Computing Science

TODO TITLE

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TODO FINALISE Honours Project

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1 Introduction

Intro

2 Literature survey

Pricing is seen as a major problem in public transportation. Transport planning and pricing has recently started to investigate microeconomic models based on individual agents, allowing variable pricing to be used thus improving system efficiencies. (Emele et al. 2013; Kaddoura et al. 2013; Neumann and Balmer 2011)

2.1 Taxis

Taxis (also known as *taxicabs*) are an important part of public transportation. Because of their prevalence worldwide and importance in transportation a wide range of literature has been produced on taxis. For this project, the most relevant area of this literature is economical modelling of taxi markets, an overview of which is given by Salanova et al. (2011). A major topic in the research and discussion on taxis is taxi market regulation, and parts of it are relevant and will be considered in some detail. Three different types of taxi markets can be distinguished: cruising taxi market when a passenger hails the taxi on street with visual contact, phone-order taxi market, and taxi ranks where multiple taxis wait for passengers.

2.1.1 Regulation

Regulation is a controversial topic in taxi market research as no consensus has been reached on whether it is recommended. Cairns and Liston-Heyes (1996) investigated economic workings of taxi markets and incorporated results of earlier research in their economic equilibria findings. They concluded that regulation is needed to achieve non- negative profits (the so-called economic second best). OECD (2007), cited by Salanova et al. (2011) listed arguments both for and against regulation as observed in different countries, and noted that markets with widely varying regulation can operate successfully. It is important to note that some markets considered *deregulated* still have some form of fare regulation, for example, taxis in New Zealand are required to list their maximum fares based on time and distance, but are not forced to follow them (Gaunt 1995).

2.1.2 Economic modelling

Taxi market modelling was first done by Douglas (1972), according to Salanova et al. (2011). He investigated a regulated cruising-taxi market and defined the fundamental taxi problem to be finding an equilibrum of an optimal level of service matching an optimal price. His limited model has been used as reference by all the later authors cited by Salanova et al. (2011) that have extended it to other taxi markets and factored in more environmental influences.

De Vany (1975) researched regulated taxi markets organised as a franchised monopoly, using a medallion system, and having free entry. With the goal of finding equilibrium output, capacity and utilisation he suggested a formula tor passenger demand depending on taxi fare, passenger value of time and waiting time. Manski and Wright (1967) analysed the taxi market from a purely economical point of view and conclude that in addition to exogenous variables, passenger demand for taxi services is also directly related to taxi supply through waiting time. Similarly, taxi supply is influenced by taxi utilisation, which in turn directly depends on passenger demand.

The most recent publications in this area are sophisticated models based on the network model for cruising-taxi market by Yang and S. Wong (1998). This network was modelled as a graph and assumed constant taxi demand and supply, passenger demand was represented as origin-destination matrices. Finally, this paper suggested an algorithm to find an equilibrum for the optimal number of taxis in a market and equations to calculate taxi utilisation and customer waiting time.

In contrast, Yang, Lau, et al. (2000) focused on supply and demand to recommend optimal policies for taxi regulation in Hong Kong and based their model on various data sources. A number of exogenous and endogenous variables affecting taxi market were identified, and equations were suggested to calculate them: passenger waiting time, percentage of occupied taxis, vacant taxi headway, number of daily taxi passenger trips and taxi waiting time. This model can be used to forecast taxi demand, taxi utilization and service quality, although the authors warned that it does not take in account all of the complex supply-demand relationships in taxi market.

Consequently Yang, S. C. Wong, and K. Wong (2002) continued to evaluate the supply- demand equilibria of taxi market started by Yang and S. Wong (1998) and Yang, Lau, et al. (2000), resulting in the conclusion that the spatial characteristics of a network where taxis are operating strongly influence supply and demand, and should bear weight when evaluating regulatory policies.This study focused on social surplus (the sum of customer surplus and producer surplus) as the key objective of taxi markets. Four different regulatory frameworks that could be applied to taxi markets were investigated: free entry and unconstrained fare, free entry and regulated fare, regulated entry and unconstrained fare, and regulated entry and regulated fare. All of these cases were investigated with both competitive and monopilistic markets, and equilibria were found.

K. Wong et al. (2008) extended this model to heterogenous vehicle and user classes, and included congestion which is a major issue in reality but was ignored by earlier research. Yang, Fung, et al. (2010) proposed a nonlinear fare structure to correct market and regulatory inefficiencies, and applied it to a similar model.

The way how cruising taxis and customers find each other was researched by Yang, Leung, et al. (2010), paying particular attention to customer behaviour: this study permitted customers to use other modes of transport e.g. public transit or walking to find taxis and/or reach their destinations. However, this study was based on a taxi market with fixed fares. When fares can be negotiated, taxis and customers are likely to do some bargaining over the amount of fare.

