the state of the cells and initiate the vehicle movement. The route of the vehicle is selected based on the distance from the attraction centroids. Once the vehicles reaches the cells with high attraction values, they become static and the matching function is initiated. The cells with vehicle agents continue to retain their state unless a match is found. The total time and the distance traversed to the demand gravity is estimated and static waiting time for the vehicles is calculated. This data is updated in the simulation database.

The spatial location of every cell is stored in an $m \times n$ matrix(Khakpour & Rød, 2016). $P_{\varepsilon}^{t}\{idx\}$is estimated randomly based on attraction value at driver cell $A_t V\{idx\}$and $RAND^{t}\{idx\}$is a random binary variable (which checks the matching conditions and is considered to be one when no match is found) that is generated in every iteration(Khakpour & Rød, 2016).

$$P_{\varepsilon}^{t}\{idx\} = (A_t V\{idx\} \times RAND^{t}\{idx\}) \tag{8}$$

whereidx refers to the matrix index of a cell {i,j} in an $m \times n$ matrix. The probability estimated provides the basis for movement of the vehicle towards the attraction centroids. The movement towards such centroids is ensured if there are no available match in the surroundings.The attraction value at driver cell, $A_t V\{idx\}$ is formulated as(Khakpour & Rød, 2016),

$$A_t V\{idx\} = \max\left(\frac{A_1 W_1\{idx\}}{D_1\{idx\}}, \frac{A_2 W_2\{idx\}}{D_2\{idx\}}, \ldots, \frac{A_N W_N\{idx\}}{D_N\{idx\}}\right) \tag{9}$$

where N denotes the total number of attraction points and the attraction weight is calculated for the rider cells which is given by $A_t W_n = \{A_1 W_1, A_2 W_2, \ldots, A_N W_N\}$. $D_i\{idx\}$is given by the Euclidean distance between the attraction points in the rider cells and the occupied driver cell. The weights are generated for each of the TAZ based on the z-score estimated by $G_i^*$ statistic. The attraction value at vehicle cell determines the attraction centroid of rider cell to which the vehicle will move. The route to the attraction centroid is then selected. $P_{\varepsilon}^{t}\{idx\}$is estimated at every step to check for the availability of matches (riders waiting for rides) along the route.

### *1.9 Scenario Evaluation*

The simulation will generate various scenarios based on the strategies discussed above. The evaluation of the scenarios will help to determine the optimal distribution for demand and supply. In order to evaluate the scenarios, it is important to identify the decision variables and the objective function. The decision will be evaluated based on the output generated by the simulation.

Decision variables - The decision variables are the parameters which will affect the results of the simulation. This study has identified the following inputs of the simulation as decision variable, the demand synthesised for the system, $d_0$, the supply synthesised, $s_0$, user waiting time threshold, $T_0$, driver waiting time threshold, $t_0$, permissible working hours, $t_0'$.

Objective Function- The results generated from the simulation is stored in the database in form of four variables, which are, Vehicle Miles Travelled (VMT), Total user waiting time, total driver waiting time (accounts for both moving and static vehicle) and total trips lost. The objective function for this study is given by,

$$\min\left(f_{VMT}, f_{WT_u}, f_{WT_d}, f_{TT}\right) \tag{10}$$

$$f_{VMT} = \sum_i D_i^{Trip} + D_i^{Dead-trip}; f_{WT_u} = \frac{\sum_u^{N_u} WT_u}{N_u}; f_{WT_d} = \frac{\sum_d^{N_d} WT_d}{N_d}; \; f_{TT} = d_0 - \sum_i Trip_i \tag{11}$$

where, $f_{VMT}$ refers to the total VMT,$f_{WT_u}$ denotes the average waiting time of the users, $f_{WT_d}$refers to the average waiting time of the drivers, $f_{TT}$ refers to the total trips lost by the vehicles in the system. The scenarios so formulated by the simulation will be evaluated on the ground to navigate to the appropriate demand-supply combination which provides the minimum optimal values for the above mentioned parameters.

## 4. Conclusion

The ridesourcing services have exhibited an exponential growth since its inception during 2010 till the present days. As these services are expanding their network, ridesourcing services have begun to emerge as an alternative transit option for commuters in metropolitan areas. The pace of growth of this industry suggests that, the next decade would witness expansion in their network with addition of more fleets to the urban road. The most important concern is that the fleets of these services thrive in the urban roads unregulated. This implies that the addition of fleets is unrestricted, a possible situation of monopoly and obstruction in the entry of new players in this market. Moreover, the lucrative services offered by this industry have urged a shift in mode of the choice riders putting forward a challenge for the urban public transit. Such disruption caused by the introduction of this industry has, in turn, challenged the resources of the urban areas. Certain cities of the world have banned these services, but this industry has brought in certain revolutionary ideas which have affected the human travel behavior. So, instead of banning these services, this industry need to be brought under control through well thought out strategies and regulation.

The most important concern among the issues highlighted above is the number of vehicles of these services running on urban roads. Since, there is no restriction in the addition of more fleets, they are most likely to pose challenges in urban road congestion and emission issues raising environmental concerns (Unless electric vehicles are deployed). Apart from the hurdles posed to the urban resources, the addition of fleets can lead to inefficient fleet utilization. The additional mile traveled by an empty vehicle in search of a passenger, disparity in supply distribution to converge to the demand lead to the increment of operational costs. Inefficient fleet management can lead to the increase in passenger waiting time, which in turn, can give rise to passenger dissatisfaction. Hence, it is necessary to decide on the optimum fleet size of these services which will optimise the city level resources and the business interest of the operators.

This simulation will test various strategies of vehicular movement based on the driver behavior identified from the previous studies and from the survey conducted. The challenge of this study is posed by the validation of the simulation. This is because of the availability of open-sourced data of ridesourcing companies. The Perth Uber Company releases certain dataset but it is aggregated to the level of Traffic Analysis Zones (TAZs) giving rise to the modifiable areal unit problem (MAUP). Besides, the dataset from other ridesourcing companies are not available. This makes the validation quite challenging for the simulation this study intends to develop. This study will not consider the pricing and fare strategy of the ridesourcing companies.

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