Modelling an electricity price and journey time trade-off routing decision for electric vehicles

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Abstract

This paper introduces an electricity price extension to the intention-aware routing system (IARS) for electric vehicles (EV). The existing intention-aware routing system is used to route electric vehicles who require to charge en-route through a road network. To achieve the objective of minimizing the average journey time, the intentions of EVs and waiting times at charging stations are communicated. Instead of only minimizing travel time, the model extension presented in this paper makes it possible to express a decision trade-off between price and time. A vehicle computes its routing policy such that the combined utility of price and time is as high as possible. In this paper the performance of IARS with a price extension is compared to a greedy maximizing algorithm (MAX) in several settings. The increase in utility by using IARS depends on the population of electric vehicles. However, in most experiments conducted in this research IARS achieves a significantly higher average utility.

1 Introduction

The sales of electric vehicles has soared this decade and according to the Global EV Outlook 2021, even in a conservative scenario, sales will keep increasing with 30% annually and electric vehicles will "account for about 7% of the road vehicle fleet by 2030" [3]. This increasing adaptation of electric vehicles demands charging infrastructures and EV routing policies over the network which avoid congestion at charging stations as much as possible. An efficient allocation of EVs over the different charging stations in a road network is important since charging a car takes significantly longer than refuelling (e.g. Tesla's V3 Supercharger will charge a Tesla Model 3 in 15 minutes [9]), which makes congestion more likely to occur.

The area of route guidance and information systems (RGIS, [1]) has already extensively studied optimal vehicle routing using real time information. Research into coordination mechanism to prevent congestion is done in [5] and [6]. However, all these approaches do not take into account en-route charging. De Weerdt et al. [2] introduced an intention aware routing system for EVs to tackle the problem of congestion at charging stations when EVs have to charge en-route. In their work they describe a model where EVs communicate their intentions to charging stations, charging stations communicate expected waiting times back and EVs use this information to construct an optimal routing policy. In some cases, this intention aware routing system "leads to over 80% improvement in waiting times at charging stations and a more than 50% reduction in overall journey times" [2].

Even though the IARS distinguishes between EV types in terms of battery capacity, the decision policy of all EVs is set to minimize the expected journey time. Minimising travel time makes sense if we assume electricity costs are equal at all charging stations. However, in a real world scenario, the price of electricity at charging stations might be correlated with the popularity of that station. This paper will extend the IARS model and simulation such that each charging station has its own electricity price.

The main research questions this paper tries to answer is

From the perspective of an individual vehicle, when presented with the choice of several stations who each charge a certain price for electricity, how can we best model the choice of which station to go to?

This question is split up in several subquestions:

- Q1) How can we extend IARS to incorporate different electricity prices at charging stations in the model and simulation?
- Q2) How can we model a price/patience trade-off for an individual electric vehicle driver?
- Q3) How can we model the decision policy of the individual vehicles?
- Q4) Which decision policy achieves the highest average utility given the drivers preferences towards time and price?

By answering these questions this paper contributes to the existing state of the art by formalizing the aspect of price differences in the IARS and giving insights into the effects of these differences on individual decisions.

The remainder of this paper is structured as follows. First, in section 2 we describe the problem and formalize the model behind IARS. The price extension on this model and simulation is then described in section 3. In section 4 we explore several decision models that can be used by individual EVs. The results of running two of these decision models in several situations are presented in section 5, followed by a note on reproducibility of this research in section 6. A discussion is presented in section 7 and section 8 concludes and presents directions for further research.

2 Problem Description

In this section the problem of routing EVs with limited charge through the road network is formalized by describing the base model as presented by De Weerdt et. al. [2].

The EV routing problem is formalized using "a stochastic time-dependent model, where roads and charging stations are represented by probability distributions of their travel time or waiting time" [2] (including actual charging time), respectively.

The domain of this EV routing model is given by $\langle V, E, T, P, S, C \rangle$. The set V contains all the vertices, which indicate decision points in the road network. Vertices are connected by directed edges $e = (v_i, v_j) \in E$, where an edge represents either a road segment, $E_{roads} \subset E$ or a charging station, $E_{stations} \subset E$. If we assume an EV has unlimited charge it should never be required to pass by a charging station on the route from A to B, therefore charging stations are represented as edges which form a self loop.

An edge incurs a probabilistic amount of time (travel time or waiting time, depending on the edge type), described by the probability mass function P which is dependent on the time of the day $t \in T$. This dependence on the time of day models the fact that the time it takes to traverse a certain road segment highly depends on the traffic conditions.

