SMU
SINGAPORE MANAGEMENT UNIVERSITY

IS418: INTELLIGENT BUSINESS GAMING

[G1T1]

Final Report

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Background Introduction

This project aims to simulate the competition between Taxis and Private Hire (PH) companies in Singapore (Grab/Uber) and to determine if Taxi drivers can come out with a better strategy such that they can still be able to compete effectively against Private Hire cars, as well as what the Taxi companies in Singapore can do against the two new entrants in Singapore.

Private Hire industry in Singapore

Private Hire vehicles refer to privately owned or registered cars which offer Taxi-like services, but are subjected to less regulation in comparison to Taxis. One of the key differences between Taxis and PH vehicles is that PH cars are not allowed to pick up passengers off the streets without prior booking. The availability of PH services has allowed commuters to conveniently book a vehicle at a cheaper rate then Taxis via mobile applications, which is often shorter than the time taken via a street hail. Grab claims that its "JustGrab" services save commuters up to 5 minutes off the waiting time for a ride and is cheaper with its dynamic flat fare structure.

Since the entry of Grab in 2012 and Uber in 2013, they have been increasingly eating up the market share for point-to-point transportation services, with commuters being spoilt for choice as they now enjoy a much more convenient and cheaper mode of taxi-like transportation. As of 2017, Transport Minister Khaw Boon Wan mentioned that the Private Hire services have claimed about half of the market, which has doubled since the inceptions of the two Private Hire companies.

With the Taxi companies and drivers becoming increasingly disgruntled with the competition from these two PH companies, there are calls for the government to step in and regulate the industry for a more level playing field. It is therefore interesting to find out whether on an individual and company level what changes can be made to help Taxi companies and drivers better compete, rather than to depend on regulation from the top to enforce fair competition.

Rationale for ABMS

The objective is to determine if the Taxi and PH revenues can be affected with variation in driving or even pricing strategies. The use of ABMS allows for the creation of 3 classes of agents, namely the Taxis, the PH cars and the commuters, with each agent being assigned different attributes. By varying strategies such as pricing or how the drivers drive as well as the environment such as the demand for the services in an area, we can observe how the agents interact differently.

All the agents behave independently at individual level, i.e. a commuter makes his choice of a PH car or Taxi based on his price sensitivity, while an empty PH car might head to a different nearby area depending on the demand. With the different self-interests and motivation of the agents, the introduction of ABMS can provide us with valuable insights on the interaction between the 3 agents and knowledge of the operation of the industry without having to do a real physical experiment.

Literature Review

There is no existing literature on the use of ABMS to handle the problem of our project, but we found two related articles to the use of ABMS relevant to our domain which is mainly about the dispatch system for Uber vehicles as well as to simulate taxi services. On the other hand, our simulation aim to demonstrate the competition between Taxis and PHs, as well as how varying strategies can improve the revenue of Taxi companies and its drivers.

Scope	Article, Author	Findings
Domain	Optimizing a dispatch system using an AI simulation framework, Uber Science Team (2014)[6]	ABMS used to simulate the thousands of drivers/client interactions and behaviors within a city to optimize the dispatch system. Optimizing of dispatch radius, the farthest distance between a passenger and driver where a request will go through.
Domain	Agent based modelling for simulating taxi services, Josep Maria Salonovam Grau and Miquel Angel Estrada Romeu (2015)[7]	Using of ABMS to simulate taxi services in urban areas, by grouping them into aggregated, equilibrium and simulation models to obtain the number of vehicles and performance indicators of taxi services under the dispatching operation mode.
Domain	An Agent-based model to assess the impacts of introducing a shared-taxi system in Lisbon (Portugal), Luis M. Martinez, Goncalo Gorreia, Jose M.Viegas (2012)[8]	Use of ABMS to assess the market potential for the implementation of a new shared taxi service in Portugal. Tests the set of rules of space and time matching to present an algorithm that considers the minimum cost per passenger per km, maximum revenue per vehicle km, minimum vehicle idle time and minimum passenger in-vehicle time.

Model Description

Overview

Commuters are generated every 12 ticks (each tick representing 5 minutes) based on a demand projection obtained from the dataset. The commuters make their decision based on their price sensitivity to determine the allowance they have, which is how much more they are willing to pay over a cheaper PH fare to see if they would choose a PH, a Taxi, or am okay with both.

