Smart Bidirectional Charging of Electric Vehicles – an Analysis of Revenue Opportunities

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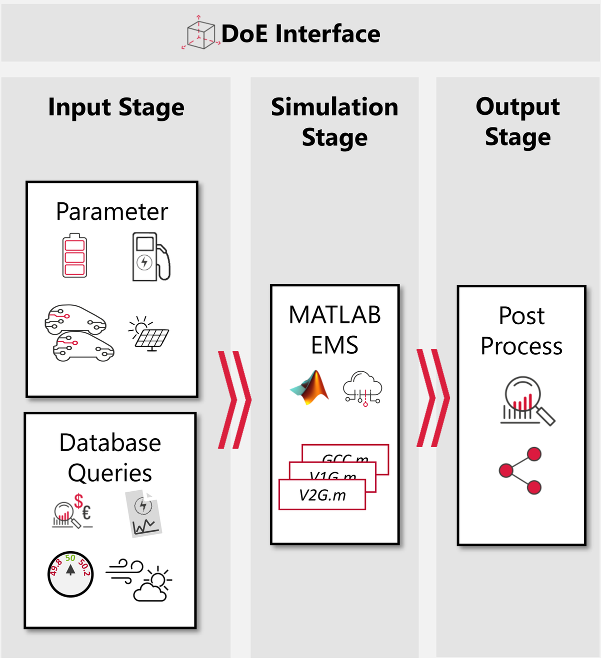
Simulation based revenue analysis for bidirectional EV fleets

1 Simulation model overview

The developed simulation package includes four main features:

- DoE Interface to define experimental framework
- Aggregation of data via API of several databases
- EMS algorithms including V2G related energy / cost optimization features
- Simulink electrical model from grid to battery



2 Challenges

- If the current smart grid model is used to simulate three years of total costs, the calculation time will be very long.
- How to reduce the simulation time ?
- Analysis of the typical charging scenario.

3 Analysis the typical charging scenarios by clustering

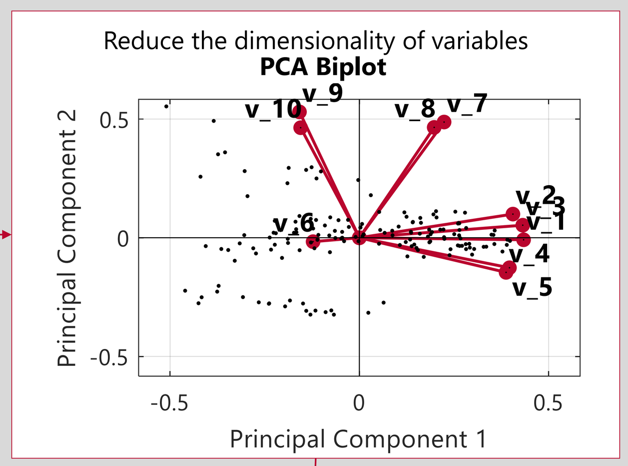
Weather data, grid energy mix, grid prices, holiday data 2019, 2020, 2021

Principal components analysis (PCA)

Summarize some variables for clustering

Variables	Describe
v_1	Max temperature per week
v_2	Min temperature per week
v_3	Average temperature per week
v_4	Max irradiance per week
v_5	Average irradiance per week
v_6	Total days of work per week
v_7	Max renewable energy rate
v_8	Average renewable energy rate
v_9	Grid price deviation in a week
v_10	Average grid price per week

