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Integrated modelling framework for the analysis of demand side management strategies in urban energy systems

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Declaration of Originality

I hereby declare that the content of this thesis is the result of my own work, and that all the work done by others and external sources have been appropriately referenced.

Copyright Declaration

Abstract

Influenced by environmental concerns and rapid urbanisation, cities are changing the way they historically have produced, distributed and consumed energy. In the next decades, cities will have to increasingly adapt their energy infrastructure if new low carbon and smart technologies are to be effectively integrated. In this context, advanced planning tools can become crucial to successfully design these future urban energy systems. However, it is not only important to analyse how urban energy infrastructure will look like in the future, but also how they will be operated. Advanced energy management strategies can increase the operational efficiency, therefore reducing energy consumption, CO_2 emissions, operational costs and network investments. However, the design and analysis of these energy management strategies are difficult to perform at an urban scale considering the spatial and temporal resolution and the diversity in users energy requirements. This thesis proposes a novel integrated modelling framework to analyse flexible transport and heating energy demand and assess different demand side management strategies in urban energy systems. With a combination of agent-based simulation and multi-objective optimisation models, this framework is tested using two case studies. The first one focuses on transport electrification and the integration of electric vehicles through smart charging strategies in an urban area in London, UK. The results of this analysis show that final consumer costs and carbon emissions reductions (compared to a base case) are in the range of 4.3-45.0% and 2.8-3.9% respectively in a daily basis, depending on the type of tariff and electricity generation mix considered. These reductions consider a control strategy where the peak demand is constrained so the capacity of the system is not affected. In the second case study, focused on heat electrification, the coordination of a group of heat pumps is analysed, using different scheduling strategies. In this case, final consumer costs and carbon emissions can be reduced in the range of 4-41% and 0.02-0.7% respectively on a daily basis. In this case, peak demand can be reduced in the range of 51-62% with respect to the baseline. These case studies highlight the importance of the spatial and temporal characterisation of the energy demand, and the level of flexibility users can provide to the system when considering a heterogeneous set of users with different technologies, energy requirements and behaviours. In both studies, trade-offs between the environmental and economic performance of demand side management strategies are assessed using a multi-objective optimisation approach. Finally, further applications of the integrated modelling framework are described to highlight its potential as a decision-making support tool in sustainable and smart urban energy systems.

"Cities have the capability of providing something for everybody,

only because, and only when, they are created by everybody."

Jane Jacobs, 1961

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List of publications

This is the list of all publications and conference presentations in which the author collaborated during his PhD period:

1. Ralitera T., Ferard M., Bustos-Turu G., H. van Dam K. and Courdier R. (2017) Steps Towards Simulating Smart Cities and Smart Islands with a Shared Generic Framework - A Case Study of London and Reunion Island.In Proceedings of the 6th International Conference on Smart Cities and Green ICT Systems - Volume 1: SMARTGREENS, ISBN 978-989-758-241-7, pages 329-336. DOI: 10.5220/0006371203290336
2. van Dam K.H., Bustos-Turu G., Shah N. (2017) A Methodology for Simulating Synthetic Populations for the Analysis of Socio-technical Infrastructures. In: Jager W., Verbrugge R., Flache A., de Roo G., Hoogduin L., Hemelrijk C. (eds) Advances in Social Simulation 2015. Advances in Intelligent Systems and Computing, vol 528. Springer, Cham.
3. Riveros, M., Guo, M., Van Dam, K. H., Bustos-Turu, G. & Brandon, N. (2017) Carbon Arbitrage with Stationary Batteries in the City of London. In: Espuña, A., Graells, M. & Puigjaner, L. (eds.) Computer Aided Chemical Engineering. Elsevier.
4. Crémel, S., Guo, M., Bustos-Turu, G., Van Dam, K. H. & Shah, N. (2017) Optimal design of urban energy systems with demand side management and distributed generation. In: Espuña, A., Graells, M. & Puigjaner, L. (eds.) Computer Aided Chemical Engineering. Elsevier.
5. Hayden Dahmm, Gonzalo Bustos-Turu, Maria Anna Chatzopoulou, Salvador Acha and Nilay Shah (2017) Techno-Economic Analysis and Trade-Offs of Cooperative Community Energy Planning Schemes in the UK. Proceedings of ECOS 2017 – The 30th International Conference On Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, July 2 - July 6, 2017, San Diego, California, USA.
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7. Bustos-Turu, G., van Dam, K.H. & Shah, N. (2016) Exploring the influence of household behaviour on energy demands with an agent-based model. Social Simulation Conference (SSC2016), 19-23 September, 2016, Rome, Italy.

8. Clifford, M., van Dam, K., Bustos-Turu, G. & Watson, S. (2016) Decision support for the evaluation of sustainable urban masterplans, Energy Systems Conference, London, UK, 14-15 June 2016.
9. Bustos-Turu, G., Guo, M., Van Dam, K., Acha, S. & Shah, N. (2016) Incorporating life cycle assessment indicators into optimal electric vehicle charging strategies: An integrated modelling approach. 26th European Symposium on Computer Aided Process Engineering: Part A and B, 2016a. Elsevier, 241-246.
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11. Bustos-Turu, G., van Dam, K.H., Acha, S., Markides, C.N. & Shah, N. (2016) Simulating residential electricity and heat demand in urban areas using an agent-based modelling approach, IEEE International Energy Conference (EnergyCon16), 4-8 April, 2016, Leuven, Belgium.
12. Acha, S., Bustos-Turu, G. & Shah, N. (2015) Modelling the Business Case to Run on-Site Generators in UK Commercial Buildings through Real-Time Electricity Pricing, 2015 ASHRAE Energy Modeling Conference, 30 September- 2 October, 2015, Atlanta, GA.
13. Bustos-Turu, G., van Dam, K.H., Acha, S. & Shah, N. (2015) Integrated planning of distribution networks: interactions between land use, transport and electric vehicle charging demand. 23rd International Conference on Electricity Distribution (CIRED), 15-18 June, 2015, Lyon, France.
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16. Bustos-Turu, G., van Dam, K.H., Acha, S. & Shah, N. (2014) Estimating plug-in electric vehicle demand flexibility through an agent-based simulation model. 5th IEEE PES Innovative Smart Grid Technologies (ISGT) European 2014 Conference, 12-15 October, 2014, Istanbul, Turkey.

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18. Bustos-Turu, G., van Dam, K.H., Acha, S. & Shah, N. (2014) Integration of plug-in electric vehicles into urban energy systems: an agent-based modelling approach. Sino-German Symposium: Smart City Processes, 22-26 June 2014, Xiamen, China.

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Nomenclature

Acronyms

ABM	Agent-based modelling / agent-based model
DSM	Demand-side management
HP	Heat Pump
MOO	Multi-objective optimisation
OPT	Optimisation model
PEV	Plug-in electric vehicle
UES	Urban energy system(s)

Indexes

i	Index of PEV agent, $i = 1, 2, \dots, N_{pev}$
j	Index of spatial unit/building, $j = 1, 2, \dots, N_{su}$
k	Index of optimisation periods, $k = 1, 2, \dots, K$
t	Index of simulation periods, $t = 1, 2, \dots, T$

Variables

$distance_{i,t}$	Distance travelled by agent i in time step t (km)
$evCO2(evP_{j,k})$	Total carbon emissions related to the PEV charging
$evCosts(evP_{j,k})$	Total PEV charging costs
$evP_{j,k}$	Charging demand in spatial unit j for period k (kW)
$evP_{j,k}^{P\&F}$	Charging demand in spatial unit j for period k in plug-and-forget scenario (kW)
$hpP_{j,k}$	Heat pump electricity consumption for building j at period k (kW)
$intTemp_{j,k}$	Internal temperature of spatial unit/building j at period k (°C)
$maxEvE_{j,k}$	Maximum aggregated energy to be charged in spatial unit j for period k
$maxEvP_{j,k}$	Maximum aggregated charging power rate in spatial unit j for period k
$maxStaticP_j$	Maximum static residential demand in spatial unit j
$Npev_k^j$	Number of vehicles plugged-in spatial unit j in period k
$pevs_j$	Number of electric vehicles simulated for each spatial unit j
$Qgain_{j,k}$	Heat gains of building j for period k

$Qloss_{j,k}^{cond}$	Conductive losses of building j for period k
$Qloss_{j,k}^{conv}$	Convective losses of building j for period k
$Qnet_{j,k}$	Net heat load of building j for period k
$resOcc_{j,t}$	Residential occupancy in spatial unit j at time t (%)
$red_{j,t}$	Residential electricity demand in spatial unit j at time t (kW)
$rhd_{j,t}$	Residential heat demand in spatial unit j at time t (kW)
$rhpd_{j,t}$	Residential heat pump electricity demand in spatial unit j at time t (kW)
$resAwakeOcc_{j,t}$	Active resident occupants in spatial unit j at time t
$soc_{i,t(k)}^{e}$	State of charge of agent i at time step t (or time period k) (kWh)
$soc_{i,t(k)}^{\%}$	State of charge of agent i at time step t (or time period k) (%)
$staticP_{j,k}$	Total static residential electricity demand in spatial unit j for each period t
$Tin_{j,k(t)}$	Indoor temperature in spatial unit/building j at simulation time t , or optimisation period k
$totEvE_j$	Total energy required by the PEV fleet during the whole simulation period for spatial unit j
$totEvE^{P\&F}$	Total energy demand in the plug-and-forget scenario
$totEvE^{pcs}$	Energy charged in public charging stations in smart charging scenario
$totEvE^{scs}$	Total energy required by the PEV fleet in participating in the smart charging scheme

Parameters

η	Round-trip efficiency of electric vehicle (%)
ρ_{air}	Air density
c_{air}	Air heat capacity
Δk	Optimisation time step (h)
Δt	Simulation time step (h)
ω_{cost}	Charging costs weighting coefficient
ACH_j	Air change rate of building j
$area_j$	Footprint area for spatial unit j (m^2)
AS_i	Activity schedule for agent i

$battCap_i$	Battery capacity of the PEV related with agent i (kWh)
$BldVol_j$	Air volume of building j
$chRate_i$	Charging power rate of the charging point where agent i is charging
$co2Grid_k$	Carbon content of the grid for each period k (tonCO_2eq/MWh)
$COP_{j,t(k)}$	Coefficient of performance for building j at simulation time t or k
TMP_j	Thermal mass parameter of building j (kJ/K/m^2)
$deltaTemp$	Temperature difference for HP smart operation
$enConRate_i$	Energy consumption rate of PEV related with agent i (kWh/km)
$HPAL_j$	Adoption level of heat pumps in spatial unit/building j
$hpCap_j$	Heat pump nominal thermal output capacity for spatial unit/building j (kW)
HH_j	Number of households in spatial unit j
HLP_j	Heat loss parameter for spatial unit/building j
$inhab_j$	Number of residents in spatial unit j
$Lbase_j$	Base-load residential electricity demand per household in spatial unit j (kW)
$Lpeak_j$	Peak-load residential electricity demand per household in spatial unit j (kW)
$pevAdopLevel$	PEV adoption level for the whole urban area (%)
$PM10Grid_k$	Particulate matter content of the grid for each period k (tonPM10eq/MWh)
$priceGrid_k$	Electricity price for each period k (£/MWh)
RFA_j	Residential floor area in spatial unit j
$SOCini$	Initial state of charge (%)
$SOCmax$	Maximum state of charge in public charging station (%)
$SOCmin$	State of charge at which agents start searching for a charging point (%)
$tempSP_{j,k}$	Temperature set point for spatial unit/building j for each period k (°C)
$Text_{t(k)}$	Outdoor temperature at simulation time t, optimisation time k
U_j	Equivalent U-value for building j
$vehicles_j$	Number of vehicles for each spatial unit j
ESA_j	Envelope surface area for each spatial unit/building j

Chapter 1. Introduction

1.1. Future smart urban energy systems

Currently, more than half of the world's population lives in urban areas and if this projected rate of urbanisation is sustained, it is expected that 66% of the population will live in cities by 2050 (United Nations, 2014). With this level of urbanisation, most of the energy is consumed in cities, and as it is mostly supplied by fossil fuel technologies, cities represent the main source of greenhouse gas (GHG) emissions released into the atmosphere. It is estimated that 75% of the global final energy demand is used in cities with probably a similar proportion of direct and indirect CO_2 emissions (GEA, 2012). In addition to global scale impacts, cities have to deal with local environmental challenges too. Air quality represents the biggest risk to health in cities, with 3 million deaths attributable to outdoor air pollution in 2012 (World Health Organization, 2016a). Unfortunately, air quality in cities has worsened in the last decade, with partial data showing there has been an 8% increase on global urban air pollution between 2008 and 2013 (World Health Organization, 2016b).

