The influence of a charging station's location on its profitability

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Abstract

With the increasing number of electric vehicles on the road, the routing problem has become more complex. As charging electric vehicles takes longer than fueling non-electric vehicles, congestion can occur at charging stations. This might lead to the shortest route not being the fastest route, due to long waiting times at the stations. By communicating the intentions of each vehicle, they can spread out over multiple stations. This paper investigates the effect of such a routing system on the profitability of charging stations in comparison to a more simple shortest-path algorithm. In particular, the influence of a charging station's location on its profitability has been researched for both routing algorithms. In order to do this, a pricing model has been developed to extend the routing models used for both the shortest-path algorithm and the intention-based routing algorithm. Throughout several simulations, it became clear that for the shortest-path algorithm, more centralised stations obtain a higher profit, whereas for the intention-based routing algorithm there were no significant differences in profitability between the more central stations, and the ones on longer routes.

1 Introduction

In the past years, the number of electric cars has significantly increased with increases of 40% in 2019, 63% in 2018 and 58% in 2017 [1]. With this increasing number, new challenges arise. One of the drawbacks of electric vehicles over non-electric vehicles is the long charging time. This can cause long waiting times at charging stations if multiple vehicles go to the same station. In order to overcome this issue, de Weerdt et al.[2] have proposed a way of routing electric vehicles such that they take into account the waiting times at charging stations. This solution, called Intention-Aware Routing, keeps track of the intentions of each vehicle connected to the system. These vehicles can then retrieve the expected waiting times at each station from the system, and calculate their fastest route.

This, however, is only one way of looking at the electric vehicle routing problem. In other work that has been done so far, different approaches are considered, such as routing with minimal energy consumption [3] or routing based only on the competition in price between buyer and consumer, without taking into account route lengths [4]. What most of these papers have in common, is that they look at the perspective of the vehicles. But, optimizing the road network itself can also improve the efficiency of routing and charging those vehicles. Also, looking at the perspective of a charging station can give insights in how a charging station can raise its profits, or whether multiple charging stations can change their prices, capacity or queuing policies to reduce congestion.

In this paper, the relation between the location of a charging station and its profitability is described. In other words, given a road network with charging stations, we will find out which charging stations are more profitable than others. In order to do this, we extend the model of de Weerdt et al. with a pricing model. This model is then simulated using various graph topologies to obtain a relation between the location of a station and its profit. In doing so, we will compare the performance of a shortest-path algorithm (MAX) and the intention-based routing algorithm (IARS).

The research question that will be answered is

How does the location of a charging station for electric vehicles, within a road network modelled as a graph, affect its profitability?

This question is divided into three sub-questions, which are:

1. In a situation where prices are not taken into account (i.e. prices are equal in all stations), how does the location of a charging station influence the number of times it is visited?
2. How can we add the possibility to charge different prices into the model?
3. What is the effect of charging different prices based on the location of a charging station?

The paper is structured in the following manner. Section 2 contains a description of the problem this paper intends to solve. Section 3 describes the main ideas related to how we can find the profitability of a station based on its location. In Section 4, the setup of the simulations and the results of each sub-question are presented. Section 5 contains an analysis of the reproducibility and integrity of this research. A discussion of the results is given in Section 6. Finally, Section 7 contains the conclusions taken from this research and suggestions for future work.

2 Profitable location problem

From the perspective of a charging station owner, even more for someone willing to build a new charging station, it is very useful to know which locations are the most profitable. Not only can this be used for determining the location of the new station, but if one knows the expected number of visits, the owner can also decide its charging capacity or its price on this.

The problem that this research thus tries to solve, is to find a pattern between the location of a charging station and its profit. By location, we mean the vertex within a graph where a station is located. The mathematical model that we will use to model such a road network is obtained from the paper by de Weerdt et al.[2] and will be discussed in more depth in Section 4.1. This research will focus on the number of visits of charging stations and compares two different algorithms. The first algorithm is the MAX algorithm, which always maximises the expected utility without taking into account waiting times. In the paper by de Weerdt et al., this was called the MIN algorithm because it minimises the expected journey time. But, because we will update the utility function to also include price, we renamed it to the MAX algorithm. The second algorithm is the IARS algorithm, which also maximises the expected utility, but does take into account waiting time, by registering the intentions of each vehicle.

