Agent-Driven Variable Pricing in Flexible Rural Transport Services

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Abstract. The fares that passengers are asked to pay for their journey have implications on such things as passenger transport choice, demand, cost recovery and revenue generation for the transport provider. Designing an efficient fare structure is therefore a fundamental problem, which can influence the type of transport options passengers utilise, and may determine whether or not a transport provider makes profit. Fixed pricing mechanisms (e.g., zonal based fares) are rigid and have generally been used to support flexible transport services; however, they do not reflect the cost of provision or quality of service offered. In this paper, we present a novel approach that incorporates variable pricing mechanisms into fare planning for flexible transport services in rural areas. Our model allows intelligent agents to vary the fares that passengers pay for their journeys on the basis of a number of constraints and externalities. We empirically evaluate our approach to demonstrate that variable pricing mechanisms can significantly improve the efficiency of transport systems in general, and rural transport in particular. Furthermore, we show that variable pricing significantly outperforms more rigid fixed price regimes.

Keywords: rural transport, flexible transport, agents, fares, variable pricing.

1 Introduction

There are particular transport challenges in rural areas, which are characterised by limited transport service provision, low population density, sometimes inappropriate and rigid fare structures, and highly uncertain transport demands [1]. The adoption of flexible transport services is seen as a promising option to mitigate some of the challenges faced by travellers in rural areas. Many previous attempts to encourage advances in flexible and demand responsive transport service design in rural areas have been problematic [2]. This is partly, because many flexible transport services in rural areas are standalone, small scale, and offer passengers limited travel options [3].

One important aspect of flexible transport service (FTS) design that appears neglected is the design of appropriate fare structures to facilitate flexible transport provision in rural areas. Public transport fares are well investigated in the economic literature. Many researchers approach them from a macro-economic perspective in terms of elasticities, equilibrium conditions, and marginal cost analyses with a view to deriving qualitative insights (e.g., [4–8]). Glaister and Collings [4] and Nash [9] proposed

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to treat the setting of fares as an optimisation problem, namely, to maximise objectives such as revenue, passenger miles, or social welfare subject to a budget constraint. They also considered issues such as different transport modes, peak and off-peak times, etc.

FTS in rural areas rely on subsidies from Local Authorities in order to be viable for transport providers. A recent review of 48 FTS schemes in England and Wales ([9]) found that in rural areas, 16 out of 25 FTS required more than £5 subsidy per passenger trip. Brake *et al.* [2] note that fare setting is often constrained by the need to make a certain level of revenue, or rather to limit the subsidy payments required. This is a delicate issue since the number of passengers multiplied by the fare will provide the fare-box revenue. The cost side of the equation can present more problems and it is necessary to identify the cost elements of a flexible service – these are normally divided into administrative, capital and operating (including dispatching) costs. Total fare revenue often doesn't even cover drivers wages and the bulk of the revenue to providers comes from subsidy payments. Wright [10] offers a new approach to identify realistic acceptable levels of subsidy for rural transport services which are density-related and therefore flexible in this dimension. However, to date, no work (to our knowledge) has looked at designing a flexible fare structure for rural transport.

In this paper, we argue for a more flexible fare structure, which reflects the quality of service, and the externalities of the environment, and takes into account the characteristics and constraints of the transport provider and/or passenger to more adequately reflect the cost of service provision. Given that fixed pricing mechanisms (for example, zonal based or even flat fares) are rigid and inefficient (in the sense that it is insensitive to factors like quality of service, passenger constraints, etc.), we advocate the use of variable pricing and present a framework that utilises agents to represent the actors in the system. Our model allows intelligent agents to vary the fares that passengers pay for their journeys on the basis of a number of constraints and variables (see Section 3).

In the research presented in this paper, we intend to validate the following hypothesis: utilising variable pricing can significantly improve the performance of rural transport in at least two dimensions, namely: (i) increased number of passenger requests met; and (ii) increased average passenger benefit. This may promote the sustainable implementation of FTS in rural areas, particularly where higher and more predictable demand for transport is desirable.

