Grid-integration of electric vehicles: flexibility options of autonomous driving

IEEE PES GM 2020, August 2020

Panel on "Electric Vehicles as Flexible Demand-side Resources: Research Progress, Obstacles and Pilot Projects"

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Supported by ERA-Net Smart Energy systems' focus initiative Integrated, Regional Energy Systems and European Union's Horizon 2020 research and innovation programme under grant agreement No 775970.

Based on the work: F. Sossan, B. Mukherjee, Z. Hu, "Impact of the Charging Demand of Electric Vehicles on Distribution Grids: a Comparison Between Autonomous and Non-Autonomous Driving", to be presented at IEEE EVER 2020, 2020.

Context

- The uncoordinated charging of many electric vehicles (EVs) can lead to exceeding line ampacities, statutory voltage limits, and substation transformer rating.

- Smart charging has been widely proposed to achieve coordination among EVs to avoid congestions and postpone expensive network reinforcements.

Research question

- Autonomous electric vehicles (AEVs) will replace conventional EVs in the next decades.
- Thanks to autonomous driving, AEVs can pick a suitable charging station autonomously and support local distribution grids operations.

- **How can we augment smart charging algorithms to use the option of autonomous driving to improve charging times and reduce grid congestions?**
- To reply, we formulate an optimal power flow (OPF) -based smart charging algorithm for EVs and AEVs and compare their performance.

EVs' battery state-of-charge model

- Non-negative charging power of vehicle v at time t:

$$P_{tv}^{(\mathrm{EV})}$$

- Battery state-of-charge (SOC) of vehicle v at time t with charging efficiency η [Stai]:

$$\mathrm{SOC}_{tv}\left(P_{tv}^{(\mathrm{EV})}\right) = \mathrm{SOC}_{t-1v}\left(P_{(t-1)v}^{(\mathrm{EV})}\right) + \eta \frac{1}{E_v} P_{tv}^{(\mathrm{EV})} T_s$$

- Charging power should be less than the charger apparent power rating (we assume operations at 1 pf):

$$P_{tv}^{(\mathrm{EV})} \leq \bar{P}_{v}^{(\mathrm{EV})}$$

Vehicle and time indexes:
v = 1 ,…, V
t = 1, …, T.

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Vehicles' charging demand and grid nodal injections

- Nodal real power injections at time t and grid node n is the net demand plus the charging demand of all vehicles connected to n:

$$P_{tn} = P_{tn}^{(\mathrm{net})} + \sum_{v=1}^{V} \underline{b_{nv}} P_{tv}^{(\mathrm{EV})}$$

Grid node index: n = 1 ,…, N.

This binary variable is 1 when vehicle v charges at node n, 0 otherwise.

For non-autonomous EVs, b_{nv} for all n and v are defined by the final parking location of each vehicle v.

For autonomous EVs, b_{nv} for all n and v are free variables because the vehicles can pick independently a charging location.

Formulation of the OPF-based smart charging problem for EVs

$$\underset{P_{11}^{(\mathrm{EV})},\dots,P_{TV}^{(\mathrm{EV})}\in R_+}{\arg\min} \left\{ \sum_{t=1}^{T}\sum_{v=1}^{V} \left(\mathrm{SOC}_{tv}\left(P_{tv}^{\mathrm{EV}}\right) - \mathrm{SOC}_{v}^{*}\right)^{2} \right\}$$

The objective is to reach the target SOC level SOC* as soon as possible (alternatively, we can minimize the cost of imported electricity too).

$$\mathrm{SOC}_{tv}\left(P_{tv}^{(\mathrm{EV})}\right) = \mathrm{SOC}_{t-1v}\left(P_{tv}^{(\mathrm{EV})}\right) + \eta\frac{1}{E_v}P_{tv}^{(\mathrm{EV})}T_s \qquad t=1,\dots,T, \quad v=1,\dots,V$$

$$0 \le \mathrm{SOC}_{tv} \le 1 \qquad t=1,\dots,T, \quad v=1,\dots,V$$

$$P_{tv}^{(\mathrm{EV})} \le \bar{P}_{v}^{(\mathrm{EV})} \qquad t=1,\dots,T, \quad v=1,\dots,V$$

SOC model, SOC limits, and charger limits

$$P_{tn}\left(\boldsymbol{P}_{t}^{(\mathrm{EV})}\right) = P_{tn}^{(\mathrm{net})} + \sum_{v=1}^{V} b_{nv}^{*}P_{tv}^{(\mathrm{EV})} \qquad t=1,\dots,T, \quad n=1,\dots,N$$

Nodal injections model.