Since the model we are using does not include pricing in the first place, the first part of the problem consists solely of finding out whether there is a relation between the location of a station and the number of times it is visited. In graph theory, centrality measures can often be used to extract some information on locations in graph. There are a lot of such measures, such as betweenness centrality or degree centrality [5]. It has been found that betweenness centrality can play a role in finding congestion in road networks, i.e. nodes with a higher betweenness centrality are often more congested [6]. The objective is to find out whether this relation also holds for charging stations, and if not, whether there is another alternative pattern between locations and the number of visits. This will be found out by running several simulations on different graph topologies.

The next step in answering the research question is adding variable pricing to the model. In order to do this, each vehicle in the model should have a variable indicating the amount of money that has been spent, while the stations should have a price value indicating the price per unit of charge. Moreover, the utility function has to be updated so that each vehicle has a price/time-tradeoff. When we have obtained a suitable pricing extension, we can run new simulations to see whether stations located, such that they obtain more visits, can charge higher prices to increase their profit.

3 Variable pricing and location-based profit analysis

The contribution of this research to the field of routing electric vehicles is two-fold. This paper namely extends the model by de Weerdt et al.[2] with a pricing model, and also analyses the influence of a charging station's location on its profitability.

The first contribution makes it possible to take into account different charging costs at different stations. Each station can charge its own price, and vehicles can base their routing decisions upon these prices as well. Each driver can namely indicate its preference for price and time. In order to do this, the parameter γ is used, which is a value between 0 and 1. $\gamma = 0$ indicates that the driver fully prefers to minimise price, while $\gamma = 1$ indicates that the driver fully prefers to minimise time. This γ is then used in the utility function. The utility function is a weighted average between the normalised time and normalised price of a vehicle, and the goal is to maximise the utility function. The pricing model and utility function can be used by multiple algorithms such as MAX, which maximises the expected utility assuming zero waiting times, and IARS, which maximises the expected utility using the intentions of each vehicle to predict waiting times. The pricing extension has been developed in collaboration with two other students for a bachelor project.

The second contribution is less theoretical and more experimental. By running several simulations with both the original model and the extended pricing model, a lot of conclusions could be made about the influence of a charging station's location on its profitability. These simulations had the goal to develop a relation between the centrality of a station and the number of visits, but also other factors were investigated. For the MAX algorithm there is a clear pattern between the number of visits of a station and the betweenness centrality. For the IARS algorithm, however, centrality seems to have a much smaller effect, and the cars spread out over all stations. Also, both the price of a charging station and the capacity seem to have a significant effect on the number of visits.

4 Experimental Setup and Results

This research uses the model formulated by de Weerdt et al. [2] to investigate whether there is a relation between the location of a charging station and its profitability. In Subsection 4.1, we introduce the mathematical formulation of this model, so that we can refer to the model and extend it. Subsection 4.2 uses the model to find a relation between the location of a charging station and the number of times it is visited for both the MAX and the IARS algorithms. The model is then extended by adding variable pricing in Subsection 4.3, after which it is used to investigate the effect of changing prices on the profitability in Subsection 4.4.

4.1 Routing model

In this subsection we will formulate the mathematical model by de Weerdt et al. [2], which will be referred to throughout the rest of this paper. The domain for this model is described by $\langle V, E, T, P, S, C\rangle$. The road network is represented as a graph with vertices $v \in V$ and edges $e = (v_i, v_j) \in E$. Both the roads, as well as the charging stations are represented as edges, where a charging station is represented as a loop from a vertex to itself. Furthermore, $T = 1, ..., t_{max}$ is the set of discrete time points considered, and P is a probabilistic function indicating the driving or charging time for a certain edge. Finally, $S = 0, ..., s_{max}$ and C represent the current charge and a function which gives the charging cost for each edge, respectively.

The decision of a vehicle is determined by a routing policy $\pi : V \times T \times S \rightarrow V$. The policy determines, given a current vertex, time and charging state, which vertex to go to, by maximising the expected utility function. This function is given by

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

where s' is the state of charge after taking the edge e, and $U(t_c, s_c) = -\infty$ if $s_c \leq 0$ and $-t_c$ otherwise. In other words, the goal of the utility function is to minimise the travel time.