The remainder of this paper is organised as follows: Section 2 discusses the theoretical background to this work and Section 3 describes our approach. Section 4 reports the results of our empirical evaluation and Section 5 presents discussion and conclusions.

2 Background

Economists and transport researchers have long recognised the need for efficient pricing policy for transport services [5, 6, 11–13]. Irrespective of whether the transport service is provided in a rural or urban context, the level of fares charged should be such that the total revenue earned by a service provider is sufficient to cover the total cost of providing the service and, possibly, some profit. Thus, one of the greatest challenges for transport providers is the design of a fare structure that reconciles the passenger's need for an affordable transport service with the business objectives of the provider. It must be recognised that this is further complicated in rural areas where many services require additional financial support, in the form of subsidies provided by local authorities, in order to return a profit for the transport provider. In general, there are two major pricing categories, namely: (1) Journey-based; and (2) Passenger-based [11].

2.1 Journey-Based Pricing

In journey-based pricing, the fare is determined by the characteristics of the journey (for example, distance travelled, transport mode, time of travel, etc.), and can be broken down into the following categories:

– Flat fare: This system is the simplest and most rigid. All passengers are charged uniform fares irrespective of distance, type of passenger, route, etc.
– Route fare: Here, different routes are charged differently similar to some bus fare models that calculate fares based on approximate route length.
– Zonal fare: In this category, the route or network is divided into zones - with a flat fare set for each zone. A passenger's fare is determined by the number of zones visited by the passenger.
– Distance-based fare: This type of fare applies a price per km travelled. Typically, each network or route is divided into fare stages, with a clearly identifiable boundary point for each stage. The interval between fare stages may be varied to consider different demand characteristics, segments of a route, and different operating costs. Taxi pricing is a variation of this fare, which is based on distance and time, and includes an initial flat minimum fare.

2.2 Passenger-Based Pricing

Passenger-based pricing considers the situation where the fare is influenced by the characteristics of the passenger (for example, income, age, requirements for group travel, etc.). Some social groups that may be entitled to concessionary fares include: (1) Members of the armed forces; (2) Elderly people and pensioners; (3) Unemployed people; (4) Pupils and students; (5) Disabled; (6) Children.

In both journey-based and passenger-based categories, a time-based fare can be implemented to reflect the time of day the journey was undertaken (i.e., peak or off-peak). Usually, fares are higher at peak periods and lower otherwise.

3 Approach

Most prior work on fare planning has adopted fixed pricing because it is easier to implement and manage. In many domains, there is significant evidence about the benefits of flexible pricing mechanisms (e.g., auctions), and it seems counterproductive to ignore it. For example, in many auction applications, researchers have often reported higher revenue for the seller, and in some cases cheaper deals for the buyer [14].

In our setting, the fare planning problem considers a transportation network represented as a directed graph $G = (V, E)$, where the nodes V represent the pickup and drop-off points in the network, while edges E are routes/paths that can be followed to complete a journey from one node to another. We define a relation $D : V \times V$ of *origin-destination pairs* (OD-pairs) representing possible journeys within the system. Further, we define a path, $P_{o \to d}$ as a set of routes that link nodes o and d in the network such that an agent can travel from o to d. We assume that there is at least one path (i.e., $P_{o \to d} \neq \emptyset$) through the network that transport providers can follow when transporting a passenger between each OD-pair (o, d). We utilise A-star algorithm [15] to generate the shortest path, and we assume that transport providers will follow the optimal shortest path covering requested pick-up and drop-off points between any two nodes in the network. Furthermore, we consider n nonnegative fare variables $x_1, \cdots, x_n$, which is used to determine what the fare for each journey is. Examples of fare variables include: the driver's hourly pay, the distance to be travelled to pickup and drop-off the passenger, time of travel (peak or off-peak), discount for sharing the vehicle with another passenger, and so on.

