Road Traffic Optimisation Using an Evolutionary Game

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ABSTRACT

In a commuting scenario, drivers expect to arrive at their destinations on time. Drivers have an expectation as to how long it will take to reach the destination. To this end, drivers make independent decisions regarding the routes they take. Independent decision-making is uncoordinated and unlikely to lead to a balanced usage of the road network. However, a well-balanced traffic situation is in the best interest of all drivers, as it minimises their travel times on average over time. This study investigates the possibility of using an Evolutionary Game, Minority Game (MG), to achieve a balanced usage of a road network through independent decisions made by drivers assisted by the MG algorithm. The experimental results show that this simple gametheoretic approach can achieve a near-optimal distribution of traffic in a network. An optimal distribution can be assumed to lead to equitable travel times which are close to the possible minimum considering the number of cars in the network.

Categories and Subject Descriptors

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence – *Multi-agent Systems*.

General Terms

Algorithms

Keywords

Evolutionary game, Game theory, Multi-agent system, Traffic Assignment, Road Traffic Optimisation.

1. INTRODUCTION

The primary concern of a driver in a road network is to reach the destination. A driver's choice of a route from the origin to the destination is independent of other drivers' choices. The choices of the drivers cause the traffic flow on the roads.

Traffic Assignment (TA) concerns itself with the route choices of the drivers between their origin-destination (OD) pairs. TA results in a distribution of the cars on the roads. A distribution of cars in proportion to the capacities of the roads can be regarded as an equilibrium which is fair on all participating drivers.

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During normal office hour commuting, drivers expect to reach the destination on time. Based on experience, the drivers usually have realistic expectations how long the trip will take at the time of the day the commute regularly takes place. If a driver reaches the destination within the expected time, we consider the travel time reasonable. If drivers of the same OD pair experience similar travel times when travelling at roughly the same time, we consider the drivers' travel times as fair.

Researchers have attempted to help drivers minimise their travel times by providing real time traffic information to the drivers [3, 9, 11, 16], as well as by allowing communication with other drivers [18]. Both approaches are based on unrealistic assumptions as using available technology, traffic information will always be incomplete and drivers cannot cooperate with all other parties involved.

Also Braess' Paradox showed that increasing capacity of roads or adding a new road to the road network may have adverse effect on individual travel time [5, 13, 15]. Routing games have also been introduced [14] but these are mainly based on the assumption that each driver possesses all essential information about the traffic situation which places it beyond the scope of this paper.

Again, as the drivers are independent entities and their decisions affect each other, researchers have also attempted to solve the TA with game theoretic models [7]. However, the presence of a traffic controller added significantly to the complexity of the approach which was based on modelling the interaction between the traffic controller and the traffic on the roads. Our aim is to simplify the system by not involving the traffic controller.

In this study, we propose a method based on simple evolutionary game theoretic model, named Minority Game [6], which will not require communication among the drivers and will not use real-time information, only past experience on the chosen routes by the drivers. By avoiding the requirement of real-time information, our proposed approach will be significantly simpler than the approaches which use real-time information provided by Advanced Traveller Information System (ATIS) devices. Moreover, our approach ensures reasonable and fair travel times to the drivers as well as distributes the cars on the road network near-optimally.

2. TRAFFIC ASSIGNMENT

2.1 **Problem Description**

A road network can be represented as a set of nodes (origins, destinations, intersections) and links between the nodes. There are costs associated with the links such as travel time, monetary cost, and distance. A chain of links is referred to as a route. Each traveller who is travelling on a road network from an origin to a destination (known

as 'OD pair') typically has some alternative routes to choose from. Travellers who travel from an origin to a destination have their own preferences which guide their choices of a route. Travellers cause the traffic flow on the road network.

The selection of a route for an OD pair is known as traffic assignment (TA). TA is the cause of the distribution of traffic on the road network. To find out an optimal distribution of traffic on the road network is the Traffic Assignment Problem (TAP).

A common behavioural assumption is that drivers choose the route between an OD pair according to the principle of minimum travel time [8]. As there are other drivers on the routes, the travel time between an OD pair depends on the choices of these other drivers who also aim to minimise their travel time. When all drivers succeed in choosing the optimal route which minimises their travel times, this is referred to as Equilibrium or User Equilibrium or Wardrop's Equilibrium [17]. According to Wardrop's first principle, no travellers can reduce their travel time by choosing other routes between their OD pairs at equilibrium [17]. To reach the equilibrium, all travellers would have to know the perfect travel times throughout the road-network [8]. However, the assumption of perfect information is unrealistic.

