Modeling Strategic and Operational Policy Decisions for Autonomous Electric Vehicle Sharing Platforms

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Abstract

Around 24% of direct CO_2 emissions are contributed to by the transportation sector due to fossil fuel consumption, in which nearly three-fourth are contributed by the road vehicles. The use of electric vehicles (EVs) has gained prominence around the world as a response to these adverse environmental impacts of fossil-fuel usage and rapidly depleting fossil-fuel reserves. However, the penetration of EVs is very less and around only 1% of the global fleet of cars is electrified. The issues that hinder the large-scale adoption of EVs are the customer's range anxiety, the cost of the electric vehicles, and inadequate charging infrastructure, especially in the case of non-autonomous, private consumer markets.

With better charging infrastructure, it is anticipated that driverless vehicles will become an increasingly sustainable option in the future and consumers will abandon their personal vehicle ownership and leverage shared vehicles for mobility. Further, ABI Research forecasts that there will be more than 11 million shared driverless vehicles operating on the roads globally by 2030, serving an average of 64 users per shared driverless vehicle (https://www.abiresearch.com/press/driverless-cars-and-shared-mobility-transform-trad/).

Today, vehicle sharing platforms operating autonomous electric vehicles (AEVs) such as RideCell (https://ridecell.com/solutions/autonomous-vehicles/) provide a more efficient and eco-friendly alternative mode of urban transportation. Additionally, an AEV fleet ensures 24-by-7 operation with platform-governed specific and optimized operational policies. It also removes the driver's discretion for ride refusal/acceptance. Studies have shown how replacing existing car-sharing systems with an autonomous taxi system could reduce the number of vehicles required by 2.8 to 3.7 times to satisfy the same demand, which in turn reduces the fares. However, autonomous electric vehicle sharing platforms face various new strategic and operational decisions. While the strategic decisions include decisions such as the optimal number and location of charging stations, and the number of charging points per station; the operational decisions include decisions such as customer-vehicle allocation, distribution of vehicles to the stations and charging policies (the type of charging - full vs. partial, and the threshold energy level of the AEV to be considered for charging).

We analyze the decisions using a three-stage sequential modeling approach. We consider a station-based EV Sharing system, in which customers are picked-up and dropped-off by the AEVs at charging stations only. AEVs are classified based on their energy level. If the energy level of an arriving AEV at the charging station is below a threshold value, it undergoes either partial or full charging. The platform broadcasts the availability of the AEVs to the customers at different charging stations. An AEV is classified as available for the customer trip only if its energy level is above the charging threshold, the same as used for the charging decision. We also consider different traffic conditions which affect the battery consumption as well as the travel time of AEVs.

In the first stage, we develop a detailed vehicle simulation model that characterizes longitudinal vehicle dynamics while considering standardized drive cycles. The output of the simulation model serves as an input to the second-stage queuing network model. The simulation model uses vehicle parameters such as mass, wheelbase, maximum speed, CG location, and battery energy rating to extract time and energy consumption for traveling from one charging station to another under different traffic conditions, by using AVL CRUISE™, a commercial powertrain simulation software. These time and energy parameters form the input to the second stage queuing network model, where we analyze the performance of the platform operations using a multi-class open queuing network with class switching, and derive the queue length and utilization of the queuing nodes. The output from the second stage along with the network flows form the input to the third-stage model. In the third-stage, we propose a mixed-integer nonlinear optimization program which provides the profit-optimal number of chargers at each charging station, as well as, the vehicle repositioning fractions. We develop a heuristic to obtain the performance bounds by simplifying the model constraints. The numerical experiments suggest that the bounds are reasonable, and the optimal value of the decision variables lie within 6% of the bounds.

To summarize, we contribute to the literature and practice by (1) considering detailed vehicle dynamics including battery charging and energy consumption under different drive cycles (traffic conditions), (2) considering different charge upto policies - full and partial charging, and (3) integrating vehicle dynamics with platform's operational and infrastructural policy parameter optimization.

Keywords: E-Vehicles, Queuing theory, Simulation, Logistics, Vehicle dynamics