Modelling the impact of integrated electric vehicle charging and domestic heating strategies on future energy demands

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1. ABSTRACT

The next 30 years could see dramatic changes in domestic energy use, with increasingly stringent building regulations, the uptake of building-integrated microgeneration, the possible electrification of heating (e.g. heat pumps) and the use of electric vehicles (EV). In this paper, the ESP-r building simulation tool was used to model the consequences of both the electrification of heat and EV charging on the electrical demand characteristics of a future, net-zero-energy dwelling. The paper describes the adaptation of ESP-r so that domestic electrical power flows could be simulated at a temporal resolution high enough to calculate realistic peak demand. An algorithm for EV charging is also presented, along with the different charging options. Strategies by which EV charging and electrified heating could be controlled in order to minimise peak household electrical demand were assessed. The simulation results indicate that uncontrolled vehicle charging and the use of electrified heating could more than double peak household power demand. By contrast, a more intelligent, load-sensitive heating and charging strategy could limit the peak demand rise to around 40% of a base case with no vehicle or electrified heating. However, overall household electrical energy use was still more than doubled.

Keywords: EV, zero energy dwelling, electrical demand, simulation

2. INTRODUCTION

The next 30 years are likely to herald a substantial change in the demand characteristics of new and refurbished dwellings, brought about by a combination of improved thermal performance, increased integration of microgeneration technologies such as PV, the possible electrification of heat through the use of heat pumps and the widespread adoption of plug-in hybrid electric vehicles (PHEV) and all-electric vehicles (EV). Together, these changes would result in household demand characteristics radically different from those seen today.

Improved thermal performance in both newbuild and retrofitted housing will reduce the primacy of domestic space heating demands and place more of a focus on electrical demands and hot water use. For example, in a typical UK house, space heating accounts for around 65% of its overall energy demand (Palmer and Cooper, 2012), whilst in Passive House designs, heating can account for as little as 40% of the household's overall energy demand (Feist, 2006). This reduction in heating demand is becoming evident now, with total UK household space heating demand declining by 21% since 2004. Conversely, total household energy demand associated with electrical appliance use has increased by approximately 15% over the same period (Palmer and Cooper, 2012).

In parallel with changes in fabric performance, the supply of energy to UK dwellings is also undergoing a transformation, through the provision of thermal and electrical energy from local, low-carbon sources. For example, more than 2GW of microgeneration capacity has

been installed in the UK since the introduction of a feed-in-tariff (FIT) in 2010 (OFGEM, 2013); this provides small scale producers (i.e. householders) with a guaranteed payment for each kWh of electricity produced by a household renewable source such as photovoltaic panels (PV).

If the UK is to achieve its ambitious targets for an 80% carbon emissions reduction by 2050, then the use of fossil fuels for space heating will need to be virtually eliminated (DECC, 2008) and replaced with zero carbon sources such as biomass (which realistically could only supply a fraction of heat demand [Castillo and Panoutsou, 2011]), and renewable electricity. The latter source requires the widespread uptake of heat pumps, shifting the demand for space and water heating from the gas grid to the electricity network. Given that the vast majority of UK dwellings likely to be extant in 2050 are already constructed (Hinnels *et al*, 2007) a widespread heat pump retrofit programme would be required. Air source heat pumps (ASHPs) have the potential to act as a replacement for the fossil-fuelled boilers commonly found in UK housing. Additionally, their relatively low cost of installation and the lack of a requirement for ground works makes ASHPs a more feasible mass retrofit option than ground source heat pumps (GSHP). However, Wilson *et al* (2013) indicate that a shift of only 30% of domestic heating to heat pumps could result in an increase in the total UK electrical demand of some 25%.

The final development likely to have a significant impact on the characteristics of domestic demand is the growth in the use of electric vehicles (EVs). In the UK, the number of electric vehicles is still small as a percentage of the total fleet: some 0.1% of the total passenger cars licenced on UK roads. However, their number is increasing exponentially (DfT, 2014). EVs shift the energy used for transportation from refined fossil fuels to the electricity network. In the UK, the domestic sector accounts for around 29% of UK final energy consumption, whilst the transport sector accounts for another 36% of demand (DECC, 2014). The deployment of EVs at an increasing rate and the widespread electrification of domestic heating could lead to a massive rise in the demand for electricity and necessitate the upgrading of the UK's electricity distribution infrastructure. In this paper, the potential increase in electricity demand at the individual dwelling level is examined along with an investigation into the strategies that could be employed to mitigate the worst effects of this increase.

2.1 Previous Work on EV Integration with Buildings

There are large bodies of literature looking at the thermal performance of future buildings (e.g. Attia *et al*, 2013), microgeneration and the electrification of heat, and the potential impact of EVs on the electrical network (e.g. Pudjianto *et al*, 2013). However, there is a paucity of material looking specifically at the combinatorial effects of heat pumps and EVs on domestic energy demands, and strategies to mitigate their impact. Typically, studies treat the two topics separately. There are some examples in the literature that look at the integrated control of EV charging within a domestic context in order to mitigate demand peaks, but the majority of work focuses on the charging of vehicles at the larger scale. Robinson *et al* (2013) analysed the results from a large UK field trail of electric vehicles, where the charging times of vehicles were unconstrained and vehicles could be charged at home or when parked away from home. Their results indicated a significant amount of peak-time charging. Razeghi *et al* (2014) used real domestic electricity demand data coupled with stochastic vehicle charging profiles to look at the potential impact of EV charging on distribution transformers. The authors concluded that only in the case of uncontrolled fast charging of vehicles would there be the risk of transformer overloading. In a study using economic optimisation, Hedegaard *et al* (2012) looked at the possible impact of EV charging, indicating that coordinated charging of EV's can boost investment in wind power and reduce

future investment requirements for thermal power plants. However, the study did not look at the implications for the transmission and generation infrastructure.

Of the studies looking at both the dwelling and EV, Asare-Bediako *et al* (2014) looked at the potential effect of heat electrification, micro-CHP and electric vehicles on domestic load profiles in the Netherlands using a bottom-up modelling approach. The authors concluded that the electrical load profile characteristics changed dramatically with reduced electrical peak demand in summer and increased demand in winter. The authors did not investigate the possibility of co-operation between the house and vehicle to limit peak demand, nor did they address the issue of heat pumps. Munkhammar *et al* (2013) used a stochastic, high-resolution model to examine the impact of EVs on domestic load and the self-consumption of PV-generated power. Their paper highlighted the increase in domestic power consumption with the introduction of EVs and also noted that in many cases the use of EVs decreased the amount of load covered by the PV. This was due to the temporal mismatch between when PV power was available and when the EV charged (typically early morning or evening). Haines *et al* (2009) looked at the so-called vehicle-to-home concept (V2H), using the vehicle battery to co-operatively limit the peak demand of a household. The authors concluded that EVs could be used to limit peak demand and improve domestic load factors, other than in cases where the EV was used for a sizable commute. However, the study did not consider electrification of heating, nor of the impact of microgeneration such as PV.