Reduce the dimensionality of variables



k-medoids clustering

Clustered typical CWs for simulation

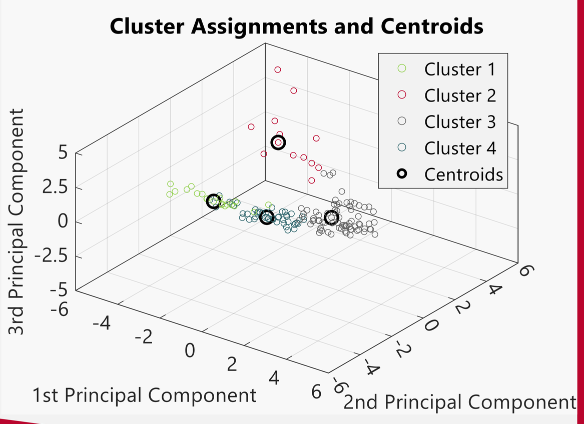
- Here we mainly extracted four categories of variables, ten in total, these four categories are:
  - temperature-related,
  - Solar radiation-related
  - working time related
  - energy price-related variables
- Since ten variables are still too many for clustering, PCA (Principal components analysis) was used here to reduce the dimensionality of the variables from 10 to 4. The **PCA Biplot** shows the composition of the two most important of these principal components.

4 Clustered typical charging scenarios

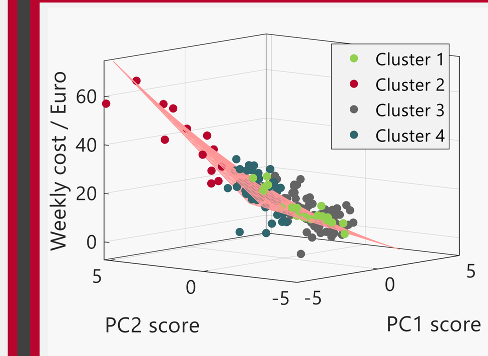
Cluster number	Cluster centroids (Typical CW)	Time slot	Avg. Irradiance range W/m^2	Temp. Range $°C$
1	2019.CW8	Feb.18-24	86.7	1.7-15.7
2	2020.CW2	Jan. 6-12	15.6	3.3-10.6
3	2020.CW37	Sep. 7-13	160.6	8.6-25.9
4	2021.CW46	Nov. 15-21	21.0	3.0-13.2

Four typical weeks were eventually obtained, as shown in the table and the following figure. (CW: Calender week number)

As seen from the three-dimensional diagram, PC1 and PC2 can distinguish the data points to the maximum extent, but there are still times when they cannot be distinguished, and then the help of PC3 and PC4 is needed to get a better clustering result.

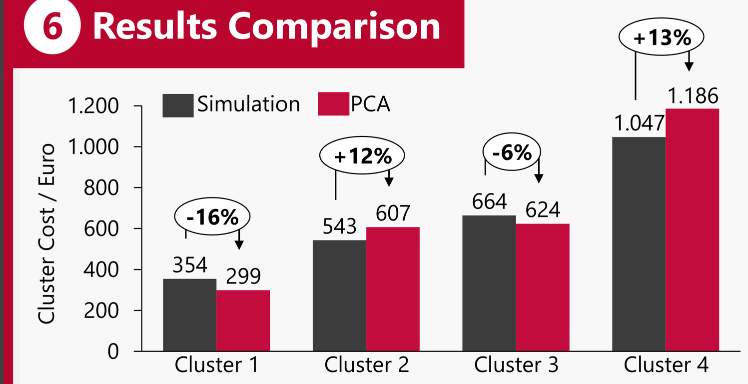


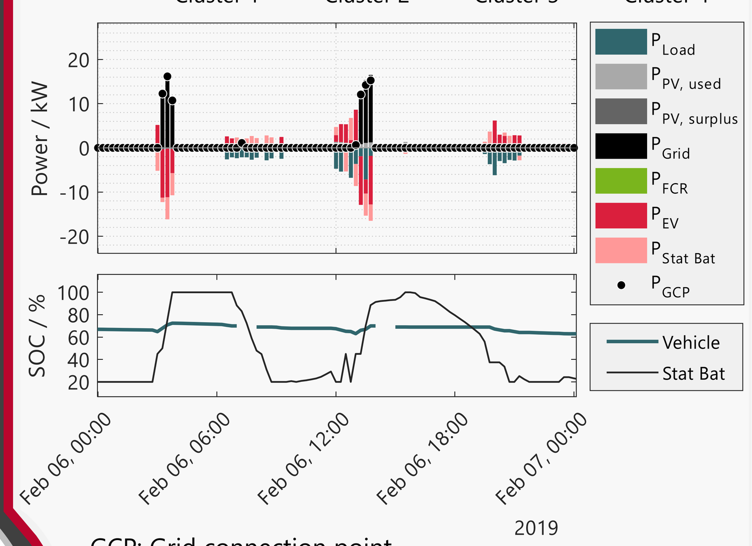
5 Scaling up of simulation results based on typical charging scenarios