Both MAX and IARS try to maximise the expected utility, but IARS takes into account waiting times based on other vehicles' intentions, while MAX assumes waiting times are zero.

4.2 Most visited station

This subsection describes the relation between the location of a charging station within a road network and the number of times it is visited, in a situation where price is not taken into account, for both MAX and IARS. This situation can be seen as the situation that all charging stations charge equal prices, because then the price does not influence the decision of a single vehicle. In order to develop a relation between the location and the number of visits, we explore three different graph topologies and try to find a pattern between the location of a charging station and the number of times it is visited. For each graph topology, we also determine the betweenness centrality of the stations and see whether this reflects the results from the simulation.

The betweenness centrality of a node reflects the number of shortest paths going through that node and is given by:

$$g(v) = \sum_{s \neq t \neq v} \frac{\sigma_{st}(v)}{\sigma_{st}},$$

where σ_{st} is the total number of shortest paths between s and t, and $\sigma_{st}(v)$ is the number of shortest paths between s and t going through v.

The first graph that is used for the simulations is a simple bottleneck graph with four charging stations, and is shown in Figure 1. This graph consists of four routes from a starting point to an ending point, with each route encountering exactly one station.

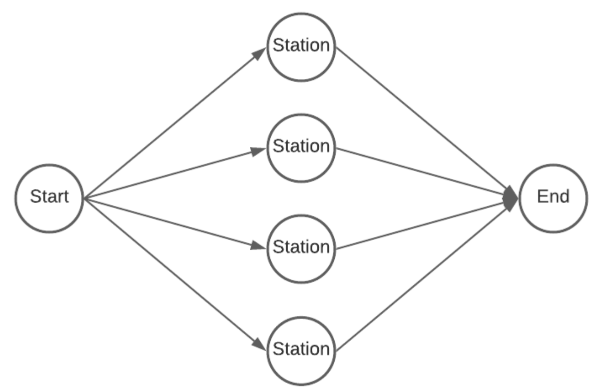

Figure 1: Bottleneck graph with four charging stations

For our first simulation, we consider that all edges take 1 unit of time to travel along them, so each route from start to finish takes 2 units of driving time. We also made sure every car has to charge on its route. In this case, each node has a betweenness centrality of $\frac{1}{4}$. We run a simulation with 500 cars and a capacity of 2 for each charging station for both the MAX algorithm and the IARS algorithm. This gave the following distribution over the stations (Figure 2). The stations are numbered from top to bottom.

Figure 2: Station visits for bottleneck graph with equal edge lengths

Station	Number of visits (MAX)	Number of visits (IARS)
1	500	125
2	0	125
3	0	125
4	0	125

We observe that with the MAX algorithm all cars go to the first station, as they do not take into account what the other vehicles do, whereas for IARS the vehicles equally divide over the stations.

It is more interesting to see what happens when some nodes have a higher betweenness than others. For the bottleneck graph, we can investigate this by having different edge lengths. For the following simulation, we again have

500 vehicles and a capacity of 2 vehicles per charging station. This time, however, we have different edge lengths for each edge, which are random lengths between 1 and 10 time units. The following table (Figure 3) shows the number of visits per station for a single simulation, for both the MAX and the IARS algorithms. Also, the route length indicates the sum of the driving time if you take the two roads that make you go through that station.

Figure 3: Station visits for bottleneck graph with different edge lengths

Station	Route length	Visits (MAX)	Visits (IARS)
1	10	0	138
2	18	0	55
3	9	500	169
4	10	0	138

From the route lengths we can conclude that station 3 has a betweenness centrality of 1, while the other stations have a betweenness centrality of 0. It is also obvious that all vehicles using the MAX algorithm charge at station 3. For the IARS algorithm, however, not all vehicles go to the station with the highest betweenness. The reason for this is the fact that congestion will occur at station 3 if all vehicles go to that station. So in order to reduce their waiting time, and thus their total travel time, several vehicles also charge at another station. The influence of the waiting times thus reduces the number of visits for the station on the shorter route.