In this scenario of rapid urbanisation as well as global and local environmental concerns, cities are changing the way they historically have produced, distributed and consumed energy (Rutter and Keirstead, 2012). If cities want to reduce the carbon footprint related to the energy services they provide, such as transport, electricity and heat, but without compromising energy security and affordability, they should evolve towards creating a more sustainable, flexible and integrated energy infrastructure. Deployment of renewable power generation, implementation of energy efficiency measures in buildings, and adoption of low-carbon technologies for transport and heat sectors are some of the most important initiatives cities are taking action on for their decarbonisation and air quality improvements (C40 and ARUP, 2014). However, the implementation of some of these measures will impact the traditional way of operating energy networks. In particular, the electrification of the transport and heat sectors will increase the interconnections between sectors that were historically developed individually. If this new electricity demand is properly coordinated through demand side management (DSM) or smart control strategies (Strbac, 2008, Lund et al., 2017), it can provide valuable flexibility to support a more efficient operation of an integrated energy system, avoiding unnecessary upgrades in the distribution and transmission networks as well as reducing additional generation capacity (Siano, 2014). The new interdependencies between energy technologies and infrastructures can be positively exploited, creating co-benefits such as carbon emissions reduction, increase in asset utilisation, increase in power system reliability, reducing capital and operational costs, among other (Abeysekera et al., 2016, Kroposki et al., 2012). In this sense, novel integrated energy management strategies that take advantage of this new energy demand flexibility will need to be developed, tested and implemented. As the results of one of the largest smart grid trials in UK suggest, a future low carbon energy system can only be achieved if smart energy infrastructure is in place to support it (UK Power Networks, 2014). In this thesis, the term "smart" is used in the context of "smart grid" and "smart energy systems" (Lund et al., 2017), specifically regarding the active participation of energy consumers in the electricity market through demand-side management schemes (Siano, 2014).

But the design of these smart solutions is not without challenges from the modelling perspective, as the complexity of energy systems increases with the integration of multiple energy vectors. This complexity is further augmented when it is considered that the system operation is strongly influenced by individual users and their energy consumption behaviour. However, according to Pfenninger et al. (2014), there is a tendency in energy systems modelling to focus only on techno-economic factors, neglecting complex factors such as human behaviour and non-financial barriers for technology deployment. After reviewing a diverse set of modelling approaches, Keirstead et al. (2012) conclude that in order to address the complexity of the urban energy systems analysis, the integration of different models considering the description of behavioural processes for the design of supply systems is a sensible strategy.

This thesis presents a modelling framework with which various aspects of the operation, design and planning of smart and sustainable urban energy systems can be explored and analysed systematically under different scenarios. The main hypothesis this work is attempting to explore is that *smart energy management systems are a critical element in the planning of urban energy systems as they would help to reduce investment costs while reducing operational costs and environmental impacts, without compromising user energy requirements*. The main novelty of the proposed modelling framework is that it is composed of a set of descriptive and normative models that consider not only the technical aspect of urban energy systems, but also the urban design and building environment, socio-demographic and behavioural aspects of energy users, and the national electricity market under which an urban area operates. To achieve this, this work focuses on two aspects of modelling and analysis of urban energy systems. The first one is the characterisation of the energy demand flexibility that new technologies can provide to the system, considering the diversity among users. The second one corresponds to the assessment of different energy management strategies that optimise the operation of low carbon technologies under different urban energy scenarios considering the flexibility previously determined. The integrated methodological framework is tested with two case studies focused on transport and heat electrification. After characterising the spatial and temporal scales of the flexibility these new demands can provide, operational strategies are compared in terms of electricity costs, carbon emission, peak demand and user comfort. Finally, this thesis also presents some further applications of the proposed framework, combining it with external models to analyse problems of planning, life cycle assessment and multi-energy network operation, among others.

1.2. Transport electrification

To decarbonise the transport sector, currently accounting for 23% of global energy-related GHG emissions, low carbon targets would most likely require the adoption of new cleaner vehicle technologies. Among these, electric vehicles (EVs) represent one of the main options to decarbonise urban mobility (Hawkins et al., 2012). According to the International Energy Agency, it is expected that 20 million EVs will be on the road by 2020 if we want to keep on track in the pathway to prevent the global average temperature from rising more than to 2°C (International Energy Agency, 2016).

However, the integration of plug-in electric vehicles (PEVs) into the electricity networks can create possible negative effects such as network overload, increased energy losses, imbalances, etc. (García-Villalobos et al., 2016). Additionally, the power generation needed to supply this extra demand may cause considerably higher emissions if the generation mix is carbon intensive (Hawkins et al., 2012). To avoid these situations, novel charging strategies can be implemented taking advantage of the flexibility PEVs can provide, as source of distributed and mobile energy storage, to the energy system. Demand response, frequency regulation, renewable energy integration, and operational reserves are some of the energy services PEVs could deliver to the grid for a more efficient management of the existing power infrastructure (Sekyung et al., 2010, Mullan et al., 2012). As all these technical and environmental challenges are strongly influenced by the spatial and temporal characteristics of PEV energy demand, the design of strategies to mitigate these impacts necessarily requires the explicit representation of these spatiotemporal features. A diverse set of strategies to better integrate PEVs in electrical networks have been presented and discussed in the literature, under the concept of “smart” charging strategies (Vayá and Andersson, 2012, García-Villalobos et al., 2014). A more detailed discussion about these will be provided in 0.

In this work, a micro-simulation approach will be used to characterise these PEV charging requirements throughout the day for the different areas within the city. Then, these charging profiles are used as input in an optimisation model to evaluate different smart charging scenarios. The details of these two models are given in 0.

1.3. Heat electrification

Heat represents more than 50% of final energy consumption globally, and it is supplied mainly by fossil fuels (International Energy Agency, 2017). In the UK, heating demand accounts for 46% of final energy use, with 75% of this demand associated with households and commercial and public buildings. Due to historical low gas prices, domestic supply and comprehensive infrastructure, the UK supplies 81% of this demand through the use of gas-fired boilers connected to the main natural gas network (Chaudry et al., 2015). Among the different supply technology options for the decarbonisation of the heat sector, heat pumps (HPs) have been shown to be a cost-effective alternative to reduce CO_2 emissions, especially when installed in new energy efficient homes or in buildings not connected to the main gas network (Committee on Climate Change, 2016). In the case of district heating networks, some studies have shown that the CO_2 savings are greater when heat pumps supply low or medium temperature networks, so the temperature difference between the source and the sink is lower, increasing the heat pump efficiency (Department of Energy and climate Change, 2016). However, similarly to the case of electric vehicles, their uptake needs to be coupled with the deployment of renewable electricity to assure a low carbon electricity supply for their operation.

Similarly to the transport electrification, the uptake of heat pumps could bring some negative impacts on electricity networks requiring additional investments at both distribution and transmission level (Akmal et al., 2014). One example is the increment of an existing, or the occurrence of a new, electricity peak demand, especially when a large group of buildings require heat at the same time. This additional load would require an expansion of the network capacity. In this case, however, the academic literature shows some of these investments could be avoided if the operation of heat pumps is coordinated so the overall demand curve is smoothed out. The same "smart" scheduling control philosophy can be applied in order to improve the performance of the system or to reduce some of the impacts such as final user costs, utility generation costs, or emissions embedded in the electricity. This future scenario calls for the development of novel and integrated control and energy management strategies that, taking advantage of the flexibility of heat pumps and buildings, can reduce the impacts or increase the benefits these low carbon technologies can bring into the current energy system. Some previous studies have shown the potential of heat pumps' flexibility to contribute to the balancing of the electricity networks (Bhattarai et al., 2014) and in general to provide demand response services, specifically shifting heat demand according to the system's economic, environmental and/or technical conditions (Patteeuw et al., 2016). To characterise this flexibility, first it is necessary to understand the drivers of heating demand in the domestic sector. Previous studies have shown heating demand is influenced by numerous factors such as environmental conditions, building attributes, heating technologies, occupant behaviour, among others (Wei et al., 2014). A more detailed discussion about the characterisation and use of this flexibility through different operational strategies will be provided in Chapter 4.

In this thesis, the proposed framework will be used to design and compare different smart operational strategies for HPs. For the flexibility characterisation, two different modelling approaches will be considered. First, a half-hourly static demand model is implemented taking a heating degree hours approach to explore the impact of different HP adoption levels on the electricity network. Then, a dynamic thermal demand model is used to characterise the flexibility of the systems, depending on a combination of technology, building and user parameters. Using the previous heating demand flexibility characterisation, an optimisation model is implemented to assess smart energy management strategies, and to evaluate the potential of a group of HPs to reduce energy consumption, particularly at times when the cost and carbon emissions are highest, while accounting for end-user comfort temperature preferences. The details of these modelling approaches are presented in 0.

1.4.Modelling challenges and thesis contributions

The urban energy challenges described above represent one of the main drivers of technological innovation nowadays. Energy utilities, urban planners, local authorities, and academia are working together in finding low carbon technology solutions that can be implemented in cities in a cost-effective way (Abeysekera et al., 2016). In this planning process, one of the main tasks is to estimate the consequences of different interventions or strategies and compare them before their implementation. For this task, decision support systems, based on computational tools, can help in the process of multi-criteria evaluation of a diverse range of possible solutions (Pohekar and Ramachandran, 2004, Wang et al., 2009). Although it is not always possible to perfectly validate these tools, computational models can be a useful starting point to explore options in a multi-stakeholder and multi-disciplinary environment, supporting the discussion in terms of the effect of different parameters on the multi-criteria performance of the system, making clear the underlying set of assumptions behind the explicit model. According to Epstein (2008), even if a model cannot be validated and used for prediction, it can represent a valuable tool for other important research activities such as the explanation of the studied phenomenon, guiding of data collection, description of the general dynamics of the system, among others.

The work presented in this thesis responds to a growing interest and need among industry and academia to have or to develop their own decision support tools for the analysis of urban energy systems. Due to the complexity of a city-scale analysis, it is not possible to find a tool that suits every analysis. And depending on the specific aspect of the energy system, there can be more than ten available tools that could support a stakeholder decision, each one with its own capabilities and limitations (Lyden et al., 2018, Allegrini et al., 2015). In the last decade there has been a great effort from academia to review and categorise these tools. For example Keirstead et al. (2012) and (Allegrini et al., 2015) reviewed 309 and 198 papers respectively, categorising them according to the specific areas of analysis (e.g. building design, urban climate, renewable energy, seasonal storage). Based on these reviews, most of the available tools are focused on the supply side with less consideration regarding the characterisation of energy demand. As discussed by (Lyden et al., 2018), generally these tools have a limited representation of demand flexibility and DSM strategies.

One relevant group of literature is related with building energy assessment (Reinhart and Cerezo Davila, 2016). In this group, steady state and dynamic simulation methods are used to estimate energy consumption in buildings. On one hand, static methods are simpler and useful to scale up the analysis to district or city level. With these models, energy efficiency measures or different urban design can be assessed. However, the temporal resolution is usually not high enough for a proper assessment of DSM strategies. Examples of these works are (Dall'O' et al., 2012, Nault et al., 2018). On the other hand, dynamic building simulations usually use sophisticated model to describe the thermal behaviour of buildings for a detailed energy assessment (Lauster et al., 2014, Wang et al., 2018). Although this is useful for incorporating thermal control strategies in individual buildings, it makes it difficult to scale the analysis up for a district and city level, where large amount of data would be needed. In some cases, the diversity in building properties can be simplified using archetypes (Wang et al., 2018). However, generally the technical representation of heating control systems is not detailed enough to evaluate DSM strategies for a large group of buildings. Additionally, in all these works, the analysis is mainly focused on buildings systems, with no consideration of other energy systems such as transport and electricity networks.

One of the most relevant works in the area of combining transport and building analysis is the SynCity toolkit, presented in (Keirstead and Sivakumar, 2012, Keirstead et al., 2009). In the demand module of this toolkit, authors used an activity-based simulation model to simulate urban resource demand (transport, electricity and gas) with high spatial and temporal resolution. Natural gas and electricity demand profiles can be estimated for an urban area taking into account user's activity schedules. However, and as stated by the authors, the regression-based method, used to convert schedules into energy demand profiles, has their limitations in terms of the possible scenarios that can be tested. This approach does not explicitly capture the energy demand processes behind transport and building systems (e.g. EV charging and discharging, heat losses and gains), making it difficult to explore the effects of different variables in the energy demands such as weather, user behaviour, building and electric vehicles parameters, and control mechanisms such as DSM.

Specifically related to the design and analysis of DSM strategies, the literature has reported their benefits and challenges (Strbac, 2008, Gelazanskas and Gamage, 2014). In (O′Connell et al., 2014) authors provide a critical analysis of the challenges in the modelling and implementation of DSM strategies. According to them, most of the literature take simplifying assumptions regarding the level of demand flexibility and participation on DSM schemes, such as assuming economic rationality in end-user consumption decisions, or disregarding diversity inherent to different types of users, including diversity related with the temporal and spatial distribution of energy demands. Within these DSM studies, a couple of papers are worth highlighting due to their consideration of the interactions between DSM and power systems. In (Galus et al., 2012a, Papadaskalopoulos et al., 2013) authors consider demand-side technologies such as electric vehicles and heat pumps to estimate the impact of shifting part of their consumption in the electricity market, depending on the power system conditions. Although these examples represent the state of the art in terms of DSM analysis, none of them consider the different aspects of urban energy system analysis in a holistic way. For example, in (Galus et al., 2012b) authors did not consider flexibility of buildings and heating systems as part of the analysis. (Papadaskalopoulos et al., 2013) on the other hand, did not include a detailed representation of the transport behaviour and their temporal and spatial features within an urban area.

