INVADE flexibility centralized algorithm to manage electric vehicles under DSO requests in buildings with limited information

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***Abstract*—This paper exposes a flexibility management algorithm to optimize the operation of behind-the-meter charging infrastructure in a building including external flexibility requests from the local distribution system operation. It includes the electricity cost minimization including drivers' comfort cost and it uses the limited information available in conventional slow charging points like electricity consumption and charging point status.**

***Index Terms*—Electric vehicle; Smart charging; Energy management system; demand response;**

I. Nomenclature

A. Sets

T	Set of time periods in the planning horizon
T^{const}	Sub-set of constrained periods according to the DSO request
V	Set of electric vehicle charging points
G	Set of photovoltaic generation units
N	Set of charging point sessions per charging point

B. Parameters

Prosumer model parameters:

$P_t^{retail-buy}$	Price at energy part of retail contract for buying electricity in period *t* [€/kWh]
$P_t^{grid-buy}$	Price at energy part of grid contract for buying electricity in period *t* [€/kWh]
P^{VAT}	Parameter that adds VAT to the amount bought [fraction]
$P_t^{retail-sell}$	Price at energy part of retail contract for selling electricity in period *t* [€/kWh]
$P_t^{grid-sell}$	Price at energy part of grid contract for selling electricity in period *t* [€/kWh]
$X^{imp-cap}$	Maximum import capacity [kWh]
$X^{exp-cap}$	Maximum export capacity [kWh]
N^{hour}	Periods per hour [#]

Charging point model parameters:

$W_{v,t}^{CP}$	Baseline charging schedule for EV *v* in period *t* [kWh]
$T_{v,n}^{CP,start}$	Arrival time of each EV charging point *v* of session *n* [#]
$T_{v,n}^{CP,end}$	Departure time of each EV charging point *v* of session *n* [#]
$P_v^{CP,shift}$	Price for deferring 1 kWh energy demand for one time period for charging point *v* [€/kWh]
$P_{v,n}^{CP,NS}$	Price for non-supplying 1 kWh of the expected charging demand of charging point *v* of session *n* by the end of the charging sessions [€/kWh]
FR_t	DSO flexibility request per period *t* as the maximum consumption for all charging points [kWh]

Photovoltaic generator model parameters:

$W_{g,t}^{gen}$	Baseline production from generation unit *g* in period *t* [kWh]
$P_{g,t}^{G,r}$	Price of reducing generation output of the unit *g* during period *t* [€/kWh]

C. Variables

Prosumer model variables

χ_t^{buy}	Amount of electricity bought in period *t* [kWh]
χ_t^{sell}	Amount of electricity sold in period *t* [kWh]
δ_t^{buy}	Binary variable = 1 if site is importing/buying electricity in period *t*, else 0
δ_t^{sell}	Binary variable = 1 if site is exporting/selling electricity in period *t*, else 0

Charging point model variables:

$\theta_{v,t}^{es}$	Amount of electricity supplied to the EV unit *v* in period *t* [kWh]
$\theta_{v,t}^{ch}$	Amount of electricity charged to EV unit *v* in period *t* [kWh]
$\theta_{v,t}^{cd}$	Amount of demanded electricity to the EV unit *v* in period *t* (charging demand) [kWh]

Photovoltaic generator model variables:

$\psi_{g,t}$	Amount of electricity produced from generating unit g in period t [kWh]

Flexibility costs:

$\zeta^{flexibility}$	Total cost for utilizing internal flexibility [€]
$\zeta^{EV,flex}$	Total cost for utilizing EV flexibility in the planning horizon [€]
$\zeta^{EV,shift}$	Cost for shifting EV charging [€]
$\zeta^{EV,NS}$	Cost for non-supplied EV charging [€]

II. Introduction

The current amount of electric vehicles (EVs) in the Dutch distribution systems is raising doubts about their feasible massive penetration in the forthcoming years. Different initiatives are designing innovative solutions to reduce the need of grid reinforcements and grid tariff price increase. One of these initiatives is the INVADE H2020 project [1]. It aims to develop a centralized platform managed by a flexibility operator (FO) which interacts with distribution system operators, balance responsible parties and EV charging stations. The FO is responsible of a subpart of the aggregator activities e.g. pooling small flexibilities of customers or network users through the centralized platform in order to make use of their flexibility in the grid management or participating in energy markets.