$$v_{tn}\left(\boldsymbol{P}_{t}^{(\mathrm{EV})}\right) = f_n\left(\boldsymbol{P}_{t}^{(\mathrm{EV})}, \boldsymbol{b}_{n}^{*}\right) \qquad t=1,\dots,T, \quad n=1,\dots,N$$

$$i_{tl}\left(\boldsymbol{P}_{t}^{(\mathrm{EV})}\right) = h_l\left(\boldsymbol{P}_{t}^{(\mathrm{EV})}, \boldsymbol{b}_{n}^{*}\right) \qquad t=1,\dots,T, \quad l=1,\dots,L$$

$$S_t\left(\boldsymbol{P}_{t}^{(\mathrm{EV})}\right) = g\left(\boldsymbol{P}_{t}^{(\mathrm{EV})}, \boldsymbol{b}_{n}^{*}\right) \qquad t=1,\dots,T$$

Grid model. We use linearized grid model based on sensitivity coefficients [Christakou] calculated based on point predictions of the net demand.

$$\underline{v} \le v_{tn}(\cdot) \le \bar{v} \qquad t=1,\dots,T, \quad n=1,\dots,N$$

$$i_{tl}(\cdot) \le \bar{i}_{tl} \qquad t=1,\dots,T, \quad l=1,\dots,L$$

$$S_t(\cdot) < \bar{S} \qquad t=1,\dots,T$$

Constraints on voltage limits, current, and apparent power flow at the substation transformer.

Extension to autonomous electric vehicles

- **Intuition**: AEVs can pick independently a charging station, so the variables b_{nv} are now part of the decision problem.

$$P_{tn} = P_{tn}^{(\text{net})} + \sum_{v=1}^{V} \underline{b_{nv} P_{tv}^{(\text{EV})}}$$

- However, in this way we have computationally complex bilinear terms due to products among decision variables b_{nv} and $P^{(\text{EV})}$.

Extension to (…) – McCormick inequalities [Sossan]

- We use McCormick envelopes to write the bilinear term

$$z_{nvt} = b_{nv} P_{tv}^{(\mathrm{EV})}$$

as a set of three linear inequalities

$$z_{nvt} \le b_{nv} \bar{P}_{v}^{(\mathrm{EV})}$$
$$z_{nvt} \le P_{tv}^{(\mathrm{EV})}$$
$$z_{nvt} \ge P_{tv}^{(\mathrm{EV})} - \bar{P}_{v}^{(\mathrm{EV})}(1 - b_{nv}).$$

- As b_{nv} is binary and P is bounded, the relaxation holds tight and is exact [McCormick].

Formulation of the OPF-based smart charging problem for AEVs

- Same formulation as for non-autonomous EVs with the following differences:

$$\underset{\substack{P_{11}^{(\mathrm{EV})},\dots,P_{TV}^{(\mathrm{EV})}\in\mathbb{R}_+ \\ b_{11},\dots,b_{nv}\in\{0,1\}}}{\arg\min} \left\{ \sum_{t=0}^{T}\sum_{v=1}^{V} \left(\mathrm{SOC}_{tv}\left(P_{tv}^{\mathrm{EV}}\right) - \mathrm{SOC}_v^*\right)^2 \right\}$$

We now minimize over the binary variables too.

$$\sum_{n=1}^{N} b_{nv} \leq 1$$

Non-multilocation constraint (physical constraint to ensure that AEVs charge at one node only, for all v).

$$P_{tn}\left(\boldsymbol{P}_t^{(\mathrm{EV})}, \boldsymbol{b}_n\right) = P_{tn}^{(\mathrm{net})} + \sum_{v=1}^{V} z_{nvt}$$

$$z_{nvt} \leq b_{nv}\bar{P}_v^{(\mathrm{EV})}$$

$$z_{nvt} \leq P_{tv}^{(\mathrm{EV})}$$

$$z_{nvt} \geq P_{tv}^{(\mathrm{EV})} - \bar{P}_v^{(\mathrm{EV})}(1-b_{nv})$$

$$P_v^{(\mathrm{EV})} \leq \bar{P}_v^{(\mathrm{EV})},$$

Nodal injections model and McCormick inequalities (for all relevant indexes).

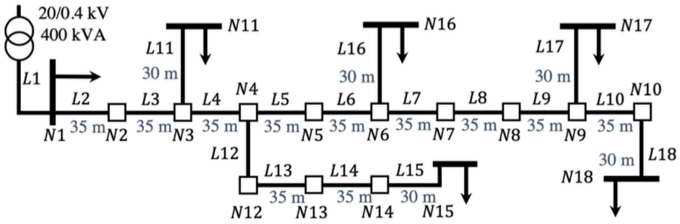
Additionally, we apply the following pre- and post-processing heuristics to model the additional charging demand of autonomous driving:

- If the residual SOC of a vehicle is less than a threshold, it charges locally.
- The final SOC of AEVs that changed location for charging is decreased to account for the energy consumed in returning back to the original parking location.

