Optimal Control in a Smart Grid Aggregator: Connecting PV, EV, Energy Storage, and Heating Systems to Solve the Power Problem

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***Abstract*—The main challenge for many Distribution System Operators (DSOs) when it comes to the integration of Electric Vehicle (EV) charging on their grids is not a problem of *energy* but rather of *power*. Critical peak power (CPP), already a difficulty during winter months, is exacerbated by the increasing presence of EV charging stations as the use of electric mobility becomes widespread. As a result, DSOs are showing an increased demand for peak-shaving and peak-shifting technologies.**

The project "Coordinating Power Control" ("Växlande Effektreglering" in Swedish, referred to as "VäxEl" in this paper), which began in January of 2017, is based on the increased interest of rural households for solar panels, home batteries, EVs and other "smart home" equipment. The ambition of the VäxEl project is to create a cost-effective optimization of a distribution grid by addressing various technical, regulatory, and psychological challenges.

By bringing together a community of market actors, including smart grid service providers, governmental regulatory bodies, research departments, and a local grid owner (DSO), VäxEl seeks to uncover and propose solutions to such challenges. In May of 2018, the International Smart Grid Action Network (ISGAN), a cooperation within the International Energy Agency (IEA), presented the VäxEl project with its prestigious Award of Excellence for world-leading activities in the area of smart grids for power flexibility.

Through partial funding provided by the Swedish Energy Agency and by assisting homeowners in applying for the economic assistance available to purchasers of EVs, home batteries, and solar arrays, VäxEl has been able to martial a formidable amount of power flexibility, including the installation of 500 connected water-based heating systems, 60 sites with rooftop solar panels (providing 200 kW of production), 36 kW of Electric vehicle charging, and 70 kWh of home energy storage (providing 60 kW of instant power flexibility).

This paper presents some of the progress made within the VäxEl project, primarily focusing on two key aspects: the modeling and design of an optimization algorithm for integrating the resources within the project for the purpose of reducing CPP, and the reduction in CPP achieved during February of 2018 by connected heating systems within the Upplands Energi electric grid.

I. Introduction

In December of 2017, physicists Bengt Pershagen and Jacob Weitman wrote a debate article in the Swedish daily newspaper *Expressen* arguing that if half of all of Sweden's cars were EVs, totaling 2.5 million, and if they were all plugged in at the same time, collectively they would load the electrical grid with an additional 5 GW of power [1]. They then pointed out that a power shortage of 5 GW during at least 765 hours per year would be the result if Swedish nuclear power were replaced with wind and solar, referring to a 2014 Kungliga Tekniska Högskolan (KTH) study [2]. Finally they put two and two together and concluded that it would be mutually exclusive to achieve both a transition to renewable energy sources *and* to replace half of Sweden's cars with EVs.

The *Expressen* article was quickly refuted by Lennart Söder [3], KTH professor of Electric Power Systems and the researcher who authored the original study cited [2]. However, Pershagen and Weitman are not wrong in their concern over the impact of 2.5 million electric cars on the problem of CPP. As Söder pointed out in his rebuttal, it will be necessary to develop and implement new technologies for "smart charging" of EVs, demand-side flexibility, and automated demand response (ADR) in order to deal with the challenge of CPP.

The purpose of this paper is to present a mathematical model for an ADR platform that facilitates the optimization of EV charging by coordinating with residential energy storage, heat pump control, and solar production. The model is presented in the context of the VäxEl project, in which the smart grid service providers Ngenic, chargestorm, and Ferroamp collaborate with the DSO Upplands Energi to create a testing environment for these technologies.

II. Mathematical Model

The goal of our ADR platform is to find a sequence of control steps that can dictate the power-usage of an EV-charging device as well as the behavior of a household energy storage unit (whether charging or discharging) based on current *and future* power values (production and consumption). Thus, given an expected future state the system can adjust its present state in such a way that is optimal with respect to what is known about the future. Well-suited to this problem-formulation is the *model predictive control* (MPC) algorithm, which optimizes a cost function aggregated over a specified time horizon.