A framework of the opportunities and challenges of EV technologies connecting with the grid was presented by Liu et al. [2].

An important part of the literature studies how to optimally manage EV charging sessions in residential-smart buildings thanks to Home Energy Management Systems (HEMS) including vehicle-to-grid potential. Jin et al. [3] presented a problem of scheduling EV charging session from an electricity market perspective, having into account the aggregator energy trading in the day-ahead and real-time markets. A communication protocol is described for interactions among the aggregator and EVs. Mohseni et al. [4] studied an energy consumption model of a residential microgrid with EVs, based also on the day-ahead energy management.

Sattarpour et al. [5] developed a multi-objective HEMS function where the EV can charge and discharge at home and the SOC of the EV's battery at the arrival time is a known parameter. A decentralized charging control strategy assuming to know the EV battery SOC is presented by Hu et al. [6]. Thomas et al. [7] also managed a bi-directional EV energy trading in an office building considering a stochastic EVs' driving schedule. Lamedica et al. [8] focused on smart buildings that use batteries of EV present in the parking areas as supplementary storage systems. The algorithm controls EVs bi-directional power flows individually. Paterakis et al. [9] determined the optimal day- ahead appliance scheduling of a household under peak power-limiting having into account EVs. The degradation of the EV battery is neglected. [10] evaluated a dynamic-pricing and peak power limiting-based DR strategies with a bi-directional utilization possibility for EV. The objective is to minimize the total daily cost of electricity consumption.

Unlike other literatures, this paper presents a novel model that can be used in real application by aggregators, flexibility operators or retailers, to schedule EVs with limited information from cloud-based platforms. The current available information by third-parties is coming from charging points and it is only about the energy consumed, the charging point status which is used to know the past arrival and departure times. It is not possible to know the EV battery SOC, capacity or vehicle ID through the vast majority of slow charging points, which complicates the use case significantly. Therefore, it is necessary to include forecasting algorithms capable of predicting the future based on the past events.

The paper is structured as follows: Section 2 presents the Dutch pilot case study, section 3 presents the optimization problem mathematical formulation, section 4 shows the inputs and outputs obtained and the section 5 includes the paper conclusions.

III. CASE STUDY

The current case study is the ElaadNL headquarter located in Arnhem, The Netherlands. It is part of the INVADE Dutch pilots, covering the small-scale public office use case. This office building of 3.062 m^2 houses around 100 full-time employees. It has installed 4 kWp of photovoltaic panels and a central battery of 100 kWh and 200 kW. Moreover, the building has several EV charging points (CP) but only nine of them are considered in the scope. Eight CPs charge only one EV during the day and one charges two EVs. A general overview of the case study site is shown at Figure 1. The white boxes represents metering and sub-metering points.

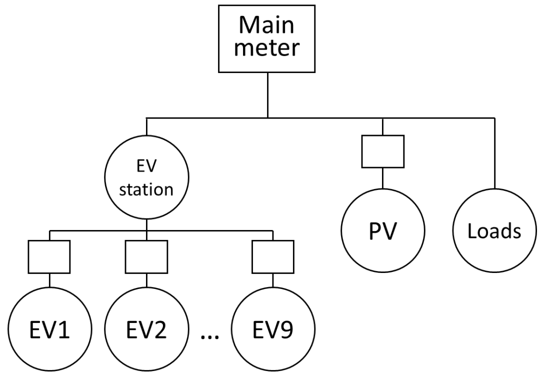

Figure 1. Components of the case study.