3. SCOPE OF THE PAPER

There is a gap in the literature in that the impact of wholesale domestic electrification (extending to heating and transportation) is rarely considered, and by extension, most mitigation strategies focus on only one aspect of demand. Consequently, this paper explores a range of integrated strategies aimed at limiting the impact of both heat pumps and EVs on the electrical demand of future dwellings. The paper examines the peak electrical demand and the increase in household electrical energy use as both will have an impact on electrical infrastructure. Increased electrical energy use will lead to higher temperatures in electrical equipment and ultimately a shortening of its lifespan. However, a radical increase in peak demand could have the most acute impact, necessitating the wholesale replacement of electrical infrastructure such as cabling and electrical transformers.

A simulation model of a hypothetical future zero-energy dwelling (described in detail later) was used to calculate the total electrical demand at high resolution, accounting for electrified space heating, hot water demand, appliance and vehicle charging loads. The specific demand-limiting strategies to be investigated using the model were as follows.

- Time shifting of heating: where the operation of a heat pump is moved to periods of off-peak electrical demand. This required that the heat pump was coupled to the heating system of the dwelling via a buffer tank.
- Fast and slow battery charging rates, at 3.3 and 6.6 kW, respectively.
- Time shifting of battery charging: battery charging was restricted to periods of off-peak electrical demand.
- Co-operative battery charging: the battery was only charged when the load of the dwelling fell below a user specified threshold of 7.5 kW[1].

[1] IEA EBC Annex 42 measured data (IEA, 2014) was reviewed to determine a typical dwelling maximum electrical demand limit for many of the scenarios above; this data shows maximum demand in UK-housing varying between 3.5 and 7.5 kW. In order to mitigate the effects of vehicle charging and electric heating on the existing electrical infrastructure it would be necessary to keep overall demand below these peaks. Consequently, the upper demand value of 7.5kW was used in this

Later, these individual strategies were combined into a set of modelled scenarios, which explored increasing levels of demand intervention in both vehicle charging and heating use.

4. MODELLING TOOL AND ADAPTATIONS

Hawkes and Leach (2005) and Knight and Ribberink (2007) argue that to properly capture the electrical demand characteristics and the exchange of electrical power between a dwelling and the grid, simulation time steps of less than 10 minutes are required. Consequently, to fully assess the impact of vehicle charging and the electrification of heating, the version of ESP-r (ESRU, 2014) used for this paper has been upgraded to enable it to work at high resolution and simulate vehicle charging loads. Further, a hypothetical zero-energy dwelling simulation model has been developed (Hand *et al*, 2014), complete with an EV.

ESP-r, allows the energy and environmental performance of the building and its energy systems to be determined over a user defined time interval (e.g a day, week, year). The tool explicitly calculates all of the energy and mass transfer processes underpinning building performance. These include conduction and thermal storage in building materials, all convective and radiant heat exchanges (including solar processes and long wave exchange with the sky), air flows, interaction with plant and control systems. To achieve this, a physical description of the building (materials constructions, geometry, etc.) is decomposed into thousands of "control volumes". In this context, a control volume is an arbitrary region of space to which conservation equations for continuity, energy (thermal and electrical) and species can be applied and one or more characteristic equations formed. A typical building model will contain thousands of such volumes, with sets of equations extracted and grouped according to energy system. The solution of these equations sets with real, time-series climate data, coupled with control and occupancy-related boundary conditions yields the dynamic evolution of temperatures, energy exchanges (heat and electrical) and fluid flows within the building and its supporting systems.

4.1 Adaptations to ESP-r

The ESP-r software has been extended from the standard release to enable its electrical systems model to use stochastic, electrical appliance demand data as a boundary condition. This data was generated at a 1-minute time resolution using a customised version of a domestic appliance demand profile tool (Richardson *et al*, 2010), which also produced matching thermal gains profiles. Additionally, a new algorithm was developed, based on the work of Jordan and Vagen (2005), which enabled stochastic, sub-hourly resolution domestic hot water draws to be generated during a simulation. Finally, using the work of McCracken (2011), 1-minute solar data was generated, based-on the existing hourly solar data found in ESP-r's climate data files. This allowed the electrical output from PV to reflect the variability observed in solar radiation levels for a maritime climate like the UK's. This variability is lost when using the hourly-averaged climate data typically used by building simulation tools. These adaptations to ESP-r are described in more detail by Hand *et al* (2014). Figure 1 shows typical high-temporal-resolution simulation output including appliance electrical demand and demand associated with the operation of a heat pump.

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paper in the control of heating and vehicle charging. However, the impact of varying the demand limit merits further investigation.

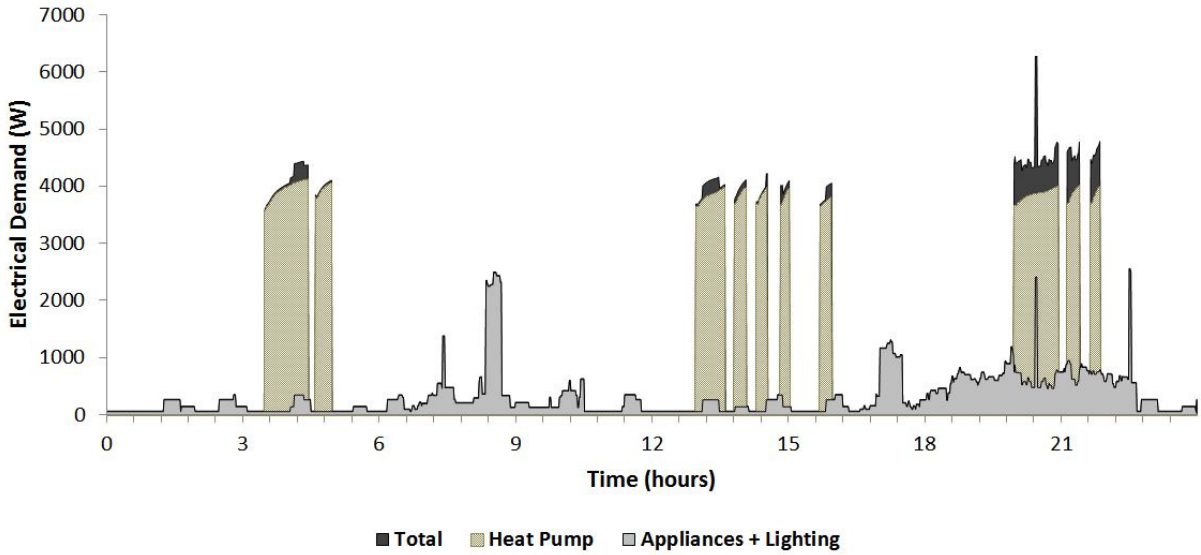

Figure 1: simulation output at 1-min time resolution.