A. Model Predictive Control

For the simulations presented in this paper, we use the following MPC formulation:

$$
\begin{aligned}
\underset{u}{\text{minimize}} \quad & f(x, x^r, u), \quad t \in \Omega && \text{(1a)}\\
\text{subject to} \quad & x_{t+1} = Ax_t + Bu_t + Dw_t, \quad t \in \Omega, && \text{(1b)}\\
& C^x x_t \leq c_t^x, \quad t \in \Omega, && \text{(1c)}\\
& C^u u_t \leq c_t^u, \quad t \in \Omega, && \text{(1d)}\\
& C^f x_N \leq c_f^x, && \text{(1e)}
\end{aligned}
$$

where

- x_t is a multivariate timeseries of state variables, x_t^r is the desired reference state, u_t is a vector of control signals, and w_t are the uncontrolled inputs, all at time t;
- A, B, and D are matrices that describe the system; A describes how the system develops without control, B describes how the system reacts to control, and D describes how the state variables are affected by uncontrolled inputs;
- C^x and c_t^x, C^u and c_t^u, and C^f and c_f^x denote the time-dependent constraints on the state, control signal and the final state, respectively;

and

$$
\begin{aligned}
f(x, x^r, u) = \sum_{t=0}^{N-1} \left[x_t^T Q_1 x_t - 2x_t^T Q_1 x_t^r + u_t^T Q_2 u_t \right] \quad (2)\\
+ x_N^T Q_f x_N - 2x_N^T Q_f x_N^r,
\end{aligned}
$$

is the cost function, where Q_1 are weights placed on x_t and x_t^r, Q_2 are weights placed on u_t, and Q_f are weights placed on the final states x_N and x_N^r. N is the time horizon within which the optimization is performed and we use $\Omega = 0, ..., N-1$ to denote the set of time incidies.

The simulations have been carried out in the context of the VäxEl project, and the parameters and inputs have been chosen so as to reflect the real situation in Uppland; that is, we optimize heat pump operation, EV charging, and home battery use based on the combined household power usage (under a single substation) and local solar production. While incorporating wind power generation is outside the scope of VäxEl, such a signal can be easily incorporated by expanding the dimension of w_t.

We regard household consumption and solar generation as uncontrolled inputs; in a sense, they are considered to be noise on the evolving system and are included in the state space description (1b) because they are in fact the primary drivers of the optimization. In practice these "uncontrolled inputs" are forecasts of solar production and household consumption. When these forecasts show a global peak (within the time horizon), the system will adjust its state accordingly, i.e. charge the battery in anticipation of a discharge at CPP.

The use of a reference variable x_t^r allows the algorithm to track a desired signal, for example the charging curve of an EV. The corresponding coefficient in the cost matrix Q_1 determines how hard the system is punished for deviating from the preferred curve. This is the dynamic by which we achieve "smart charging." The coefficients in Q_1 must be chosen intelligently to reflect whether or not charging is to be prioritized. The separation of x_N from $t = 0, ..., N-1$ with its own cost coefficient matrix Q_f allows the system to optimize for a specific final state.

B. Numerical Considerations

By inserting (1b) into (2), (1c), and (1e) and rewriting the cost and constraints in terms of u_t, the optimization problem (1) reduces to a standard quadratic programming (QP) problem which can be solved by traditional QP solvers. The resulting QP is well-defined given the following criteria:

- the problem is *convex* with respect to the cost function (2) and the constraints (1c - 1e);
- the cost-weight matrices $Q_1 \geq 0, Q_2 > 0, Q_f \geq 0$ are symmetric;
- the constraints (1c - 1e) are linear.

Given the above criteria, asymptotic stability for the solver can be assured by a sufficiently large horizon length N.