The algorithm presented in this paper is an EV flexibility management system (EV-FMS) dedicated to apply smart charging control signals for congestion management and maximum power control (kWmax control) [11]. However, the stationary battery is operated locally with the purpose of reducing the peak load. However, the battery is not sufficient in some cases like in the case study and the building needs to include smart charging control. Therefore, this paper is focused on managing EVs and the battery is inflexible from the EV-FMS point of view. The FMS could include the battery in the decisions but in some cases it could be beneficial to use the local battery control if it includes a specifically designed battery aging model capable of taking better decisions than a third-party cloud platform.

Simultaneous EV charging can cause grid congestions or voltage limit violations in weak or remote areas. In such situations, the DSO could be interested in offering, through the FO, economic discounts to EV drivers if they delay or even reduce their charging load when there is grid scarcity.

Figure 2. shows the sequence to prevent network congestion. The DSO measures the load on the local electricity network and based on its maximum capacity, the DSO sends out the maximum available capacity for EV charging to the Charging Station Operator (CSO). Then, the CSO redirects the available capacity to the Capacity Management System (CMO), which calculates the aggregated optimal EV charging profile for the whole charging station (CS). Based on this charging profile, the CSO can tell its charging points their maximum charging power for the next period of time.

This sequence is based on the Open Capacity Management Protocol (OCMP) [12] standard for exchanging information between the Charging Station Operator (CSO) and the DSO. The goal of this new standard is to define a protocol for smart charging electrical vehicles based on available capacity that is provided by the DSO. OCMP is a development name to the INVADE pilot project specific version of the Open Smart Charging Protocol (OSCP). This protocol will be used as input for the new OSCP 2.0 protocol to be published also by the Open Charge Alliance.

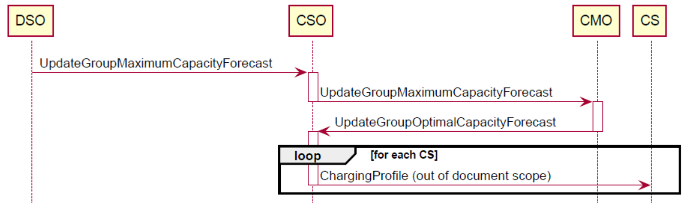

Figure 2. Sequence diagram of the OCMP in which the DSO distributes capacity to a CSO.

In the considered case study, the DSO sends a maximum available capacity for EV charging of 10 kW from periods 30 to 40. At the same time, the building is limited to consume a maximum of 260 kW in total for each period, including the EVs.

The generation and total inflexible load data of the studied office are obtained from ElaadNL monitoring system. The used data belongs to the 25th July 2018. This data is not open source. However, specific data for the charging sessions of the office is not yet available. To solve this, 10 alternative real charging profiles from ElaadNL are used. They are selected from the open data sets that can be downloaded from the ElaadNL platform [13].

In order to avoid the effect of energy price variability, the used energy prices are constant for the whole optimization window. In addition, this is the most common end-user energy tariff type used in The Netherlands.

IV. Flexibility Algorithm

The algorithm is structured according to Figure 3. There are two main data sources: historic time series about the main meter load and generation values, and the external data about the weather forecast, electricity prices, and charging booking if available.

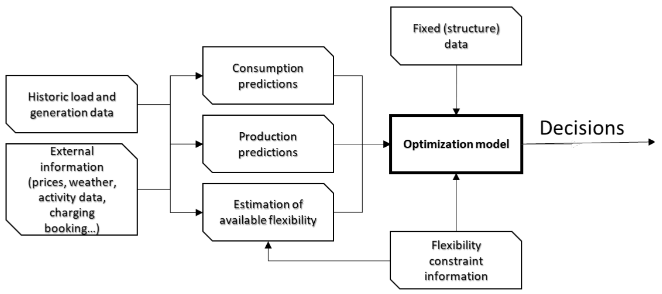

Figure 3. EV-FMS algorithm inputs and outputs.