Moreover, a road segment edge $e \in E_{roads}$ incurs an amount of charge $C(e)$ and a charging station $e \in E_{stations}$ resets the state of charge to $s_{max} \in S$. So the new state of charge after traversing edge e is given by:

$$SOC(e_c, s_c) = \begin{cases} s_c - C(e_c) & \text{if } e_c \in E_{roads} \\ s_{max} & \text{if } e_c \in E_{stations} \end{cases}$$

Given this domain description, the problem for a single EV is to find an optimal routing policy $\pi^* : V \times T \times S \to V$ which maximizes the expected utility without running out of charge during the journey.

The expected utility for a certain policy is given by $EU(e_c = (v_c, w), t_c, s_c, |\pi)$. The value is computed using a recursive formulation with two base cases. The first base case is when the EV runs out of charge by traversing the next edge, in which case the expected utility is $-\infty$. The second base case is when the EV reaches its destination when traversing the next edge. In this case, the expected utility is calculated as $\sum_{\Delta t \in T} P(\Delta t | e_c, t_c) \cdot U(t_c + \Delta t, s')$. Here $P(\Delta t | e_c, t_c)$ is the probability of traversing the edge in Δt time units, given that we are at e_c at time t_c and $U(t_c + \Delta, s')$ is the final utility calculated from the destination node s' at arriving time $t_c + \Delta t$.

When the EV still has charge and is not yet at its destination, we use the same formula as in base case two but instead of using the final utility we recursively use the expected utility at the destination node s': $EU((w, \pi(w, t_c + \Delta t, s')), t_c + \Delta t, s' | \pi)$. The full formulation is then as follows:

$EU(e_c = (v_c, w), t_c, s_c, |\pi) =$

$$\begin{cases} -\infty & \text{if } s_c \leq 0 \\ \sum_{\Delta t \in T} P(\Delta t | e_c, t_c) \cdot U(t_c + \Delta t, s') & \text{if } w = v_{dest} \\ \sum_{\Delta t \in T} P(\Delta t | e_c, t_c) & \\ \cdot EU((w, \pi(w, t_c + \Delta t, s')), t_c + \Delta t, s' | \pi) & \text{otherwise} \end{cases}$$

where $s' = SOC(e_c, s_c)$.

The utility function is a function of time and charge $U : T \times S \to \mathbb{R}$:

$$U(t_c, s_c) = \begin{cases} -\infty & \text{if } s_c \leq 0 \\ -t_c & \text{otherwise} \end{cases}$$

This utility function makes sure an EV chooses a policy that minimizes the expected time of arrival while not running out of charge (if possible).

3 Price model

In this section we will introduce the price model, which is an extension of the base model described in section 2. This section will provide the answer to subquestion 1 and 2. In subsection 3.1 the price extension to the base model is formalized and subsection 3.2 describes the used utility function in this extended model.

3.1 Model extension

In the base model (see section 2) the state of an EV is described by $(v_c, t_c, s_c) \in (V \times T \times S)$. To include the price attribute, we extend this to $(v_c, t_c, s_c, m_c) \in (V \times T \times S \times M)$, where $m_c \in \{0, \ldots, M_{max}\}$ indicates the money an EV has already spent during its trip. The amount of money spent is initialized as 0 when the EV starts its journey.

Each $e \in E_{stations}$ will increase the spent money m_c of an EV by $P(e)$ once the EV travels over e. Here, $P : E \to \mathbb{R}$ is a price function indicating the price paid when traversing edge e:

$$P(e) = \begin{cases} 0, & \text{for all } e \in E_{roads} \\ p_e, & \text{for all } e \in E_{stations} \end{cases}$$

where p_e is a fixed electricity price at station e and can be used to introduce price differentiation between stations. Note that a road segment, i.e. $e \in E_{roads}$, does not effect the money spent attribute of the EV in this model. However, it is straightforward to extend the model to allow to pay for charge while driving, which means this allows for modelling scenarios where vehicles charge while driving [4].