For the application of MPC to aggregation in a smart grid, a prediction horizon of at least 1 day is advantageous, given the daily-periodicity of solar generation and household consumption. With a time step of 5 minutes the resulting QP is of dimension $[Nm \times Nm] = [6 \cdot 288 \times 6 \cdot 288]$ where m is the number of controlled units (in this simulation we use 1 heat pump "collective", 1 home battery, and 4 cars). With reasonably chosen cost parameters this dimension size is sufficient for stability. See [4], [5], [6], [7], and [8] for more information on the stability criteria of the MPC algorithm.

III. Simulation

A. Scenario

For the purposes of this paper, we have produced a simple implementation of the model described in Section II and conducted a simulation to illustrate the ability of this approach to successfully reduce CPP. The scenario which provides context to our simulation is summarized by the following points:

- a residential area comprised of 60 households;
- 30 households are connected to *Ngenic Tune*;
- the area is serviced by a solar array with a 37 kW production capacity;
- the area is equipped with a FerroAmp *Energy Storage Module* of type $Li(FePO_4)$ with a charge/discharge capacity of 6 kW and a storage capacity of 7.2 kWh;
- 4 households are outfitted with chargestorm *Wallbox EVA Connected* with a charging capacity of 3.7 kW;
- 4 householders drive EVs with different charge profiles.

This parameter space has been choosen because it reflects the real situation in the neighborhood of Ramsjöåsen, serviced by one of the substations operated by Upplands Energi.

B. Forecasting

The multivariate time series w_t in (1b) consists of those elements of the optimization which are not available for direct control. In the context of the VäxEl project, that is household consumption and solar generation. Since the MPC algorithm operates over a time horizon, forecasts are needed in order for the optimization to be meaningful. Obviously, the more accurate the forecast, the better the optimization.

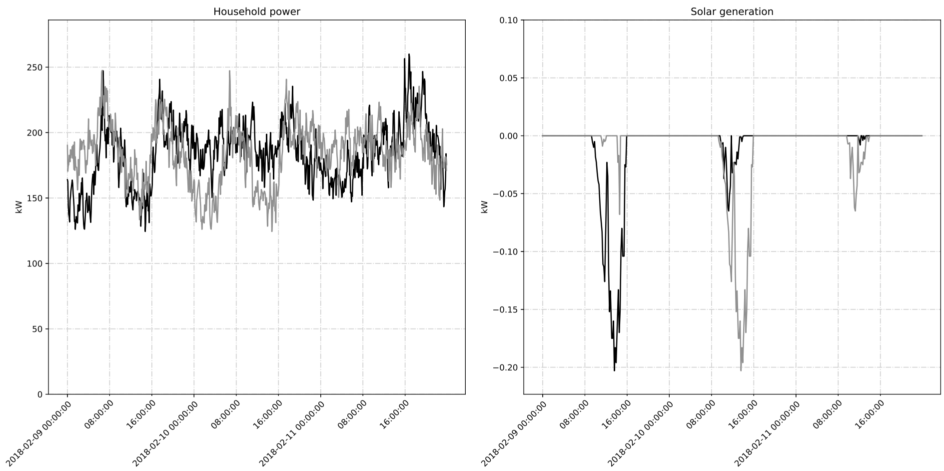

Figure 1. The naive forecast (gray) compared to the actual values (black) for household consumption (left) and solar generation (right). These data are the driving factors in the optimization described in Section II and are comprised of real measured values gathered by the VäxEl project during February of 2018 from the substation operated by Upplands Energi at Ramsjöåsen, Sweden.

In numerical experiments, such as the one presented here, we have discovered that even without a very accurate forecast the MPC algorithm is not only stable but able to achieve a meaningful reduction in CPP. For the simulation presented here, we have used the most naive and easily-obtainable forecast imaginable: the previous day's values. That is, if the current time is 2018-02-10 00:00:00, then the forecast for household consumption at 2018-02-10 00:05:00 is the household consumption value that was measured at 2018-02-09 00:05:00. The forecasted and actual values are shown side-by-side in Figure 1. In Section IV we will show an example of a reduction in CPP resulting from this level of forecast accuracy.

C. Data Sources

The simulation data consist of real household consumption and solar production values, at five minute intervals, collected by the VäxEl project from the Ramsjöåsen neighborhood in Uppland, Sweden, along with "typical" charging profiles provided by chargestorm.