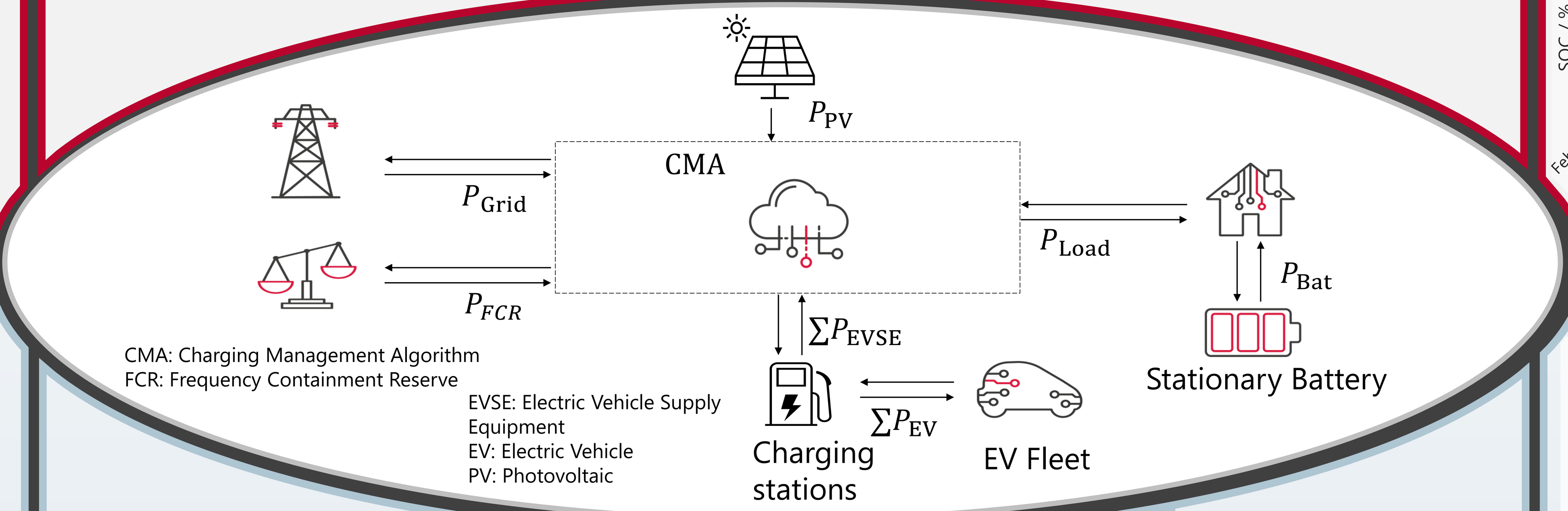
The four clustering centroids allow to obtain a regression surface that represents the cost for three years after scale-up. The scaled-up cost of three years has an error of about 4% with the actual three-year simulated cost.

6 Results Comparison





GCP: Grid connection point



CMA: Charging Management Algorithm
FCR: Frequency Containment Reserve

EVSE: Electric Vehicle Supply Equipment
EV: Electric Vehicle
PV: Photovoltaic

5 FCR Reservation

FCR

$f_{FCR} = f - P_{FCR} \cdot c_{FCR} + \epsilon_{FCR} \cdot c_{Fee}$

$c_{Fee} \gg c_{FCR}$

$c_{Emin} > c_{FCR}$

Offered FCR Power cannot be higher than the charging power of the connected EVs or the GCP

$P_{VL,E_{cap}} = \frac{E_{cap}}{2 \cdot 1{,}25 \cdot 0{,}25\,h}$

$0 \le P_{FCR} \le \min\left(P_{VL,E_{kap}}, P_{VL,P_{max}}, P_{VL,P_{min}}\right)$