This data is used in the INVADE integrated platform to generate the forecasted values needed in the EV-FMS. Therefore, the optimization model creates decisions and the CSO sends the corresponding control signals to each CS or directly to each CP. The EV-FMS is executed only once based on the forecast received at 12 am. The optimization horizon is 24 hours ahead.

The objective function is presented in (1) and it represents the cost of buying ($P_t^{buy}\chi_t^{buy}$) and selling ($P_t^{sell}\chi_t^{sell}$) energy including taxes (P^{VAT}), and the flexibility cost (ζ^{flex}). Therefore, the decision variables are $\chi_t^{buy}, \chi_t^{sell}, \zeta^{flex}$.

$$\min z = \sum_{t\in T}\left(P_t^{buy}\chi_t^{buy}P^{VAT} - P_t^{sell}\chi_t^{sell}\right) + \zeta^{flex} \tag{1}$$

Being buying and selling costs obtained from (2) and (3) as the composition of the retailer contract price ($P_t^{retail-buy}, P_t^{retail-sell}$) and the grid operator contract price ($P_t^{grid-buy}, P_t^{grid-sell}$). The flexibility cost in the EV-FMS considers only the EV flexibility cost equation (4) and it is composed by the shifting cost ($\zeta^{EV,shift}$) and the non-supplied energy ($\zeta^{EV,non-supplied}$). The shifting cost (6) is a penalty ($P_v^{CP,shift}$) for the energy shifted from the baseline between the arrival time ($T_v^{EV,start}$) and every time period t. Moreover, there is a cost ($P_v^{CP,NS}$) for the curtailed energy ($\theta_{v,n}^{cd} - \theta_{v,T_{v,n}^{EV,end}}^{es}$) at departure time in (7).

$$P_t^{buy} = P_t^{retail-buy} + P_t^{grid-buy} \tag{2}$$

$$P_t^{sell} = P_t^{retail-sell} + P_t^{grid-sell} \tag{3}$$

$$\zeta^{flex} = \zeta^{EV,flex} \tag{4}$$

$$\zeta^{EV,flex} = \zeta^{EV,shift} + \zeta^{EV,non-supplied} \tag{5}$$

$$\zeta^{EV,shift} = \sum_{v\in V^c}\sum_{n\in N(v)}\sum_{t=T_{v,n}^{EV,start}}^{T_{v,n}^{EV,end}} P_v^{CP,shift}\sum_{T_v^{EV,start}}^{t}\left(W_{v,t}^{CP} - \theta_{v,t}^{ch}\right) \tag{6}$$

$$\zeta^{EV,non-supplied} = \sum_{v\in V^c}\sum_{n\in N(v)} P_v^{CP,NS}\left(\theta_{v,n}^{cd} - \theta_{v,T_{v,n}^{EV,end}}^{es}\right) \tag{7}$$

The site energy balance constraint is (8) and it relates the inflexible load (W_t^{inflex}), PV generation ($\psi_{g,t}$) and the grid energy import (χ_t^{buy}) and export (χ_t^{sell}). It includes the set v for each CP and g for each generation unit in the same site.

$$\sum_{g\in G}\psi_{g,t} + \chi_t^{buy} = \sum_{v\in V}\theta_{v,t}^{ch} + W_t^{inflex} + \chi_t^{sell}, \qquad \forall\, t \in T \tag{8}$$

The CP model and constraints are based on the assumption of the previously mentioned forecasted input parameters as the unique information available from the FO point of view. Forecasted values are translated into:

- EV CP status: $V_{v,n}^{EV,start}, V_{v,n}^{EV,end}, T_{v,n}^{CP,start}, T_{v,n}^{CP,end}$
- EV CP baseline consumption: $W_{v,t}^{CP}$