4.2 Vehicle and Battery Algorithm

In addition to the modifications outlined in the previous paragraphs, a stochastic, electric vehicle (EV) algorithm has been developed. The primary role of this algorithm is to mimic the effect of electric vehicle charging on the dwelling's overall electrical demand. The model has several functions, these are: 1) determine when a vehicle leaves and then returns from a trip; 2) calculate the trip distance and subsequent depletion of the battery; and 3) re-charge the battery according to a user-selected control strategy.

The EV model can take three basic states: 'idle' – the vehicle is present and not charging; 'absent' – the vehicle is on a trip and 'charging'– the vehicle is present and charging, depending on the battery control strategy. Also, there is an explicit assumption made in the algorithm that all trips have 1 outward and 1 return leg and that the distance travelled in the return leg is the same as the outbound trip.

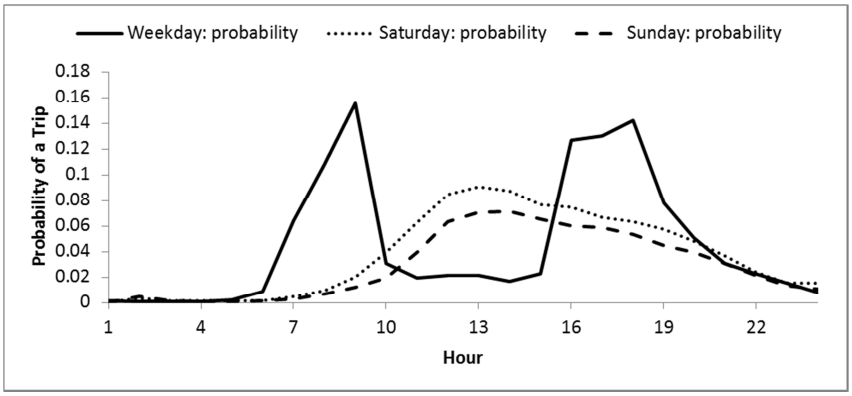

Figure 2: hourly probabilities of a trip leg being taken over a 24-hour period (Huang and Infield, 2010).

To determine if a trip leg is made, the algorithm generates a random number, x, at each simulation time step and this is tested against a time-dependent trip probability $p(t)$ (see Table 1) to determine:

a) whether the EV will depart on a trip (if the vehicle is present); or

b) when it returns home from a trip (when the vehicle is absent).

The time-varying hourly probabilities for one leg of a trip for weekdays, Saturdays and Sundays are shown in Figure 2; these were taken from the 2013 UK travel survey (DFT, 2014) and Huang and Infield (2010). The probabilities needed to be modified as follows to account for sub-hourly time steps and the assumption that each vehicle trip comprises two legs.

$$p(t) = p_h(t)(\frac{\Delta t}{3600})n \tag{1}$$

Here, $p_h(t)$ is the probability that a trip leg will be made in a particular hour, Δt is the simulation time step and *n* is the assumed number of legs per trip.

Table 1: vehicle status changes.

Test result	**Vehicle status**	**Vehicle Status changes to**
$x \geq p(t)$	Home	Absent
	Absent	Home
$x < p(t)$	Absent	Absent
	Home	Home

The model also includes an allowance for 'range anxiety'. It is assumed that if the state of charge (SOC) is below 35% (i.e. enough charge for an average trip) then the vehicle will continue to charge and a trip will not be made. If the vehicle has returned from a trip (status has changed from 'absent' to 'home'), the model calculates a feasible distance travelled and then the state of charge of the battery. The probability of particular trip distance being travelled could be best characterised using a Weibull distribution with a λ value of 22.4 and a *k* value of 0.8.

$$F = 1 - e^{-(\frac{d}{\lambda})^k} \tag{2}$$

To calculate the total distance travelled (over the two legs) a random number, y, is generated, with a value between 0 and 1 and the distance, d, is calculated using Equation 3.

$$d = \lambda(-\ln(1-y))^k \tag{3}$$

This distance is checked against the time the vehicle has been absent (Δt) and the maxium speed that the vehicle can legally travel,v_{max}, giving a maximum permissible distance travelled $d_{max} = v_{max}\Delta t$: if the distance travelled exceeds this, then d is set to d_{max}.

The SOC of the battery on returning from a trip is calculated using Equation 4, where *D* is the nominal discharge rate of the battery in kWh/km and *L* represents any user-defined parasitic losses for the battery when the car is moving (e.g. any draws on the battery from the heating or cooling system not accounted for in D).

$$SOC(t + \Delta t) = SOC(t) - (D + L)v \tag{4}$$

Finally, the model encompasses a range of charging strategies, as outlined in Table 2. Depending on the strategy chosen for the model, the vehicle state will change from 'idle' to 'charging' on return.

Note that the random number generator in both the hot water draw algorithm, mentioned previously and the vehicle algorithm employs a seed, which generates a unique pseudo-random series. Additionally, the high resolution solar data and electrical demand use pre-simulated profiles. Consequently, the simulations described later are repeatable, provided that the same seeds are used in the random number generator.

Table 2: vehicle battery charging strategy summary.

Strategy	**Comments**	**Criteria**
Fast charge	Vehicle will charge at the maximum allowable rate $P_{V\ FAST}$ until the battery is fully charged	$SOC < SOC_{MAX}$
Slow charge	Vehicle charges at a reduced rate P_{SLOW}	$SOC < SOC_{MAX}$
Off peak fast or slow charge	Vehicle charged at $P_{V\ SLOW/FAST}$ if within the off peak period 11pm-7am	$SOC < SOC_{MAX}$; $t_{OP-START} < t < t_{OP-END}$
Load sensitive fast or slow charging	Vehicle charged at $P_{V\ SLOW/FAST}$ only if the house demand is below a user defined maximum. Otherwise the charging is stopped or the charging rate is modulated.	$SOC < SOC_{MAX}$; $t_{OP-START} < t < t_{OP-END}$; $P_H < P_{H\ MAX}$.

4.3 ESP-r Model

The ESP-r model of the zero-energy dwelling is shown in Figure 4. The model is divided into three main thermal zones: a loft zone and two composite zones describing (respectively) the areas of the dwelling hosting active occupancy such as the living room and kitchen and those areas that have low occupancy rates or that are occupied at night such as bathrooms and bedrooms, respectively. The geometric characteristics are summarised in Table 3; this geometrically aggregated form of the model captures the pertinent thermodynamic characteristics of the building's performance and has been deployed successfully in other studies, e.g. (Clarke *et al*, 2008).