In our approach, *variable pricing* is defined as the use of both journey and passenger characteristics/constraints to determine the fare to be charged for a journey. Such characteristics may include distance, time of the trip, passenger preferences and requirements, other operator variables such as vehicle occupancy, vehicle operating cost, and so on, whereas *fixed pricing* uses flat, route-based, zone-based or distance-based fares, which is generally based on the approximate route length, time of day and passenger type (in terms of concessionary fares).

Let $\mathcal{A}$ be the set of transport providers. A fare vector is a vector $x \in \mathbb{R}^n_+$ containing the fare variables. We define our fare function as follows:

Definition 1. *The fare function is given as* $\mathcal{F}^a_{o \to d} : \mathbb{R}^n_+ \to \mathbb{R}_+$ *for each OD-pair* $(o, d) \in D$ *and each transport provider* $a \in \mathcal{A}$ *such that*

$$\mathcal{F}^a_{o \to d}(x) = \sum_{i=1..n} x_i . k_i \tag{1}$$

where k_i *is the weighting for each variable (and we assume linearity).*

The fare function $\mathcal{F}^a_{o \to d}(x)$ determines the fare that a passenger will pay for travelling with transport provider a from o to d depending on the constituents of the fare vector x.

Table 1. A table showing some of the variables in the fare vector

Hourly wage (£)	Distance (miles)	Time of travel	$\cdots$	Occupancy
5.50	5.7	off-peak	...	single
6.00	7.2	peak	...	shared
5.80	3.6	off-peak	...	single
7.55	6.4	off-peak	...	shared
...	...	...	...	...
5.85	9.3	off-peak	...	shared

3.1 Preferences and Requirements

We consider a finite set C of travel constraints that passengers possess. These constraints may be *hard constraints* or *soft constraints*. Hard constraints are requirements, which must be met for a given passenger to travel. For example, a *wheelchair* user needs a vehicle that is *wheelchair-friendly*. Another passenger may require assistance to move and so may need an escort in order to travel – that is a hard constraint. Yet another hard constraint may be in the form of an upper limit for a given journey (which we refer to as a *threshold*) beyond which a passenger would rather not travel. On the other hand, soft constraints can be conceived as preferences that passengers express regarding their journeys. Examples of journey attributes that passengers may express preferences about include (i) single or shared vehicle occupancy; (ii) number of changes; (iii) overall journey time, and so on. The hard constraints help to shortlist the transport providers that have the capability and capacity to provide the services requested by the passenger. In other words, it helps to filter who may be approached for a bid to deliver on the passenger's request. Similarly, soft constraints aid decision making with regards to which transport provider to select for the journey. We present the following definition.

Definition 2. *Given a set of soft constraints, S, we define a preference ordering $\succ$ on S such that $x \succ y$ means that x is preferred to y, where $x, y \in S$.*

3.2 Contract Net Protocol

We utilise the Contract Net Protocol (CNP) to support the interaction between distributed agents (passengers and transport providers - see Section 4) engaging in automated negotiation through the use of agreements called contracts. The protocol enables tasks to be distributed among a collection of agents [16]. The Contract Net allows the creation of an electronic marketplace to support buying and selling. An underlying assumption in this protocol is that agents are self-interested and will act in their best interests. However, this means that the final solution may not necessarily be globally optimal. In a CNP setting, a passenger could specify the journey they want to make together with any hard and soft constraints they may have. Such constraints could include pricing limits, seating preferences and the like. In general, the interaction protocol for CNP involves five steps, which agents must go through to conclude each contract:

1. The initiating agent sends out a request to a broker (see Section 4 for details).
2. The broker sends out a Call for Proposals (CFPs).
3. Each participating agent reviews the CFP and sends in a bid, if feasible.
4. The broker then chooses the best bid (using some utility metric) and awards the task to the chosen agent.
5. The broker rejects the other bids.