The aim of this thesis is to develop, implement and test a computational tool to analyse demand side management strategies in the context of sustainable and smart urban energy systems. Based on the previous literature analysis, the following points represent the research gaps this thesis aims to address, highlighting the novelty of the developed tool:

- The geospatial representation of the urban environment, including heterogeneity in land use and building properties, allows an assessment of transport and building energy demand with high spatial resolution.
- The agent-based modelling approach allows the explicit representation of user behavioural rules related with energy requirements, including heterogeneity in user types, technologies, and access to charging infrastructure.
- The transparency and modularity of the tool allows its continuous development in a collaborative modelling environment.
- The multi objective optimisation approach allows the characterisation of the trade-off between environmental, economic and technical benefits of DSM in urban areas.

1.5. Contribution within research group

Part of the work presented in this thesis was conducted as part of different research and industrial collaboration projects in which the author actively participated. In this context, some of the modelling and tool development was built in a collaborative work environment with members of the research group at Imperial College London. Specifically, the author worked in close collaboration with his supervisor Professor Nilay Shah, and with three research fellows (Dr. Koen van Dam, Dr. Salvador Acha, and Dr. Miao Guo). Throughout this document, these collaborations have been clearly acknowledged with reference to joint publications or to industrial projects. In this section, the specific individual contributions in relation to the rest of the research group are specified in four different areas: general modelling framework, agent-based modelling, multi-objective optimisation, and case studies.

In terms of general modelling framework, an initial exploration of using an agent-based model and an optimisation tool to analyse smart charging of electric vehicles was presented by the research group in (Acha et al., 2012). The modelling framework presented in this thesis is inspired by this previous work and expanded by the author to fully describe the different aspects of urban energy system and the interaction between technologies, users, infrastructure, energy markets and urban environment. In this sense, the formalisation, description and implementation of the general framework is part of the individual contribution of the author.

The development of the agent-based model (ABM) was done in close collaboration with Dr. Koen van Dam, who developed the first version of the ABM used in (Acha et al., 2012). This first version included a simple representation of the urban environment, transport behaviour and charging infrastructure, and it did not include the building energy demand estimation. All these elements were improved, and more details were added during this thesis. These are described in section 2.1 of this document. Most of these developments were discussed and planned with Dr. van Dam, where the final description, modelling and implementation were done by the author.

The smart PEV charging and HP scheduling model, based on a multi-objective optimisation model was developed by the author in collaboration with Dr. Acha and Prof. Shah. In the case of the smart PEV model, a first version was developed by the research group and presented in (Acha et al., 2012) and Acha (2013). In this thesis, the approach is similar, but some network constraints were simplified, and new constraints related with maximum peak demand and PEV energy flexibility were included (see section 2.2 for more details). Most of these changes were discussed with the research group but the final modelling and implementation were done by the author. In the case of smart HP scheduling, the theoretical formulation was discussed with Prof. Shah and the final modelling and implementation were done by the author. Finally, the development of the dynamic electricity tariffs and carbon content model were developed and implemented by the author in collaboration with Dr. Acha.

Finally, all the data processing, implementation, simulations and scenario analysis involved in the development of the case studies presented in this thesis were done by the author with regular discussions with the rest of the research group. In these cases, all the necessary extensions of the agent-based simulation and optimisation models were done by the author. Results and analyses performed by other members have been acknowledged throughout the document.

1.6. Thesis structure

The structure of this thesis is as follows. After the introduction, some background information is given about transport and heat electrification to give the reader an idea of the integration challenges in those two cases. The first chapter finishes with a discussion of the role of modelling tools in the analysis or urban energy systems. Then, in the second chapter, the proposed modelling framework is described in detail in terms of both the general structure and the specific models within the framework. In chapters 3 and 4, two case studies focused on transport and heat electrification, respectively, are presented and analysed to test this modelling framework. Relevant literature regarding smart PEV charging and smart HP operation is embedded in these last two chapters, rather than having a separate literature review section. Then, in chapter 5, further applications of the proposed framework are presented to show the potential of the developed framework as a decision-making support tool. Finally, chapter 6 presents the conclusions and outlines future work in this research area.

Chapter 2. Modelling framework

The modelling framework is designed to be an integrated set of models and tools to analyse urban energy systems (UES), particularly related with the energy management of flexible demand-side technologies such as electric vehicles and heat pumps. This framework, as shown in Figure 2-1, is designed to consider not only the physical aspects of UES but also other important social, economic and environmental elements that influence the operation of low-carbon technologies in UES.

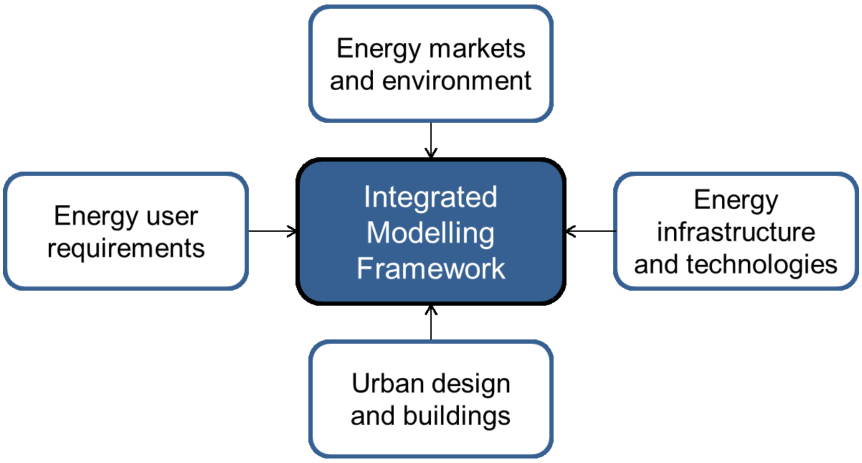

Figure 2-1. Integrated modelling framework.

For example, the operation of low carbon technologies (e.g. heat pumps, PEVs) can be coordinated so the carbon emissions, embedded in the electricity these technologies use, are minimised, or aggregated infrastructure constraints can be considered. In the case of carbon emission minimisation, the carbon content of the electricity grid is dependent on the real-time power generation mix. Therefore, the optimal operational strategy will be necessarily influenced by the time in which individual households require the energy service (e.g. lighting, heating, transport). The final electricity demand would be determined by the conversion efficiencies and by the primary energy requirements, which in turn, are influenced by physical phenomena (e.g. heat losses in the building, energy consumption of PEVs). These energy demands are determined not only by the physical properties of the system but also by energy user preferences and requirements (thermostat set points, PEV driving speed, etc.). In this context, this work proposes an integrated modelling framework that can incorporate all these elements into the analysis in an explicit and flexible way so different scenarios can be assessed. It is worth noting that the term "integration" here is not used in the context of "energy systems integration" (O'Malley et al.,

2016) or “multi-energy systems” (Mancarella, 2014). In this thesis, the term refers to the holistic modelling approach in which, through a combination of models, the different aspects of energy demand analysis can be integrated.

The analyses shown in the next three chapters of this thesis are presented with the aim of testing the holistic nature of the modelling framework described in this chapter. This integrated approach is realised through the consideration of multiple aspects of energy demand such as user behaviour, building thermal properties, land use and transport, etc. Due to the complexity of a comprehensive city scale analysis, a set of simplifications needed to be made. One of them relates to the technical aspects of the implementation of demand-side management strategies in urban energy systems. The framework proposed in this thesis is aimed to support a first stage analysis in which different stakeholders such as energy systems engineers, city planners, energy utilities, demand aggregators and energy policy makers can assess the economic and environmental benefits of demand side management strategies in cities. In this context, the models developed in this work can be used as general decision support tools before developing more specific analyses regarding the different aspects of demand side management such as the impact of these strategies in electricity and heat networks, or the different aspects of regulation and business models necessary to support the implementation of these smart control mechanisms. In this regard, this thesis does not consider two important aspects to be considered in future work. The first relates to the electrical network constraint. As the analysis of electricity demand is aggregated by spatial units that can be geographically bigger than the area of influence of low voltage feeders, the detailed representation of distribution networks and local technical constraints are not considered in this thesis, but it is recognised they need to be addresses before any implementation of these DSM strategies in a real system. The second aspect that was not considered in the development of the modelling framework is the detailed analysis of stakeholders, regulation and business models of smart urban energy systems. In related literature (Eid et al., 2015, Eid et al., 2016, Siano, 2014, Strbac, 2008) readers can find detailed analyses of different market incentives (including price-based and direct control methods) for demand flexibility management, and the role of new market actors (such as aggregators) in the implementation of these strategies.

The modelling framework presented in this chapter defines the general structure of the methodology used in this work. In this sense, the case studies presented in this work (see 0 and Chapter 4) are examples of how this framework can be used in two specific contexts. However, according to the nature of the specific analysis, this set of models could be used in diverse ways.

Chapter 5 shows some examples on how this framework can be expanded or integrated with other external models.

As part of this integrated modelling framework, two groups of models are developed. The general data flow between these two groups is shown in Figure 2-2. The first group represents a set of simulation models, to characterise the spatial and temporal variations of energy service demands. In this work, this characterisation is focused on the transport, electricity and heat demand related with the domestic sector. With these tools, the energy requirements and flexibility can be estimated for different type of users, depending on the socio-demographic, urban design, building properties, and technological parameters. These energy service demand and flexibility profiles are then used for the design of optimal energy management strategies using a second group of modelling tools. This second group of models is based on mathematical programming, and these models are used to optimise the operation of the system considering the energy user requirements. Using a multi-objective approach, trade-offs between different operational criteria such as the minimisation of emissions, costs, or peak demand can be assessed.

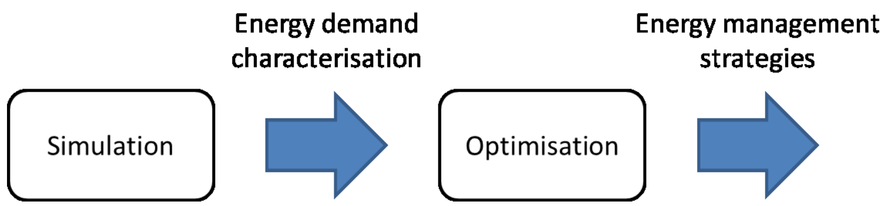

Figure 2-2. General modelling framework data flow.

It is important to note here that the modelling framework developed in this thesis does not assume any "a priori" operational criteria. Although is it recognised that the economic objective is the most common among current DSM analysis (Lyden et al., 2018, Stoll et al., 2014), the model implemented in this thesis includes also environmental objectives to analyse the trade-offs between these different criteria. The carbon reduction through DSM strategies has been discussed in the literature and it could be argued than carbon emissions are reduced indirectly when DSM strategies are used to minimise peak demand (Stoll et al., 2014). On one hand, this will reduce the need for upgrades in the capacity of the whole electricity system (generation, transmission and distribution), therefore reducing embedded emissions. On the other hand, it will reduce operational emissions if peak loads require electricity production from more CO2 intensive production units. When electricity prices are used in DSM to influence the shift in the demand, a reduction on carbon emissions can be expected if there is a positive correlation between electricity price and carbon intensity of the generation mix. In this work, the multi-objective approach is formulated through a basic weighting method to generate a visual comparison (pareto frontier) between the two objectives (more details are presented in sections 2.2.2 and 2.3.2). Other two alternative approaches could be considered. The first one would be to internalise the carbon emission costs in a single objective. However, with the current EU Emission Trading System, the cost of a tonne of CO_2 is too low compared to the electricity cost to have any influence in the economic decision[1]. The second option would be to use the epsilon constraint method in which emissions are considered as part of the constraints (this is the method considered in the case study presented in section 5.1.).

Following the general data flow, simulation and optimisation models are described in the next sections.

2.1. Agent-based simulation model

In this research, the main simulation model uses the agent-based modelling (ABM) approach. This modelling and simulation technique allows the analysis of complex socio-technical systems through the representation of the dynamic interactions between a set of heterogeneous individuals (agents) and a socio-technical network spread in space and time (environment). In this modelling approach, each agent is characterised by an internal state and a set of behavioural rules to define its interaction with other agents and with the environment (Macal, 2016, Van Dam et al., 2012). According to Gilbert (2007), four main characteristics are associated with the agent: perception, performance, memory and policy. *Perception* is associated with the awareness of the agent's environment, including other agents in its vicinity. *Performance* is related with the set of different behaviours the agent performs, such as motion, communication, or any other action. Also, agents have a *memory* in which they record previous perceptions about their states or actions. Finally, the *policy* represents the set of rules, heuristics, or strategies that the agent uses to decide which behaviour they will to execute. Using this agent description, the decision processes of individual energy users in urban areas can be represented to characterise energy services demands.