For the Taxi and PH vehicles, they are normally distributed around the 11 locations based on the numbers specified in each taxi type's slider, and would pick up passengers if they are not occupied. For PH vehicles, they might move to a nearby surge area, if they realize that it is worth their time. For each pickup, the fare is taken added to the revenue for each type (Taxi/PH) to have a performance measure.

On the click of "Go", each empty Taxi/PH will then attempt to pick up a passenger, based on whether a nearby commuter is looking for him, and head to the destination as indicated in that commuter's attributes.

Setup

11 locations are generated to signify the 11 regions in Singapore based on the data set of 87 pickup and drop-off locations obtained. For each location, 3 types of agents are also created upon setup, which are the Taxi vehicles, the PH vehicles and the commuters.

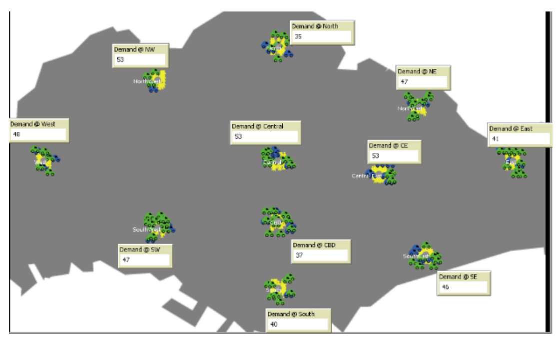


Figure 1: Setup

Proportion of commuters within each region

For the commuters, they represent the demand for the Taxi/PH services and this demand is modelled after the dataset whereby we estimate the demand to be based on the number of trips from each of the 87 location for each hour, which is then mapped to the 11 location in the simulation. For each hour (12 ticks), the summation of trips from the dataset for each pickup location is then expressed as a ratio for each region, and this ratio is then used to calculate how many commuters to generate out of the total number of commuters. This is depicted in Figure 2.

Day	Hour	Region	% of Total	Sum of Tri	ID
1	0	CBD	0.038481	624	10
1	0	Central	0.352923	5723	0
1	0	Central East	0.044524	722	1
1	0	East	0.111063	1801	4
1	0	North	0.035706	579	2
1	0	North East	0.025839	419	8
1	0	North West	0.025345	411	9
1	0	South	0.120067	1947	3
1	0	South East	0.139122	2256	7
1	0	South West	0.075358	1222	6
1	0	West	0.031574	512	5

Figure 2: Ratio of commuters (Demand) for each

Destination of commuters

To determine the destinations of each commuter within each location, the same dataset was used whereby the number of trips ending in the various locations starting from each location was expressed similarly as a ratio. Using this ratio, we can determine the probability of each commuter choosing a destination for every hour, from which we then applied a random distribution based on the probability to assign a destination for each commuter.

Day	Hour	Region	% of Total	Trip Count	ID
1	23	CBD	1.14%	253	10
1	23	Central	23.02%	5121	0
1	23	Central Ea	6.17%	1373	1
1	23	East	11.86%	2638	4
1	23	North	7.36%	1638	2
1	23	North East	7.25%	1612	8
1	23	North We	6.88%	1531	9
1	23	South	8.00%	1781	3
1	23	South East	15.25%	3392	7
1	23	South We	8.17%	1817	6
1	23	West	4.91%	1093	5

Figure 3:Probability of commuter having a destination for each location and hour

Commuters' Decision

For each commuter, the choice of a PH or Taxi depends on their price sensitivity. Based on the estimated distance and time taken computed for each location to another location, we calculate how much would the fare be via a PH or Taxi, using publicly available data. The price sensitivity is used to calculate an allowance, which is how much more a commuter is willing to pay and is calculated as such:

Allowance = Private Fare + (1 – Price Sensitivity) * Max difference between Taxi and PH fare

For each commuter, the choice will be made by comparing the Taxi fare against the PH fare to see if it falls within the allowance. If the difference is within the allowance, the commuter will be okay with either a Taxi or PH, and takes whichever is nearest to him. If it is out of the allowance, then the commuter will only stick with taking a PH car. In the event a Taxi fare is cheaper than a PH fare due to the area experiencing high surge demand for PH, the commuter will then take a normal Taxi.