Given the new state description of an EV the policy function will now be $\pi^* : V \times T \times S \times M \to V$ and the expected utility formulation will change to:

$$EU(e_c = (v_c, w), t_c, s_c, m_c|\pi) =$$

$$\begin{cases} -\infty & \text{if } s_c \leq 0 \\ \sum_{\Delta t \in T} P(\Delta t|e_c, t_c) \cdot U(t_c + \Delta t, s', m') & \text{if } w = v_{dest} \\ \sum_{\Delta t \in T} P(\Delta t|e_c, t_c) & \\ \cdot EU((w, \pi(w, t_c + \Delta t, s', m')), & \\ t_c + \Delta t, s', m'|\pi) & \text{otherwise} \end{cases}$$

where $m' = m_c + M(e_c)$.

In this model the EV driver pays for a full charge $P(e)$ at charging station e. We made this assumption to make sure there is no advantage of charging early. However, it is straightforward to extend the model to charge dependent payments at the charging stations. Although this would require to take into account left over charge at the end of the trip, otherwise charging early (or not at all) would be beneficial.

3.2 Utility function

Whereas we previously only took the arrival time into account in the final utility function, we now also consider the spent money during the trip. In this revised utility function we model a price/patience trade-off using a parameter $\gamma \in [0, 1]$ which expresses the weight of the preference towards time of the EV driver. The weight towards price is then computed as $1 - \gamma$, since the weights should add up to 1.

$$U(t_c, s_c, m_c) =$$

$$\begin{cases} -\infty, & \text{if } s_c < 0 \\ \gamma * \frac{T_{max} - t_c}{T_{max} - T_{min}} + (1 - \gamma) * \frac{M_{max} - m_c}{M_{max} - M_{min}} & \text{otherwise} \end{cases}$$

M_{max} and M_{min} are used to normalize the price factor and T_{max} and T_{min} are used to normalize the time factor. M_{max} indicates the maximum the driver can pay for the journey, which is given by the highest price of all charging stations. M_{min} is the minimum amount of money that should be paid for the journey and is given by the lowest price charged by a charging station in the road network. T_{max} is the maximum arrival time a driver is willing to accept and T_{min} is the minimum time to get from the source to the destination, so including unavoidable travel and charging time. This utility function will make sure an EV chooses a policy that maximizes the weighted sum of the price and time factor according to the predefined weights, while not running out of charge (if possible).

4 Decision models

Electric vehicles who need to charge en-route have to choose between potentially more than one charging station. Which station they choose depends on the decision model used and the expected utility of each choice. In this section we answer subquestion 3 by describing three different decision models.

- **MAX**: a greedy decision strategy that always takes the path with the highest expected utility (i.e. the path with the lowest expected travel time in the base model). This greedy maximizing approach resembles the way navigation systems lead cars through a road network.
- **RANDOM(λ)**: a decision strategy which models suboptimal behavior of humans [7] by choosing the next road segment with a certain probability. This probability relates to the expected utility of the road segment in the following way:
  $P(e|v_c, t_c, s_c) = \frac{e^{\lambda * EU(e, t_c, s_c|\pi')}}{\sum_{\{e'|(v_c, w)\}} e^{\lambda * EU(e', t_c, s_c|\pi')}}$
  This strategy also assumes zero waiting time at the charging stations. The λ parameter describes the level of rationality. A high value will result in more rational behaviour, i.e. choosing the road segment with the highest expected utility. A low value will result in more randomness in the behaviour.
- **IARS**: a decision strategy which follows from the intention aware routing system as presented in [2].

De Weerdt et. al [2] compared these decision models and confirmed the following hypothesis "the average journey time for IARS is lower than for any other approaches". In the remainder of this paper we will only use MAX and IARS to evaluate the performance of the price model on.

5 Experiments and Results

In this section we present the experiments we conducted along with the results. These results provide the answer for subquestion 4. In subsection 5.1 we describe the road networks we tested on and the configurations we used. In subsection 5.2 and subsection 5.3 we present the results of running several vehicle types on the bottleneck network and grid network respectively. In subsection 5.4 we give an insight in the performance when varying in the vehicle population structure.

5.1 Experimental setup

To analyse how well the different decision models perform in terms of average utility, we have to construct a certain road network to evaluate them on. In our experiments we use two different road networks, a bottleneck network and a grid network, see Figure 1 and Figure 2 respectively. Charging stations charge different prices for their electricity in both networks. To create a suitable environment for the price and time trade-off, their exists an inverse relationship between the edge weights near a charging station and the price at the charging station. That is, a charging station that provides electricity at a low price is on a route which would take longer than a route through a charging stations at which the electricity price is high. Note that the edge travel times are thus constant over the whole day, this is a simplification compared to the base model introduced by de Weerdt et. al [2]. We made this simplification to examine the effect of the price model in a more isolated manner.