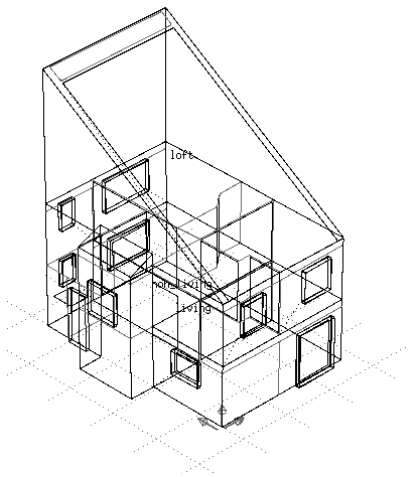

Figure 4. Wireframe view of the zero-energy dwelling model.

The model features a mono pitch roof to accommodate the 45m^2 (8 kWp) of PV panels used to offset the regulated electrical demands and appliance energy demands. Note that the PV does not offset the electrical demand of the EV. The building has a wooden frame construction, is super-insulated with triple-glazed windows, has high airtightness, mechanical ventilation heat recovery (MVHR) and meets passive house standards. The characteristics of the key fabric elements are as shown in Table 4.

Table 3: summary of dwelling geometric characteristics.

Floor area (m^2)	82.7
External surface area (m^2)	151
Heated Volume (m^3)	230
Glazed Area (m^2)	21.45
'Day' zone floor area (m^2)	34.8
'Night' zone floor area (m^2)	47.9

Table 4 characteristics of constructions used in the dwelling model.

Construction	Details	U-value (W/m^2K)
External walls	Weatherboard air SIP panel with 300mm insulation service void plasterboard 484mm	0.104
Floor	200mm insulation under concrete slab with void and carpet over plywood	0.151
Ceiling	Plasterboard with 400mm glass wool 420mm	0.098
Roofing	Slate roof over battens (cold roof)	3.636
Glazing	Triple glazing argon filled low-e coatings 42mm	0.89

The heating ventilation and air conditioning (HVAC) system used with the dwelling is shown in Figure 5. This is modelled using a network, which comprises a linked collection of plant components. Each component (e.g. duct, heat exchanger, pipe, etc.) is modelled explicitly using a dynamic plant component algorithm.

The primary heat source is an air source heat pump (ASHP) with a 6kW capacity and nominal coefficient of performance (COP) of 3. In the model, both COP and the heating capacity of the ASHP vary with the ambient temperature and the 500L buffer tank temperature. The buffer allows the heat pump to be operated flexibly in time: the heat pump charges the thermal buffer, which then supplies the heat for space heating and hot water at a later time. The primary means of heat distribution in the system of Figure 5 is convective, via the MVHR.

The system also includes a dedicated 500 L solar domestic hot water (DHW) tank and $3m^2$ of roof-mounted solar thermal collectors. Another feature of the model is a 200 L grey-water-heat-recovery-system (GWHR): this collects wastewater from the baths, showers, etc., which pre-heats the incoming cold-feed to the DHW tank via a heat exchanger.

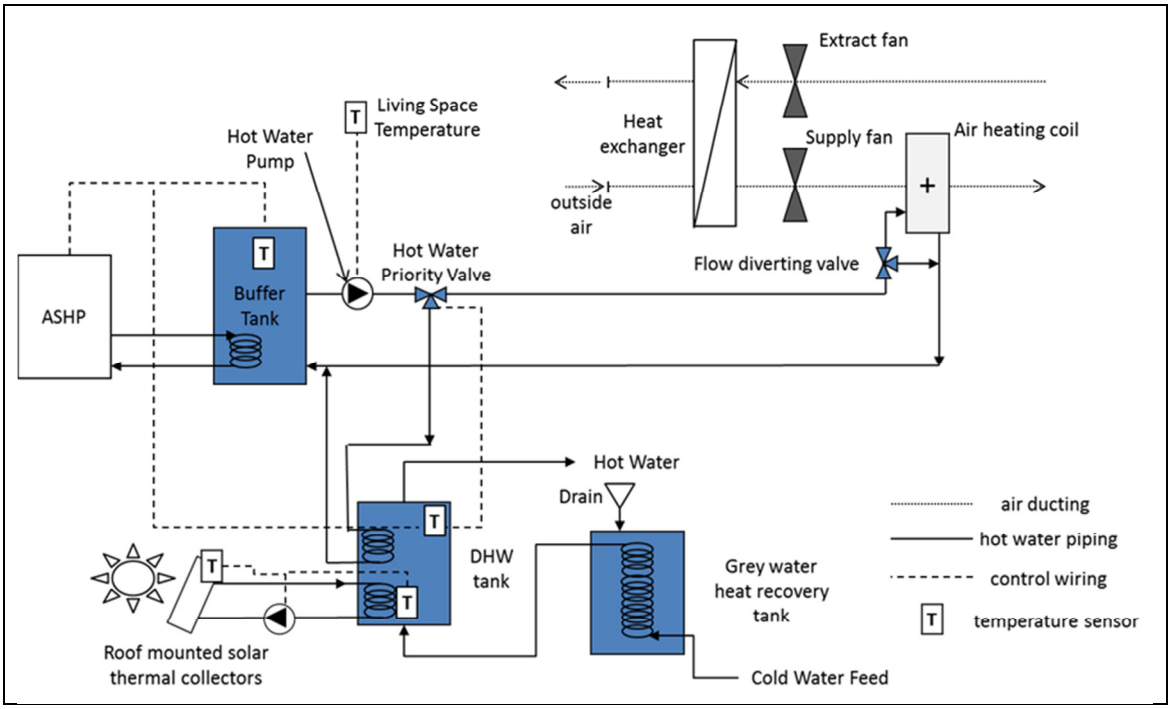

Figure 5: systems model for the dwelling.

The EV model used in the simulations is based on a Nissan Leaf (Nissan, 2014) and the key model parameters are shown in Table 5.

Table 5: key EV model characteristics (Nissan, 2014; DFT, 2014).

Battery capacity (kWh)	24
Fast charging power (kW)	6.6
Slow charging power (kW)	3.0
Minimum (SOC %)	20
Range anxiety (SOC %)	35
Charge/discharge efficiency (%)	90
Discharge rate (kWh/km)	0.15
Nominal annual distance travelled (km)	13,600
Nominal trip distance (km)	22.1
Distance equation ‘λ’ (-)	22.4
Distance equation ‘k’ (-)	0.8

Finally, in order to capture all of the electrical power exchanges within the building and between the building, vehicle and the grid, an electrical systems network was developed. This features explicit representations of the cabling and electrical infrastructure coupling the local micro-generation and power consuming devices (fans, pumps, heat pump, appliances, etc.). The network also features a coupling point to the local grid. The electrical network was solved to predict the main electrical real power flows associated with the dwelling model, particularly supply and demand, import and export with the grid and losses, including inverter and cable losses.