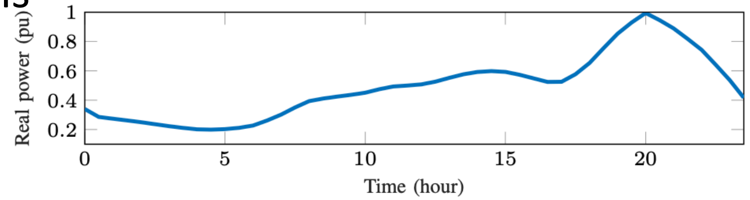
(In our small network case study, it was observed that additional charging demand plays a minor role).

Case study for the comparison EVs vs AEVs

- CIGRE benchmark system for LV grids (single-phase equivalent for the initial proof of concept).



- Demand profile from CIGRE specs. Active power is voltage independent, reactive power calculated assuming a constant power factor.

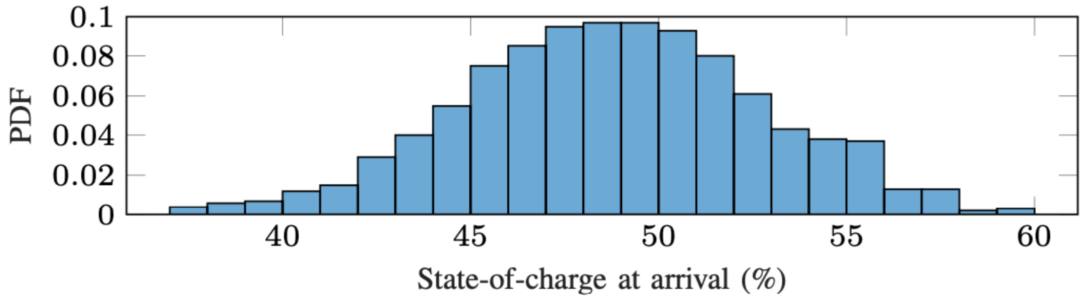


- 98 EVs distributed in the network considering one EV per household (number of household approximated from the nominal demand per node) with a 16 kWh battery.

Node	Nominal demand (kW)	Power factor	Number of parked EVs
1	200	0.95	50
11	15	0.95	3
15	52	0.95	12
16	55	0.95	14
17	35	0.95	8
18	47	0.95	11

Case study (...) – cont'd

- 3.7 kW chargers (16 A at nominal voltage).
- Electric vehicles with distribution of SOC at arrival as in the test-an-EV experiment in Denmark [testDK]:



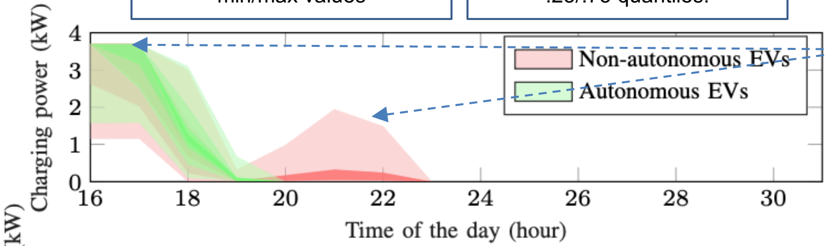
- We assume that all EVs end their trips and are available for charging at the same time (4 PM).
- Time resolution of the scheduling problem is 1 hour. Scheduling horizon 15 hours (4 PM – 7 AM of next day).

Results: charging schedule of EVs vs AEVs

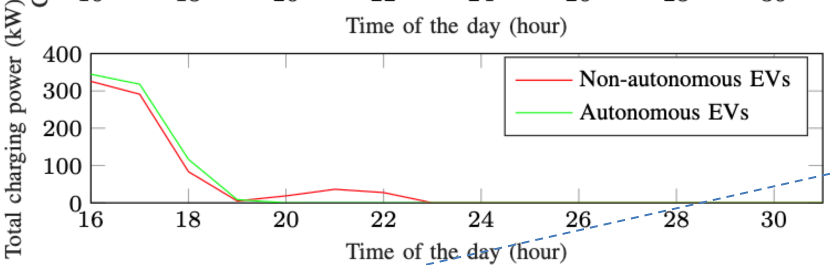
Lighter shaded areas are min/max values

Darker shaded areas are .25/.75 quantiles.