Throughout our experiments, we assume that charging an EV takes 15 minutes [9]. In order to produce consistent and reproducible results we repeat all the simulations several times and average the results. Furthermore, in all the graphs a 95% confidence interval is shown on every bar. For a more

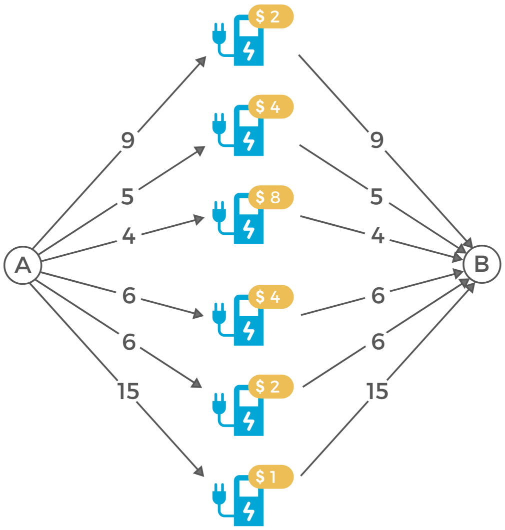

Figure 1: The bottleneck road network with electricity prices and travel times

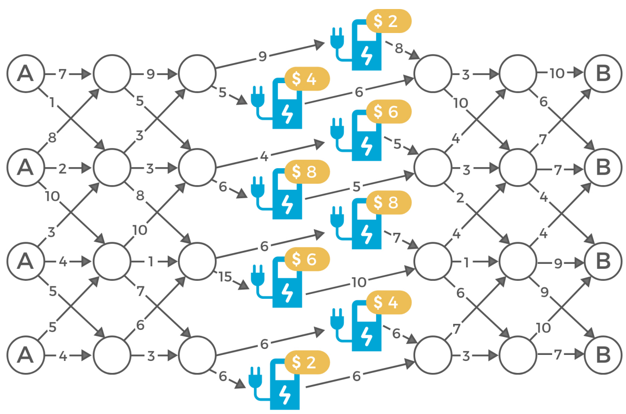

Figure 2: The grid road network with electricity prices and travel times

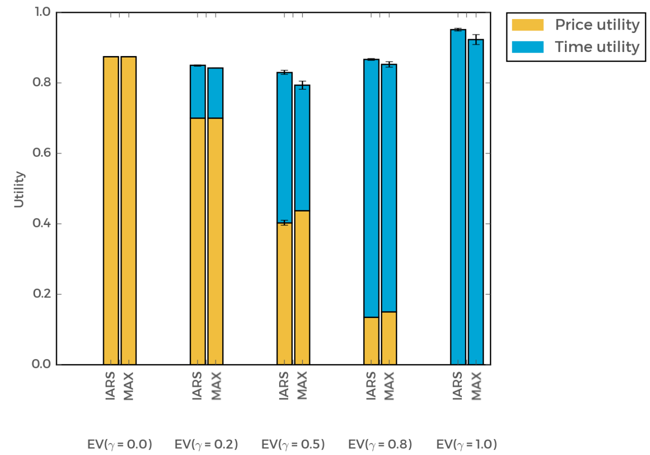

Figure 3: Average utilities of several vehicles types on the bottleneck road network

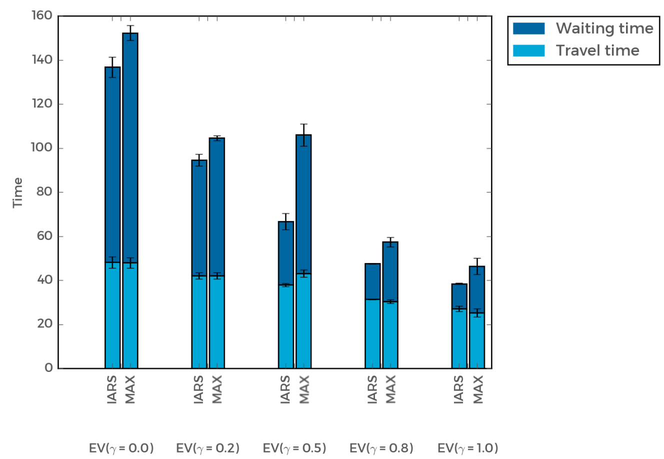

Figure 4: Average journey times of several vehicles types on the bottleneck road network

elaborate note on the reproducibility of these experiments see section 6.