Cairns and Liston-Heyes (1996) gives a quick overview of bargaining and its implications in different markets, with customers having more power in taxi rank and phone order markets due to easily available competition, and high costs to search for alternatives in cruising taxi market for both parties resulting in higher willingness to agree. Bargaining of minimal-intelligence agents in competitive markets was investigated and implemented in software by Cli (1997), where a bargaining performance similar to humans was achieved. Rubinstein (1982) described equilibria for a bargaining model where each round of barganing has costs to participants.

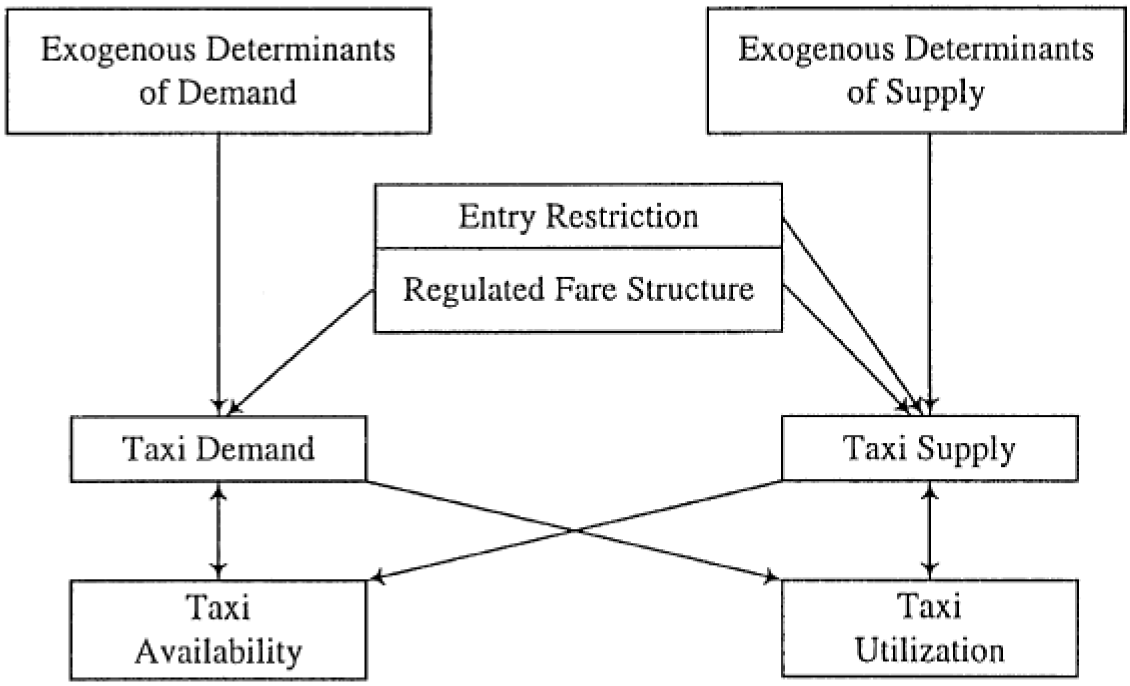

Figure 1: Demand-availibility-utilization-supply relation in a taxi market. **NEED PERMISSION**

2.1.3 Demand and supply

Taxi demand is a part of the total demand for transportation. There are two approaches to modelling demand for public transportation: aggregate and disaggregate. Aggregate models are macroeconomic, while disaggregate models are microeconomic and based on the individual agents in a system. Recently disaggregate models have emerged as the main method of modelling demand, but these models require detailed microeconomic data for a system. Because of difficult processing of the large datasets, applying disaggregate models usually involves some form of aggregation. Customers' value of time (VOT) and value of reliability (VOR) are the most important quantities determining the demand for public transportation, the sum of whom are a customer's total willingness to pay for some trip. Both VOT and VOR derive on customers' characteristics and environment they are in, for example, their income, whether the planned trip is for pleasure or a commute to work, and even the tax rates. Aggregate models using VOT and VOR have been developed as well, although VOR has been researched significantly less. (Small and Verhoef 2007)

Yang, S. C. Wong, and K. Wong (2002) cites Manski and Wright (1967) on the complex structure of demand in taxi markets, shown in Figure 1. Both taxi demand and supply are infulenced by exogenous variables (and regualtion policies, if any). Taxi demand influences taxi availability and vice versa. Similarly, taxi supply influences taxi utilization and vice versa. Taxi demand influences taxi utilization and thus indirectly influences supply, similarly taxi supply influences taxi availability and thus indirectly influences demand.

