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LEARNING FROM HISTORICAL DATA TO PREDICT ELECTRIC VEHICLE TAXI CONSUMPTION AND CHARGING TIME

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ABSTRACT

Electric taxi fleet simulation calls for a lot of uneasily accessible data. We learned from historical data in order to predict electric vehicle consumption and charging time. Although simulation was the main goal, the developed models will be used by the dispatching team of the company. Moreover, the data analysis process allowed us to discover flaws in the infrastructure (e.g., defective stations and defective batteries).

1 INTRODUCTION

Teo Taxi (Montreal, Canada) runs a fleet of 100% electric taxis (170 cars right now; 300 by the end of the year) leading to energy savings and a reduction of CO_2 emission (electricity is from a hydro power source). The company uses electric vehicles (Nissan LEAF, KIA Soul EV, Tesla Models S and X) that do not offer as much range as gazoline cars. Teo has charging stations disseminated in the city. Taxis are owned by the company and drivers are salaried. The management of the fleet is centralized, leading to global optimization opportunities. For instance, the drivers are assigned to a new car instead of waiting for their previous car to charge. Route dispatch and charging decisions are carried on using heuristic-based algorithms and there is a great improvement potential. Teo Taxi, Université Laval, and the Institut du Véhicule Innovant created an R&D program to develop dispatch algorithms and to evaluate their impacts with simulation. Existing simulators (Cheng and Nguyen 2011) in our specific context calls for a lot of uneasily accessible data. This paper describes the model we had to develop to feed our simulations. In our study, we were able to extract data from the company's database and establish how many trips were completed per hour of the week, per week of the year, etc.

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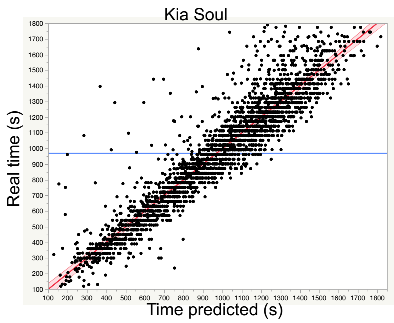

Figure 1: Kia Soul charging model.

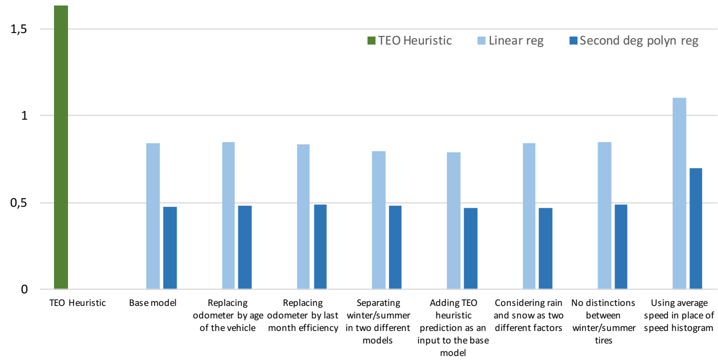

Figure 2: Consumption models.

2 CHARGING TIME AND ENERGY CONSUMPTION MODELING

Charging time varies according to the vehicle model, degradation of the battery, temperature, and starting and desired charging levels (going from 0 % to 5 % is quicker than from 95 % to 100 %). Using historical data, we developed fitting models based on random forests, decision trees, support vector regression models, and regression models (Shalev-Shwartz and Ben-David 2014). A regression model (polynomial, second degree) with level-two interactions was the best one. Figure 1 illustrates how we fit charging time (average error under 10%) for a Soul EV despite duration variations in the data (charging time triples during winter).

Energy consumption needs to be estimated before allocating a given customer/route to a specific car. Imprecise evaluation calls for errors and to a less efficient fleet (the usable battery capacity is artificially reduced). Energy consumption depends on: travelling distance, speed, air-conditioning or cabin heating, temperature, weather (rain, snow), and the presence of winter tires. We developed different regression models and compared them with the heuristic used by Teo (which supposes an all-year-long fixed efficiency plus a surcharge for cabin heating and accessory during winter). We compared different estimations of the battery state of health (odometer value, age of the vehicle, using the efficiency of the vehicle during the last month) and the impact of removing other data in comparison with our base model. Our best model decreased the average error by 71% (Figure 2). The most important factor is to include in the input data the distance driven for each speed (e.g., 2 km at 50 km/h, 7 km at 90 km/h) instead of only using the average speed.

3 CONCLUSION

We developed charging models and consumption models needed to simulate the impact of route allocation algorithms. Although simulation was the main goal, the developed models will be used by the dispatching team. It should greatly reduce the needed margin of error and improve the fleet efficiency. Moreover, the data analysis process allowed us to discover flaws in the infrastructure (e.g., defective stations and defective batteries). Based on this, the company developed a dashboard to detect those situations in real time.

REFERENCES

Cheng, S.-F., and T. Nguyen. 2011. “Taxisim: A Multiagent Simulation Platform for Evaluating Taxi Fleet Operations”. In *Proceedings of the 2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology-Volume 02*, 14–21. IEEE Computer Society.

Shalev-Shwartz, S., and S. Ben-David. 2014. *Understanding Machine Learning: From Theory to Algorithms*. Cambridge University Press.

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