This relation can be investigated a bit further by changing the capacities of the charging stations. A higher capacity should result in more visits for the station on the shortest route. By running the same simulation as before, but with different capacities, we get the following results (Figure 4) for the IARS algorithm. The x-axis shows the capacity at each station, whereas the y-axis shows the number of visits per station.

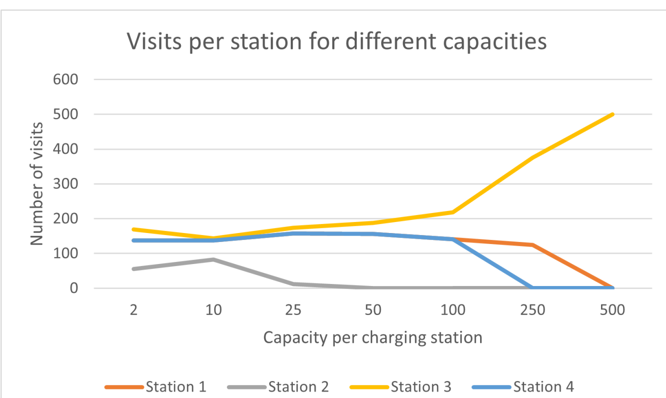

Figure 4: Results for simulations on bottleneck graph with different station capacities

These results clearly support the fact that waiting time has a large influence on the decisions taken by the vehicles using IARS. The general trend in these results is that with a bigger capacity, the stations on shorter routes get visited more often, until only the station on the shortest route is being visited. This indicates that stations on a shorter route benefit from expanding their capacity, whereas for stations on a longer route, this would only increase their costs.

We can investigate the relation between the route lengths and number of visits even further by running multiple simulations with different edge lengths. We use the same settings as before, so 500 vehicles and a charging capacity of 2, and we combine the results of all 5 simulations in one graph (each one in a different colour). This graph (Figure 5) shows the route length through a certain station divided by the sum of all route lengths in the graph on the x-axis. On the y-axis, the number of visits of that station divided by the total number of visits for that simulation is displayed. The total number of visits is always 500 as every car has to charge to reach the goal.

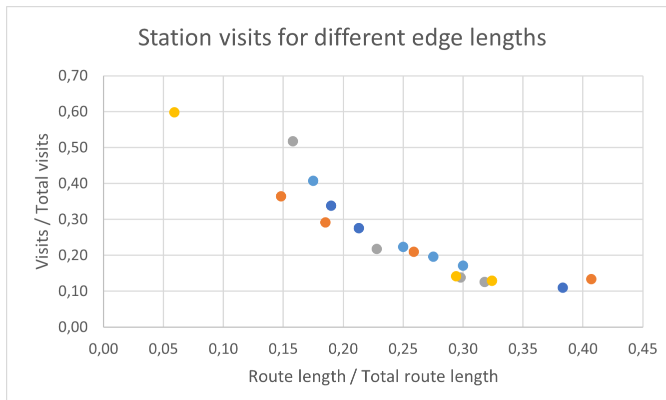

Figure 5: Results for simulations on bottleneck graph with different edge lengths

The graph in Figure 5 shows a clear downward trend, which means that a station on a longer route is visited less often. Even throughout different simulations, this trend is still clearly visible. This is as expected, but it does show that although charging capacity is a major blocking factor, with 500 cars and only 2 charging spots per station, the route length still has a big influence on the number of visits per station.

The bottleneck graph gave us some clear insights in the relation between route lengths and the number of visits of a station, but it is more insightful to look into more complex graph topologies. We will now look at a graph with a grid topology, with four rows and four columns. The two middle columns contain four stations, whereas the other two columns contain the source nodes and the destination nodes. So each vehicle starts at a random source node and ends at a random destination node. Also all nodes in a column have edges to the nodes in the next column that are one row higher, in the same row, or one row lower. An illustration of this type of graph is shown in Figure 6.