Customer demand is modelled as a function of waiting time and fare price in many studies:

Douglas (1972), De Vany (1975), Cairns and Liston-Heyes (1996), and Yang, S. C. Wong, and K. Wong (2002) all used customer waiting time as a proxy for service quality. According to Salanova et al. (2011), Manski and Wright (1967) used a Poisson process (a stohastic function) to simulate demand.

Yang, S. C. Wong, and K. Wong (2002) use a disaggregate demand model (separately for each origin-destination pair), where waiting time depends on the number of vacant taxis in an area near the customer and price depends on the distance covered; Yang, Fung, et al. (2010) added travel time as an additional variable indicating service quality and assumed that demand decreases as waiting time increases. Yang, Leung, et al. (2010) took a slightly different approach by modelling customer demand as their willingness to pay to reach a destination, based on their subjective monetary value for using different modes of transport for reaching a destination; therefore the demand for taxis in this study was only a part of the total demand for transportation.

2.2 Reinforcement learning

2.2.1 Basics

Reinforecement learning is software agents being rewarded or punished (receiving negative reward) for their actions so that they can hopefully learn an optimal policy for acting in some environment, maximising the utility of the outcome. Policy is a mapping of actions from any possible state to the highest utility outcome from that state. Thus for each state there is a maximum utility that can be reached. Agents have a set of possible actions that they can take, depending on the state they are. Agents also have a set of rules for what they can observe from the environment. (Russell and Norvig 2010)

Rules for transitioning and rewards

Observation rules

Two types of learning are distinguished: passive and active. This distinction is made for simplicity as the problems that active learning solves is mostly a superset of those of passive learning. Therefore it is reasonable to look at the common issues in isolation while investigating passive learning, and extending the solutions to work with active learning later.

Agent designs: Utility-based agents (model-based), Q-learning agents (model- free), Reflex agents

Three approaches to estimate utilities are developed and tested: direct utility estimation, adaptive dynamic programming and temporal difference. (Russell and Norvig 2010) discusses these approaches and gives the basic algorithms. Initially a perfectly observable passive learning situation is discussed, followed by adapting the same approaches to active learning by introducing exploration in partially observable environments.

2.2.2 Passive learning

Direct utility estimation uses the fact that utility of a state is the expected total reward from that state onward, called the reward-to-go. (Widrow and Hoff, 1960 cited by Russell and Norvig (2010)) After a large number of estimations giving samples for the states, the observed reward-to-go is likely to converge to the actual utility of a state. However, this approach is inefficient, mainly because it ignores that utilities of states are related to each other. (Russell and Norvig 2010)

Adaptive dynamic programming (ADP), unlike direct utility estimation, takes in account the interdependence of utilities of states by learning the transition model that connects them, and uses dynamic programming to solve the corresponding Markov decision process. A Markov decision process is a model of a discrete time stochastic control process: a decision maker (the agent) who is in a certain state can choose an action, and the process will stochastically move to a new state and reward the agent. (Russell and Norvig 2010)

Utility estimates can then be learned by solving this model and there are multiple ways to do it. Modified policy iteration is the simplest, but its results are based on the estimated transition model which may be incorrect. To cater for a range of possible models, Bayesian reinforcement learning and an approach derived from robust control theory are suggested. (Russell and Norvig 2010)

Temporal difference (TD) does not use a transition and therefore is simpler and requires less computation, alas at a price of slower learning. TD works by adjusting the utility estimates based on the differences observed in the last state transition, and over time the *average* utility values converge to the correct values. To ensure that utility values in TD converge to the correct value, visited states can be stored and their repeated impact reduced. (Russell and Norvig 2010)

ADP's efficiency can be improved by using prioritised sweeping heuristic which only takes in account utility transitions that are significantly large. This approximated ADP can learn about as quickly as the basic ADP, but is magnitudes more efficient because it operates on a much smaller state space. (Russell and Norvig 2010)

2.2.3 Active learning

2.2.4 Inductive learning

2.2.5

3 Software and simulation design

This section formalises the simulation based on related work in Section 2 and applying the results to the context of this project. Firstly, models for passengers and taxis are described in Section 3.1. Then Section 3.2 discusses how these models are going to be implemented as software.

3.1 Simulation design

The approach suggested by this project is not compatible with a market where fares are regulated, at least in the current form of regulation that specifies a formula to calculate fares based on some variables, usually time and distance. Other ways of regulation that do not affect pricing, for example, market entry conditions, are compatible with the suggested variable pricing approach.