The drivers on the road are independent entities who make decisions usually without communication with other drivers. Each driver's decision has an effect on the traffic flow and thus on others' decisions. Hence, the Traffic Assignment Problem (TAP) can be viewed as a game-theoretic problem [7] where choices affect each other. The drivers are independent; they share limited information and try to minimise their travel time and thus, inadvertently, to form the equilibrium. Achieving the equilibrium is not a trivial task. Nonetheless, Challet and Zhang showed that their Minority Game (MG) model can achieve an equilibrium among agents by self-organisation [6]. Their MG model is simple to implement and the system characteristic is very similar to the road traffic characteristic. This suggests that the MG might be well suited for solving the Traffic Assignment Problem.

MG was introduced to simplify Arthur's [2] El-Farol bar problem. However, the original MG formulation is not sufficient to solve the TAP. Therefore, in this work an extension of MG and a variation of El-Farol bar problem is integrated and proposed as an approach to solve the TAP. This hybrid approach ensures a reasonable travel time for the travellers and a near-optimal distribution of cars on the road network.

2.2 Previous Approaches to TA

All-or-nothing and multipath or stochastic proportional approaches are two traditional TA techniques where congestion was not considered [12]. Hence, these approaches are not entirely realistic. Chen and Ben-Akiva attempted to achieve the system-optimal distribution as well as the minimum total travel time for all drivers by applying their game theoretic formulation [7].

Bazzan and Klugl investigated the behaviour of agents under the effect of real-time information and thus how the agents change their route mid-way [3]. Precise information about the travel time on the routes may improve the network flow negligibly if the drivers repeatedly make route choices from the same origin to the same destination on the same road network around the same time of the day [11].

Providing real-time information to the drivers has some drawbacks. If the drivers do not have perfect information, their travel time may increase compared to those having perfect information [1]. The quality of the information provided to the drivers affects the choice of the drivers [10]. Moreover, the drivers tend to ignore the information if they are informed regularly or they tend to concentrate on certain roads if they are informed about congestion on other roads [4]. Providing information to the drivers is not an easy task and ensuring the quality of the information so that it is of use to the drivers is complicated.

Zhu et al proposed an agent based route choice model where nodes, links and travellers are modelled as agents [18]. The agents communicate with each other to share information and finally, the traveller agents choose their routes. A model where independent entities can take decisions without communication and coordination through self-organisation may be applicable to the traffic domain. Challet and Zhang's Minority Game model [6] is one such approach where coordination among the agents occurs through selforganisation with minimal information and without communication among the agents.

3. MINORITY GAME

Minority Game (MG) was introduced to simplify Arthur's El Farol bar problem. Arthur formulated El Farol Bar Problem as an inductive reasoning and bounded rationality problem [2] and defined it as follows. N agents decide independently and without any communication, each week, whether to go to the bar which has a fixed capacity. If the number of attendants exceeds the capacity, patrons do not enjoy themselves.

Each agent has predictors which map the history of past attendances to a prediction. The agents whose preferred predictors anticipate the attendance would not exceed the capacity go to the bar, all others stay at home. Thus, there are two possible actions for each agent: 'go to the bar' or 'stay at home'. The agents rank their predictors by evaluating the predictions after each decision. If a predictor predicts correctly for an agent, that predictor scores a point regardless of whether it was used to make the decision. To make a decision, an agent uses the preferred predictor which is the predictor having the highest score.

To predict the exact number of attendants using the past *m* days' history, the length of each predictor would have to be N^m which is a rather large number even for a moderate *N* (see table 1 for an illustration). In order to simplify Arthus' El Farol Bar problem, Challet and Zhang introduced Minority Game (MG) [6]. MG was defined as follows. An odd number, *N*, agents repeatedly take an action, either +1 for going to the bar or -1 for staying at home (figure 1). The agents on the minority side win. In the simplest version, all winners gain a point.



Figure 1. A set up of Minority Game for N agents with m = 3.