5. SIMULATIONS

A scenario-based approach was adopted in this paper in order to assess the impact of different combinations of heating and EV charging strategies. These are summarised in Table 6.

Table 6 Scenarios modelled.

Base Case – no EV, no Heat Pump	The house is assumed to be heated using biomass and there is no EV.
Case 1 – unrestricted slow charging	Both heating system operation and vehicle charging are uncontrolled. The vehicle is slow charged (3.3kW – up to 6.5 hrs) when it returns from trips and heat is supplied when required.
Case 2 – Unrestricted fast charging	Both heating system operation and vehicle charging are uncontrolled. The vehicle is fast charged (6.6kW – up to 3hrs) when it returns from trips and heat is supplied when required.
Case 3 – load sensitive vehicle battery slow-charging	The vehicle battery is only slow charged at full power if the dwelling and vehicle demand would be less than 7.5 kW.
Case 4 – load sensitive vehicle battery fast-charging	The vehicle battery is only fast charged at full power when the overall dwelling and vehicle demand would be less than 7.5 kW.
Case 5 – off-peak heating and unrestricted slow charging	The heating buffer tank (figure 5) is charged during off peak periods (11 pm – 7am), slow vehicle charging is unrestricted.
Case 6 – off peak heating and unrestricted fast charging	The heating buffer tank (figure 5) is charged during off peak periods (11 pm – 7am), fast vehicle charging is unrestricted.
Case 7 – off peak slow charging and heat load shifting	Both slow vehicle charging and heating system buffer tank charging are shifted to off peak periods (11 pm – 7am).
Case 8 – off-peak fast battery charging and heat load shifting	Both fast vehicle charging and heating system buffer tank charging are shifted to off peak periods (11 pm – 7am).

All of the scenarios were simulated at 1-minute time resolution over the winter months of January and February using a southern UK climate data set. A winter period such as this constitutes a 'worst case' scenario for electrical demand, as the dwelling heating demand will be at its highest and consequently this provides a useful test bed for the demand mitigation scenarios.

6. RESULTS AND DISCUSSION

Three key areas were analysed using the results from the scenarios listed in Table 6, these were: 1) the combined electrical demand of the dwelling and vehicle, specifically looking at the peak demand and overall electrical energy use; 2) the performance of the EV over the simulated period, looking at the number of trips and charge times; and 3) the energy performance of the heating system under load-shifted and normal operating conditions. The simulation results are summarised in Tables 7a – 7c.

Comparing the results from scenarios 1 and 2 shown in Table 7a (unrestricted slow and fast vehicle charging, respectively, and unrestricted heating operation) to the base case indicates that the addition of the EV and shift to heat-pump-based-heating more than doubles the overall electrical demand. For the two winter months simulated, demand increases from approximately 390 kWh in the base case to over 1000 kWh in all other scenarios. The peak electrical demand in the base case is 5.1 kW, which occurs around 7pm. The peak demand increases to 10.1 kW with unrestricted heating operation and unrestricted slow charging, or 12.2 kW with unrestricted heating and fast charging: these peak demands occur in the morning period (7am-9am). Figures 6a and 6b show the resulting electrical demand profiles. Table 7b shows maximum charge times, these were 328 minutes with slow charging, and 172 minutes with fast charging. With slow charging, the vehicle was used for 107 trips and 112 with fast charging. The distance travelled with fast charging was 2588 km compared to 2388 km with slow charging, indicating slightly reduced availability of the vehicle with slow charging in this instance. In both the fast and slow charging cases, the self-consumption of PV-generated electricity (Table 7a) was increased at the expense of electricity exported to the network. In the base case, for the two months simulated, self-consumption was 84.4 kWh, whilst 139 kWh of electricity was exported. With the addition of the EV and heat pump, self-consumption in the slow and fast charging cases rose to 111 and 108 kWh, respectively. Conversely, electrical exports dropped to 113 and 116 kWh, respectively, over the same period. The same trend was evident in all of the other 6 scenarios simulated.

In scenarios 3 and 4, charging of the battery was subject to a demand limit of 7.5 kW, with charging being modulated or stopped if the household demand (including the heat pump) exceeded this limit. Table 7a shows the maximum demand of the house occurring in this scenario: this was approximately 8.0 kW in the slow charging case and 8.3 kW with fast charging. Overall, electrical demand still exceeded 1000kWh. The maximum battery charge time (Table 7b) increased slightly for slow charging from 328 to 368 minutes and for fast charging from 172 to 190 minutes, indicating some modulation of both the and slow fast charge due to the 7.5kW constraint. The modulation of full-power charging is clearly shown in Figure 6d. The number of trips taken was unaffected.

In scenarios 5 and 6, fast and slow vehicle charging was unrestricted. However, the operation of the heat pump was re-scheduled to off-peak periods between midnight and 7am as shown in Figures 6e and 6f, with the heat pump charging the buffer tank during this time. Table 7a shows that the peak electrical demands in these scenarios were 8.0 and 11.3 kW for fast and slow charging, respectively. Both peaks occurred around 1am in the morning. Focusing on the heat pump results, its energy use reduced from approximately 280 kWh to 270 kWh. However, this was not a genuine energy saving as it resulted from the restricted operational hours. Further, the shift to off-peak heating increased the occurrence of low air temperatures (<18°C) in the dwelling to approximately 4% of occupied hours, as shown in Table 7c.

In scenarios 7 and 8, both the charging of the vehicle and the operation of the heat pumps were restricted to off peak periods; this resulted in peak demand of 9.1 and 11.6 kW for slow and fast charging, respectively (Table 7a). Both peaks occurred around 1am in the morning as shown in figures 6g and 6h. The results for these scenarios, shown in Table 7b indicate that there was a slight reduction in the number of trips taken: down from approximately 110 and over in the other scenarios to 103 and 105 for slow and fast charging scenarios, respectively; this indicated that the SOC of the battery was occasionally below the range anxiety limit of 35% when a trip was required. The performance of the heating systems was the very similar to scenarios 5 and 6, with Table 7c showing that air temperatures drop below 18°C for approximately 4% of occupied hours.

7. CONCLUSIONS

The simulations of this hypothetical, zero-carbon building indicated that the use of an electric vehicle and the electrification of domestic heating more than doubled the electrical consumption of the dwelling in all of the cases simulated bar the base case, which featured biomass heating and no EV. The use of the EV and heat pump also increased the self-consumption of PV generated electricity and decreased the amount of power exported to the grid.

In the worst case of unrestricted vehicle charging and heat pump operation (Scenarios 1 and 2), the peak demand was increased 96% to 10kW for slow vehicle charging and increased 155% to 13 kW for fast charging. As the electrical distribution network is sized for peak demand, this would result in the possible need for network reinforcement to accommodate EVs and heat pumps, if replicated on a large scale.