Three different operational types of taxi markets were introduced in Section 2.1: phone-order market, cruising taxi market and taxi rank market. In the phone-order market and taxi rank customers are actively seeking a taxi, while in the cruising taxi market passengers can only wait for a taxi to drive by. Therefore the cruising taxi market is chosen as the easiest target for simulation, extending it to phone-order and taxi rank markets if the initial experiment is successful.

3.1.1 Competition

The relationship between taxi demand and supply and vice versa was established in Section 2.1.3. This relationship largely depends on the competitive situation in a taxi market. As the simulation initially involves only a single taxi, the competition needs to be replicated by other means. When the simulation is expanded to multiple taxis

3.1.2 Demand: modelling passengers

Customer demand was reviewed in Section 2.1.3 where two approaches to modelling demand were shown: aggregate and disaggregate. An aggregate demand model ”for some portion of the travel market is a function of variables that describe the product or its consumers” (Small and Verhoef 2007) The disaggregate approach specifies a set of variables for each individual passenger. The project goal is investigating taxi pricing on an individual basis, therefore a disaggregate approach is preferrable as it allows individual modelling of passengers. **review this claim!** Of course, to express demand as a single variable it needs to be an aggregation of the relevant individual variables.

Therefore each passenger's demand is a function that of some variables. The different types of variables affecting taxi demand were discussed in Section 2.1.3. Exogenous demand variables are value of time and value of reliability that can be derived from a passenger's income, hour of day when travelling, purpose of travel, social status, cost of waiting and others; these can be modelled for each individual passenger. Taxi availability is a variable directly depending on the number of vacant taxis in an area, this is something that passenger's perceive in reality. However, for the simulation, taxi availability needs to be assumed a constant, at least until machine learning capabilities are added to passengers and a competitive market established beyond the very basic simulation, so that passanger agents can learn the availability on their own.

Let P be the set of the relevant variables $p_1,..,p_n$ for a passenger: $P = \{p_1,..,p_n\}$,
where each $p_i : i \in \{1,..,n\}$ has a function $f_i(p_i)$ that returns a unity-based normalised value of p_i,

and each p_i has a weight w_i representing its relative importance compared to other variables, where $\sum_{i=1}^{n}(w_i) = 1$.
Then demand Q for a taxi ride from origin o to destination d at a fare price F can be expressed as:

$$Q_{o\to d}(P,F) = \sum_{i=1}^{n}(w_i \cdot f_i(p_i)))$$

If Q is greater than a certain threshold, then the passenger accepts the fare, and declines otherwise. This exact threshold **what will it be?**

The relevant variables for passengers can be generated using a stochastic process. Similarly, passenger distribution within the network can be generated using a stochastic process. These processes can take in account some characteristics observed in reality such as demand variance during the day, lower passenger income in some areas resulting in lower willingness to pay, whether a trip is for pleasure or business, and others.

3.1.3 Supply

Let taxis have variable costs VC consisting of driver's wage costs w and fuel expenses f, and a sum of fixed costs FC including e.g. deprecation, insurance, business overheads, lease payments. For simplicity it is assumed that wages are paid for all of the time that a taxi is operating, and a constant amount of fuel costing f is used for a unit of distance covered. Then total taxi costs TC for a total time t and an amount total distance covered d can be expressed as:

$$TC = VC + FC = t \cdot w + d \cdot f + FC$$

3.1.4 The Market

The market is represented as a graph constructed of edges (roads) and vertices (origins/destinations). Each vertex has associated properties: a list of connected edges, a list of passengers, potentially a list of taxiss. Each edge has associated properties: length, potentially speed limit, toll Taxis can travel between vertices using edges. Taxis are assumed to take the shortest routes and travel at a constant speed. Passengers appear at nodes and when taxi is at a node it is assumed that they can interact.

When taxis interact with customers in reality in a market with no fare regulation, bargaining is likely to happen: taxis bid passengers a fare, and passengers can agree with it, or decline it and give a countering bid or abandon the process. Bargaining allows taxis and passengers to agree on a mutually acceptable price, but has a cost (caused by the time used for communication) that can be assumed constant for each bid. To simulate real- world behaviour, the bargaining process will use reinforcement learning as described in Cli (1997).

Behaviour: AI

3.1.5 Benchmark

To evaluate the variable pricing approach, benchmarks measuring taxi profitability need to be established using the linear pricing approach. Market equilibrium demand and fare prices can be calculated from the stochastic processes, and a linear tarriff set and a simulation ran with it.

3.1.6 Data

Data on profitability will be gathered and recorded as simulation progresses. This data will later be used to find environmental conditions where variable pricing is more profitable than a set linear fare and vice versa.

3.2 Software design

4 Implementation and results

5 Evaluation and discussion

6 Conclusion

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