The previous winning decisions form the history. If the agents taking decision +1 were in the minority last time, the history will be +1. Thus the history can be denoted as a binary sequence. The agents are provided with the common history of last m winning sides. Each agent has a finite number of predictors which map the action +1 or -1 to the next time step based on the m-bit history. Table 1 shows an example of 3 predictors for m = 3.

History			Predictor 1	Predictor 2	Predictor 3
-1	-1	-1	+1	+1	-1
-1	-1	+1	+1	+1	-1
-1	+1	-1	-1	+1	-1
-1	+1	+1	+1	+1	-1
+1	-1	-1	-1	-1	+1
+1	-1	+1	+1	+1	+1
+1	+1	-1	-1	-1	+1
+1	+1	+1	-1	+1	-1

Table 1. Example of some Predictors for m = 3

The left side of the table contains all possible combinations of the history for m = 3 and the right side is the proposed action for that particular combination of the history. The predictors are initialised randomly and the agents cannot change their predictors in the traditional minority game. The length of the predictor is 2^m which is significantly smaller than N^m .

4. ADAPTATION OF MG IN TA

Even though it is reasonable to assume that MG might achieve fair distributions of traffic and acceptable travel times for the drivers, adaptations have to be made to the original MG before it can used effectively for traffic assignment.

4.1 Application of MG to the Traffic Domain

MG is strictly a two alternative game and can directly be used to address the traffic assignment problem when we have a two-route scenario as in figure 2.



Cars approaching point A have a choice between two links, which are assumed identical in terms of distance, while the travel time depends on the usage of the link. Drivers attempt to be part of the minority in choosing one of the links by using their predictors and rewarding them on success.

Chmura and Pitz [9] applied the Minority Game model in traffic domain to observe the behaviour of the drivers who had strictly two alternatives as shown in figure 2. They investigated two different formulations, one of which assumes that drivers only know their own experience of the links, whereas in the other they share this information with all drivers. The authors concluded that the drivers' choice of using the route with fewer cars is negatively correlated with their likelihood of route change [9]. Selten et al. performed experiments based on two experimental setups which resemble the set up of Chmura and Pitz [9] except for the capacities of the roads [16]. The authors' experiment consisted of 18 participants choosing between a main road and a side road. The travel times on the roads depended on the number of cars choosing the roads according to the authors' formulation. Selten et al. observed that the mean numbers of drivers on the roads are close to pure equilibrium according to their equilibrium formulation [16].

4.2 A NOVEL APPROACH TO TA USING MG

In this study we propose a novel hybrid method using the concept of Challet and Zhang's MG model [6] and Arthur's El-Farol Bar model [2]. We assume that each driver has an OD pair and some previous experience of travelling to the destination at this time of day. There are usually several routes to reach the destination. Some of the routes share the same links. The drivers decide at each intersection which outgoing link they will take from there. There are typically one to five links to choose from. Each driver has predictors to anticipate the usage level of the links as a percentage of the link's capacity. A predictor maps a history of previous usage levels to a prediction of the current usage level. A driver will choose the link with the minimum predicted usage. At the end of the trip, a driver will compare the experienced travel time with the expectation and score the predictors accordingly. By scoring the predictors, drivers can select the best predictor with highest score to use for prediction of the link usage in the next iteration. If several predictors share the highest score, one will be chosen randomly from them.

The algorithm of our proposed approach is given below.

Algorithm Hybrid Traffic Assignment Approach

1. For each driver

- 1.1. For each node *i* in the developing route
 - 1.1.1. For each link j in the driver's list for node i
 - 1.1.1.1. Select best predictor for link j
 - 1.1.1.2. Predict the percentage usage by mapping current link history to the best predictor
 - 1.1.2. End For
 - 1.1.3. Select link *l* with minimum weighted prediction
 - 1.1.4. Set the current node i to the end node of link l
- 1.1.5. End For
- 1.2. End For
- 2. Update the link histories for each driver for the links they travelled
- 3. Update the score of the predictors used by each driver for each link
- 4. Calculate experienced/actual travel time for each driver along their OD pair
- 5. Calculate new weights for each link using the current experienced travel time.

4.2.1 Number of Agents

Challet and Zhang's original MG could only be applied to an odd number of agents. This was necessary to determine the minority side. However, in our traffic scenario, we are applying the concept of the MG without the limitation of odd numbers of agents as the success of a choice is not determined by minority allocations but according to the actual travel times experienced.