Figure 4: Fare prices travelling from CBD

Region	Code	Destination	Code	Time Taken	Distance (km)	TaxiFare	PrivateFare	Difference
CBD	10	Central	0	10	4	8.7	6.1	2.6
CBD	10	Central East	1	20	8	13.8	7.2	6.6
CBD	10	East	4	35	15	22	13.1	8.9
CBD	10	North	2	35	15	22	13.1	8.9
CBD	10	North East	8	25	10	16.35	9	7.35
CBD	10	North West	9	25	10	16.35	9	7.35
CBD	10	South	3	20	8	13.8	7.2	6.6
CBD	10	South East	7	20	8	13.8	7.2	6.6
CBD	10	South West	6	35	10	19.25	10.6	8.65
CBD	10	West	5	40	15	23.45	13.9	9.55

PH Drivers’ Decision

Each PH driver who are unoccupied could potentially move to a nearby area with a higher surge pricing, in the hopes of obtaining a higher fare. For example, a PH driver within the CBD location might want to move to any of the 5 locations surrounding him, if he determines it is worth his while, based on the distance he must move. The equation for comparison will be:

Current Surge Multiplier for each nearby location / Distance to location

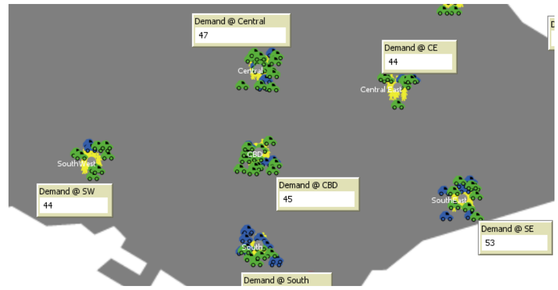


Figure 5: Possible nearby areas a PH driver might move to

For the location that the driver is currently in, we will then then take the current surge multiplier divided by 5, where we assume the radius of that location to be 5km. The driver will then choose to head to another location or stay depending on which location has the highest value.

Model Parameters

The model involves 3 agents, the Taxis, PH cars and commuters, which have their own attributes being assigned.

Global Parameters	
Attributes	**Explanation**
hourHand	Represents the hour of the day, ranges from 0 to 23.
dayCounter	Represents the day which ranges from 1 to 5 (Monday to Friday).
areaDemandFile	Represents the CSV file to determine how much commuters to have in each location every hour.
distanceMapFile	Represents the CSV file which contains the distance and time taken to travel to all the locations for every of the 11 locations in Singapore
locationIds	Ranges from 0 to 10, and is the id of each of the 11 locations in Singapore.
nTaxiRevenues	Used as the performance measure to calculate the revenue of all normal Taxis based on the fares as the Taxis pick up passengers.
pTaxiRevenues	Used as the performance measure to calculate the revenue of all PH cars based on the fares as the PHs pick up passengers.
lastPopByArea	Used to store the
nTaxiSurges	This stores the global surge for all Taxis for each location if they implement a dynamic pricing model.
pTaxiSurges	This stores the surge for all PHs for every location, which is global.
nTaxiBaseRate	Sets the basic rates and charges for Taxis. Base Fare: $3.60, Per KM Charge $0.55, Per Minute Charge $0.29 (Public information)
pTaxiBaseRate	Sets the basic rates and charges for Grab. Base Fare: $2.50, Per KM Charge $0.50, Per Minute Charge $0.16 (Public information)
testCurrentRevenue	Used to calculate the revenue of the test agent (Taxi).
PH Cars	
Attributes	**Explanation**
baseStrat	Stores the distribution of strategies drivers default to if there are no commuters.
multiplier	The multiplier, if any for a PH car after picking up a passenger.
state	The state of the vehicle, which can be “PSG” if a passenger is on board, “DROPPED” if a passenger has just been dropped and “LOOKING” if the PH is on the lookout for a passenger (Unoccupied). If state is “DROPPED”, the PH might move to another area with higher surge.

withPsger?	A Boolean value to determine if a passenger is on board.
currentLoc	The current locationId of the PH.
distTravelled	The distance travelled for the passenger trip, or if it moves to another location.
estFare	The fare paid by the passenger for each trip, based on the distance and time taken to travel to the destination from the CSV file.
locationSegment	Represents the areas a vehicle will keep to if they choose the strategy to keep within a certain region.