3.3 Bids

Each passenger sends his/her request to the marketplace agent (see Figure 1) who then sends out a call for bids to all registered transport providers taking into account the requirements of the passenger (e.g., assistance to get on/off vehicles is required for the journey). Interested transport providers will send in their bids to the marketplace agent. It is worth noting that transport providers may have made certain information on those service characteristics, constraints and limitations they can influence (e.g., eligibility criteria, vehicle capacity, price structure, locations covered and boundaries) available to the marketplace agent during registration. Such information does not constitute a bid because it does not specify real-time availabilities of such service nor does it constitute a commitment to make the required resources available when requested. However, such information could be utilised by the marketplace agent in shortlisting the provider agents to approach for a bid. The bid may specify things like tentative pickup (and drop-off) time (or window), the route, the journey time, cost (if appropriate), and so on.

Definition 3. *A passenger's request $\mathcal{R}$ is a tuple $\langle D, T_p, T_d, H, S\rangle$, where D is an OD-pair (o, d), T_p is the pickup time, T_d is the drop-off time, and H and S are hard and soft constraints respectively.*

For example, a passenger may send the following request: $\langle$*(Peterhead, Fraserburgh), 08.30, 11.00,* $\{\}$, $\{$*Cost of journey* $\succ$ *Overall journey time*$\}\rangle$.

Definition 4. *A bid $\mathcal{B}$ is a tuple $\langle D, T_{ap}, T_{ad}, \mathcal{F}^a_{o\to d}, O\rangle$, where D is an OD-pair (o, d), T_{ap} is an approximate pickup time, T_{ad} is an approximate drop-off time, $\mathcal{F}^a_{o\to d}$ is the fare for the journey, and O is the set of other details about the journey (e.g., whether or not the vehicle would be shared with others).*

For example, a transport provider may return the following bid: $\langle$*(Peterhead, Fraserburgh), 09.35, 10.50, 12.60,* $\{$*single*$\}\rangle$.

The bidding system can be instrumented to support the automation of the bidding process such that the level of information provided initially by transport providers on service design characteristics, eligibility criteria and preferences can be utilised to enable bids to be automatically generated by transport providers.

3.4 Utility of Bids

After transport providers send bids in response to the call for bids (see Figure 1) then the marketplace agent computes the *utility score* of each bid received (in terms of how closely it matches the request of the passenger) while taking into account the preferences and requirements of the passenger. In computing the *utility score*, the marketplace agent utilises the following function:

Definition 5. *The utility score of a bid is given as $\mathcal{U}_{o\to d} : \mathcal{R} \times \mathcal{B}_a \to \mathbb{R}$ such that OD-pair $(o, d) \in D$, and transport provider $a \in \mathcal{A}$ responded to a request $\mathcal{R}$ from a given passenger with a bid $\mathcal{B}_a$.*

3.5 Passengers' Provider Choice

This aspect of the bidding process allows the passenger to decide which of the available transport options best meet his needs and preferences. There might be scenarios where the passenger may be willing to stick to certain aspects of the service that are most

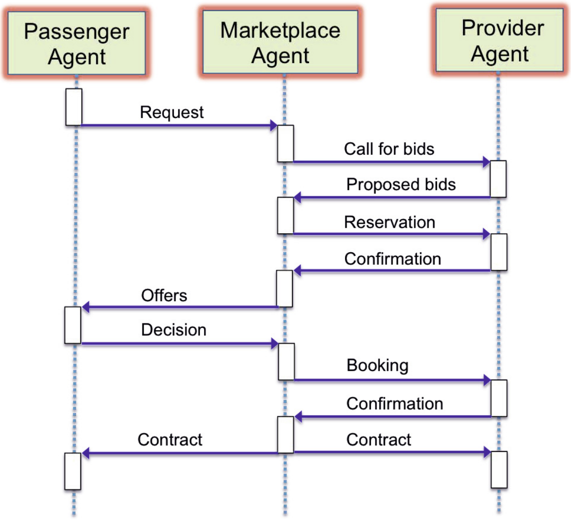

Fig. 1. Contract Net Protocol (CNP)

important to him, and some other times where he is willing to make compromises based on the options available. In the initial request, a passenger might have stated that the cost of the journey is more important to them than the overall journey time. However, if there is little difference in price but a huge difference in drop-off times then a passenger may want to temporarily relax his preference for cost and, therefore, choose the slightly more expensive journey with shorter overall journey time. For example, suppose passenger *P1*'s request for transport service is as follows:

– Origin: x
– Destination: y
– Pickup time: 7.00
– Drop-off time: 12.00
– Hard Constraints: None
– Soft Constraints: cost of journey $\succ$ overall journey time $\succ$ window seat

Let us assume that the following bids from transport providers *T1* and *T2* (respectively) were shortlisted.