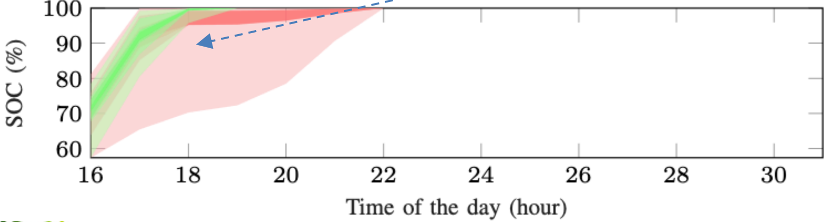
Charging power across the population



Fleet total charging power



SOC across the population

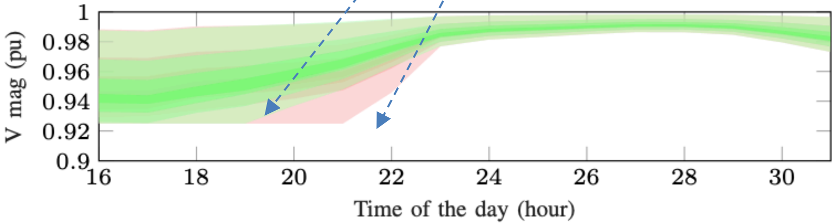


The charging period of the EV population is split into two ...

... due to voltage congestions determined by the concomitance with the peak load.

AEVs achieve to recharge faster than EVs.

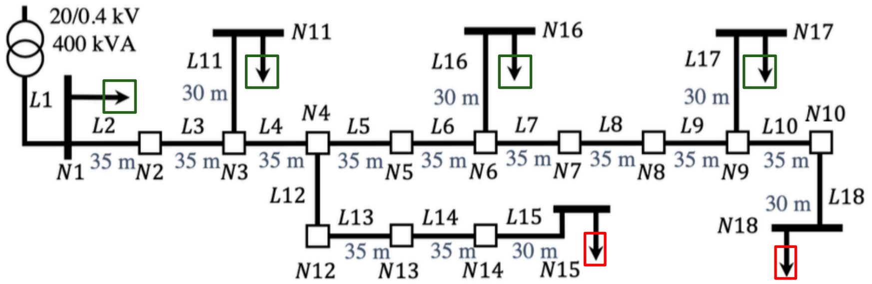
Nodal voltages in the grid



Results: where do the AEVs go to charge?

Node	Nominal demand (kW)	Power factor	Number of parked EVs	Number of charging AEVs (*from results*)
1	200	0.95	50	54
11	15	0.95	3	6
15	52	0.95	12	5
16	55	0.95	14	15
17	35	0.95	8	10
18	47	0.95	11	6

- Some of the AEVs move closest to the grid connection point.



Conclusions

- AEVs add an additional degree of freedom to the charge scheduling problem.
- Smart charging of AEVs contributes to reducing congestions effectively thanks to selecting suitable charging points in the grid.
- We propose smart charging for AEVs with an optimal power flow augmented with binary variables with bilinear terms (exactly) linearized with McCormick envelopes.
- **Final recommendation for distribution system operators (DSOs):** AEVs will avoid grid congestion and postpone cable replacement. If grid congestions are a problem for non-autonomous EVs, in the meanwhile of the transition to AEVs to happen, DSOs can opt for temporary solutions to solve them (e.g., battery energy storage systems).

References

- This presentation is based on the work in [Sossan].

- [Christakou] K.Christakou, D.-C.Tomozei,J.-Y.LeBoudec, and M.Paolone,“GECN: Primary voltage control for active distribution networks via real-time demand-response,” IEEE Transactions on Smart Grid, vol. 4, no. 2, pp. 622–631, 2013.
- [CIGRE] CIGRE Task Force C6.04, “Benchmark systems for network integration of renewable and distributed energy resources,” Cigre’ International Council on large electric systems, Tech. Rep., July 2009.
- [Gupta] Gupta, R., Sossan, F., and Paolone, M. (2019, June). Performance Assessment of Linearized OPF-based Distributed Real-time Predictive Control. In 2019 IEEE Milan PowerTech (pp. 1-6). IEEE.
- [McCormick] G. P. McCormick, “Computability of global solutions to factorable nonconvex programs: Part i—convex underestimating problems,” Mathematical programming, vol. 10, no. 1, pp. 147–175, 1976.
- **[Sossan]** F. Sossan, B. Mukherjee, Z. Hu , “Impact of the Charging Demand of Electric Vehicles on Distribution Grids: a Comparison Between Autonomous and Non-Autonomous Driving”, to be presented at IEEE EVER 2020, 2020.
- [Stai] E. Stai, F. Sossan, E. Namor, J. Y. L. Boudec, and M. Paolone, “A receding horizon control approach for re-dispatching stochastic heterogeneous resources accounting for grid and battery losses,” Elsevier Electric Power Systems Research, 2020.
- [TestDK] “Test-an-ev project: Electrical vehicle (EV) data,” http://mclabprojects.di.uniroma1.it/smarthgnew/Test-an-EV/?EV- code=EV8, accessed: 2020-02.