Therefore, the total expected energy consumption per CP v and charging session n ($\theta_{v,n}^{cd}$) is calculated in (9). Notice expected energy consumption is from the CP point of view and there is no efficiency to be considered. The total energy decided to supply to each v at period t ($\theta_{v,t}^{es}$) is calculated in (10) and it is updated according to the previous period value and the charging control signal at t ($\theta_{v,t}^{ch}$). $\theta_{v,t}^{es}$ is initialized at the beginning of each charging session *N(v)*. Equation (11) is a disjunctive constraint to limit the CP power control signal between a maximum ($Q_v^{CP,max}$) and minimum value ($Q_v^{CP,min}$). Finally, the total energy supplied per CP v and session n is limited to the expected energy consumption in (12).

$$\sum_{t=V_{v,n}^{EV,start}}^{V_{v,n}^{EV,end}} W_{v,t}^{CP} = \theta_{v,n}^{cd}, \qquad \forall v \in V^c, \forall n \in N(v) \tag{9}$$

$$\theta_{v,t}^{es} = \theta_{v,t-1}^{es} + \theta_{v,t}^{ch}, \qquad \forall v \in V^c, \forall n \in N(v), t \in [T_{v,n}^{CP,start}, T_{v,n}^{CP,end}] \tag{10}$$

$$Q_v^{CP,min}\big/N_{hour} \le \theta_{v,t}^{ch} \le Q_v^{CP,max}\big/N_{hour} \;\; \vee\, (OR)\;\; \theta_{v,t}^{ch} = 0, \qquad \forall v \in V^c, t \in T \tag{11}$$

$$\theta_{v,t}^{es} \leq \theta_{v,n}^{cd}, \qquad \forall v \in V^c, \forall n \in N(v), t = T_{v,n}^{CP,end} \tag{12}$$

The PV model cannot be remotely curtailed as the present framework does not allow DSO send downregulation flexibility requests as [14]. Therefore, the PV generation ($\psi_{g,t}$) is equal to the forecasted PV value ($W_{g,t}^{prod}$) in (13).

$$\psi_{g,t} = W_{g,t}^{prod}, \qquad \forall\, g \in G^i, t \in T \tag{13}$$

The buy and sell decisions are limited due to the kWmax control to a maximum import (14) and export capacity (15) and they cannot happen simultaneously (16).

$$\chi_t^{buy} \leq \delta_t^{buy} X^{imp-cap}, \qquad \forall\, t \in T \tag{14}$$

$$\chi_t^{sell} \leq \delta_t^{sell} X^{exp-cap}, \qquad \forall\, t \in T \tag{15}$$

$$1 \leq \delta_t^{buy} + \delta_t^{sell} \tag{16}$$

The DSO flexibility request (FR_t) for the CPs is included in (17) as a limitation to the aggregated consumption of all CPs. Notice it does not consider the building consumption.

$$\sum_{v \in V^c} \theta_{v,t}^{ch} = FR_t, \qquad t \in T^{const} \tag{17}$$

V. Simulation and Results

The case study problem results in the control signals to all charging points as shown in Figure 4. The charging points are listed in ascending shifting cost from 0.1 EUR/kWh in steps of 10% increase. Therefore, CP1 is shifted more periods than CP9. As the electricity price is constant, $\zeta^{EV,flex}$ is the only decision factor in this specific case study and results are easier to understand.

The DSO EV charging request constraints CPs from 30 (7:30 am) to 40 (10 am). To meet the request, CPs 2, 3, 4, 6, 7, 8 are shifted to later periods. For instance, CP2 and CP6 are totally shifted to period 40. In contrast, CP7 and CP8 are barely reduced and CP9 is not shifted.

According to Figure 5. , during the periods 50 and 51 the base net load is above the limit of 65 kWh per quarter. Thus, CP1, 2, 4, and 8 are shifted or partially curtailed in the optimized result to meet the 260 kW limitation. Therefore, the optimal EV scheduling produces a constant consumption at 65 kWh per quarter between periods 42 and 58 reducing the peak load.

TABLE I shows charging points data from ElaadNL office. All profiles correspond to arrival and departure times within typical office working hours and at least they have 2 hours of flexibility time. It also shows how the decisions allow to charge the EVs completely because the non-supplied energy penalty ($P_v^{CP,NS}$) is 5 €/kWh. The transaction ID is included for comparing results in future works.