– **Bid 1:** *T1* offers to pickup passenger *P1* from x at about 10.00 and drop-off at y at about 11.35, window seat is available, and the fare will be £20.10, while
– **Bid 2:** *T2* offers to pickup passenger *P1* from x at about 8.30 and drop-off at y at about 11.05, no window seat is available, and the fare will be £15.80.

In real life scenarios, some passengers may prefer Bid 1 over Bid 2, while some others may prefer Bid 2 over Bid 1. The decision to choose one over the other lies with the passenger, and can be simulated using a number of heuristics. In our implementation, we assume that passengers will stick to their preferences for that journey and will choose the option that best suits their specified preferences, irrespective of whether there is another option that is similar or may be better in some other respects. Thus, in our system passenger *P1* will select Bid 2 if the threshold set by *P1* for that journey is not less than £15.80.

4 Evaluation

In order to evaluate our approach, we developed a simulated flexible transport system where a set of passenger agents interact with a set of transport provider agents in a marketplace. The interactions are mediated by a brokering agent (called the marketplace agent). The rest of this section will present our system architecture, describe the experimental setup and report initial results of our empirical evaluation.

4.1 System Architecture

The framework developed to evaluate the ideas in this paper (illustrated in Figure 2) is a multi-agent system involving passengers ("*P agents*"), transport providers ("*T agents*"), and a marketplace agent ("*M agent*"), which acts as a broker in the system. The framework enables passengers to send their transport requests to a broker who then sends out a call for bids and transport providers can assess these requests and send in bids.

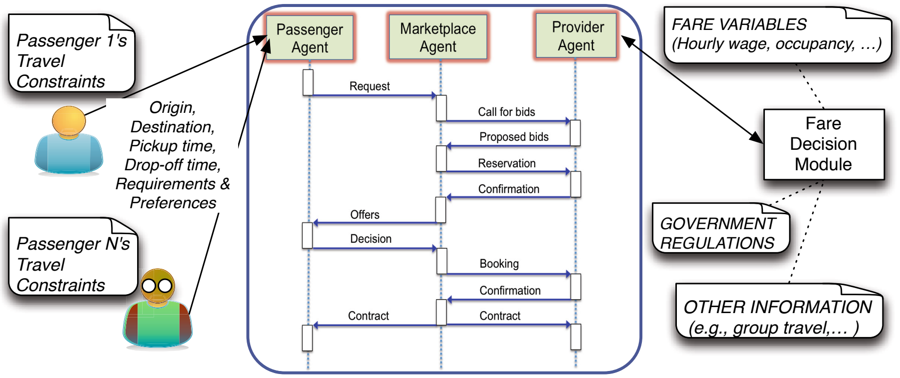

Fig. 2. System Architecture

P agents: In our system, these agents are provided with a map (i.e., a directed graph with nodes and edges that link the nodes) and a built-in journey generator, which generates feasible journeys for passengers. For example, each journey generated must lie within the map and the *origin* must not be the same as the *destination*. A number of other checks are made, such as the difference in time between pickup and drop-off cannot be less than the time it will take to travel at constant speed limit between the two points on the map. For example, if the distance by road connecting points x and y is 20 miles and the speed limit for that road is 30*mph* then the difference between pickup and drop-off times for any journey going from x to y is not allowed to be less than 40 mins.

Each *P agent* has a number of constraints for each journey generated. The journey details and the preferences/requirements form passengers' travel constraints and they are communicated to the *M agent* in the form of a request for transport.