$0 \le P_{buy} \le P_{buy,max} \cdot bit_{buy} - P_{FCR} \cdot X_{FCR}$

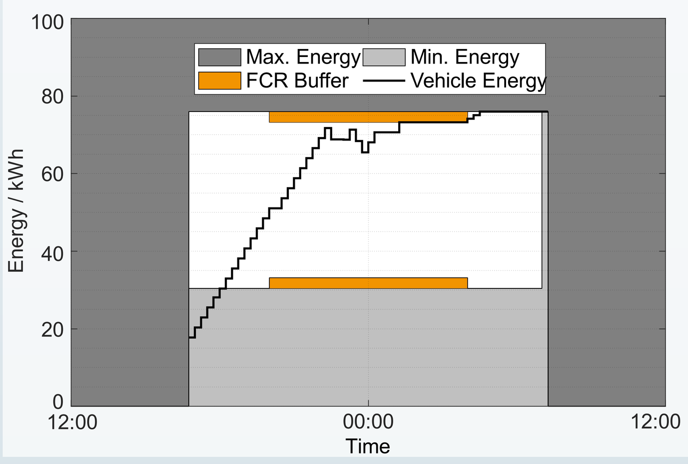
$P_{sell,min} \cdot bit_{sell} + P_{FCR} \cdot X_{FCR} \le P_{sell} \le 0$

Total Energy E_{act}^{tot} should be sufficient to store/provide FCR Energy if requested

$P_{FCR} \cdot X_{FCR} \cdot 0.25\,h - \epsilon_{FCR} \le E_{act}^{tot} - E_{min}^{tot}$

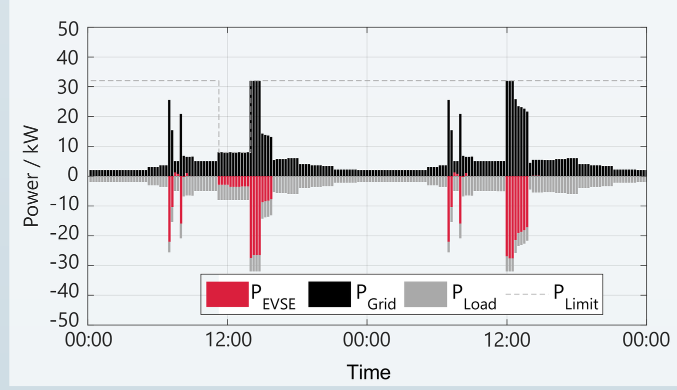
$P_{FCR} \cdot X_{FCR} \cdot 0.25\,h + \epsilon_{FCR} \le E_{max}^{tot} - E_{act}^{tot}$

X_{FCR} is activated (>0) based on grid frequency deviations



4 Dynamic Power limitation

If available grid Power is reduced the optimizer reacts accordingly



2 Economic Moving Horizon Optimizer

Energy convention

absolute: $E_{EV,max}$, $E_{EV,target}$, $E_{EV,actual}$, $E_{EV,min}$

relative to present energy:

$E_{max} = E_{EV,max} - E_{EV,actual}$

$E_{target} = E_{EV,target} - E_{EV,actual}$

$E_{min} = E_{EV,min} - E_{EV,actual}$

Legend

soft constraint
key take–away
fcr related
prediction values

Formulation

$$\min f^T x \text{ subject to } \begin{cases} x(intcon) \text{ are integers} \\ Ax \le b \\ A_{eq}x = b_{eq} \\ lb \le x \le ub \end{cases}$$

$lb \le x \le ub$: Expressed via A

$A_{eq}x = b_{eq}$

Power Balance $\Delta P = P_{charge}(k) - P_{charge}(k-1) + P_{discharge}(k) - P_{discharge}(k-1)$