4.2.2 History

In MG, the history is merely an indication of the winning alternative. In TA, we have more than two alternatives to choose from. Therefore, the history is a percentage of road usage with respect to the capacity of the road. A history of 80-120-90 indicates that a driver experienced road usages of 80%, 120% and 90% capacity on three consecutive occasions. The range of the historic usage values is limited to between 60 and 140 as we found through experiment that values smaller than 60% or larger than 140% usage are of no consequence in the decision-making.

4.2.3 Predictors

The predictors had to be modified to match the historic values expressed in percentage of usage. This generalises the applicability of the approach from a distinct two choices to an unknown number between zero and ten. In El-Farol bar problem, the predictors predict the exact number of attendants, which leads to an unmanageable length of the predictors. In our hybrid approach, the predictors predict an approximate percentage of congestion on the roads. If the length of a predictor is L_p and number of possible history L_{comb} , each (L_{comb}/L_p) sequential combinations will predict the same approximate prediction. Table 2 shows two predictors for a history length of three. According to these predictors, if the history is 60-60 or 60-60-61, predictor 1 will predict 91% and predictor 2 will predict 120% congestion on the road.

Possible history				Predictor 1	Predictor 2
60	60	60			
60	60	61		01	120
				91	120
					•
•					
90	91	92		•	•
90	92	91			
			107	93	
•					•
				117	101
140 140 140					

Table 2. The mapping of a predictor

4.2.4 Decision Making

In MG and El-Farol bar problem, the agents take the actions according to the prediction. In this work, we let the drivers choose the link which has the minimum weighted prediction. The weight is the ratio of the actual travel time for the route taken and the expected travel time and is calculated as

$$W = \frac{ATT_R}{ETT_{R^*}} \tag{1}$$

Here, ATT_R is the actual or experienced travel time on route R, and $ETT_{R'}$ is the expected travel time of a driver between the OD pair on the optimal route R^* . The optimal path is the path which includes the minimum number of nodes as we are not considering the physical distances between the nodes. If some routes share the same number of nodes, one was chosen randomly. The drivers are assumed to have an approximate impression of the current road usage based on their current observations as well as previous experience. ATT_R and ETT_{R^*} are calculated as

$$ATT_R = \sum_{a \in R} tt_a \tag{2}$$

$$ETT_{R^*} = \sum_{a \in R^*} fftt_a [1 + (\frac{eX_a}{C_a})^2]$$
(3)

Where tt_a is the travel time on link a, which is calculated as

$$tta = fftta[1 + \alpha (\frac{Xa}{Ca})^{\beta}]$$
(4)

Where $fftt_a$ is the free flow travel time, C_a and X_a are the Capacity of and number of cars on the link *a*, respectively, α and β are two control parameters [12]. eX_a is the expected number of cars on the link *a* of the optimal route R^* .

4.2.5 Updating the Predictors' Scores

The score of the predictor is calculated as follows.

$$\theta_{a,t+1} = (1-\mu)\theta_{a,t} + \mu[(C_a / X_a) - 1]ATT_R$$
(5)

Where, $\theta_{a,t}$ is the score of the predictor for link *a* at time *t*, and μ is a number in the range {0,1}. Note that if the number of cars on the link exceeds the capacity, $[(C_a / X_a) - 1]$ will become negative, which decreases the score, otherwise it increases the score.

5. EXPERIMENTAL SETUP

The road network used in these experiments consists of the nodes and links shown in figure 3. The drivers have their OD pairs and thus they have several alternative routes/paths which consist of sets of links. In the decision-making, we only consider unidirectional links. We can reasonably assume that drivers who commute are aware which links are options for a route to the destination. Also, we assume that the cars from the opposite direction have no effect on our drivers' travel time.



Figure 3. A complex road network used to test and evaluate our proposed method

In our initial problem instance, there are 1001 drivers travelling in the network. The network has 10 nodes which represent intersections, 24 links which represent the roads. Each link has a capacity which was assigned randomly in a range {130, 250}. There are three origins and three destinations, resulting in nine combinations of OD pairs. Nodes 1, 2 and 3 are origins i.e. cars start their trip from nodes 1, 2 and 3. Nodes 8, 9, and 10 are destinations. Each driver knows the last m = 3 trips' history as percentages of usage of the links. Each driver has 2 predictors for each link in all possible routes between the OD pair. Each driver has a list of possible links for each node. We assume that each driver expects that there would be eX number of cars on each link being part of the optimal route. If the number of drivers for an OD pair is *n*, *eX* is in the range of {n-50, n+50}. The control parameters α and β in (2) were set to $\alpha = 1$ and $\beta = 2$.