5.2 Results on the bottleneck network

For the analysis of the overall performance and comparison between routing policies on the bottleneck network we use an environment with five different vehicle types who differ in their γ value but all use the same decision model. We ran this environment for the two decision models, IARS and MAX, to compare them. In all simulations the prices are set in the same way as in Figure 1.

In Figure 3 the resulting average utilities of running this experiment can be found. In Figure 4 and Figure 5 the resulting average journey time and money spent is shown, respectively.

In these graphs we can see that as the γ parameter increases the total journey time decreases and the money spent increases. This result can be observed for both decision models and is as expected, since the γ parameter expresses the importance of the price factor.

However, there is a difference between IARS and MAX. In Figure 3 we see that all vehicle types have a higher or equal utility when using IARS. Since IARS is a coordinated system, the load of vehicles is divided better over the network and charging stations. This coordination in the network explains why we see that the waiting time at charging stations is significantly lower for IARS than MAX in Figure 4. Furthermore it is interesting to see here that a higher γ, i.e. a higher preference for time, is translated better in a lower journey time when using IARS compared to MAX. The total journey time decreases more consistently when γ increases for IARS, see Figure 4.

5.3 Results on the grid network

The experiments on the grid network are conducted in the same environment as on the bottleneck network. There are five different vehicle types, we use two different decision models and the prices are set as presented in Figure 2.
The resulting average utilities, average journey times and av-

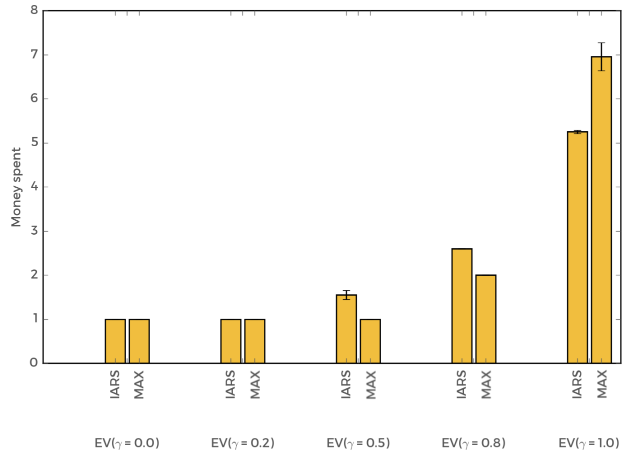

Figure 5: Average money spent of several vehicles types on the bottleneck road network

erage money spending of running this experiment in the grid network scenario can be found in Figure 6, Figure 7 and Figure 8, respectively.

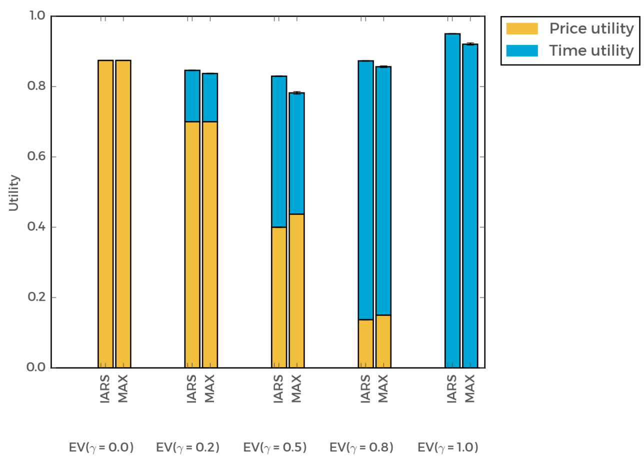

Figure 6: Average utilities of several vehicles types on the grid road network

Although the numbers are different the patterns in the results on the grid network correspond to the ones on the bottleneck network. Again, the utility for IARS is equally good or higher than MAX. Moreover, the relationship between γ and the journey time and money spent is also better expressed when using IARS.