Taxi Vehicles	
Attributes	**Explanation**
baseStrat	Stores the distribution of strategies drivers default to if there are no commuters.
multiplier	The multiplier, if any for a PH car after picking up a passenger.
state	The state of the vehicle, which can be "PSG" if a passenger is on board, "DROPPED" if a passenger has just been dropped and "LOOKING" if the Taxi is on the lookout for a passenger (Unoccupied). If state is "DROPPED", the Taxi might move to another area with higher surge if dynamic pricing is on.
withPsger?	A Boolean value to determine if a passenger is on board.
currentLoc	The current locationId of the PH.
distTravelled	The distance travelled for the passenger trip, or if it moves to another location.
estFare	The fare paid by the passenger for each trip, based on the distance and time taken to travel to the destination from the CSV file.
locationSegment	Represents the areas a vehicle will keep to if they choose the strategy to keep within a certain region.
testAgent?	The Boolean value to set one of the Taxi agents as the testAgent for us to test our strategies.
suppStrat	Variation of the strategies for the test (Taxi) agent to try if it would help to perform better.

Commuters	
Attributes	**Explanation**
origin	The locationId of the location where the commuter is picked up.
dest	The locationId of the location where the commuter is dropped off.
urgency	The urgency of the commuter to get to his location.
priceSens	The price sensitivity of the commuter, which will directly affect how much more a commuter is willing to pay when choosing a Taxi or a PH.
pref	The decision or preference of the commuter, which can be both types, only PH or only Taxis.

Methods	
Method Name	**Explanation**
findAreaProp	Determine the proportion of the commuters for a location based on the entire commuters in Singapore, which can be found from the CSV file. This helps in generating the required number of commuters for every location every hour.
generateLocations	Creates all 11 locations during the setup phase.
findSegment	Determines nearest surrounding locations that a driver can possibly head to.
findSurge	Determines the surge for a location if the demand (commuters) is more than the number of Taxis/PH there, which can range from 1 to 2.4x depending on how much more is the demand over supply.
findFare	Calculates the fares for the trip for PH/Taxi based on the estimated distance and time taken.

chooseTaxis	Determines the choice of the commuter for either PH or Taxi, or both. This is based on the price sensitivity and allowance.
moveTaxis	Movements of the PHs/Taxis, where they can be heading towards a passengers' destination, deciding whether to move to a high surge location or moving elsewhere based on the strategy implemented.
balancePopByArea	Based on the commuters to be generated at each location every hour, determines if there is a need to kill of extra commuters, or to generate more commuters to match the projected demand.

Model Results

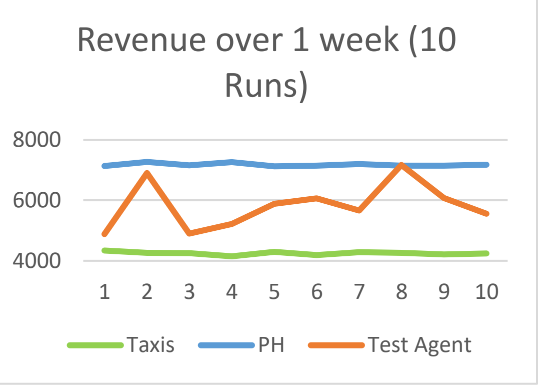
Base Model

The base model shows that with the current situation where the base prices of PHs fares are cheaper than the Taxi fares, commuters would choose PHs over Taxis, and only choose Taxis in regions where there are high surges making Taxis a cheaper alternative. The average revenue of a PH over 1 week for 10 runs is about $7164.85, which is about 67.5% higher than that of an average Taxi's revenue at $4276.64.

PH Revenue	Taxi Revenue	Percentage Difference
$7164.85	$4276.64	67.5%

Drivers' Strategy – Spying on PH Surges

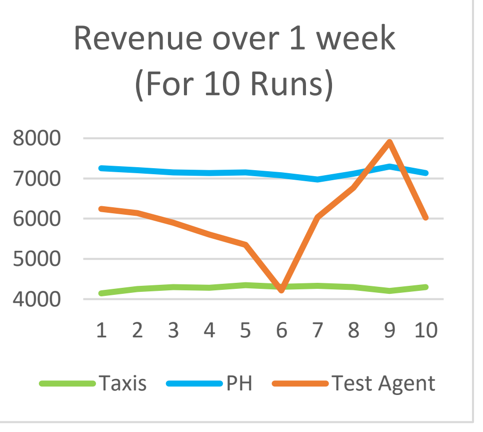
Noticing that the key factor to whether a Taxi or PH is chosen is due to the fare difference and whichever alternative is cheaper, we came out with a strategy whereby a Taxi driver is supposed to "spy" on the various PH platforms and identify areas of high surges. The aim is to head to these areas such that the taxi driver can become the alternative cheaper option instead.