M agent: This agent mediates between *P agents* and *T agents*. When *M agent* receives requests from *P agents*, it sends out a call for bids to *T agents*. When *T agents* send in their bids, the *M agent* computes the *utility score* of each bid and those that exceed a certain *threshold* are shortlisted for reservation. The *utility score* is used to determine how closely a bid matches a passenger's request. The *M agent* then sends shortlisted bids to the *P agent* to choose from. Upon receipt of a decision from a given *P agent*, the *M agent* confirms the reservation that has been selected with the *T agent*. Thereafter, a contract is created between that *P agent* and the appropriate *T agent*.

T agents: When a call for bids is received, *T agents* check whether they can fit the request into their current schedule. If yes, then they send in a bid. A bid contains the fare to be paid for the journey, approximate pickup and drop-off times, and so on. In order to compute the fare for a journey, *T agents* have built-in fare generator called a *fare decision module* (see Figure 2). The fare decision module takes as input a number of fare variables (such as occupancy, hourly wage, etc.) and other information (for example, traffic information) and recommends a fare that the transport provider should charge the passenger for the journey. Based on availability, current commitments and traffic information (or time of travel), *T agents* can generate approximate pickup and drop-off times for each request they receive.

Shared Occupancy Negotiation. When a *T agent*, say *T1*, already has at least a passenger (*P1*) on board but receives a new call for bids for a journey that can be shared in part (or whole) with the current journey *T1* engages in a negotiation with *P1* regarding changes in the journey plan. *T1* may want to negotiate about pickup and drop-off times, as well as a discount in the fare for sharing the vehicle/journey with another (potential) passenger (*P2*). At the end of the negotiation if *T1* and *P1* come to an agreement then *T1* sends a bid to the *M agent*. If *T1*'s bid is shortlisted and then chosen by the new passenger, then a new contract is established between *T1* and *P1*. In the same vein, a contract is then established between *T1* and *P2*.

4.2 Experimental Setup

In evaluating the contributions of our approach, we test the following hypothesis:

> *Hypothesis:* Utilising *variable pricing* can significantly allow more passenger requests to be met as well as increase the average passenger benefit when compared to *fixed pricing*.

In our experimental scenario, there are 5 passengers that wish to travel from different points on the map to another. We have 32 flexible transport providers in the system who can carry passengers from any point on the map to another. Each transport vehicle can carry up to 5 passengers (i.e., capacity).

We consider two experimental conditions, namely: Fixed Pricing and Variable Pricing. The operating cost for each transport provider is fixed throughout the experiment, and is set at $5 \leq y \leq 10$. In order to simplify the computation, we assume that the price of fuel (be it diesel or petrol) is identical and all vehicle have the same fuel consumption rate. We also assume that fuel consumption depends only on distance travelled and the journey time such that the cost of fuel for a journey can be computed as $C_F = d \times k_d + t \times k_t$, where C_F is the cost of fuel, d and t are distance and time respectively while k_d and k_t are their respective weightings.

We conducted 10 runs of the experiment, and in each run each of the five passengers randomly generates 10 (feasible) journeys sequentially (every 30 minutes) and seeks transport options to use in making the journeys. For each journey generated, a *threshold* (i.e., upper limit) is also generated. In total, each passenger generates 100 journeys throughout the experiment. In the *variable pricing* scenario, each of the 32 providers receives the call for bids for each of the passengers' journey requests. In the *fixed pricing* scenario, providers utilise distance-based pricing and so the fare that a passenger pays is determined by how many zones they travel across and the time of day.

4.3 Results

Figure 3 illustrates the performance of the two *pricing* categories that we considered in this paper. The results show that *variable pricing* constantly outperforms the *fixed pricing* approach throughout the experiment. The total number of passenger requests met by transport providers in *variable pricing* scenarios was consistently and significantly higher than those recorded in *fixed pricing*. For example, in the sixth run of the experiment, while the total number of requests met by transport providers that utilised *variable pricing* was 47, the value recorded by their counterparts was about 41. It is worth noting that in as few as 50 journeys (since each of 5 passengers generate 10 journeys per experiment) there is a significant difference in the total number of journey requests met in the two scenarios. The reason for this is simply because *variable pricing* allows more passenger requests to be met because there is flexibility in providers meeting passenger thresholds when setting the fares - this is not possible in fixed pricing.