5.4 Results of different populations

In these last experiments we evaluate the overall performance when varying with the population construction. In all runs we use 100 vehicles.
First of all, we investigate how the average utility of two vehicle types change when their population changes. The vehicles in all these runs have either $\gamma = 0.8$, i.e. a high preference for time or $\gamma = 0.2$, i.e. a high preference for money. The runs

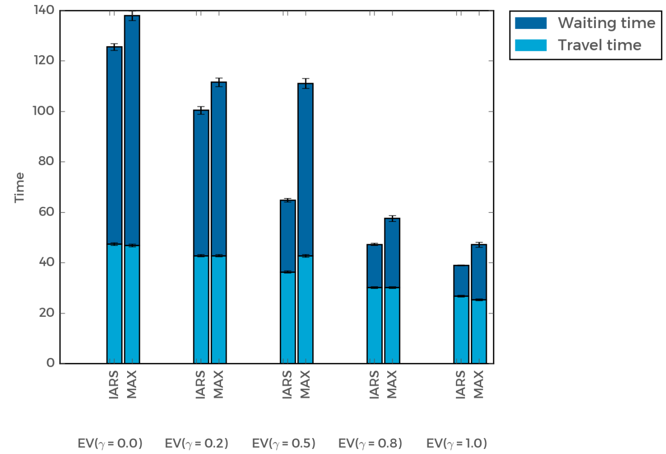

Figure 7: Average journey times of several vehicles types on the grid road network

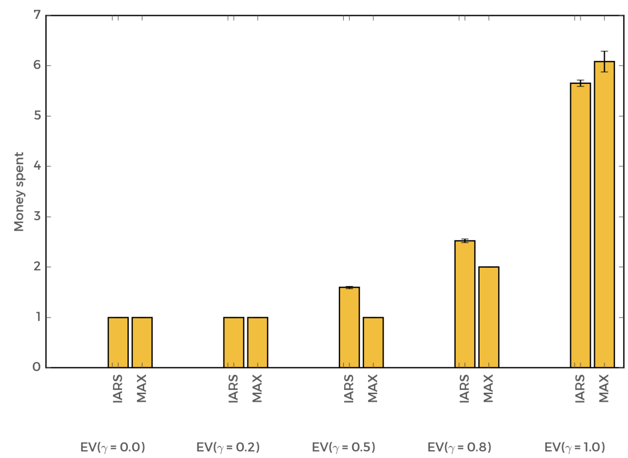

Figure 8: Average money spent of several vehicles types on the grid road network

vary in the proportion of vehicles with $\gamma = 0.2$ and $\gamma = 0.8$. The result of this experiment using the MAX decision model is presented in Figure 9 and the results for the IARS equivalent can be found in Figure 10. In all these graphs the population construction can be found on the x-axis.

Interesting to see in these results is that when all the vehicles use IARS, the utility does not significantly depend on the construction of the population, see Figure 10. On the other hand, when all vehicles use MAX, the utility of the vehicles with $\gamma = 0.8$ decreases as the amount of them increases, see Figure 9. This effect can be explained by the absence of a coordination system in the MAX decision model. No coordination means that all vehicles use the same path, i.e. they pick the one with the highest expected utility in a greedy manner, which leads to congestion on that path.

In a second experiment we evaluate the scenario where each vehicle has a different gamma drawn from a uniform distribution $U(\alpha, \beta)$, where $\alpha \geq 0.0$ and $\beta \leq 1.0$. We ran this scenario several times, each time with a different α and

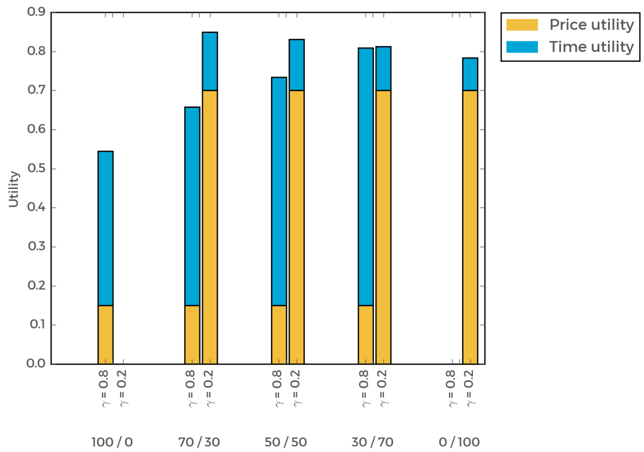

Figure 9: Utility of vehicles using MAX in different populations on the bottleneck road network