IV. Results

A. Reduced Critical Peak Power

The main simulation results can be seen in Figure 2, where the household consumption data, including the charging of 4 EVs, are shown both with and without the ADR platform activated. For this simulation we define critical peak power (CPP) to be simply the daily maximum power consumption measured *without* the ADR platform activated.

On the first day, CPP occurs at 17:30:00 and is measured at 269.68 kW. The optimized system, with the model described in Section II in operation, shows a value of 238.26 kW, achieving a reduction of 31.42 kW over 60 households. Similar results for the second and third days of the simulation, along with the average values, are shown in Table I. This constitutes an average CPP reduction of 10.3%.

B. Smart EV Charging

As described in Section III, the simulation used for this paper incorporates the charging of four EVs. We assume the use of chargestorm *Wallbox EVA Connected* charging units, each with a charging capacity of 3.7 kW, since this is the equipment provided within the VäxEl project. For simulation purposes, we have devised a fictitious charging schedule based on "typical" charging profiles provided by chargestorm. These profiles can be seen in Figure 3.

We assume that one of the cars is of a fast-charging type, where the EV asks the Wallbox for more power than it is capable of providing. This can be seen in the upper left graph of Figure 4, where the grey line represents the incoming signal from the EV. The resulting control signal (the power to each Wallbox) can be seen in Figure 5.

The ad-hoc schedule for the three fictitious EVs is summarized as follows. EV 1 arrives home at 16:00 and remains plugged-in until 18:00. At 20:00 they arrive home again and remain plugged-in all night. EV 2 arrives home at 17:00 and remains plugged-in all night. EV 3 arrives home at 18:00 and remains plugged-in until 19:00. At 20:00 they arrive home again and remain plugged-in all night. EV 4 arrives home at 16:00 and remains plugged-in all night.

Note that what is shown in Figure 4 is not necessarily the battery level of the EV. The model described in Section II does not have or need such knowledge of the EV, i.e. whether or not the EV is half-charged, empty, etc. when it is plugged in. Figure 4 shows rather the amount of energy transfered to the battery, not its present status.

C. Home Energy Storage

Figure 6 shows the charging status of the FerroAmp *Energy Storage Module* with the time stamps of the daily power max shown as three vertical lines. The optimization results in a behavior where the battery charges during periods of low load (at night and during the early afternoon) and discharges during periods of high load (during the early morning and early evening).

V. Discussion

A. Parameter Tuning

In the simulation presented in Section IV, parameters of the optimization problem (1) have been chosen such that the

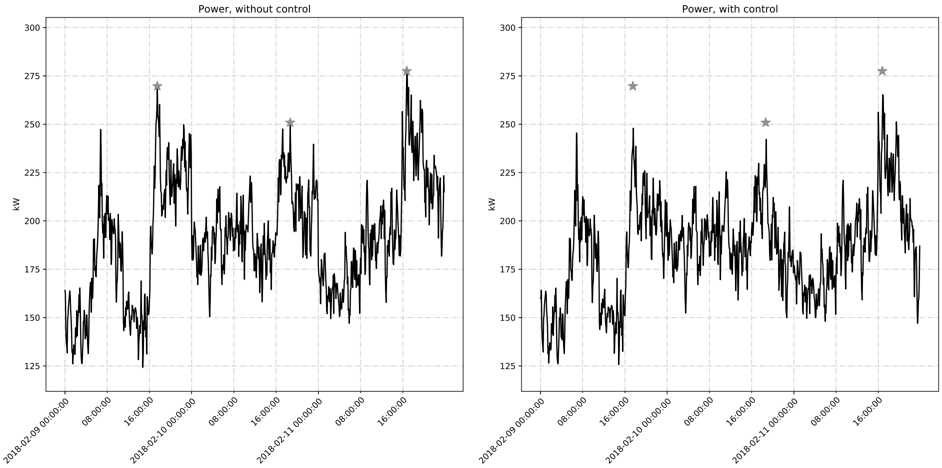

Figure 2. Household consumption, including EV-charging, with (right) and without (left) the ADR platform in operation. The daily max power without the ADR in operation is marked in both graphs with grey stars, illustrating the CPP reduction.