[1] Carbon allowances have been traded, under the EU Emission Trading System, at a price between 5 and 20 EUR/tonCO_2 in the last 5 years. Source: https://markets.businessinsider.com/commodities/co2-emissionsrechte.

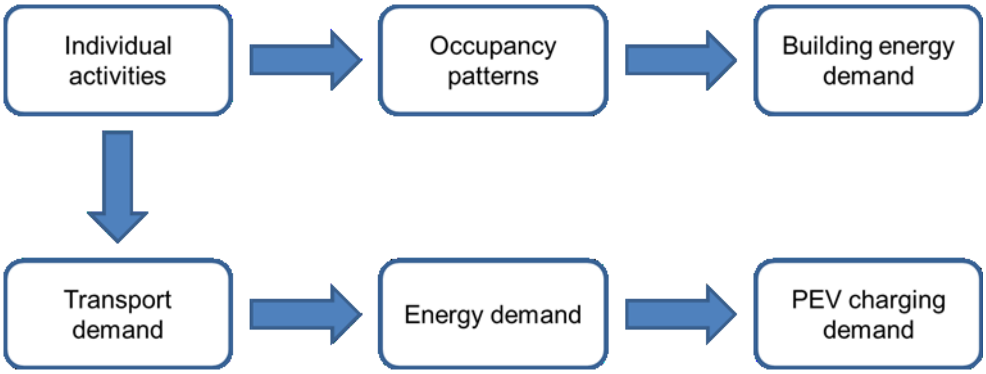

Figure 2-3. Agent based simulation data flow.

As shown in Figure 2-3, the ABM is developed to generate stationary and mobile energy demand profiles related with the residential sector and the (privately owned) electric vehicle fleet; respectively. These profiles are generated from a bottom-up approach in which the individual activities energy users perform according to the land use distribution of the urban area under study, are the main driver for transport demand and for building occupancy patterns. These, in turn, generate the final PEV charging and building energy demands, when combined with the physical and environmental properties of the system. In the process, different influencing factors such as the city layout, land use distribution, socio-demographic characteristics of users, technical parameters of demand side technologies, and the charging and transport networks, are considered. More details of the sub-models are presented in the next sub-sections.

The ABM is implemented in Java, using the free and open source java library Repast Simphony (North et al., 2013) and built on top of the *RepastCity* model (Malleson, 2012) and the work done in (Bustos-Turu, 2013). The code of this tool, under the name of *SmartCityModel* is currently hosted in a private repository (Van Dam and Bustos-Turu, 2016). It has been regularly updated during the last five years and the intention is to release a consolidated version publicly as open-source software.

The general structure of the *SmartCityModel* is shown in Figure 2-4 where the main inputs and outputs are depicted. In the next sections, a more detailed description of each of the modules of the ABM (namely synthetic population generator, transport and charging model, electric vehicle model and residential energy model) are presented.

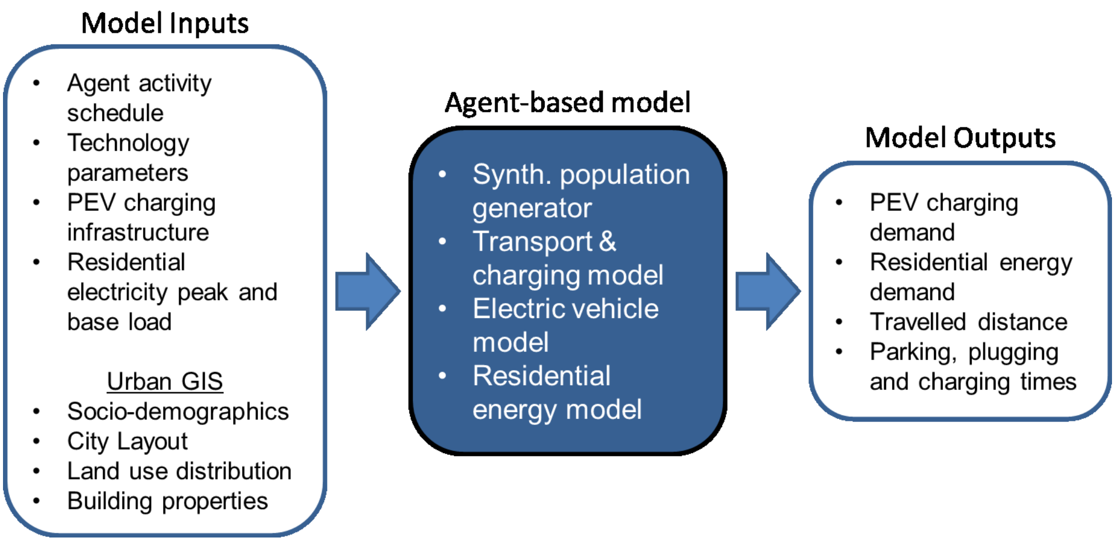

Figure 2-4. Agent-based simulation model structure.

2.1.1. Urban GIS model

To incorporate the spatial elements of the urban environment in which agents behave, a GIS-based representation is created using a variety of data sources. In this model, different layers can be defined with their own attributes, and then exported as geospatial vector data (shapefile) for the *SmartCityModel*. In this thesis, a set of vector data layers are used to represent the urban area and the agents who move around. The first vector layer is made of polygons representing building or geographical areas used as the environment for the locations where synthetic agents (represented in a point vector layer) carry out their different economic activities (home, work, shopping, leisure, etc.). In this layer, the land use (residential, commercial, etc.), socio-demographic parameters (e.g. density, household size, employment rate, etc.) and some building properties (heat loss parameter, height, etc.) are defined for each geographical unit in the city (building, borough, local authority, etc.), depending to the specific case study. The parameters included in this layer are then used to generate the synthetic population, and for the energy demand estimations, as explained in the next sections. The second vector layer is made of polylines to model the road network, defined by a set of links and nodes, representing streets and intersections respectively. This allows agents to set routes and travel around the urban area between origins and destinations specified in the polygon layer. Each agent will move through a set of coordinates that are also part of the road. The distance agents travel in each time step will be determined by the speed and the time step. Both parameters can be defined depending on the case study. The distance travelled along this network, as an effect of agent activities, is then used to estimate PEV energy consumption (see section 2.1.4). When agents are not travelling, they occupy a specific geographical unit, generating the occupancy profiles that are then used in the static energy demand calculations (see section 2.1.6). In this sense, the spatial resolution of the energy demand profiles will be determined by the scale of the spatial units. For example, in the case each spatial unit represent a borough, the model will generate demand profiles with that spatial resolution. However, the model could generate demand profiles with much higher spatial resolutions if smaller polygons were used to represent, for example, individual buildings or even smaller areas[2]. However, this would have an impact of the simulation time, as more data would need to be stored for each time step. This is an important aspect to be analysed in future work, especially if city-scale energy assessment is performed at individual buildings resolution.

2.1.2. Synthetic population generator

The purpose of this module is to create a synthetic population of energy users living in the different zones of the urban area. This population, with their different activities, will then generate energy demands, spatially and temporally distributed throughout the city. Following the diagram shown in Figure 2-5, the first step is the creation of the environments based on the GIS model described previously, with each GIS layer representing a different aspect of this environment in which the agents behave.

[2] For very small scale GIS representations, an interesting example can be found here: Linzmeier, B. J., K. Kitajima, A. C. Denny, and J. N. Cammack (2018), Making maps on a micrometer scale, Eos, 99, https://doi.org/10.1029/2018EO099269. Published on 17 May 2018.

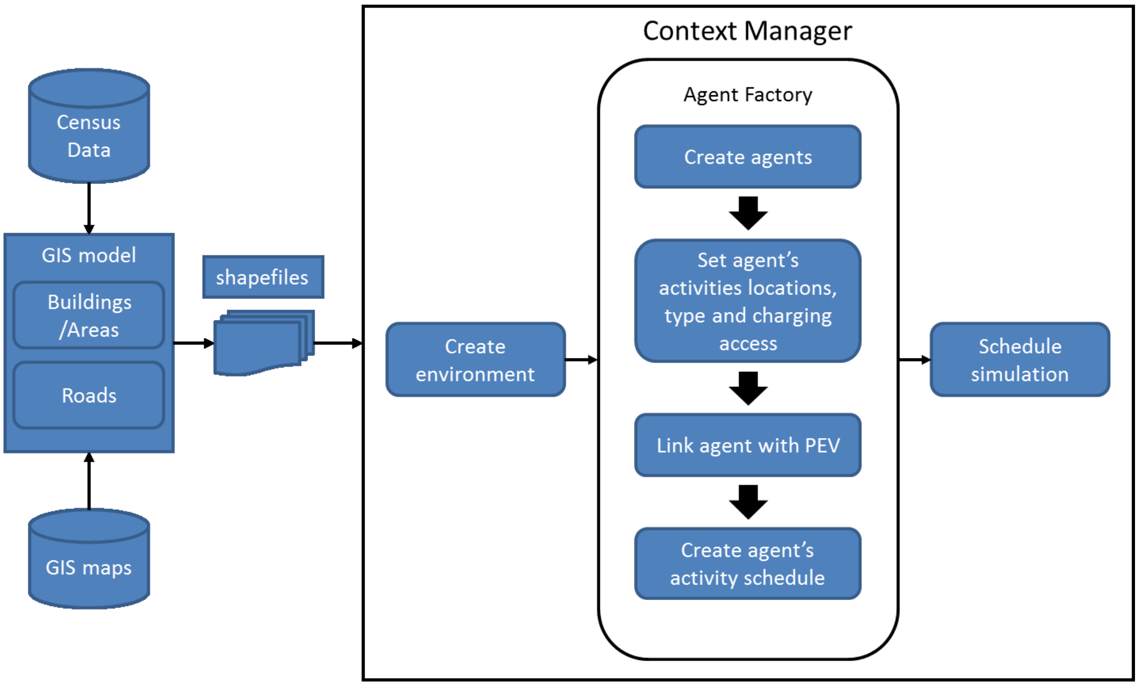

Figure 2-5. Synthetic population generation.

Once the environments are created, the next step is to generate a synthetic population of energy users (agents). This process, implemented in the *AgentFactory* class, creates the agents for each geographical unit (i.e. a building or area), according to the attributes defined in the GIS model. The methodology was first introduced in (van Dam et al., 2015) and here more details are incorporated. The steps to generate this synthetic population of energy users are the following: First, the number of agents in each geographical unit j is estimated based on the number of electric vehicles, which is dependent on the total number of vehicles and the level of PEV adoption, depending on the scenario simulated (see Eq. 1).

$$pevs_j = vehicles_j \times pevAdopLevel \qquad \text{Eq. 1}$$

Then, agent's activity locations are defined considering four different activities, each one related with different land use (i.e. home for residential, workplace for commercial, shopping for retail, and leisure activities for leisure areas). Then, for each agent, home and work locations are considered fixed and defined based on a probability proportional to the total floor space area (considering the height of buildings) linked with each activity (e.g. geographical units with higher proportions of residential/industrial floor space area will have higher numbers of agents living/working there).

Once an agent's home and work place are selected, its working status (worker, non-worker) is defined (note that a work place is defined for all agents including those with the non-worker status, potentially accounting for agents looking for jobs or visiting offices). This definition uses the employment rates for each geographical unit, defined previously in the GIS model. Next, the charging access level (defined as the probability for an agent to have a charging point of a specific type available) is set for each location. Then, each agent is associated with a PEV with a specific set of properties (more details are presented in section 2.1.4) including an initial state of charge ($SOCini$), based on whether agents have access to a charging point at home, and its activity schedule, defined according to its employment status. Based on the methodology presented in (van Dam et al., 2015), the activity schedule AS_i is created for each energy user according to its type (workers, non-workers) and it is defined with a list of 4-tuples, shown in Eq. 2.

$$AS_i = \{(ACT_a, MDT_a, SD_a, PD_a\ )\} \tag{Eq. 2}$$

For each activity ACT_a (with a representing the activity category such as work, home, shopping, leisure), a departure time is defined as a normally distributed random variable, with MDT_a as its mean departure time and SD_a as its standard deviation to account for variability in the departure time among agents. Finally, a probability of departure PD_a is included to account for the fact that not all agents will perform the same activities (e.g. irregular shifts, non-worker agents going to an office in the morning, workers going for shopping to a retail area at lunch time, etc.). These schedules are then used in the transport and charging model to generate trips; further details are presented in the next section.

2.1.3. Transport and charging model

For the transport and charging model, trips are generated based on the agent's activity schedules, defined previously in the synthetic population generation stage. Among other variables, each agent has a state variable, used to keep track of the current state of the agent (*parked*, *plugged*, *charging*, or *driving*). During the time-driven simulation, agents will keep updating these variables as they perform their activities around the city, using the road network and occupying different buildings. Each agent will remain *parked*, or *plugged* or *charging* (at a charging point) until a new activity is created (for simplification, it is assumed all agents are parked in their homes at the beginning of the simulation at 4 am). When it is time for the next activity, the agent chooses its destination. For the case of home and work, the destination is fixed and defined previously in the synthetic population generation stage (see Section 2.1.2). In the case of shopping and leisure activities, their destinations are selected during the simulation, before their starting time. The locations of these non-fixed destinations are set using the same allocation rule than in the case of home and work (i.e. randomly with a probability proportional to the specific floor space). Once the destination is defined, the route between origin and destination is set based on the shortest path between the two set of coordinates, using the algorithm implemented by Malleson (2012), and the agents starts the new journey (changing state variable to *driving*). Figure 2-6 shows the decision-making process considered for this first part of the simulation.