For $k = 1 - k = Np$

$$\begin{pmatrix} P_{PV} \\ P_{Load} \\ -\sum P_{charge} - \sum P_{discharge} - P_{Load} + P_{PV} + P_{buy} + P_{sell} \\ \Delta P + \epsilon_{power}^{+} + \epsilon_{power}^{-} \end{pmatrix} = \begin{pmatrix} P_{PV,pred} \\ P_{Load,pred} \\ 0 \\ 0 \end{pmatrix}$$

Power balance is expressed and power predictions are enforced via equality constraints

$Ax \le b$

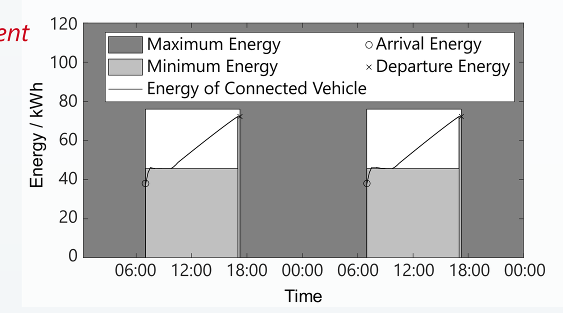
EV Energy

For $k = 1 - k = Np$

$$\begin{pmatrix} -\sum_{i=1}^{k} P(k) \cdot \Delta t + \epsilon_{Energy}(k) \\ \sum_{i=1}^{k} P(k) \cdot \Delta t \\ -\sum_{i=1}^{k_{departure}} P(k) \cdot \Delta t + \epsilon_{Energy}(k) \end{pmatrix} \le \begin{pmatrix} -E_{min} \\ E_{max} \\ -E_{target} \end{pmatrix}$$

Soft constraints results in immediate charging if current energy is below minimum

with $P(k) = P_{charge,n}(k) \cdot \eta_{charge,n} || \frac{P_{discharge,n}}{\eta_{discharge,n}}$



Energy demands from vehicles are considered within the inequality constraints

EVSE Power

Charging and discharging is limited by capabilities of EV and EVSE

$P_{charge,max} = \min(P_{EV,charge,max}, P_{EVSE,charge,max})$

$P_{discharge,min} = \max(P_{EV,discharge,min}, P_{EVSE,discharge,min})$

Integer logic prohibits simultaneous charging and discharging

Vehicle connected: $b_{charge}(\cdot|k) + b_{discharge}(\cdot|k) \le 1$

Vehicle not connected: $b_{charge}(\cdot|k) + b_{discharge}(\cdot|k) \le 0$

$0 \le b_{(dis)charge}(\cdot|k) \le 1$

$P_{(dis)charge,min} \cdot b_{(dis)charge}(\cdot|k) \le P_{(dis)charge}(\cdot|k) \le P_{(dis)charge,max} \cdot b_{(dis)charge}(\cdot|k)$

$\epsilon_{power}^{+} \ge 0$ $\quad \epsilon_{power}^{-} \le 0$

High power fluctuation is punished by introducing soft constraints

Power Grid

$0 \le b_{buy} \le 1$

$0 \le b_{sell} \le 1$

$b_{buy} + b_{sell} \le 1$

$0 \le P_{buy} \le P_{buy,max} \cdot b_{buy} - P_{FCR}$

$P_{sell,min} \cdot b_{sell} + P_{FCR} \le P_{sell}^{-} \le 0$

Integer logic prohibits buying and selling energy simultaneously

Cost

$J_{mon} = P_{buy} \cdot c_{buy} \cdot \Delta t + P_{sell} \cdot c_{sell} \cdot \Delta t$

$J_{con} = \epsilon_{energy} \cdot c_{Emin} + \epsilon_{power}^{+} \cdot c_{power}^{+} + \epsilon_{power}^{-} \cdot c_{power}^{-}$