Table I
CRITICAL PEAK POWER VALUES FOR 60 HOUSEHOLDS.

time stamp	CPP (kW)	optimized (kW)	reduction (kW)
2018-02-09 17:30:00	269.68	238.26	31.42
2018-02-10 18:40:00	250.82	225.05	25.78
2018-02-11 16:45:00	277.46	252.37	25.09
average	**265.99**	**238.55**	**27.43**

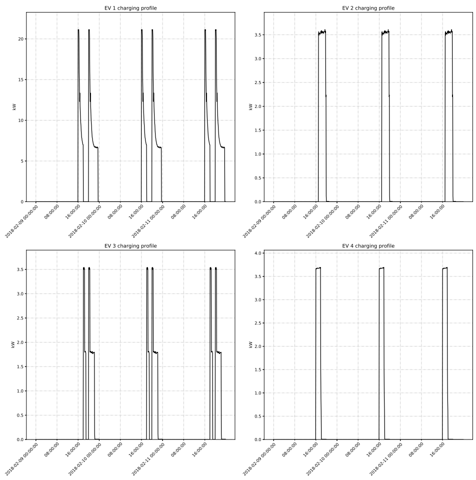

Figure 3. The four EV-charging profiles (kW) used in the simulation described in Section III. The charging profiles have been created based on common charging patterns and were provided by chargestorm.

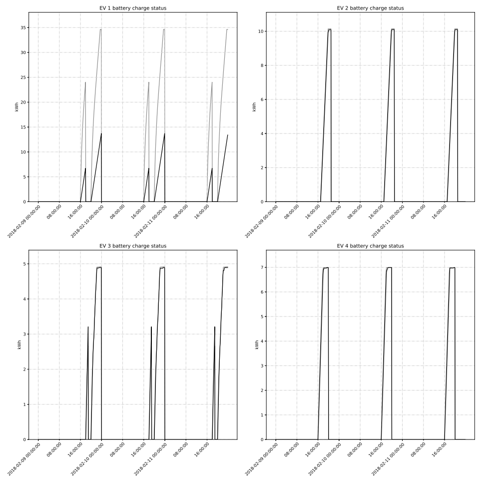

Figure 4. Energy (kWh) supplied (simulated) to each of four chargestorm Wallbox EV chargers. The upper left graph shows a fast-charging EV which asks the Wallbox for more power than it is capable of giving. Note that the supplied energy is not necessarily the same as the car battery level; the algorithm has no knowledge of the EV battery's state.

controller follows the desired charging curve of each of the EVs with very little deviation. An even greater reduction in CPP can be achieved by adjusting these parameters to reduce the priority of EV charging. Figure 7 shows an example of such an optimization.

With the parameters adjusted thusly, the reduction in CPP is shown in Table II. The simulation shows that CPP can be further reduced by restricting EV charging. In this case, CPP reduction is increased to 11.1%, as compared to the reduction of 10.3% with unrestricted charging.

The functionality for how the numerical parameters may be set to reflect the EV charging priority is beyond the scope of this paper. The key dynamic that remains to be worked-out is how an EV owner can be provided with an incentive by the DSO to accept a charging curve such as is shown in Figure 7 rather than that curve which is shown in Figure 4. Some of the participants in VäxEl are also involved in a separate project called NEMoGrid [9], which seeks to address this challenge.