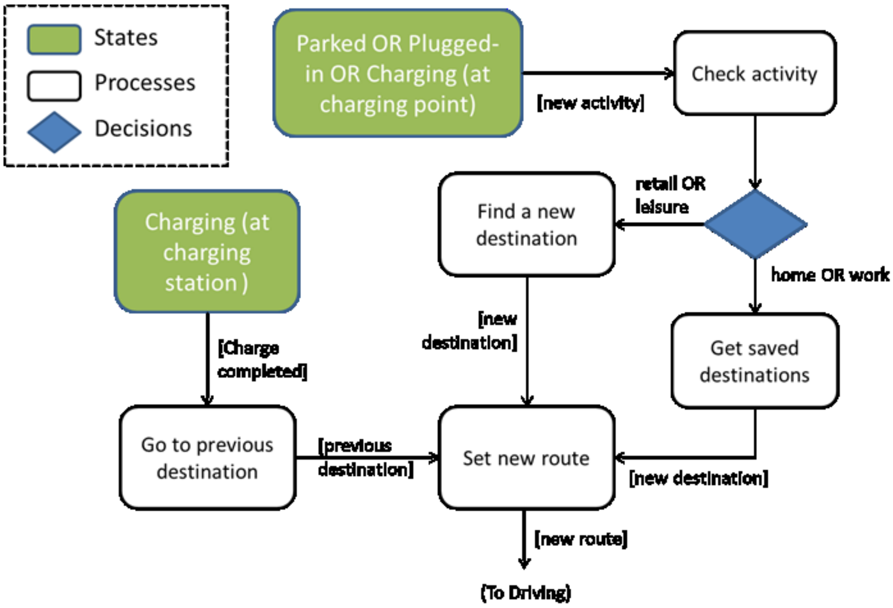

Figure 2-6. Activity diagram for transport and charging model (Part a).

Agents will keep travelling until their PEV's State of Charge (SOC) falls below a certain threshold ($SOCmin$). In this low battery condition, agents check their access to charging infrastructure at destination (it is assumed users have access to this information). If there is a charging point available at destination, agents keep traveling to their destinations where they charge their PEV on arrival (it is assumed the minimum state of charge would allow every agent to reach destination). On the other hand, if there is no access to a charging point at destination, agents set a new route to a public charging station (defined as a place with public charging points available), changing their destinations temporally. Upon arrival to the charging station, agents start the charging process and continue it until the SOC reaches a maximum value $SOCmax$. After that level is reached agents continue to travel to their original destination they had before going to the charging station. In the case agents are not running out of charge, they will keep traveling to their destination. Once they arrive, they check if there is a charging point available (independently of the SOC). In case there is no availability, agents' PEVs will remain parked until the next trip. In the case there is a charging point available, the charging process will depend on the participation of each agent in the smart charging mechanism. If an agent participates in this scheme, its PEV remains plugged-in and available for charging. This availability is considered as an input for the smart charging model (described later in section 2.2) to determine the best time to charge. On the other hand, if an agent does not participate in the smart charging scheme (plug-and-forget scenario), it will start charging its PEV until either the battery is fully charged (in which case it will remain plugged-in) or the next activity starts. The previous process is then repeated for all agents for each time step until the end of the simulation. The travelling and charging behavioural model described previously is summarised in the activity diagram shown in Figure 2-7. Additionally, an initial state of charge ($SOCini$) is established based on whether agents have access to a charging point at home.

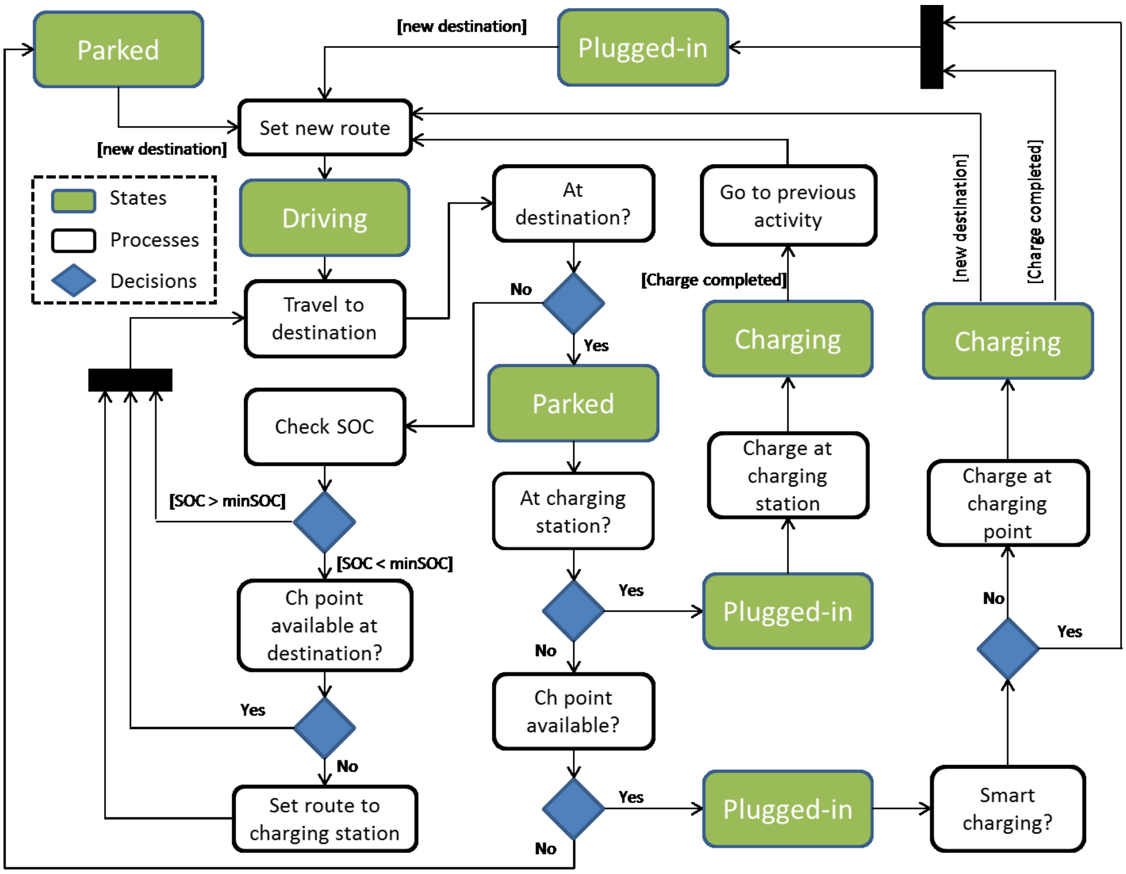

Figure 2-7. Activity diagram for transport and charging model (Part b).

2.1.4. Electric vehicle model

Plug-in electric vehicles are modelled as a generic energy storage device, with the following properties: battery capacity, energy consumption rate and round-trip efficiency. When PEVs are charging, power flows from the grid to the PEV battery and the $soc_{it}^{\%}$ (in term of percentage of battery capacity) is calculated at each time using Eq. 3. For simplicity, the effect of the round-trip efficiency is considered only during the charging process.

Eq. 3

$$soc_{i,t+1}^{\%} = \frac{1}{battCap_i}\left(soc_{i,t}^{e} + chRate_i \times \eta \times \Delta t\right)$$

Where $battCap_i$ is the battery capacity of the PEV related with agent i, soc_{it}^{e} is the state of charge (in terms of absolute energy) of agent i at time t, $chRate_i$ is the charging power rate of the charging point or charging station where agent i is currently charging, η the round-trip efficiency that accounts for the losses in the charging and discharging processes, and Δt the simulation time step.

For each time step, when the PEV is traveling to its destination, the PEV discharging process is characterised by Eq. 4,

Eq. 4

$$soc_{i,t+1}^{\%} = \frac{1}{battCap_i} \times \left(soc_{i,t}^{e} - distance_{i,t} \times enConRate_i\right)$$

Where $distance_{it}$ is the travelled distance of agent i during the time step t and $enConRate_i$ the energy consumption rate of the vehicle owned by agent i.

2.1.5. Heat pump model

The residential heat pump electricity demand ($rhpd_{jt}$) is estimated for each geographical unit j through the coefficient of performance ($COP_{j,t}$), the residential heat demand ($rhd_{j,t}$) (the method to calculate this is explained in the next sub-section), and adoption level of heat pumps ($HPAL_j$), using the following expression:

$$rhpd_{j,t} = HPAL_j \times rhd_{j,t}/COP_{j,t}$$

Eq. 5

The $COP_{j,t}$ is calculated for each time step depending on the external temperature. This effect is estimated based on the results presented in (Caneta Research Inc, 2010) for a set of commercial air-source heat pumps and are shown in Figure 2-8.

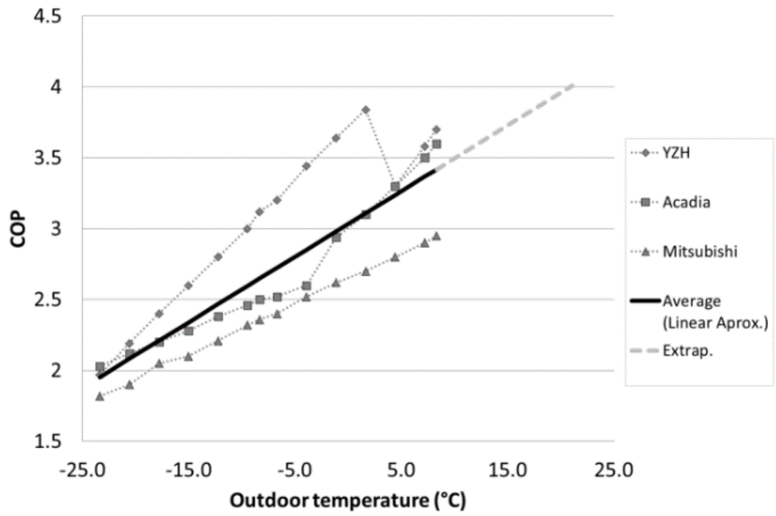

Figure 2-8. Effect of external temperature on the COP.

The linear approximation shown in Eq. 6 is used to characterise the effect of outdoor temperature $Text_t$ on the $COP_{j,t}$.

$$COP_{j,t} = 0.04627 \cdot Text_t + 3.03283 \qquad \text{Eq. 6}$$

2.1.6. Residential energy model

To assess the impact of PEV charging demand and HPs in the urban energy system, static residential electricity and heat profiles are estimated using the same modelling approach. The travel and charging behavioural rules previously described allow the simulation model to generate trips and charging events for the whole PEV fleet in the simulated urban area. These movement patterns, however, create not only the spatiotemporal charging requirements of PEVs, but also occupancy patterns for each of the geographical units defined in the city. These patterns are then used to generate electricity and heat demand profiles for residential areas. The algorithm for the generation of residential electricity and heat demand profiles is described as follows:

1. Residential occupancy $resOcc_{jt}$ is calculated at each time step t based on the number of awake residents $resAwakeOcc_{jt}$ and the total inhabitants $inhab_j$ in each geographical unit j (see Eq. 7).

Eq. 7

$$resOcc_{j,t} = \frac{resAwakeOcc_{j,t}}{inhab_j} \times 100$$

2. The residential electricity demand red_{jt} for urban zone j at simulation time step t is generated considering the base ($Lbase_j$) and peak ($Lpeak_j$) loads, the number of households per zone (HH_j) and the residential occupancy profile generated previously. This electricity demand does not consider the extra electricity demand from PEVs and HPs.

Eq. 8

$$red_{j,t} = HH_j \cdot \left[Lbase_j + \left(Lpeak_j - Lbase_j\right) \times resOcc_{j,t}\right]$$

3. The residential space heating demand rhd_{jt}, for urban zone j at simulation time step t is generated considering the difference between outdoor ($Text_t$) and indoor ($Tin_{j,t}$) temperatures, the heat loss parameter (HLP_j), the residential floor area (RFA_j), and the occupancy profile, using Eq. 9. This approach is similar to the traditional heating degree day method, but here hourly data is used instead and occupancy of the whole zone is included in the calculation.

$$rhd_{j,t} = \left(Tin_{j,t} - Text_t\right) \times HLP_j \times RFA_j \times resOcc_{j,t}/1000$$

Eq. 9

The previous agent-based model is used to characterise the mobile and static demand. In the next sections, the two different energy management models are described, as well as the way these two modelling approaches are integrated for the specific analyses.

2.2.Smart electric vehicle charging model

In this work, a multi objective optimisation (MOO) model is formulated to design smart PEV charging strategies. These strategies consider the charging requirements estimated previously (see section 2.1.3). These requirements as well as the charging flexibility are considered as the main constraints in the optimisation model.