VI. Conclusions

The present paper exposes a novel decision-making problem of scheduling EVs in frameworks of limited information. In such cases, it is necessary to rely on forecasting tools to take decisions. Related to communication standards, OCMP standard allows DSOs to send flexibility requests referred only to the aggregated EV load within a grid connection point. EVs are very attractive to reduce building load peaks and reduce grid congestions. The optimization algorithm presented in this paper shows a scheduling EV model considering this load limitation and the maximum consumption per grid connection. The results of the case study highlight the possibility of managing EV charges considering capacity limitations and DSO restrictions even though the limited available information. It is difficult to take better decisions without additional data like EV battery state of charge.

Acknowledgment

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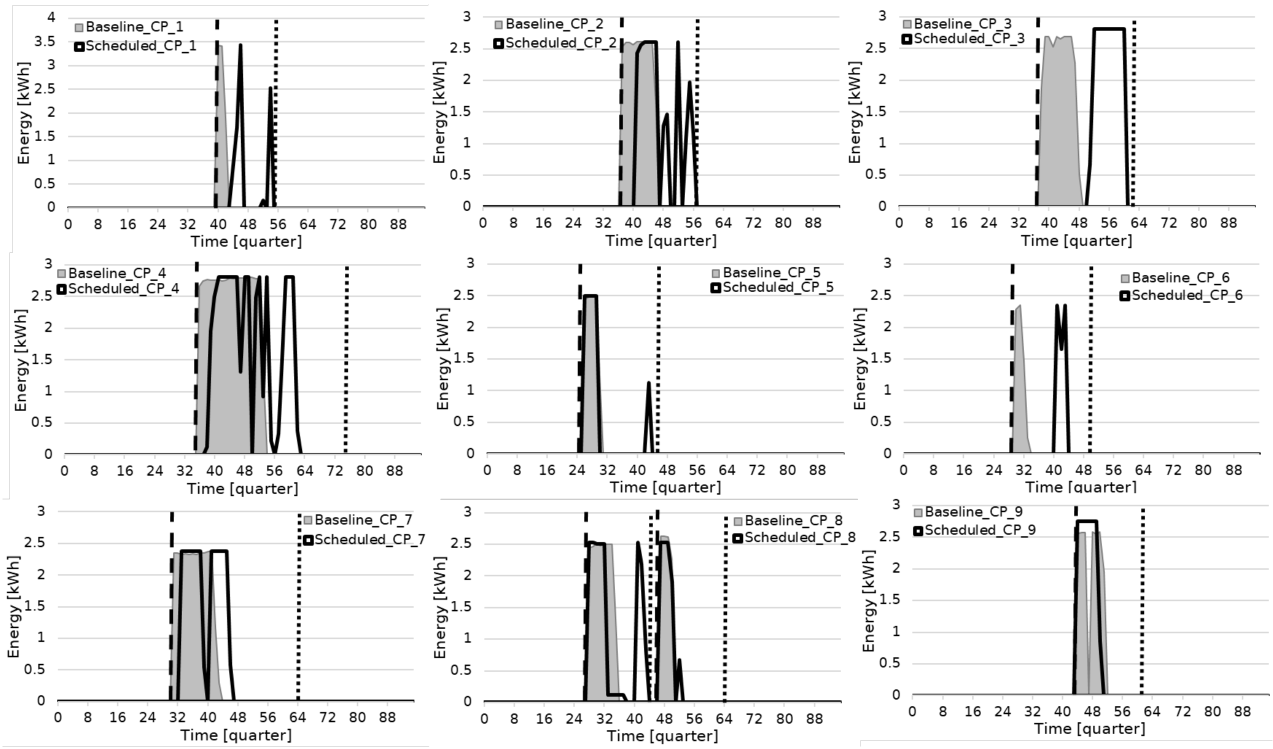

Figure 4. Charging points consumption including the arrival (dashed line) and departure times (dotted line).