B. Scaling Up

As described in Section III, the simulation behind the reduction in CPP presented in this paper involves an area

Table II
CRITICAL PEAK POWER WITH REDUCED EV PRIORITY.

time stamp	CPP (kW)	optimized (kW)	reduction (kW)
2018-02-09 17:30:00	269.68	234.01	35.67
2018-02-10 18:40:00	250.82	229.49	21.33
2018-02-11 16:45:00	277.46	246.16	31.31
average	**265.99**	**236.55**	**29.44**

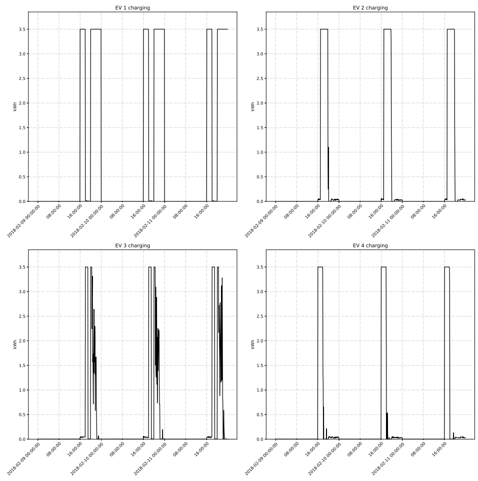

Figure 5. The optimal control signal (kW) for the four EVs corresponding to the supplied energy shown in Figure 4.

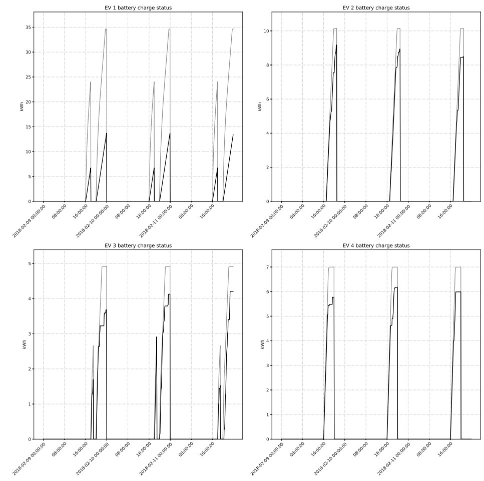

Figure 7. Energy (kWh) supplied (simulated) to each of four chargestorm Wallbox EV chargers, now with EV charging set as a reduced priority, compare with Figure 4. The gray curve shows the "prefered" energy requested by the Wallbox.

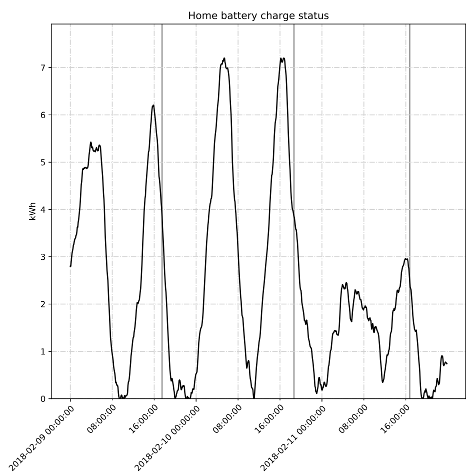

Figure 6. The optimal control of the FerroAmp *Energy Storage Module*. The three gray verticle lines show the moments when critical peak power occurs (see Figure 2).

of 60 households, with half of these equipped with Ngenic Tune, where there are 4 EVs, 1 household battery, and a solar array. This domain has been chosen because it matches the real scenario that has been created within the VäxEl project at Ramsjöåsen, Uppland, Sweden. It is natural to wonder, what does the result look like on a national scale?

A rigorous answer to such a question will require more numerical experiments and analyses. However, a simple "back of the envelop" calculation can illustrate the potential of this method if implemented at the national level. If we scale up our numbers by a factor of $40,000$, we get the following scenario:

- 2.4 million households,
- 1.2 million connected heating-systems,
- $160,000$ electric vehicles,
- $40,000$ connected home batteries (288 MWh capacity),
- 1.5 GW solar array.

If we assume the CPP reduction scales linearly, the result is a reduction in CPP of 1.2 GW.

This model indicates that, in contrary to the 5 GW increase of CPP anticipated by Bengt Pershagen and Jacob Weitman, with the equipment described above, we can reduce CPP by 1.2 GW and charge $160,000$ EVs. Obviously, this method warrants further investigation.