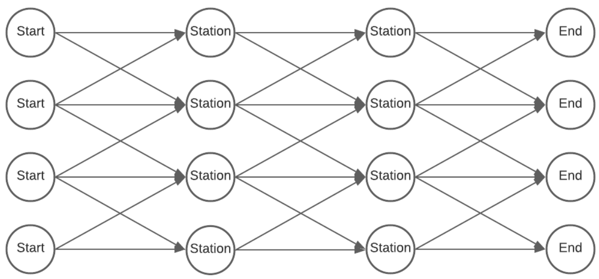

Figure 6: Grid graph with two columns of four stations

Because not every node is connected to a node in the next column, for some routes there are more possibilities than for others. For example, the route from top left to bottom right has only one possibility, whereas the route from one of the middle starting nodes to one of the middle destination nodes has multiple possibilities. Also, more routes go through one of the middle stations than through one of the top or bottom stations. So, when running multiple simulations with different edge lengths, one would expect that the middle stations are visited more often than the top or bottom stations.

We run multiple simulations with different edge lengths for this graph. For each simulation, all other factors stay the same, and are as before. So, the number of cars is 500 and the charging capacity of a station is 2. Each vehicle starts driving at the same time, but starts at a random starting node, and is assigned a random destination node. For each simulation, we determine the betweenness centrality of each station and then compare the results for the IARS algorithm and the MAX algorithm. As each simulation gave a similar result, we show the result of a single simulation in the following graph (Figure 7). The stations are numbered from top to bottom, from left to right (i.e. station 4 is the bottom left station)

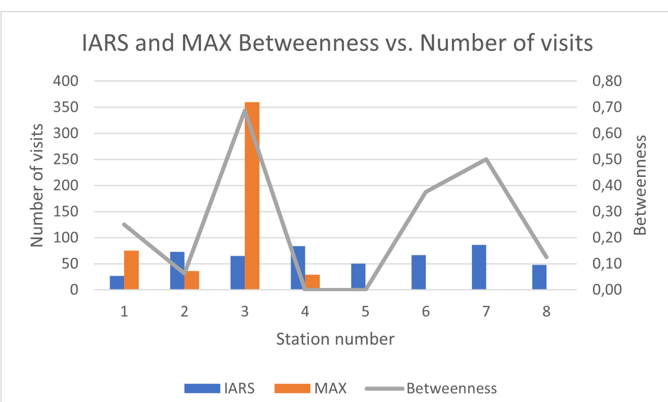

Figure 7: Comparison in number of visits between MAX and IARS for grid topology

From these results, it becomes clear that the MAX algorithm only charges at the first column of stations. As MAX assumes zero waiting times, it just charges at the first station on its route. However, we do see a clear pattern for which station in the first column is visited. A higher betweenness centrality namely results in a higher number of visits. For the IARS algorithm, however, this is not the case. The vehicles still tend to spread out over all stations to reduce their waiting times, and even if there is a slight difference between the number of visits of different stations, this difference is not necessarily in line with the difference in betweenness centrality. Thus, we can conclude, that for this type of graph topology, the centrality of a station does not really influence the number of times it is visited a lot for IARS.

In the previous two graph topologies, the bottleneck and the grid graph, there were some differences in centrality between different nodes, but there was not one node that got visited way more often than others for, especially for IARS. We will now try to find out if such clear difference can occur when using the IARS algorithm, by using a graph topology that has one node which is significantly more central than all other nodes (this will be called the centre topology).

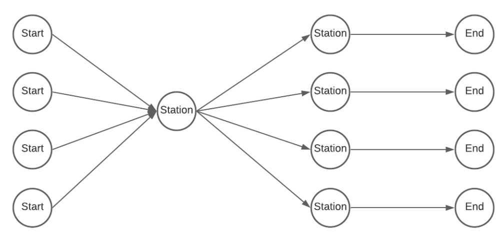

Figure 8: Graph topology with one station that is always on the route

The graph shown in Figure 8 has one station with a betweenness centrality of 1. Every vehicle has to go past that station on its route, so one would expect that this station has the highest number of visits. We again run different simulations for different edge lengths on this graph, and the parameters are the same. Each simulation is run with 500 vehicles that are randomly split over the four starting points and need to go to one of the destination nodes. The average results over 5 runs with different edge lengths are given in the following graph (Figure 9).