Several approaches to limiting the increase in peak demand were assessed, including limiting vehicle charging based on the household demand, shifting heat pump demand to UK off-peak periods (midnight-7am) and shifting both heat pump and vehicle operation to off-peak periods.

Shifting the heat pump to off-peak periods between midnight and 7am resulted in peak night time demands of 8.0 and 11.3 kW with slow and fast vehicle charging, respectively: increases of 57 and 121% on the base case peak. Peak demand was moved to 1am. Shifting of the heat pump operation also resulted in the some occurrences of low indoor air temperatures (<18°C) during occupied hours in the dwelling.

Shifting both heat pump operation and vehicle charging to off-peak periods resulted in a night-time peak demand of 9.1 and 11.6 kW for fast and slow charging; increases of 78 and 127%, respectively on the base case peak. However, this means of reducing demand was at the expense of a 5% reduction in the availability of the vehicle and a reduction in the performance of the heating system.

The most effective means of limiting the peak demand (for both fast and slow charging) was control of EV charging with a demand limit. If the limit was set such that vehicle charging was modulated or stopped when household demand rose above 7.5 kW, then the peak demands were limited to 8.0 and 8.3 kW in the slow and fast charging cases, respectively (increases of 57% and 63% of the base case peak demand). In these cases, there was no deterioration of the heating system performance and vehicle availability was little affected. Charging times however increased slightly through modulation or interruption of the charge when the demand limit was reached.

8. FURTHER WORK

This paper looks only at the impact of wholesale electrification and demand limiting measures on a single dwelling. Work is underway to extend the detailed modelling work described here to populations of dwellings in order to assess aggregate network impacts.

9. ACKNOWLEDGEMENTS

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Table 7a Electrical demand data from the base case and Scenarios 1-8.

Scenario	**Base Case**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Elec. demand (kWh)	387.8	1106.1	1136.9	1081.2	1074.6	1137.6	1133.3	1124.1	1144.2
EV demand (kWh)	-	395.8	426.4	379.8	365.0	443.4	426.4	408.8	425.9
Appl. demand (kWh)	463.7	463.7	463.7	463.7	463.7	463.7	463.7	463.7	463.7
ASHP demand (kWh)	-	279.8	273.9	273.9	271.6	269.7	269.7	269.1	269.1
PV output (kWh)	223.7	223.7	223.7	223.7	223.7	223.7	223.7	223.7	223.7
Elec. export (kWh)	139.3	112.9	116.1	110.1	118.5	106.3	116.3	128.2	128.2
Self-consumption (kWh)	84.4	110.8	107.6	113.6	105.2	117.4	107.4	95.5	95.5
BOP and losses kWh	160.4	144.0	134.7	149.9	131.0	156.6	133.9	113.1	110.1
Max P demand W	5116.52 @7d19h41m	10083.6 @4d7h46m	12222.1 @7d9h11m	8019.18 @47d19h26m	8251.56 @4d8h11m	7960.59 @42d1h6m	11327.5 @42d1h6m	9088.01 @12d1h1m	11571.9 @16d1h16m
Max P export W	2287.16 @45d11h 51m	2239.83 @45d11h51m	2239.83 @45d11h51m	2239.83 @45d11h51m	2239.83 @45d11h51m	2239.83 @45d11h51m	2239.83 @45d11h51m	2239.83 @45d11h51m	2239.83 @45d11h51m

** @44d1h6m – indicates occurrence on day 44 at 1:06am

Table 7b EV performance data from the base case and Scenarios 1-8.

Scenario	**Base Case**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
EV demand (kWh)	-	395.8	426.4	379.8	365.0	443.4	426.4	408.8	425.9
Distance travelled (km)	-	2388.4	2588.7	2292.4	2219.6	2673.5	2588.7	2547.2	2620.3
Return trips (-)	-	107.0	112.0	111.0	109.0	112.0	112.0	103.0	105.0
Maximum charge time (mins)	-	328.0	172.0	368.0	190.0	348.0	172.0	1156.0	998.0
Mean SOC (%)	-	97.1	98.3	96.8	99.0	96.0	98.3	74.1	78.2

Table 7c Heating performance data from the base case and Scenarios 1-8.

Scenario	**Base Case**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
ASHP demand (kWh)	-	279.8	273.9	273.9	271.6	269.7	269.7	269.1	269.1
ASHP heat output (kWhrs)	-	858.5	841.3	839.3	832.1	833.8	833.8	832.3	832.3
Mean air temp. occupied hours (^{o}C)	21.4	21.3	21.4	21.3	21.3	21.2	21.2	21.2	21.2
% of time air temp $< 18^{o}$C	0.17	0.1	0.1	0.2	0.2	3.9	3.9	4.1	4.1
Mean hot water temp. hours (^{o}C)	53.8	53.8	54.0	54.1	54.1	53.3	53.3	53.3	53.3

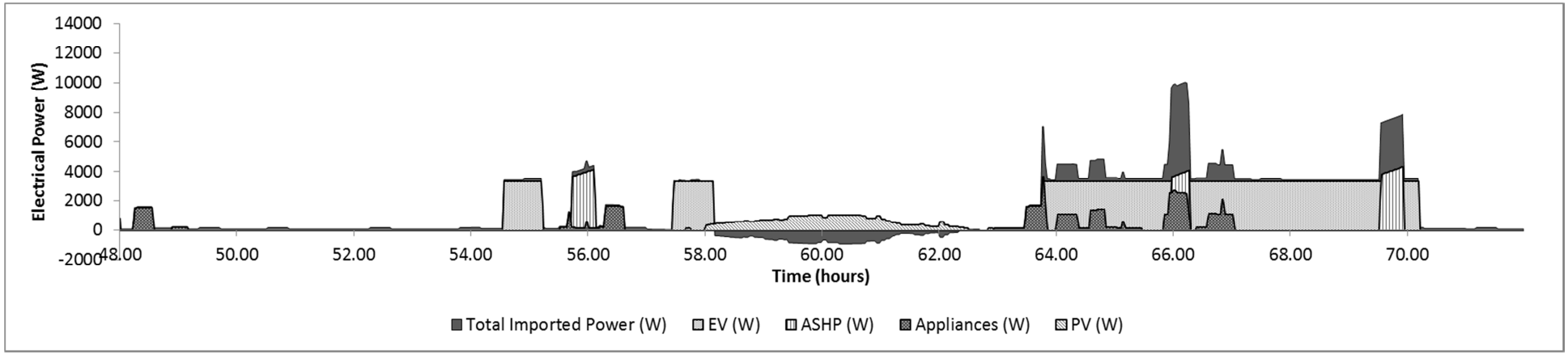

Figure 6a: typical daily profile of electrical supply and demand for unrestricted slow vehicle charging and heat pump operation.