The optimisation model is built on the work of Acha (2013) and it represents an approach to incorporate the PEVs' charging requirements on an optimal energy management model in which the main control variable is the PEV charging power. In this sense, the decision of charging the PEV is not taken by the energy user but by an external actor. In the current work, the PEV charging requirement profiles are estimated for each spatial unit (e.g. individual buildings, districts, boroughs, etc.) considering those agents participating in the smart charging scheme using the ABM described previously (see section 2.1.3). These profiles can be considered as a virtual energy storage system in which the charging power rate, maximum energy capacity and current state of charge are determined by the PEVs connected in that particular area and at that particular time. Therefore, the level of flexibility (defined as the difference between the maximum energy capacity and the state of charge) which the whole PEV fleet can provide for smart charging strategies varies spatiotemporally. The optimisation model considers these daily profiles as constraints for the optimal charging of PEVs under different objectives or criteria. Additionally, to analyse the impact of PEV charging demand in the current system, residential electricity demands are also generated for each spatial unit using the ABM described previously (see section 2.1.6). In the next sub-sections, a more detailed description of the optimisation model and its formulation is presented.

2.2.1. Single-objective optimisation

The optimal charging of the PEV fleet is determined for different single objectives, namely PEV charging costs (Eq. 10) and PEV charging emissions (Eq. 11). The charging profile $evP_{j,k}$ is estimated for each spatial unit j and for each optimisation period k.

$$\min\left(evCosts\left(evP_{j,k}\right)\right) = \min\left(\sum_{k}^{K}\sum_{j}^{N_{su}} priceGrid_k \times evP_{j,k} \times \Delta k\right) \qquad \text{Eq. 10}$$

$$\min\left(evCO2\left(evP_{j,k}\right)\right) = \min\left(\sum_{k}^{K}\sum_{j}^{N_{su}} co2Grid_k \times evP_{j,k} \times \Delta k\right) \quad \text{Eq. 11}$$

For the PEV charging cost minimisation, the charging profile is determined to reduce the costs to the final customer (in this case, the PEV owner), depending on the electricity tariff considered (see 2.4 for discussion about dynamic tariffs). For the minimisation of PEV emissions, the dynamic carbon factor of electricity during the PEV charging process is considered. These emissions are determined based on the hourly generation mix and the emissions factors for the different generation technologies (more details about these estimations are presented in section 2.4).

2.2.2. Multi-objective optimisation

In this work, the trade-offs between the different smart charging criteria presented previously are analysed using a multi-objective optimisation approach. In this case, PEVs charging costs and emissions objectives are combined using a basic weighting method to generate Pareto optimal solutions (Miettinen, 1998), as shown in Eq. 12 .

$$\min f\left(evP_{j,k}\right) = \omega_{cost} \times evCosts\left(evP_{j,k}\right) + (1 - \omega_{cost}) \times evCO2\left(evP_{j,k}\right) \quad \text{Eq. 12}$$

Where ω_{cost} is the charging costs weighting coefficient.

2.2.3. Constraints

Independently of the specific objective function, all the scenarios share the same constraints related with the PEVs charging process. Eq. 13 represents the total PEV energy consumption constraint, and it accounts for the energy all the PEVs consume during the whole simulation period for each of the spatial units. The charging power constraint shown in Eq. 14 limits the maximum charging power and it is determined in the ABM by the number of PEVs plugged-in in an area during a time interval, and by the power rate (normal, fast, etc.) of the charging point each PEV is connected to. In Eq. 15 the energy that can be charged at each time step is limited by the level of energy flexibility the PEV fleet can provide. This energy flexibility, defined by Eq. 16, is determined based on the difference between the maximum energy capacity (determined by the

PEV battery capacity) and the state of charge of all vehicles plugged-in in that area at each time step of the optimisation. Eq. 17 is included in the model to avoid new peaks in the total power load resulting from the optimisation. In this equation $maxStaticP_j$ represents the maximum value of the residential electricity profile for each spatial unit ($staticP_{j,k}$)[3], obtained from the simulation (see 2.1.6).

$$\sum_{k}^{K} evP_{j,k} = totEvE_j \quad \forall j \qquad \text{Eq. 13}$$

$$0 \leq evP_{j,k} \leq maxEvP_{j,k} \quad \forall j,k \qquad \text{Eq. 14}$$

$$0 \leq evP_{j,k} \times \Delta k \leq maxEvE_{j,k} \quad \forall j,k \qquad \text{Eq. 15}$$

$$maxEvE_{j,k} = \sum_{i}^{Npev_k^j} battCap_i - soc_{i,k}^e \quad \forall j,k \qquad \text{Eq. 16}$$

$$\sum_{j}^{N_{su}} evP_{j,k} + staticP_{j,k} \leq \sum_{j}^{N_{su}} maxStaticP_j \quad \forall k \qquad \text{Eq. 17}$$

The right-hand side of the equation Eq. 13 is obtained from the ABM simulation through the following procedure. First, the charging energy of PEVs in public charging stations ($totEvE^{pcs}$) is calculated for those agents running out of battery charge. These charging events are not considered in the optimisation, so they are subtracted from the total energy demand estimated for the rest of the PEV fleet participating in the smart charging scheme ($totEvE^{SCS}$). Then, this total energy demand is disaggregated for each area in the system proportionally to the charging demand

[3] This static electricity demand could include also the additional heat pump demand.

obtained in the plug-and-forget scenario ($evP_{j,k}^{P\&F}$). This way, the right-hand side of the equation Eq. 13 is defined through Eq. 18.

$$totEvE_j = \sum_{0}^{K} evP_{j,k}^{P\&F} \times (totEvE^{scs} - totEvE^{pcs}) \times \Delta k / totEvE^{P\&F} \qquad \text{Eq. 18}$$

Where $totEvE^{P\&F}$ is the total energy demand in the plug-and-forget scenario.

As the constraint shown in the equation Eq. 13 considers the total daily PEV energy demand aggregated for each spatial unit, it can only guarantee the system will provide the total amount of energy consumed during a day in that specific location, but it does not assure every single vehicle will be charged at each time interval with exactly the same amount of energy it consumed before plugging in or the energy it requires for the next trip. In a day simulation like the ones considered in this thesis, this individual constraint simplification might not be critical. However, for longer simulations, it is important to address this aspect as this could eventually create cases where certain drivers will not get enough energy for the next trip. This aspect is discussed in more details in (Vayá and Andersson, 2012) where authors propose a priority based method to allocate individual charge based on the flexibility of each user (based on its energy requirements and the time available to charge).

2.3.Smart heat pump scheduling model

In this work, an optimisation model is implemented to assess different optimal operation strategies for a group of individual domestic heat pumps to reduce user costs, carbon emissions and electricity demand peaks, while keeping the internal temperature of buildings within comfort limits. In the case of costs and emissions, as the price and carbon content of the electricity grid is dependent on the real-time power generation mix, this optimal operational strategy will try to take advantage of periods of cheap electricity and low carbon content. But at the same time, it will have to consider the times in which individual households require space heating. In the academic literature about smart operation of heat pumps (see section 4.1 for the literature review), it has been discussed that the benefits of these optimal strategies are strongly influenced by the level of flexibility that can be provided through thermal storage (passive or active) Therefore, the model presented in this chapter considers the structural thermal storage of the building as part of the energy balance equations.

The final electricity demand is determined by the HP coefficient of performance and by the heating requirements, which in turn, are influenced by the heat losses in the building. These losses are determined not only by the thermal properties of the building but also by the occupancy patterns and set point preferences. In the next sub-sections, a more detailed description of the optimisation model and its formulation is presented.

2.3.1. Single-objective optimisation

In this work, and similarly to the case of the electric transport, the operation of HPs is designed to minimise the electricity costs and emissions associated with the electricity used during this operation. The main control variable is therefore the heat pump electricity consumption ($hpP_{j,k}$) for each building j (or spatial unit[4]) and at each time step k. The next two equations show these two different objective functions.

$$\min(hpCosts) = \min\left(\sum_{k}^{K}\sum_{j}^{N_{su}} priceGrid_k \times hpP_{j,k} \times \Delta k\right) \quad \text{Eq. 19}$$

$$\min(hpCO2) = \min\left(\sum_{k}^{K}\sum_{j}^{N_{su}} co2Grid_k \times hpP_{j,k} \times \Delta k\right) \quad \text{Eq. 20}$$

2.3.2. Multi-objective optimisation

Using the same weighted sum method than for the previous PEV case, Eq. 21 shows the multi-objective function used for HP smart operation, combining operational costs and emissions.

$$\min f\left(hpP_{j,k}\right) = \omega_{cost} \times hpCosts\left(hpP_{j,k}\right) + (1-\omega_{cost}) \times hpCO2\left(hpP_{j,k}\right) \quad \text{Eq. 21}$$

[4] The analyses related with this section are applied to a reduced number of buildings. Therefore, in this section the use of "building" instead of "spatial unit" will be preferred.

2.3.3. Constraints

The main constraints of the optimal HP operation model are summarised with Eq. 22-28.

Eq. 22

$$tempSP_{j,k} - Tin_{j,k} \leq deltaTemp$$

Eq. 23

$$Tin_{j,k+1} = Tin_{j,k} + \frac{Qnet_{j,k}}{TMP_j \cdot RFA_j} \times \Delta k$$

Eq. 24

$$Qnet_{j,k} = Qgain_{j,k} - Qloss_{j,k}^{cond} - Qloss_{j,k}^{conv}$$

Eq. 25

$$Qloss_{j,k}^{cond} = \left(Tin_{j,k} - Text_k\right) \times ESA_j \times U_j$$

Eq. 26

$$Qloss_{j,k}^{conv} = \left(Tin_{j,k} - Text_k\right) \times ACH_j \times BldVol_j \times \rho_{air} \times \frac{c_{air}}{3600}$$

Eq. 27

$$hpP_{j,k} = Qgain_{j,k}/COP_{j,k}$$

Eq. 28

$$hpP_{j,k} \leq hpCap_j$$

The main inequality constraint of this model is the internal temperature constraint. With this, the internal temperature of the building (or spatial unit[5]) is forced to be close to the set point, defined by the energy user. A temperature difference (deltaTemp) is considered to include a level of flexibility in the optimisation. This internal temperature will be determined dynamically by the discrete-time equation Eq. 23. In this equation, TMP_j represents the thermal mass parameter of the building, RFA_j the residential floor area and $Qnet_{j,k}$ the net heat load of building j. The calculation of this net heat load is shown in Eq. 24 and its value will depend on the heat gains

[5] The analyses related with this section are applied to a reduced number of buildings. Therefore, in this section the use of "building" instead of "spatial unit" will be preferred.

($Qgain_{j,k}$), and the building losses. In this work, two main losses are considered in the heat transfer of the building: Conductive ($Qloss_{j,k}^{cond}$) and Convective losses ($Qloss_{j,k}^{conv}$).

In the case of conductive losses, these represent the heat flowing through the envelope of the building. This heat can be lost or gained by conduction through walls, ceiling, windows or floor of the building. In this work, losses related with the thermal bridge effect are not explicitly considered. Eq. 25 shows the calculation of these losses depending on the difference between the external ($Text_k$) and internal[6] ($Tin_{j,k}$) temperatures, the total envelope surface area (ESA_j), and the U-value of the building (U_j). In this work, this last value represents an approximation of the rate of heat that would be transferred through the envelope of the entire building (instead of each individual surface). Although using this simplified approach is equivalent to represent the entire building as a box made of a uniform material, this simplifies the model implementation and the data collection in case a large group of buildings needs to be simulated.

On the other hand, convective losses represent the heat that is lost due to air leakages and ventilation and it is calculated using Eq. 26. As for the conductive losses, these are proportional to the temperature difference between the exterior and the interior of the building. They are also dependant to the air change rate[7] (ACH_j), the total air mass (calculated with the air density (ρ_{air}) and air volume ($BldVol_j$)), and the air heat capacity (c_{air}).

The relationship between the heat gains and the HP electricity demand ($hpP_{j,k}$), is shown in Eq. 27, where $COP_{j,k}$ is the temperature dependent coefficient of performance. Finally, Eq.28 sets the limit of the HP load based on its nominal capacity ($hpCap_j$).

In the case of the heat pumps, the demand flexibility is not easy to define as in the case of electric vehicles (see Eq. 16). In this case, there is no direct way of quantifying how much energy "can be charged" into the buildings. Ultimately, the flexibility is determined by the capacity of the

[6] In this simplified model, the internal temperature represents an equivalent temperature of the whole building, considering the internal air volume and the whole envelope.

[7] For simplicity, this air change rate considers all levels of leakages and ventilations, from small cracks in the walls to large windows and doors openings.

building and the heat pump to shift part of the energy demand to other periods, keeping the internal temperature within the comfort levels. More details of smart control of heat pumps and different ways of characterising their flexibility are given in Section 4.1.