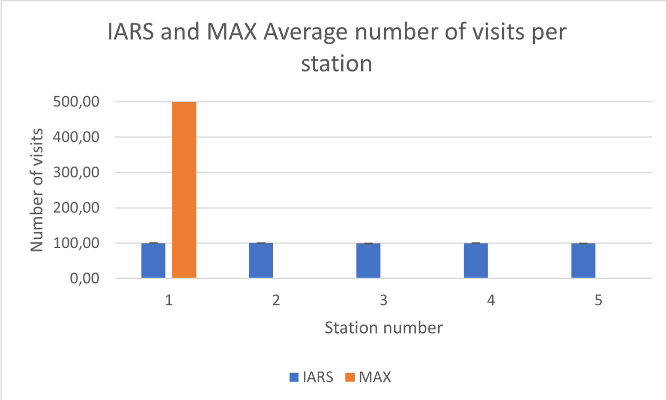

Figure 9: Comparison in number of visits between MAX and IARS for the centre topology

For the MAX algorithm, now all cars charge at the first station, because this is the first station on every route. For IARS, on the other hand, in all simulations the vehicles were nicely divided over all 5 stations. From this we can conclude that the MAX algorithm can cause a lot of congestion in situations where a charging station has a very high betweenness, whereas vehicles using IARS nicely spread over the stations to reduce congestion.

4.3 Pricing extension

We now extend the model by de Weerdt et al. [2] with a pricing model, so that we can investigate whether charging a different price based on the location of a charging station is effective. In order to extend the model with a pricing scheme a value has to be added to the state of a single electric vehicle and the utility function has to be changed. In the existing model, the state was described by $(v_c, t_c, s_c) \in (V \times T \times S)$. We extend this to $(v_c, t_c, s_c, m_c) \in (V \times T \times S \times M)$, where $m_c \in \{1, 2, ..., m_{max}\}$ indicates the amount of money an electric vehicle has spent. The cost of charging at a charging station is determined by

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

where m_e is a fixed price which is determined by the station. Note that m_e can easily be replaced by a function of time to represent a dynamic pricing system, but for simplicity we only consider static prices.

For updating the utility function of a single vehicle to incorporate the effect of pricing, three approaches are considered. The first approach is that every vehicle determines its budget for the journey, and time is minimised as long as you stay within that budget. The second approach uses a time deadline, and as long as the arrival is earlier than the deadline, the cost is minimised. The third approach models a trade-off between time and money, so every vehicle has a certain preference on whether they give more importance to time or to price and the utility is based upon that. This last option seems to fit the model best, as the other two approaches have significant drawbacks. The first approach, for instance, can spend all of the budget for a very small time benefit, whereas for the second approach it is hard to determine what to do when it is not possible to meet the deadline.

The time/money trade-off is modelled using the following utility function which has to be maximised:

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

In this function, γ represents the weights for price and travel time. γ equal to one indicates that the driver only cares about time, whereas γ equal to zero indicates a full preference for price. M_{min} and M_{max} are the minimum and maximum possible cost of the journey, respectively. The maximum possible cost could also be replaced by opportunity costs to obtain a more realistic value. T_{min} and T_{max} are the minimum possible journey time and the maximum arrival time, respectively. Both M_{min} and M_{max}, as well as T_{min} and T_{max} are normalisation factors. By normalising both the time and money spent, they are of equal importance. One could, therefore, see γ as a percentage of how much one favours time over price.

4.4 Most profitable station

Using the pricing extension from Subsection 4.3, we can run more simulations to determine the effect of changing a charging station's price based on its location. In order to only consider one factor, $\gamma = 0.5$ for all simulations. This means that every driver has an equal preference for both price and time.

Again, we first look at the bottleneck graph. We will use the same seed as in Figure 3, as this seed has two stations with equal distances, one station with a longer route length, and one station with a shorter route length. We will then start with each station having a price of 50, and observe the difference when lowering the price of the station on the long route and increasing the price of the station on the shortest route.

For the MAX algorithm this does not give very interesting results, as all vehicles go to the same station. Increasing or decreasing the price of a station just makes them all avoid or go to that station, respectively. For IARS we got the following results when increasing the price of the station on the shortest route.