When the test agent implemented the strategy of heading to the nearest highest surge area, his collected fares increased and performed better as compared to a normal taxi driver. This is due to the test agent becoming the cheaper alternative to the higher PH fares in these areas of high surge, and commuters would be trying to hail the Taxis instead of PHs.

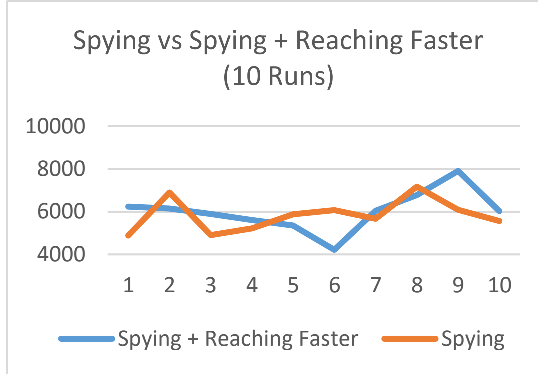
Drivers' Strategy – Getting to high surge areas faster

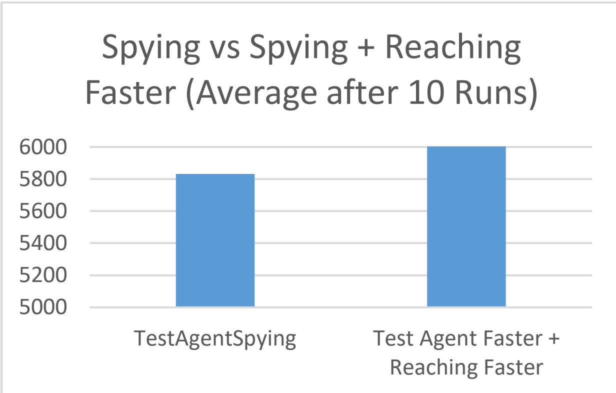
We also noticed in the simulations that surge areas tend to come and go, as PH drivers chase after the high surge areas resulting in the surges dropping drastically once there is enough supply to meet the high demand. As such, we felt that if the Taxi could reach the surge areas faster before it goes back to normal, there is a higher chance of commuters picking them over PHs. As such in this instance we increased the speed of the test agent by 2 times where he has no passenger to simulate him reaching a surge area faster.



We see that overall, the test agent generates higher revenue than before if he moves faster. We also observed that in one instance, the test agent performed slightly worse off than a normal Taxi driver, which we attribute to the destination of the passenger trips made, which resulted in him being unable to reach high surge areas fast enough, especially in areas in the West and East where the surge could be lower than other areas

Comparing the results between the test agent just spying via the PH platform against moving faster so that he can reach the surge area faster, we see that there is a marked improvement in terms of the long run average revenue collected, even though there are still some instances where he might not make as much as without moving faster.

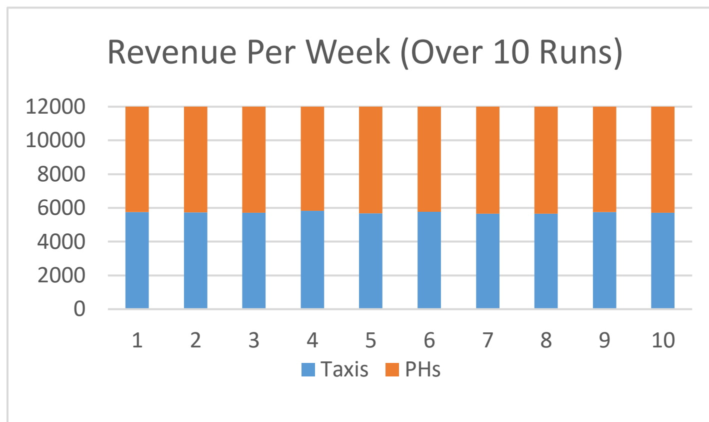




Once again this is attributed to the randomness of the trips made, whereby the passengers picked and the destination they are heading to can make a difference to the proximity to surge areas and the fares collected. Over a 10-instance run, we see that the average revenue is about $190 dollars higher.