$f = J_{mon} + J_{con}$

Monetary cost and "soft constraint"-cost are considered

State vector $x(k=1)$

$$\begin{pmatrix} P_{buy}(k=1) \\ P_{sell}(k=1) \\ P_{PV}(k=1) \\ P_{Load}(k=1) \\ b_{buy}(k=1) \\ b_{sell}(k=1) \\ P_{charge}(EVSE=1,k=1) \\ \vdots \\ P_{charge}(n_{EVSE},k=1) \\ P_{discharge}(EVSE=1,k=1) \\ \vdots \\ P_{discharge}(n_{EVSE},k=1) \\ b_{charge}(EVSE=1,k=1) \\ \vdots \\ b_{charge}(n_{EVSE},k=1) \\ b_{discharge}(EVSE=1,k=1) \\ \vdots \\ b_{discharge}(n_{EVSE},k=1) \\ \epsilon_{energy}(EVSE=1,k=1) \\ \vdots \\ \epsilon_{energy}(n_{EVSE},k=1) \\ \epsilon_{\Delta power+}(EVSE=1,k=1) \\ \vdots \\ \epsilon_{\Delta power+}(n_{EVSE},k=1) \\ \epsilon_{\Delta power-}(EVSE=1,k=1) \\ \vdots \\ \epsilon_{\Delta power-}(n_{EVSE},k=1) \end{pmatrix}$$

$x(k=1) \in \mathbb{R}^{6+n_{EVSE} \cdot 7}$

State

$$x = \begin{pmatrix} x(k=1) \\ x(k=2) \\ \vdots \\ x(k=N_p) \end{pmatrix}$$

$x \in \mathbb{R}^{N_p \cdot (6+n_{EVSE} \cdot 7)}$

N_p: Prediction Horizon

Predictive Optimization based charging strategy for EV fleets

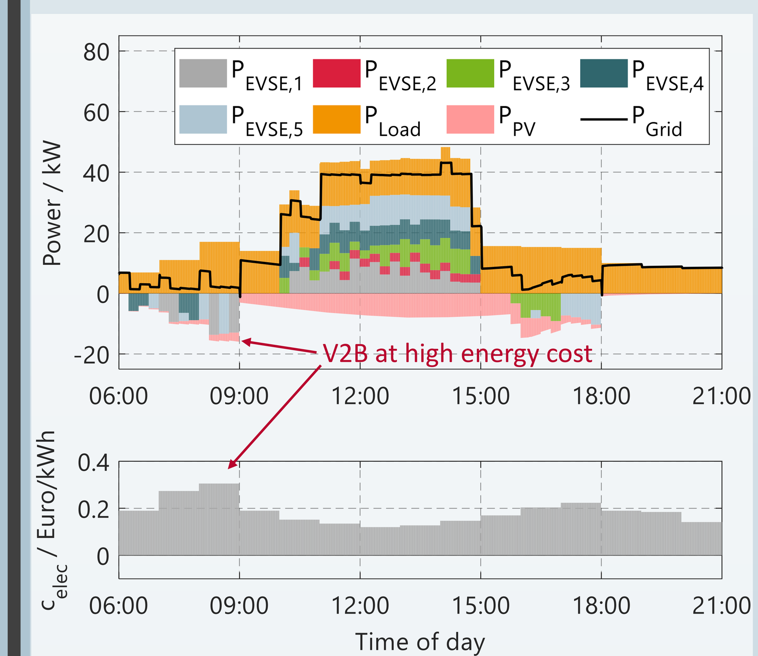
1 Explanation

An algorithmic approach to optimally charge electric vehicles is presented. The approach is based on a moving horizon optimization where as an output the optimal charging or discharging power for the EVs connected at the charging point is determined.

The algorithm provides the following features:

- Bidirectionally charge EVs while considering the respective user needs (Energy at departure, minimum Energy during charging).
- React to dynamic power limitations at charge point level
- Reserve power and energy for frequency containment reserve provision

3 Bidirectional (V2B) Charging



Standardization and Regulation Landscape within the EU

1 General Information

- Requirements, Codes and regulations ensure compatibility and safe operation of charging infrastructure
- Functional requirements cover system-based issues, e.g., Grid voltage, harmonic content, …
- Electrical safety requirements cover issues of electrical shock, e.g., touch voltage, leakage current, …
- There are different requirements for the charging station and the electric vehicle