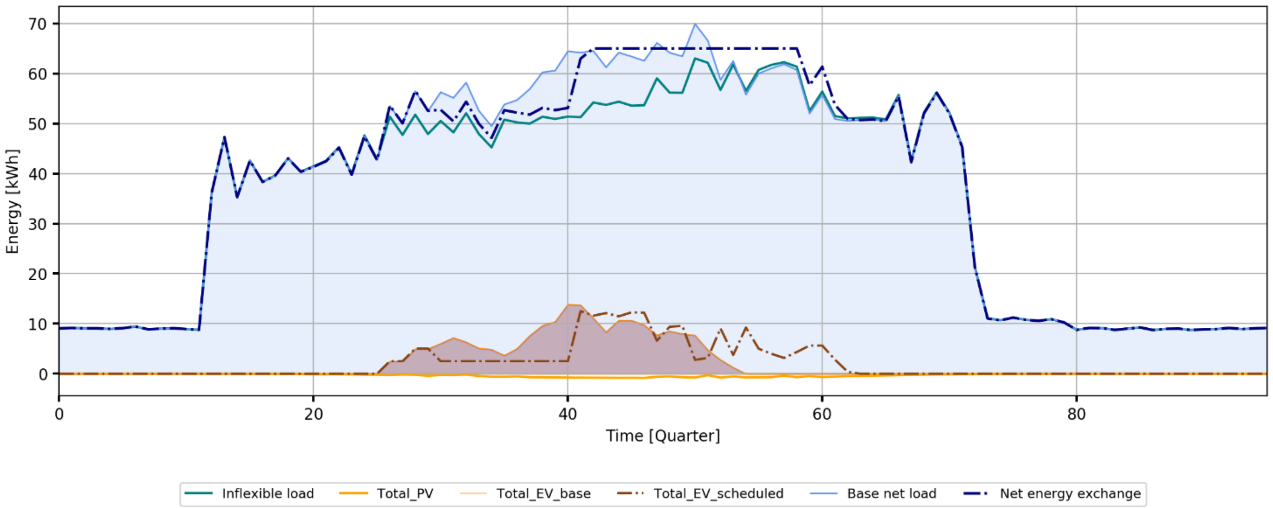

Figure 5. Building energy consumption.

TABLE I. Charging points and sessions from ElaadNL database

Charging point ID	Transaction ID	Arrival time	Departure time	Connected time [hours]	Charge time [hours]	Flexibility time [hours]	Expected energy consumption [kWh]	Delivered energy [kWh]	Shifting flexibility cost [EUR/kWh]
1	2528680	03/06/2017 9:55	03/06/2017 13:32	3.62	0.83	2.79	8.73	8.73	0.100
2	2504887	25/05/2017 9:20	25/05/2017 14:04	4.73	2.50	2.23	25.01	25.01	0.110
3	2714942	26/06/2017 9:34	26/06/2017 15:02	5.48	2.68	2.80	25.98	25.98	0.121
4	2625991	26/07/2017 9:05	26/07/2017 18:40	9.59	4.48	5.10	48.34	48.32	0.133
5	2595472	07/07/2017 6:25	07/07/2017 10:58	4.55	1.30	3.25	11.13	11.13	0.146
6	2567142	22/06/2017 7:23	22/06/2017 11:45	4.37	1.00	3.37	6.36	6.36	0.161
7	2668532	23/08/2017 7:41	23/08/2017 16:02	8.34	4.55	3.79	27.28	27.28	0.177
8	2605666	13/07/2017 7:06	13/07/2017 10:45	5.71	2.00	3.71	18.71	18.71	0.195
8	2592317	05/07/2017 11:36	05/07/2017 15:56	4.34	1.06	3.28	10.15	10.15	0.195
9	2346509	14/04/2017 10:47	14/04/2017 15:58	5.17	2.17	3.00	17.37	17.37	0.214