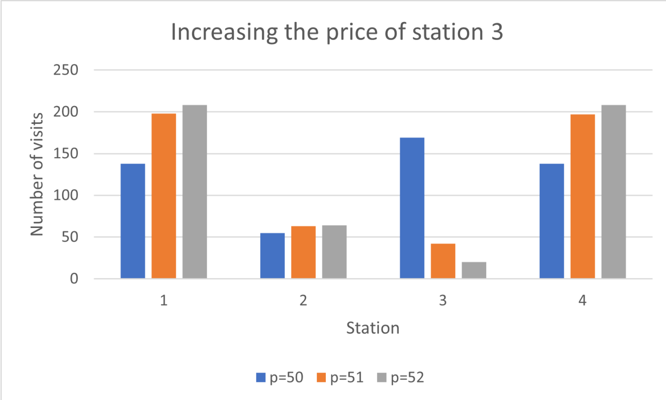

Figure 10: Increasing the price of the station on the shortest route

It can be seen that only a small increase in price, leads to a strong decrease in number of visits. Decreasing the price of the station on the longest route gives the following results.

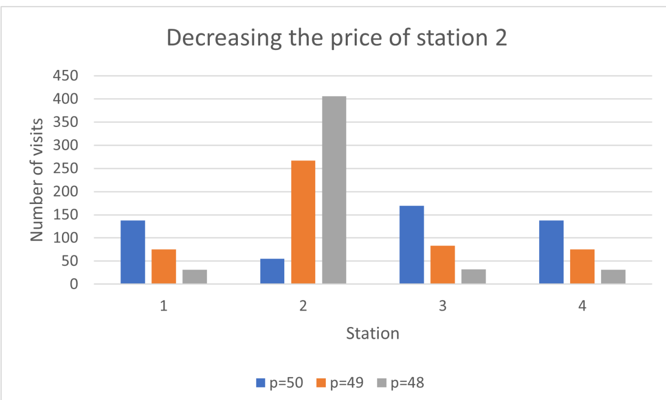

Figure 11: Decreasing the price of the station on the longest route

Again, we see a strong increase in number of visits for a small decrease in the price. So, for a station on a long route, it can be beneficial to lower the price to generate a higher profit, while a station on a short route does not benefit as much from setting a higher price.

For the grid topology, no clear relation between location and number of visits was obtained for IARS in Subsection 4.2. Therefore, increasing the price does not make any sense for any of the charging stations, as they are all equally preferred by the vehicles. Just like for the bottleneck graph, increasing the price of a random charging station did not lead to higher profits. For the MAX algorithm, increasing the price is also not beneficial, as all vehicles encounter at least one other station on their route, and zero charging times are assumed. Therefore, all vehicles avoid the station with the higher price.

The same conclusions can be applied to the centre topology. For MAX, an increase in price for the first station leads to all vehicles avoiding that station. This is as expected, since, again, all vehicles encounter at least one other station on their route. For IARS, none of the stations were visited more often when pricing was not taken into account. Therefore increasing the price is again not beneficial, and similar results as for the bottleneck graph are obtained.

5 Responsible Research

This section reflects on the research process of this project in the context of responsible research. Responsible research consists of both the integrity as well as the reproducibility of the research, which are both important for the credibility of this paper's results and conclusions.

Integrity is not only of importance for the reliability of the researcher, but also necessary for the results to be valid. An obvious part of integrity is making sure that the text written is the writer's own or well referenced. Another aspect of integrity is correctly handling the data that is used. This is especially relevant in the context of this paper. As this paper presents the data of a lot of simulations, extra care should be taken to ensure that the results are valid. While this research, of course, does not use fabricated data or a manipulated process, more simulations have been run than only those that end up in this paper. It is of importance, however, that the reason for leaving out data is not the fact that the data does not support the desired results. For this paper, we tried to overcome this by keeping a log of all simulations that have been run, and by always clearly specifying which data has been used and for what reason. Also, for the cases in which there were unexpected results, these results were not left out, but these will be referred to in the discussion of the results.