6. RESULT AND DISCUSSION

The contribution of our proposed method is twofold – we attempt to achieve a fair distribution of cars on the road network in proportion to the capacity of the roads as well as reasonable travel times for the drivers. Consequently, to establish the quality of the solutions created by the algorithm, the distributions resulting from the MG-based traffic assignment algorithm were compared with an optimal distribution, defined as the distribution of the vehicles in proportion to the capacity of the links. The optimal distribution was calculated at each node by distributing the cars present at the node in proportion to the capacity of the possible outgoing links from the node. We also compared our result with the result of the most intuitive method – the random choice, which is the natural alternative when drivers are choosing among several options given incomplete information.

Figure 4 shows the box-and-whisker chart of the average travel times of the drivers of each OD pair over 50 iterations. We observe that the distribution of average travel times for each OD pair is compact with few outliers, which is an indication of the fairness of our algorithm. The outliers with above-average travel times are often caused by situations in which the drivers had no other alternatives but to choose a congested link, as all less crowded links were not compatible with the route towards the destination. Even in the worst cases, these disadvantaged drivers experienced travel times which were only six to seven minutes longer than those of the majority of drivers within the interquartile range.



Figure 4. Box-and-Whisker Chart for average travel time (minutes) for the drivers of each OD pairs

Figure 5 shows the standard deviation of the average travel times experienced by the individuals of each group over 50 iterations. It

illustrates that the travel times experienced by the individuals of the OD pairs varied between 3 and 5 $\frac{1}{2}$ minutes (5 minutes 30 seconds) which establishes the degree of fairness in the distribution of the travel times for the individuals of the OD pairs.



Figure 6 shows a comparison between the average actual/experienced travel times for our hybrid approach (solid bars) and for the random choice approach (dashed bars). The expected travel times (dots) for the drivers of each OD pair are also included. All results are averaged over 50 iterations. The expected travel time for each driver is calculated using equation (3). There we can observe that the expected and experienced travel times are very close when our hybrid approach is used, but

iterations.



Figure 6. Comparison of average actual and expected travel times for each OD pair. Solid and dotted bars represent the actual travel times for hybrid approach and random choice respectively and the squares represent the ETT.

consistently further apart when the drivers choose randomly. Random choice leads to travel times which are significantly above the expectation as well as the travel times achieved by the hybrid approach. This indicates that the algorithm is efficient at distributing the cars to avoid unnecessary congestion on the roads.

The distribution of cars on the roads is shown in Figure 7 where the solid bars represent the optimal number and the dashed bars represent the actual number of cars on the roads. The dots represent the capacities of the roads. For most links, the distribution of the cars is close to the optimum. For the most part, the cars distributed themselves in proportion to the capacity of the roads. The differences between the optimal and actual distribution is reasonable as the drivers are experiencing travel times within their expectations. However, our future work is to reduce this gap between the optimal and actual distribution.



Figure 7. Comparison of optimal and actual numbers of cars on the links with the dots indicating capacities

We repeated the experiment using 2001 drivers and the same parameters for the network. We observe an equivalent outcome with a distribution that is close to the expectation with few outliers.

7. CONCLUSION

This work shows that MG can be helpful in facilitating the selforganisation of traffic to form a balanced distribution on the roads, which ultimately benefits all participants through shorter travel times. In practice, this approach might be integrated into existing guidance systems.

Although we could not ensure the utilisation of all roads according to their capacities, only few roads were overused, and this congestion was attributable to an absence of alternatives for some drivers. As the average experienced travel times of the drivers are close to the average expected travel times, we can conclude that our proposed approach is an improvement on the state of the art. It alleviates problems observed by other researchers when drivers make informed decisions unassisted. Even in a software-assisted scenario, we expect that not all drivers will follow the recommendations. In future work, we will explore the performance of our approach in the presence of drivers who do not use our approach.

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