Furthermore, in Figure 3 we plot the average passenger fare per journey in the two experimental conditions. Results show that, as expected, the average passenger fare recorded by *variable pricing* was consistently and significantly lower than that recorded using *fixed pricing* approach. For instance, in the sixth run of the experiment, the average passenger fare dropped to as low as 12.00 as compared to 13.40 recorded by *fixed pricing*. Again, the reason for this is simply because using variable pricing enables providers to adapt the fares to reflect the externalities and characteristics of the journey.

Tests of significance were applied to the results of our evaluation, and they were found to be statistically significant by *t*-test with $p < 0.05$. Overall, scenarios where *variable pricing* was used consistently yielded higher total revenue for transport providers as well as lower average passenger fare. These results confirm our hypothesis that exploiting *variable pricing* means that the average cost of travel to passengers can be significantly reduced while providers have the potential to meet more passenger requests.

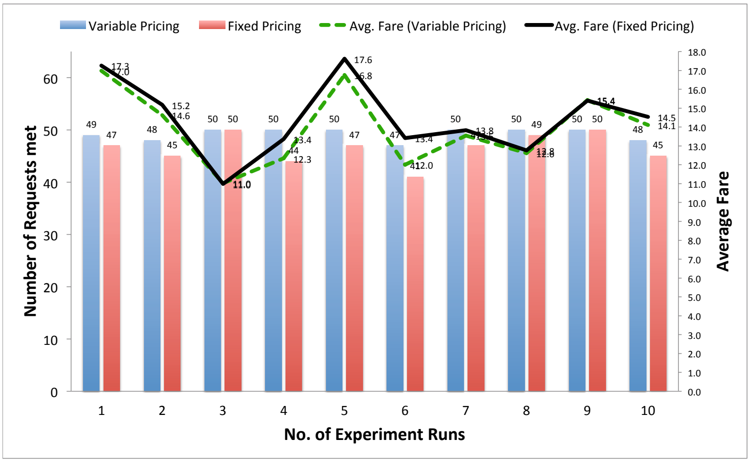

Fig. 3. Variable pricing vs. Fixed pricing

5 Discussion and Conclusions

This work has advocated for a variable pricing approach, and has shown some of the potential benefits. In Section 3, we discussed one possible way in which passengers' requests can be matched with bids from transport providers – utility assessment. Utilising utility assessment of bids (i.e., *utility score*) means that the platform can accommodate free and discounted travel entitlements since the utility function can assess other variables such as time of travel, pickup and drop-off times, number of changes, etc., which could be computed to give a utility score. In the same vein, in many cases where fares are regulated (distance-based or stage-based fare structure) and are not negotiable, utilising bid utility assessment is useful. Interestingly, in regimes that allow for variable pricing the utility function can be instrumented to allow the bidding system to be free and fair by employing a second-price sealed bid auction [17], which encourages bidders to bid their true values. In a second-price sealed bid auction, each bidder submits a sealed bid to the marketplace agent and the highest bidder wins but pays the amount offered by the second-highest bidder.

As future work, we plan to extend the framework to allow the integration of different modes of transport. Furthermore, we plan to investigate opportunistic seat sharing (e.g., going slightly out of ones way to pick up an additional passenger), and enable providers to place requests on the market place in order to further optimise their service provision.

In conlusion, we have explored in this paper mechanisms for variable pricing in rural transport where transport providers can present bids to passengers' transport requests. The question addressed in this research is how may we utilise variable pricing in the rural context? In an attempt to answer this question, we propose a virtual transport market scenario, which utilises CNP to enable transport providers to bid for transport requests that they intend to deliver on. We have empirically evaluated our approach and the results of our investigations show that exploiting *variable pricing* means that the average cost of travel to passengers can be significantly reduced while transport providers have the potential to meet more passenger requests. We believe that the research reported here will provide useful insight into numerous issues regarding optimising flexible transport services in rural areas.

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