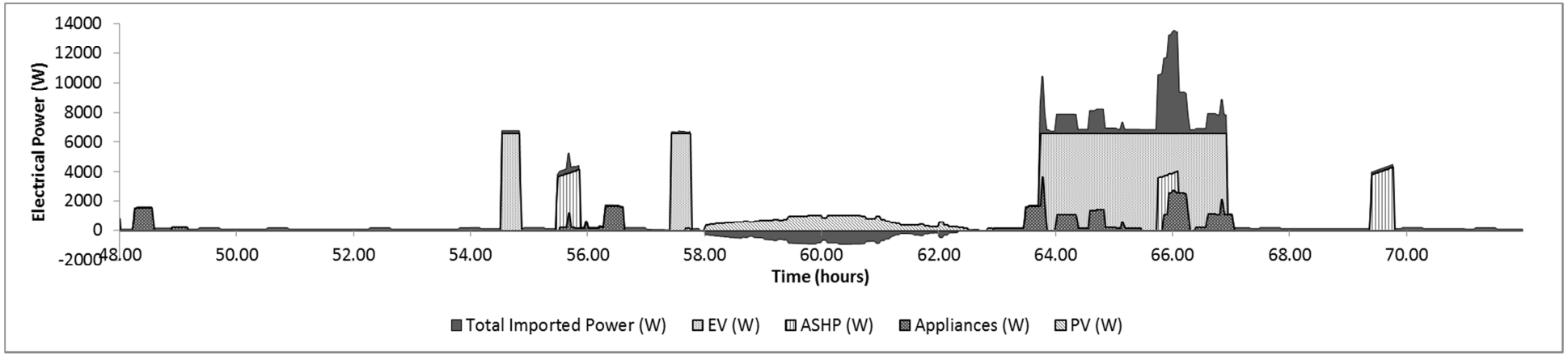

Figure 6b: typical daily profile of electrical supply and demand for unrestricted fast vehicle charging and heat pump operation.

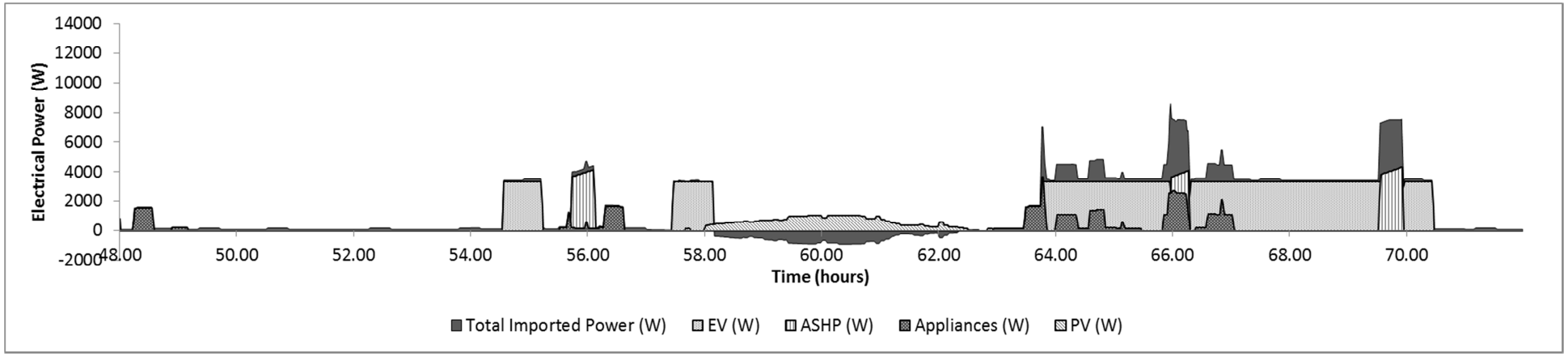

Figure 6c: typical daily profile of electrical supply and demand for load restricted slow vehicle charging and unrestricted heat pump operation.

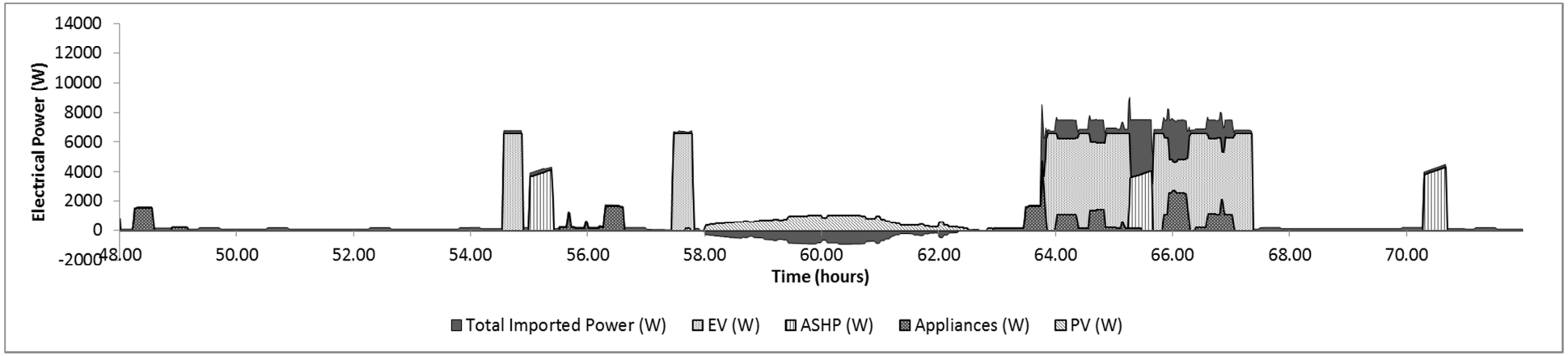

Figure 6d: typical daily profile of electrical supply and demand for load restricted fast vehicle charging and unrestricted heat pump operation.

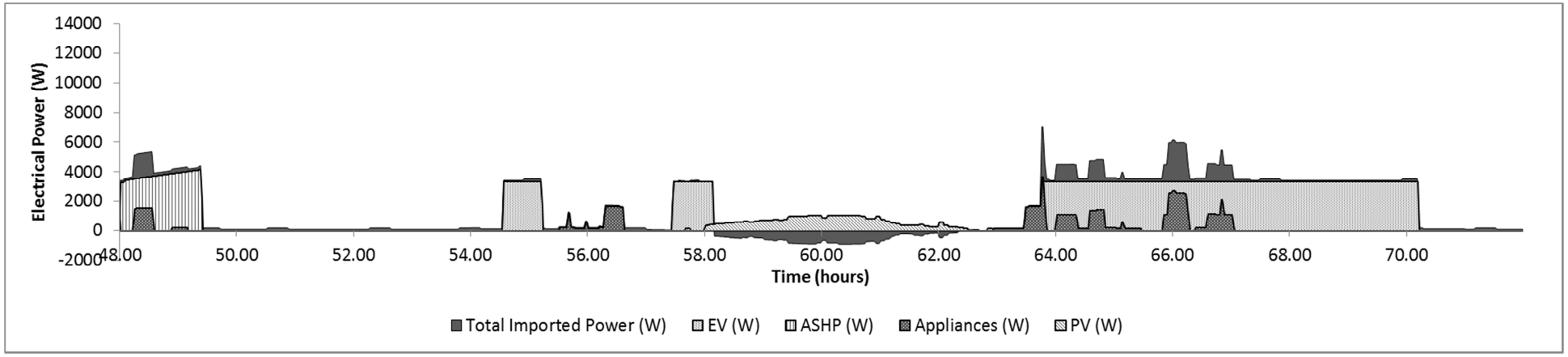

Figure 6e: typical daily profile of electrical supply and demand for unrestricted slow vehicle charging and off-peak heat pump operation.