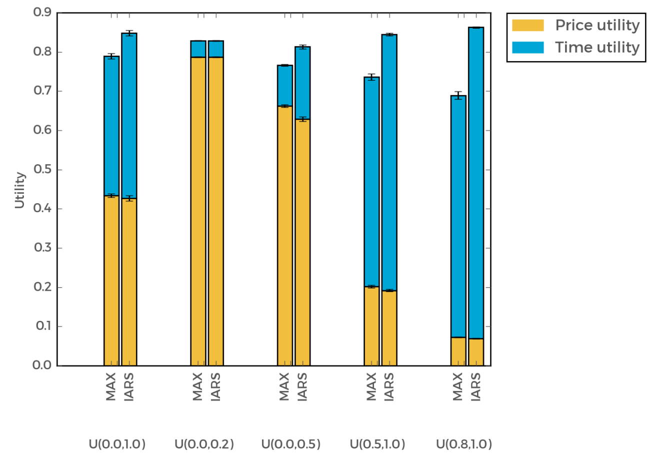

Figure 11: Average utility of vehicles with a random gamma drawn from $U(\alpha, \beta)$ on the bottleneck network

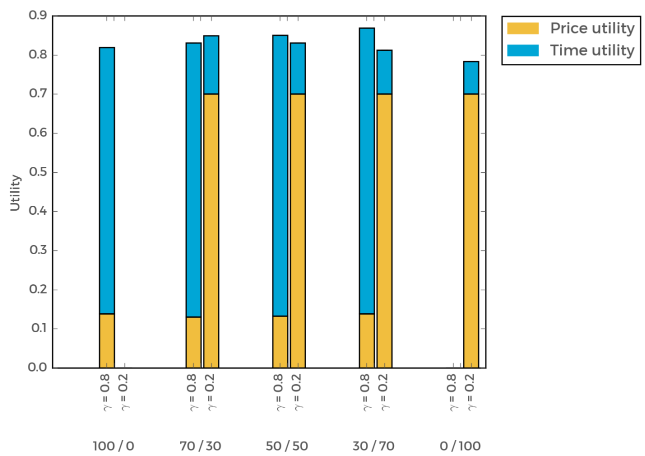

Figure 10: Utility of vehicles using IARS in different populations on the bottleneck road network

β. The results of this experiment can be found in Figure 11. The distribution we used each time is found on the x-axis.

As can be observed in Figure 11, vehicles benefit from IARS the most when the majority of the population favors time. In the scenario $U(0.0, 0.2)$, i.e. where every vehicle has a γ between 0.0 and 0.2, the average utility of MAX and IARS are almost the same. However when the average gamma's increase, a significant difference between MAX and IARS starts to emerge. IARS performs 6.2% better than MAX on average when the gamma is drawn from $U(0.0, 0.5)$. In the scenario $U(0.5, 1.0)$ IARS perform 14.7% better and in the scenario $U(0.8, 1.0)$ IARS outperforms MAX by 25.1%.

Even though using the IARS system is not that beneficial in the scenarios with low gammas, it doesn't harm. The average utility of vehicles using the MAX decision model is never higher than of the vehicles using IARS. Furthermore, in a more realistic scenario where every vehicle has a random gamma between 0.0 and 1.0, IARS clearly outperforms MAX (see the first set of bars in Figure 11).

6 Responsible Research

In this study we report results on several experiments, each conducted with different configurations. In this section, we discuss the reproducibility of these experiments and results. In subsection 6.1 we identify the random components involved in the experiments and state the implications of them on reproducibility. In subsection 6.2 we make a note about the implementation details of the code and in subsection 6.3 we discuss the environmental setup of the experiments.

6.1 Randomness

In this research we performed a number of experiments and used different algorithms and methodologies which contain a certain degree of randomness. First of all, the whole problem is modeled as a Markov decision process where roads and charging stations are represented as edges with a probability distribution for their waiting time. The time an EV takes to traverse a certain edge is drawn from the distribution $P(\Delta t | e_c, t_c)$ and is thus not a fixed variable. This means the whole simulation is exposed to randomness, as travel times are not necessarily the same in between two simulations.
Secondly, in the grid network the start positions and end goals of the vehicles are generated randomly.
Even though the earlier mentioned components used in this research contain random elements, the results presented in this paper are reproducible to a certain degree of accuracy. First of all, in most experiments we simplified the problem by fixing the travel times of edges. This already takes a way a degree of randomness. Furthermore, every experiment we reported results on during this study was repeated several times. The results of all these repetitions were then averaged to decrease the effect of randomness. Since we repeated and aggregated the results of experiments, we can report the standard error of all reported values and say something about the accuracy of these values. All the figures presented in this paper include error bars which indicate a 95% confidence interval.

