

Optimizing Electric Vehicle Charging Schedules Based on Probabilistic Forecast of Individual Mobility

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1 Introduction

The number of electric vehicles (EVs) has been rapidly increasing since the last decade. This popular trend also challenges the electricity grid system without any control. Smart charging can adapt charging schedules of EVs to gain technical and financial benefits by shifting charging schedules to off-peak hours^[1]. The information of next-day travel demand for an EV fleet should be predicted to arrange smart charging. Our study aims to incorporate individual user's mobility features to predict next-day energy consumption and parking duration for individual EVs, since predictability has been observed in individual human mobility to some extent from past behaviors^[2]. More specifically, we raise the research question: In which way and to what extent can knowledge about individual user's mobility help obtain monetary benefits and reduce charging peaks of electric vehicles? We follow the analytical procedure in Figure 1 to answer it. We first test the effects of individual mobility features in the probabilistic prediction of energy consumption and parking duration. Then, smart charging strategies are proposed based on the predicted results and further evaluated compared to uncontrolled charging from the financial and technical aspects.

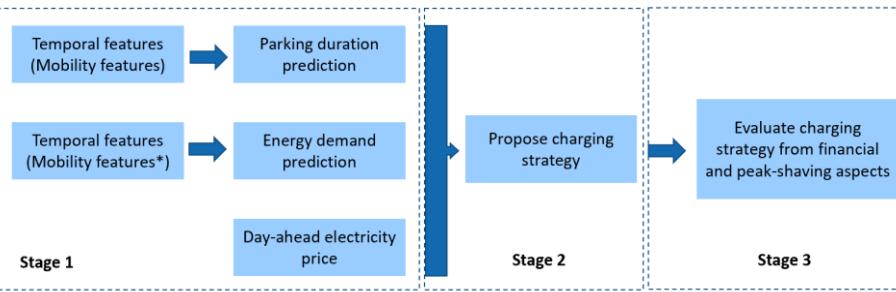


Figure 1. The analytical procedure of the research.

2 Probabilistic Prediction

Quantile regression was used to predict next-day energy consumption and parking duration. Linear quantile regression (LQR), quantile random forest (QRF), and gradient boosting quantile regression (GBQR) were used. State of Charge (SoC) was set as the target for energy consumption, and arrival and departure time was for parking duration. Temporal features and past mobility features were fed as inputs. Results are given in Table 1. A smaller outbound ratio and meanwhile a narrower average inbound range indicates a better model performance.

Table 1. Outbound ratio and average inbound range at significance levels of 95%, 90%, and 70% for all users by model for:
 a) SoC prediction, b) arrival prediction, and c) departure prediction.

	Outbound Ratio [%]			Average Inbound Range [SoC %]		
	95%	90%	70%	95%	90%	70%
LQR	46.28	49.89	60.61	68.75	56.23	28.92
LQR+Mobility	22.80	26.00	39.15	64.94	55.33	30.56
QRF	3.10	5.45	18.47	59.72	50.67	29.50
QRF+Mobility	1.58	2.59	6.25	50.61	39.34	19.89
GBQR	2.61	5.44	18.67	65.90	50.90	29.07
GBQR+Mobility	4.52	8.58	23.52	58.33	44.08	23.25
(b)	Outbound Ratio [%]			Average Inbound Range [hour]		
	95%	90%	70%	95%	90%	70%
	LQR	23.59	28.88	47.10	18.22	16.07
	LQR+Mobility	11.68	17.25	37.07	16.88	14.41
	QRF	2.88	6.36	26.17	16.77	13.62
	QRF+Mobility	4.01	5.43	10.14	12.53	9.93
(c)	Outbound Ratio [%]			Average Inbound Range [hour]		
	95%	90%	70%	95%	90%	70%
	LQR	24.19	29.14	45.82	18.08	16.10
	LQR+Mobility	10.03	15.27	33.65	17.14	14.13
	QRF	3.31	7.29	28.46	17.73	14.53
(d)	Outbound Ratio [%]			Average Inbound Range [hour]		
	95%	90%	70%	95%	90%	70%
	QRF+Mobility	4.50	6.02	11.27	12.30	9.70
	GBQR	3.12	7.98	29.00	18.61	14.80
	GBQR+Mobility	4.60	10.80	33.64	16.82	12.56

3 Charging Strategy

Uncontrolled charging (baseline), unidirectional smart charging, and bidirectional smart charging were simulated in the study.

Monetary benefits: As shown in Table 2, by giving overestimated prediction of SoC from quantile=0.55, the unidirectional strategy starts to earn money. The bidirectional smart charging strategy can save money at all given SoC quantiles' prediction results, and it can gain more benefits compared to the unidirectional one.

Table 2. Financial benefit of Unidirectional and Bidirectional Smart Charging compared to baseline with SoC prediction (QRF+Mobility) at different quantiles.)

The Quantile of SoC Prediction	Unidirectional Benefit [euro]	Bidirectional Benefit [euro]
0.5	-200.29	141.00
0.55	9.77	426.29
0.6	237.96	700.96
0.65	439.41	975.17
0.7	647.27	1213.75
0.75	868.64	1437.58
0.8	1115.80	1731.58
0.85	1335.18	2083.73
0.9	1514.87	2505.94
0.95	1661.37	3046.08

Peak-shaving effects: In Figure 2, most of the charging processes for unidirectional and bidirectional smart charging happen during off-peak hours (green zones), which help to shave peaks brought by EVs compared to the baseline. However, it is found that bidirectional smart charging will bring new peaks from 4 AM to 5 AM.

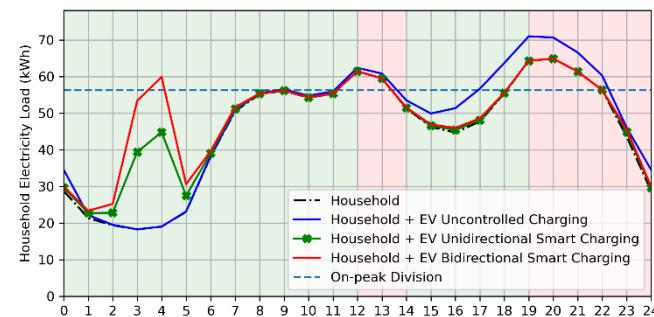


Figure 2. Hourly energy demand for Uncontrolled Charging, Unidirectional Smart Charging, and Bidirectional Smart Charging with SoC prediction (QRF+Mobility) at 0.5 quantile.

4 Conclusion and Outlook

In our research, we have the following conclusions.

- Mobility features help the prediction of next-day energy consumption for LQR and QRF at three significance levels, and arrival and departure time for LQR at three levels and for QRF at 90% and 70%.
- Unidirectional smart charging helps save expenses and bidirectional one helps gain more benefits. Both of them bring very little pressure to the original household demand during peak hours. However, bidirectional one might bring new peaks if all left energy is sold to grids.

As for future work, two main aspects could be further focused:

- To improve the performance of probabilistic models, e.g., finding the optimal temporal resolution of the mobility features for prediction.
- To enhance the applicability of smart charging strategies in reality, e.g., considering renewable energy sources, discussing the tasks and gains of different stakeholders.

5 References

- [1] João A Peças Lopes, Filipe Joel Soares, and Pedro M Rocha Almeida. Integration of electric vehicles in the electric power system. *Proceedings of the IEEE*, 99(1):168–183, 2010.
 [2] Chaoming Song, Tal Koren, Pu Wang, and Albert-László Barabási. Modelling the scaling properties of human mobility. *Nature physics*, 6(10):818–823, 2010.