2.4. Dynamic electricity tariffs and carbon content

The dynamic electricity tariffs used for the optimal PEV and HP operation are based on a commercial end user tariff model, developed in (Acha et al., 2016). This model considers all the different components of the commercial bills such as wholesale price, network charges, policy costs, etc. Using this model, half-hourly tariffs can be generated for different regions in UK, depending on the DNO area, and for different seasons and day types (weekend, weekday). In the case of the CO_2 emissions, the carbon content in the electricity is estimated based on the real-time electricity generation mix and the carbon intensity for each generation technology. Websites such as Elexon Portal[8] provides historical data for the electricity market operation in UK (Elexon Portal, 2016), and carbon intensities can be obtained from sources such as (Rogers and Parson, 2016) or (Staffell, 2017).

[8] https://www.elexonportal.co.uk

Chapter 3. Transport electrification

Using the modelling framework presented previously, this chapter presents a case study focused on urban transport electrification. A literature review is first presented to situate this case study in the context of the smart charging research area. Then, the main assumptions and data collection and processing are described. With this, the charging energy demand and flexibility are characterised and used as the main inputs for the analysis of smart charging strategies in a realistic urban area.

3.1. Smart EV charging review

As was introduced in the first chapter of this thesis, the adoption of PEVs can create problems in electrical networks if a large number of vehicles are connected to the grid and charging at the same time. To avoid these problems, different "smart" charging strategies have been proposed in the literature to optimise the charging schedule of a group of PEVs, in order to obtain technical, economical or environmental benefits. These strategies can be formulated for a diverse set of objectives such as the minimisation of charging costs, associated emissions, network losses, or the maximisation of renewable energy integration, grid services provision, etc. In this sense, through smart charging strategies, not only can the impacts be reduced but also the benefits of integrating PEVs can be promoted. For example, the results of Lopes et al. (2011) shows that a large number of PEVs can be integrated without extra investments associated with grid reinforcement when smart charging strategies are implemented. In (Clement-Nyns et al., 2010) it is shown that power losses can be reduced and power quality can be improved with a controlled charging strategy compared to an uncontrolled charging scenario. Bashash et al. (2011) show that reductions of energy costs and battery life degradation can be obtained through optimal charging strategies. Finally, the results presented in (Oliveira et al., 2013) show that overloads in distribution networks can be avoided, minimising power losses, and avoiding higher peak loads.

Regarding the control architecture, two broad groups can be identified in the literature: centralised and decentralised algorithms. Although centralised methods tend to be simpler and give better results, they present some challenges associated with privacy and scalability. Decentralised methods, on the other hand, overcome these challenges with lower communication requirements, but they would require PEVs to have more sophisticated control unit on board (García-Villalobos et al., 2014, Vayá and Andersson, 2012).

In addition to the charging strategy, it is recognised that the benefits and impacts of PEVs are strongly influenced by the user's driving and charging behaviour (Green et al., 2010). However, and probably due to the complexity involved in characterising PEV user behaviour (Azadfar et al., 2015), most of the literature in this area considers great simplifications in this respect (Davies and Kurani, 2013). Fixed periods of charging are generally assumed, and spatial characteristics of charging demand are not considered explicitly. In general, differences in PEV types, charging times and durations, and charging rate levels are disregarded, and only average values are considered. Although the previous assumptions facilitate modelling and analysis, they can lead to unrealistic results. On one hand, assuming a smooth charging of all PEVs during the night can underestimate their real effect, while on the other hand assuming all vehicles will be connected at the same time at home could overestimate the impact on the electricity network. The previous assumptions are expected to become more or less critical depending on the level of the system considered. For example, for studies at a national level, the representation of the heterogeneity of parameters such as the PEV battery capacity, charging rates, etc. could be less critical for transmission planning analysis than for a distribution level analysis where high levels of mobile demand can become comparable to the rest of the system's electricity consumption. Another crucial element in assessing the capacity of PEVs to provide grid services that is generally neglected in the literature is the level of load flexibility PEVs can provide to the system. This flexibility will be influenced not only by technical factors such as charging rate, battery capacity and access to charging infrastructure, but also by behavioural factors such as driving and charging preferences, and users' willingness to participate in flexible charging schemes. The model presented in this work and the case study developed in this chapter are an attempt to include these factors in the analysis, advancing the analysis of transport electrification and its integration in urban energy systems.

3.2. Case study description[9]

The case study presented in this chapter is based on real data of an urban area in London, UK and it is developed with the aim of testing the modelling framework and to explore to which extent it

[9] This section is based on the material published in these two conference proceedings:

can contribute to the analysis of smart charging strategies. Specifically, the case study is designed to:

- Represent the spatial and temporal characteristics of PEV charging demand based on different urban land-use and economic activities.
- Include heterogeneity of PEV technical parameters and charging infrastructure.
- Consider explicitly user charging behaviour in the smart charging analysis.
- Assess trade-offs between different smart charging objectives (technical, economic and environmental).

3.2.1. GIS Model: City layout and socio demographics

As described in section 2.1, the simulation model generates movement and charging patterns for a fleet of PEVs within an urban area. For this, it is important to define the geographical representation of the urban area with its main socio-demographic parameters and the road network for agents to move between locations. Figure 3-1 shows the area considered in central and west London, divided in seven boroughs with a total area covering approximately 176 km^2 and a total population of 1.4 million (Office for National Statistics, 2016). Geographical Information Systems (GIS) data was collected to represent each spatial unit. Data for the road network within this area is extracted from Ordnance Survey (2016), where, for simplification, only main roads are considered.

Bustos-Turu, G., Van Dam, K., Acha, S. & Shah, N. 2014. Estimating Plug-in Electric Vehicle Demand Flexibility through an Agent-Based Simulation Model. *5th IEEE PES Innovative Smart Grid Technologies (ISGT) European 2014 Conference.* Istanbul, Turkey.

Bustos-Turu, G., Van Dam, K., Acha, S. & Shah, N. 2015. Integrated planning of distribution networks: interactions between land use, transport and electric vehicle charging demand. *23rd International Conference and Exhibition on Electricity Distribution (CIRED).* Lyon, France.

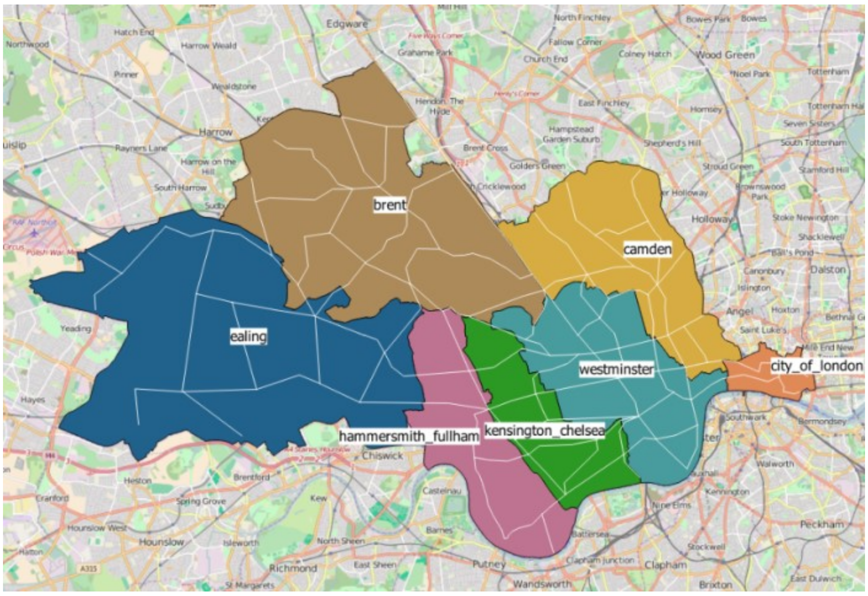

Figure 3-1. Case study in West and Central London, UK.

Each of the boroughs is associated with socio-demographic information (area, economic activity, households, vehicles and land use), extracted from census data (Office for National Statistics, 2016). To simplify the analysis, a set of assumptions are taken regarding this dataset. For the case of the economic activity, the population is classified only into two groups: *workers* and *non-workers*. Based on the categories used in (Office for National Statistics, 2016) the *worker* group is defined as including all the economically active employees and self-employed, while *non-workers* includes economically active unemployed, students and other economically inactive population (e.g. old age pensioners). Figure 3-2 shows the economic activity distribution used in the simulation for each of the different boroughs.

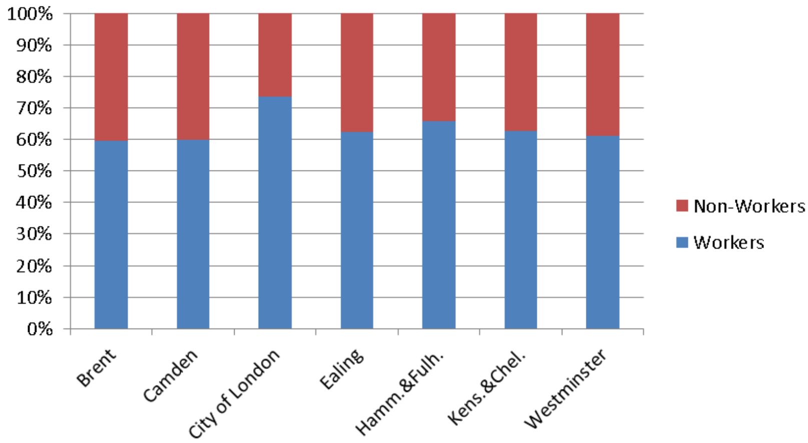

Figure 3-2. Economic activity distribution for each borough (Brent, Camden, City of London, Ealing, Hammersmith & Fulham, Kensington and Chelsea, and Westminster). (Office for National Statistics, 2016)

For the definition of the agent activities, the land use distribution is simplified into four categories, namely residential, retail, commercial and leisure. For each of these types, the floor area is estimated using the data from (Office for National Statistics, 2016) aggregated according to Table 3-1. However, in the case of the residential floor area, this information is not available and therefore it is estimated using the average floor area for all the properties in each borough (Mayor of London, 2015) and the number of households, extracted from census data.

Table 3-1. Land use aggregation.

Land use type	ONS land use
Residential	Residential
Retail	Retail Premises
Commercial	Offices, Commercial Offices, 'Other' Offices, Factories, Warehouses
Leisure	Green space[10], Other Bulk Premises

With these assumptions, the final land use distribution for the different boroughs is shown in Figure 3-3.

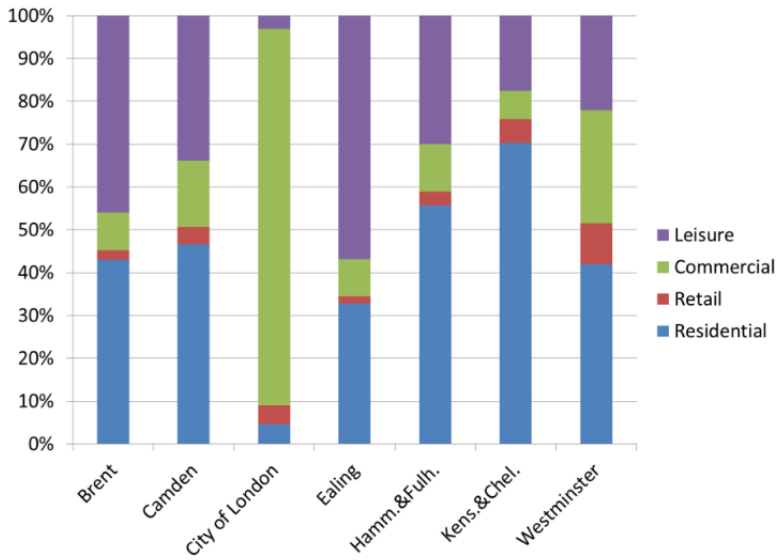

Figure 3-3. Land use distribution for the case study.

[10] For green space, it is assumed floor area is equal to the footprint area.

3.2.2. Model Input: PEV technology

The estimation of the number of electric vehicles in the simulation is based on the level of PEV adoption (which is scenario specific) and the car ownership for each borough (Office for National Statistics, 2016), assuming PEVs will follow the current vehicle ownership distribution. Figure 3-4 shows the proportion of PEV ownership among the different boroughs.

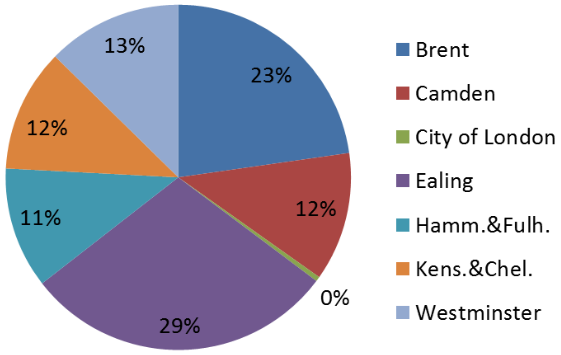

Figure 3-4. Proportion of PEV vehicle ownership. Source: (Office for National Statistics, 2016)

In this work, the total number of PEVs is disaggregated into three different PEV types to account for the heterogeneity in PEV technical parameters such as battery capacity and energy consumption rate. The definition of this PEV fleet is based on the types of vehicles eligible for the Plug-In Car Grant in UK (Office for Low Emission Vehicles, 2016). Although this definition includes plug/in hybrid vehicles, hybrid mode is not explicitly modelled as it is assumed PEV will run only in electricity mode and drivers will try to charge their vehicles once the state of charge (SOC) drops below the minimum value (see section 2.1.3). The parameters used in the simulation model are presented in Table 3-2, following the methodology used in (Bustos-Turu, 2013). The average speed is assumed to be constant and equal to 40 km/h (Pasaoglu et al., 2012). Finally, as this study is focused on the macro-scale charging dynamics of the whole PEV fleet rather than the micro-scale dynamics of an individual vehicle, the round-trip efficiency is assumed to be constant and equal to 90% (considering battery and charger).