6.2 Implementation

The results in this study do not depend on the implementation details of the algorithms. The simulation and all decision policies are implemented in an object oriented manner using Java. The Java code implements the formal description of the algorithms and is reproducible in any other language. Aside from implementation details and possible run times, the results will be similar to the ones presented in this paper. The Java code also does not rely on any language specific third party dependencies. The Java code used in this study is not publicly available, however, access to the code can be granted on request.

6.3 Experiment configurations

All experiments in this study use a different configuration, in our Java code we use a property file which contains all environmental settings as input to model these different configurations. Based on this property file the experiment is conducted. The property file specifies the number of vehicle types, their specific setting (i.e. γ parameter and used decision policy) and the layout and settings of the road network. We did not include the actual property file in this paper. However, the experimental setup and configuration settings are clearly described in subsection 5.1 of this paper.

7 Discussion

In all the results from our experiments we can see that the price time trade-off works as expected and EV drivers can thus indicate their preference clearly with the γ parameter.
Moreover, in most experiments IARS performs significantly better than MAX in terms of average utility.
A limitation on these results are that we only used two different road network setups, as described in subsection 5.1. Although these two setups represent scenarios where we can evaluate the decision policies on, they are an oversimplification of real world road networks. Due to the complexity of the problem and the fact that we did not have access to a compute cluster we were not able to run experiments on bigger graphs. It would be interesting to analyse the performance in terms of utility on bigger graphs which resemble a more real world scenario.

8 Conclusions and Future Work

The main contribution of this paper is the introduction of a price factor in the model presented by De Weerdt et. al [2] which can be used to model a price/patience trade-off for electric vehicles when they have to traverse a road network and have to charge en-route.
In this study we explored the MAX and IARS decision policies and did experiments with them. From the experiments we did, we can conclude that even after including a price factor in the model and utility functions, IARS still results in the best overall utility. Moreover, we can conclude that IARS can translate the drivers preferences more accurately. However, the advantage IARS gives over MAX depends on the type of vehicles and the number of them in the population as shown in the last experiment. In a population that highly favors time over money the IARS decision model is the most beneficial.
A lot of directions are possible for further research from here. First of all, the used model could be extended in several ways. We could extend the model to take charging between vehicles into account. This concept is introduced in [4] and will give a whole new dynamic to the system. Furthermore, we could extend the model to take discharging or selling charge into account, Tang et. al. use such a approach. [8]. Smaller extensions that could be implemented in the price model are also possible. For example, P could be made time dependent, such that charging stations will charge a different price depending on the time of the day. The price function P could also be dependent on the demand for electricity, in which case a market like scenario arises. Furthermore, it would be interesting to do a study on the actual gammas of EV drivers. We have shown in the last experiment that the advantages you get from IARS highly depend on the population of EV drivers. If we know more about the real world population of EV drivers, we could potentially optimize IARS for this. Lastly, a study to the practical application of the IARS system with price extensions is possible.

References

[1] Moshe Ben-Akiva, Jon Bottom, and M Scott Ramming. Route guidance and information systems. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 215(4):317–324, 2001.

[2] Mathijs M De Weerdt, Sebastian Stein, Enrico H Gerding, Valentin Robu, and Nicholas R Jennings. Intention-aware routing of electric vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 17(5):1472–1482, 2015.

[3] IEA. Global ev outlook 2021, 2021.

[4] Dimitrios Kosmanos, Leandros A Maglaras, Michalis Mavrovouniotis, Sotiris Moschoyiannis, Antonios Argyriou, Athanasios Maglaras, and Helge Janicke. Route optimization of electric vehicles based on dynamic wireless charging. *IEEE Access*, 6:42551–42565, 2018.

[5] Sarit Kraus, Roni Parshani, and Yuval Shavitt. A study on gossiping in transportation networks. *IEEE transactions on vehicular technology*, 57(4):2602–2607, 2008.

[6] Ilias Leontiadis, Gustavo Marfia, David Mack, Giovanni Pau, Cecilia Mascolo, and Mario Gerla. On the effectiveness of an opportunistic traffic management system for vehicular networks. *IEEE Transactions on Intelligent Transportation Systems*, 12(4):1537–1548, 2011.

[7] Daniel McFadden et al. Conditional logit analysis of qualitative choice behavior. 1973.

[8] Xiaoying Tang, Suzhi Bi, and Ying-Jun Angela Zhang. Distributed routing and charging scheduling optimization for internet of electric vehicles. *IEEE Internet of Things Journal*, 6(1):136–148, 2018.

[9] The Tesla Team. Introducing v3 supercharging, Mar 2019.