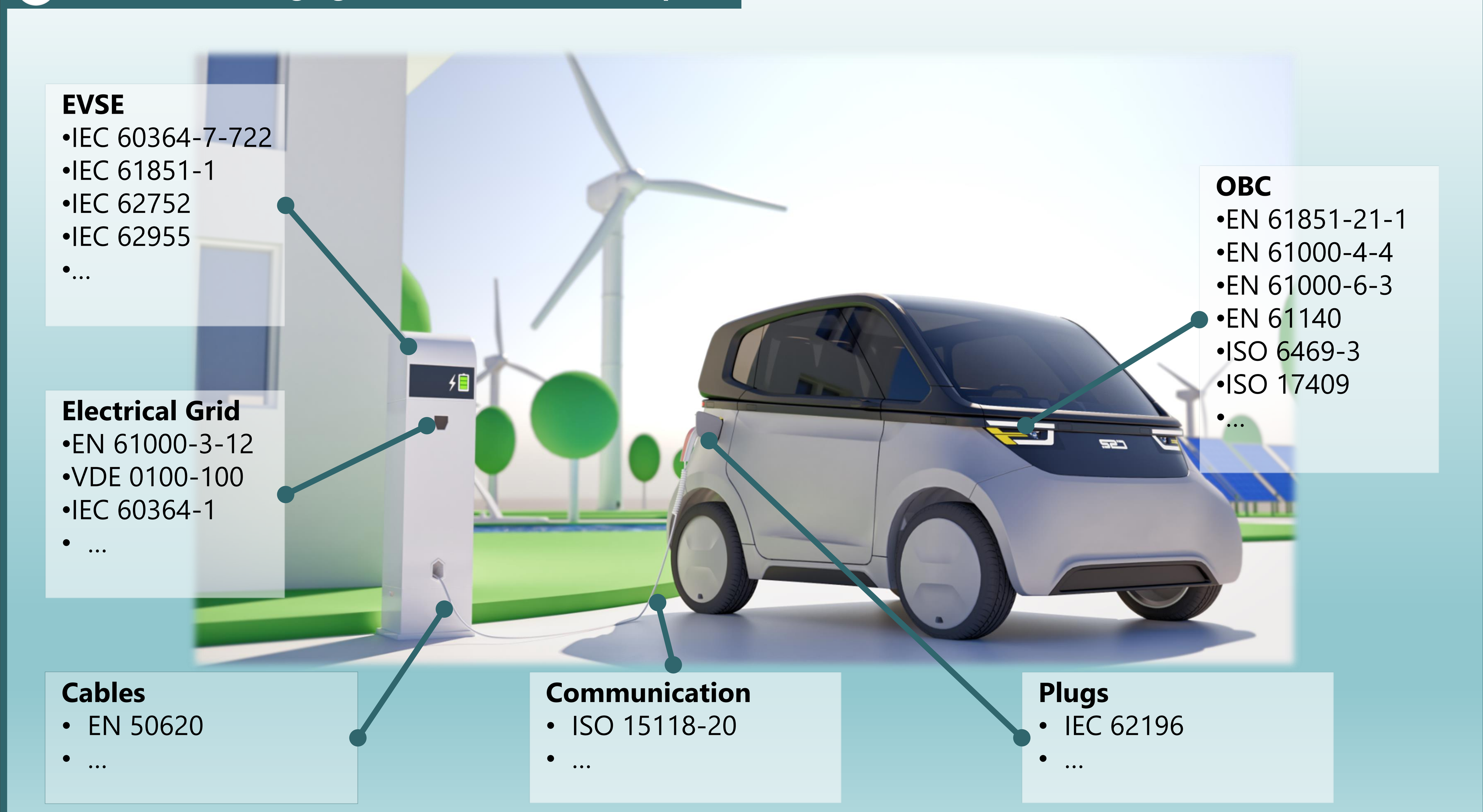
2 European Union

- Standards are harmonized for all countries in the EU
- European HD (Harmonized document) is transferred to local standard with same contents

3 Other regions worldwide

- Local regulations can cause different concepts for functional and safety requirement, which has to be evaluated individually

4 Overview EV charging standardization landscape



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