C. The Roll of Heat Pumps

A key component of the optimization presented in this paper is the integration of heat pump control. The compressor action in a heat pump runs based on the internal sequence of operations, typically with regard to outdoor temperatures, sometimes including an indoor temperature sensor as well. Each time the compressor switches on, the grid is loaded with around 1 - 2 kW, depending on such factors as make and model of heat pump, square footage of the home, thermal leakage, outdoor temperatures, etc. In addition to the compressor load, many heat pumps are augmented with an electric heating element, the so-called *elspetsvärme*, which can increase the load by an additional 7 - 10 kW.

It has long been known that heat pump operation is a significant contributor to CPP, see e.g. [10] or [11]. Therefore it is logical to draw the conclusion that control of heat pump operation, when optimized against total power consumption, has the potential to reduce CPP.

There is a natural objection to disabling the heating system of a household (e.g. preventing the heat pump from entering a new compression cycle) during cold weather, but recent studies, such as [12], have shown that there is enough thermal inertia in most households to accommodate a temporary deviation from the sequence of operations long enough to impact CPP, see also [13] for more information about the project behind the report [12]. In fact it has been shown that retrofitting a heat pump with an Ngenic controller *increases* the thermal comfort of home occupants [14].

D. VäxEl

The project *Coordinating Power Control* (*Växlande Effektreglering* in Swedish), or *VäxEl* for short, is a collaboration of several companies and research organizations along with a medium-sized DSO. The project members are

- Sustainable Innovation, project management;
- Ngenic, smart heating-system control;
- FerroAmp, home energy storage and solar integration;
- chargestorm, EV charging;
- STUNS, research collaboration;
- Upplands Energi, a DSO in Uppland, Sweden providing electricity to over 13,000 commercial properties and residences.

VäxEl, along with its sister project *New Collaborative Models in the Energy Market* [12] are Sweden's most advanced efforts in the area of demand-side flexibilty in the energy market. The relatively large number of physical installations, in the form of smart heating-system controls, solar panels, EV charge boxes, and home batteries in private households, makes for an ideal environment for experimentation and preparation for the future demands on Sweden's energy system.

The project operates a "smart grid" in collaboration with Upplands Energi, a customer-owned co-operative with a 100-year history of consumer-driven innovation. VäxEl has successfully shown that the aggregator service model of smart heatpumps performed by Ngenic towards the DSO will be vital in future energy systems.

In May of 2018, the International Smart Grid Action Network (ISGAN), a cooperation within the International Energy Agency (IEA), presented the VäxEl project with its prestigious Award of Excellence for world-leading activities in the area of smart grids for power flexibility [15].

E. Winter 2018 Results

While the technologies for EV charging and home energy storage are not yet integrated with the heating-system control, preliminary tests have been conducted to assess the ability of heating-system control to reduce CPP. During the last week of February, 2018, outdoor temperatures reached their lowest point of the 2017/2018 heating season. The Swedish Meteorological and Hydrological Institute reported temperatures as low as $-20.9°C$ [16] at nearby Uppsala airport.

During this entire week, the DSO predicted a power peak that would breach their power subscription towards the regional grid. A schedule of heating-system control was implemented by Ngenic in order to prevent the load on Upplands Energi from breaching the 60 MW level. Engineers within the VäxEl project estimate that, as a result of the heating-system control, CPP was reduced by at least 1.0 MW but probably closer to 1.8 MW across 250 households during that week of cold temperatures. This shows that optimizing heating-system operation with respect to CPP is of substantial value to the DSO, in this specific case the avoidance of a €48,500 fine incurred as the power subscription limit toward the regional grid is surpassed.

VI. Conclusion

The modelling scenario presented in Section III indicates that an automated demand response platform based on the Model Predictive Control formulation (1) can reduce critical peak power by a factor on the order of 10% by coordinating electric vehicle charging with home battery and heat pump operation, without restricting the EV charging schedule and without the benefit of advanced forecasting techniques. This hypothesis is in the process of being tested within the context of the VäxEl project in Uppland, Sweden.

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