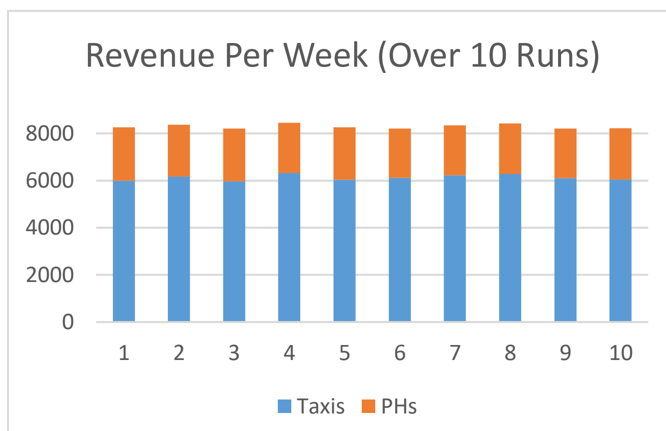
Taxis' Company Strategy – Dynamic Pricing Model

On the company level, one strategy for the taxi companies to be competitive again would be to implement a "tit-for-tat" pricing model whereby they similarly offer dynamic pricing. We observe that right away the Taxis start to increase its market share, with commuters being indifferent to both Taxis and PHs, and would simply take whichever mode of transport available. However we also observe that the Taxis' share is still slightly less than half of the total revenue, and we attribute this to the larger number of fleet size of the Taxis, where the probability of the taxis being in areas of low demand is higher, and meaning a lower occupancy rate as we simulated a normal distribution for the taxis distribution.



Taxis' Company Strategy – Price War

The next strategy would be for Taxis companies to engage in a "price war", whereby it makes some reduction in its base prices, so that it can be competitive in areas experiencing high surges. With this strategy, taxi companies would not need to implement a similar dynamic pricing model, but merely adjust and lower its price such that when areas experience high surges, the Taxis becomes a more viable option instantly.



We observed that the effect of this is the direct opposite of what is happening right now with the dynamic pricing model of PH cars. By reducing its base charges to $3.00 for the base charge, $0.25 for the Charge per Minute and $0.52 for the Charge per KM, it can effectively compete against the dynamic pricing model and gain a huge market share.

Model Validation and Verification

The model is realistic and trustable as it makes use of actual datasets that depicts the pickups and drop-offs of passengers by Taxis to help project the demand, as well as an indication of the probability of the destinations a commuter would head towards to across all hours of the day. The pricing model is based on the actual pricing of Taxis and PHs available publicly. Based on experience as an Uber driver, an average Uber driver will make about $2500 in revenue per week before rental fees, commission and petrol costs, if he drives for 10 hours per day.

The base model figure of an average of about $7000 per week over 10 instances is based on a 24-hour round-the-clock driving, which means that the driver will make about $2900 after prorating. This is a slight higher figure by about 16%, but it is considered accurate as other factors such as traffic conditions, passenger waiting times and breaks are not factored in the simulation, which will bring the figures even closer.

Conclusion

Limitations/Challenges

There are some limitations/challenges for the simulations which prevents the model and recommendations from being completely accurate. The first one would be that traffic conditions are not simulated, which would add to the travelling time and affect a commuter's price sensitivity as he might be urgent to get to somewhere.

Another challenge is that the dynamic pricing models for both Grab and Uber are kept secret, and as such we can only estimate and model a surge pricing model which will affect the fare prices.

Recommendations

1. Taxi Drivers should think out of the box and "spy" on PH's surge prices by downloading its application, so that they can head to these areas and be the cheaper option for commuters.
2. Experience, knowledge of roads and driving ability matters as the sooner a taxi driver can reach a high surge area, the higher his chances are of remaining as the cheaper option and being in demand.
3. For Taxi companies, implementing a tit for tat strategy and developing a dynamic price model can help it regain market share, but this could mean excessively high fares for commuters during peak periods such as the festive season.
4. Taxi companies can also consider changing the fare structure of its current model to reduce it to compete with the dynamic pricing models, which will effectively cancel out the dynamic pricing models when a surge is experienced, but this will mean lower fares for all transport types with commuters being the biggest winners.

Acknowledgements

The team would like to thank Professor Cheng Shih-Fen for his guidance and advice for the project, and in providing the data set for the Taxis' Pickup and Drop-off for the month of September which helped in projecting a more accurate simulation for point to point transportation services in Singapore.

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