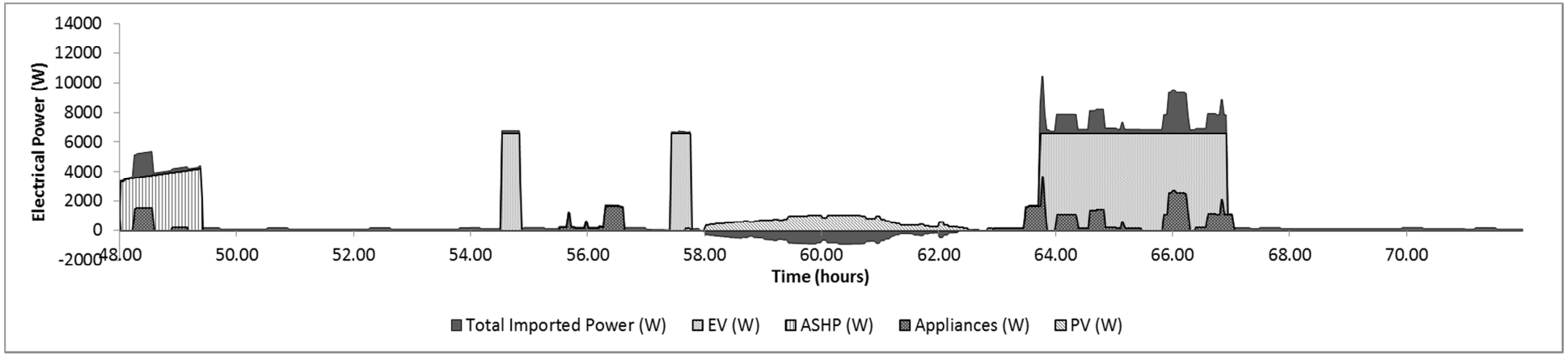

Figure 6f: typical daily profile of electrical supply and demand for unrestricted fast vehicle charging and off-peak heat pump operation.

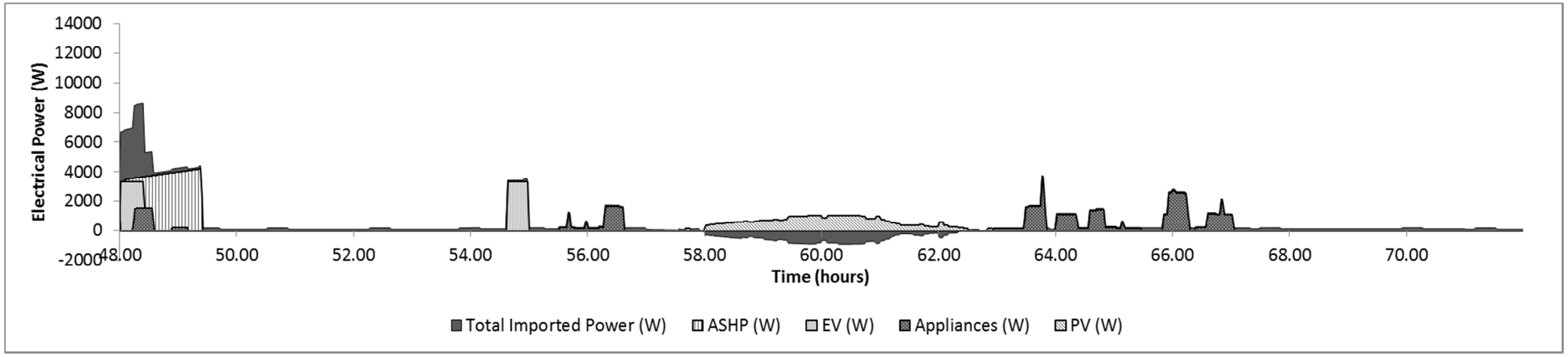

Figure 6g: typical daily profile of electrical supply and demand for off-peak slow vehicle charging and off-peak heat pump operation.

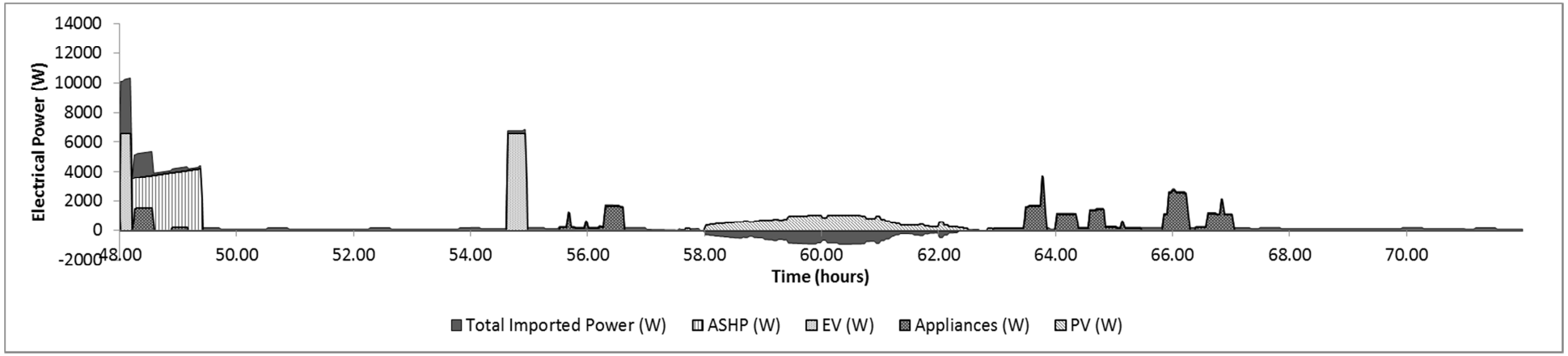

Figure 6h: typical daily profile of electrical supply and demand for off-peak fast vehicle charging and off-peak heat pump operation.