For this research, making sure that the research is reproducible takes more effort. Especially because of randomness in the simulations, it is harder to make this research reproducible. We solve this with the use of random seeds. This means that, when running a simulation, you do have random parameters, but those are based on the seed number. So, if you run the simulation with the same random seed, you will get the exact same results. A log has been created with all seeds for all simulations to supply to people willing to reproduce these results. Another issue for reproducibility is the fact that the reproducers have to rewrite the code. In this research, code was obtained from de Weerdt et al.[2] to extend on their work. This, however, could be even simplified by making the code open-source. In that case, the source code would be available to anyone willing to reproduce this research.

All in all, this research does not face too many big issues with integrity or reproducibility. Reproducibility was potentially a bigger problem, but with random seeds and open-source code, anyone should be able to reproduce or extend on this work.

6 Discussion

The most apparent result obtained from all simulations is that by using IARS the vehicles spread over the stations, whereas for MAX this is not the case. When putting this into the context of the results by de Weerdt et al. [2], this appears to be a logical result, as they showed that IARS gives a significantly lower journey time than MAX, for which spreading out over all stations could be an explanation, as less congestion will occur.

When considering the MAX algorithm only, we have seen that the number of visits per station had a clear relationship with the betweenness centrality of a station. Stations with a higher betweenness are visited more often, as long as they are the first station that occurs on a route from start to end. Theoretically, this result makes sense since the MAX algorithm, when not taking price into account, just finds the shortest path to the destination, while the betweenness centrality counts the number of shortest paths going through each station. So, it seems logical that a higher betweenness leads to a higher number of visits.

For IARS, on the other hand, no clear relation between number of visits and betweenness centrality was found. However, it cannot be concluded already that such a relation does not exist. While the grid topology and the centre topology did not show any differences between stations, the bottleneck graph did. This indicates that, in certain situations, stations can get more visits than others.

When applying the formulated pricing extension to both algorithms, we found that price had a huge effect on the station choice, even if the drivers equally valued price and time. This indicates that a station's location has a lower influence than its price, but care needs to be taken when concluding this. Especially the influence of the normalisation factors in the pricing model has to be taken into account. Since these normalisation factors are based on the road network itself(i.e. M_{max} is the maximum possible price to pay on the route), a change in a station not on the route could change the utility of a vehicle. For instance, when a station that is not used by any of the vehicles increases its price significantly, the vehicles might start to value time a bit more due to the fact that the price factor is divided by a larger M_{max}. Therefore, the influence of these normalisation parameters should be researched more in order to verify the conclusions on the effect of price in this paper.

7 Conclusions and Future Work

This paper has two main contributions to the field of routing electric vehicles. The first contribution is a pricing extension to the model used by de Weerdt et al.[2]. The extension gives drivers the possibility to set their preferred trade-off between time spent and money spent for their trip. The second contribution is the analysis of the relation between the location of a charging station and its profitability for both the MAX and IARS algorithms.

The pricing extension is not only a useful addition for several routing algorithms, but also opens opportunities for new research. We have already seen the extension being used for two different algorithms, but it could also be used for alternative routing algorithms. It could be interesting to compare how different routing algorithms are influenced by changes in price. Also, many more relations could be investigated, such as the influence of the price/money trade-off parameter γ, or even the possibility to reduce congestion by setting different prices at different stations. Also, the pricing model could easily be improved to add the possibility of dynamic pricing based on time of day or current number of vehicles at a station.

The analysis of the profitability of charging stations in the context of their location has led to several conclusions. First of all, it has become clear that IARS performs way better in spreading out vehicles over multiple stations. When the MAX algorithm was used, it was easy to predict where the vehicles would go to based on the betweenness centrality of the stations. Therefore, when all vehicles use the MAX algorithm, some stations have a significant advantage over other stations. For IARS, such a difference was only visible for the bottleneck graph, so it might be interesting to do further research on the reasons for these differences. In general, extending this research to more complex graphs or even real road networks could give more insights in the effect of the location for the IARS algorithm. Another interesting extension would be to find the best location to build a new charging station. This is especially relevant for the MAX algorithm, and could be done using the facility location problem [7].

Two other conclusions obtained are the fact that increasing the capacity of the charging stations benefits stations on a shorter route, and that increasing the price of a station on a shorter route did not increase its profitability. These two conclusions, however, could be researched more extensively by varying the according parameters, such as γ, more than is done is this paper. Also, running simulations on different graph topologies would give more insight in the influence of pricing and capacity.

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