Table 3-2. PEV parameters by segment.

Segment	Battery Capacity [kWh]	Energy Consumption [Wh/km]	Electrical Range [km]
A-Mini	15	135	115
B-Small	23	148	155
C-Medium	14	169	83

The PEV market share is estimated using data on the new car registration for the Mini, Small and Medium segments, taken from (Society of Motor Manufacturers and Traders, 2016), shown in Table 3-3. Although these figures correspond to all types of vehicles including internal combustion engines, the market share is assumed to be the same for PEVs.

Table 3-3. Market share for PEV by segment.

Segment	New car registration (2016)	Market share
Mini	70,263	4%
Small	926,241	47%
Medium	964,951	49%

3.2.3. Model input: PEV charging infrastructure

The access to the charging infrastructure at distinct locations (home, commercial, work and leisure areas) is determined based on single probabilities. For the case of residential charging infrastructure, the probability for a PEV owner to have access to a charging unit at home is assumed to be constrained by the availability of a garage or other off-street parking facility where a home charging unit can be installed. According to the English Housing Survey 2010, this availability corresponds to 76% among those people who have one or more cars (Department for Communities and Local Government, 2013). In the case of the charging infrastructure at the workplace and public spaces, and based on the information published in (Mayor of London, 2009) and in (Greater London Authority, 2009), the estimated probability to have access to a charging point is 22.5% at the workplace and 2.5% in public areas such as commercial and leisure areas. More information about this estimation is presented in (Bustos-Turu, 2013).

In this work, it is assumed that all home and workplace charging points are “Normal” chargers (3.6 kW). The “Fast” charging points (7.2 kW) are assumed to be available only in public locations such as commercial and leisure areas. To account for the cases in which the PEV is running out of battery charge, a "Fast" public charging station is considered in each borough, and for simplicity it is located at the centroid of the geographical unit.

3.2.4. Model input: PEV transport and charging behaviour

The activity schedule for each agent is created based on the statistical definition for the population given in section 2.1.2. For this case study, an example of a general weekday schedule is considered depending on the agent's economic activity. The parameters for the population are shown in Table 3-4.

Table 3-4. Activity schedule example for PEV owners by agent type.

Activity Schedule, $AS_i = \{(ACT_j, MDT_j, SD_j, PD_j)\}$	
Worker	**Non-Worker**
(wake-up, 7.0, 1.0, 1.0)	(wake-up, 8.0, 1.0, 1.0)
(work, 8.0, 1.0, 1.0)	(work, 9.0, 1.0, 0.1)
(shopping, 13.0, 0.5, 0.1)	(shopping, 11.0, 0.5, 0.3)
(work, 15.0, 0.5, 1)	(home, 13.0, 0.5, 0.7)
(home, 17.0, 1.0, 0.7)	(work, 14.0, 1.0, 0.1)
(leisure, 18.0, 1.0, 0.3)	(leisure, 17.0, 1.5, 0.5)
(home, 21.0, 1.0, 1.0)	(home, 21.0, 1.5, 1.0)
(sleep, 23.0, 1.0, 1.0)	(sleep, 24.0, 1.0, 1.0)

Finally, the parameters used for the PEV charging model (see Section 2.1.3) are presented in Table 3-5.

Table 3-5. Parameters for charging model

Parameter	**Value**
$SOCmin$	30%
$SOCmax$	80%
$SOCini$ (with charging unit at home)	100%
$SOCini$ (without charging unit at home)	60%

3.2.5. Model input: Residential demand and grid parameters

The parameters used in the residential electricity demand model (see section 2.1.5) are estimated using the weekday average for "Domestic Unrestricted" load profiles from (Elexon, 2015). The values are presented in Table 3-6.

Table 3-6. Residential electricity demand parameters for case study.

Parameter	Value	Units
$BLRED$	0.2	kW
$PLRED$	0.92	kW

Dynamic electricity price and carbon intensity profiles are considered for both the base case ("plug & forget") and the optimisation of the PEV charging process ("smart charging"). For the charging price, two different real-time tariffs are considered and compared. The first one (Tariff 1) is based on the tariff model mentioned in section 2.4. This case assumes PEV users can access a commercial tariff in case they participate in a smart charging scheme operated by an aggregator or supplier. For this, the *Distribution Use of System* (DUoS) charges are estimated based on the data published by the distribution network operator (DNO) in London[11], while the wholesale price is based on the UK power market data published in (Elexon Portal, 2016). The second tariff (Tariff 2) follows the wholesale price dynamics, but the profile is adjusted so the average value is equal to a common residential flat tariff of 15 (p/kWh). In the case of the CO_2 emissions, the carbon factor is estimated based on the electricity generation mix, taken from (Elexon Portal, 2016) and the carbon intensity for each generation technology presented in (Rogers and Parson, 2016). Table 3-7 shows these intensities.

[11] In this case, UK Power Network is London's DNO. More information about DUoS can be found in http://www.ukpowernetworks.co.uk/internet/en/about-us/duos/

Table 3-7. Carbon intensity for electricity generation technologies in UK. Source: (Rogers and Parson, 2016).

Source	**Carbon Intensity gCO_2eq/kWh**
Coal	910
Oil	610
Gas (Open Cycle)	480
Dutch Int.	550
Irish & East-West Int	450
Gas (Closed Cycle)	360
Biomass	300
Other	300
French Int.	90
Hydro, Nuclear, Pumped Storage, Solar, Wind	0

Both the electricity price and carbon intensity are estimated based on the real operation of the UK power market for an average winter (between November and February) and summer (between March and October) weekday for 2015; As these signals directly influence the times when charging events will take place, it is expected that economic and environmental charging strategies will differ according to the correlation between price and carbon signals. In Figure 3-5 and Figure 3-6 these profiles are shown for the different day types. In these graphs, the *r* value is shown to indicate the correlation coefficient between the electricity price and carbon content for both tariffs.

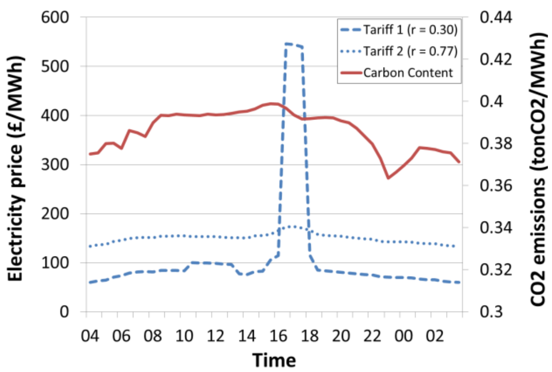

Figure 3-5. Electricity price and carbon content for a winter weekday.

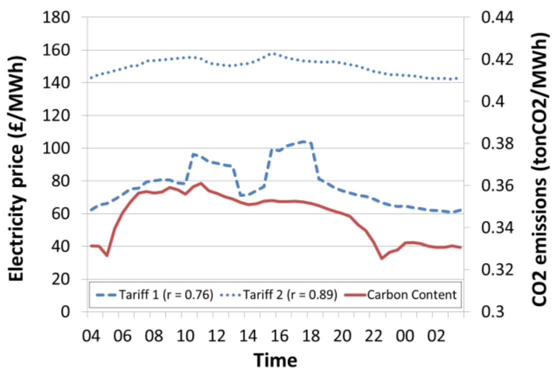

Figure 3-6. Electricity price and carbon content for a summer weekday.

Especially in winter week days, the difference between the two dynamic tariffs is considerable due to the *Transmission Network Use of System* (TNUoS) charges, applied during winter period. More details about how the different components of the electricity tariff were estimated, are presented in (Acha et al., 2016).

3.3. Results

After the definition of the case study, the model is implemented and run for a 24-hour period, starting at 4:00am on a weekday. A snapshot of the simulation is shown in Figure 3-7, where each star denotes an individual PEV with its size and colour representing the SOC (large and red for low, medium size and yellow for medium and small and green for a high SOC). In the next sections, different results are shown to demonstrate the potential of the *SmartCityModel* tool (see Section 2.1) to generate scenarios which can be used in the optimisation model to analyse different smart charging strategies in urban areas.

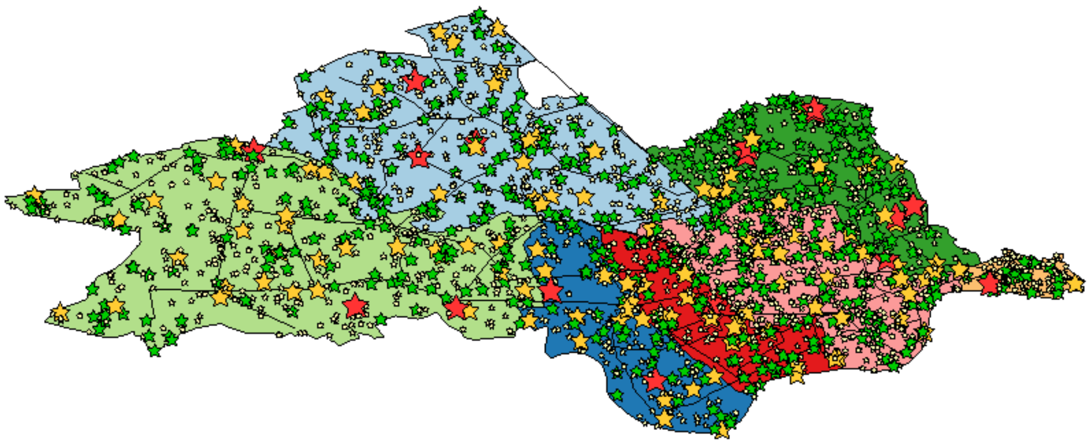

Figure 3-7. Snapshot of the agent-based simulation.

3.3.1. Travel and charging demand

For this part of the analysis, a scenario with 10% PEV adoption is considered, representing a fleet of 38,611 vehicles. The results for the transport demand are characterised by the probability density (Figure 3-8) and the cumulative distribution (Figure 3-9) functions to show the variation in travelled distances for the whole PEV fleet during a day.

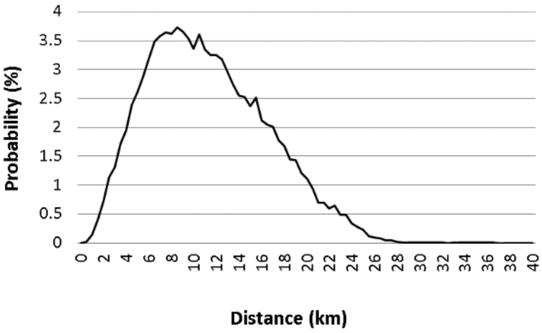

Figure 3-8. Probability density function for daily travelled distance.

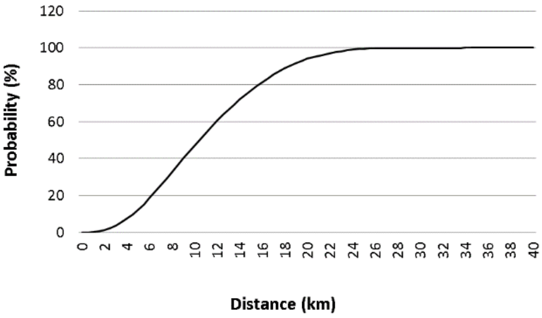

Figure 3-9. Cumulative distribution function for daily travelled distance.

Figure 3-8 and Figure 3-9 present a similar shape to results from trials and surveys found in the literature (Pearre et al., 2011, Lin et al., 2012). However, without data available from London, a more comprehensive validation is hard to perform as the results vary considerable from region to region. Nevertheless, Table 3-8 shows some relevant transport demand indicators that can be compared with statistics for England (NTS) and for London (LTDS), indicating that our simulation results are within the range of realistic values, particularly when assuming that PEVs are bought by people with above average driving distances due to the fuel economy and return on investment of the higher purchase price. As more data becomes available, the model can be updated to reflect this.

Table 3-8. Transport statistics comparison.

Parameter	NTS (all modes)	LTDS (all modes)	Simulation
Trips per vehicle per day	2.52	2.41	2.29
Average distance per trip (km)	11.33	6.02	11.00
Distance travelled per day (km)	28.61	14.50	25.25

In terms of charging behaviour, Figure 3-10 shows the temporal variation in the proportion of the PEV fleet which is parked, plugged-in or charging (i.e. whenever the vehicle is not driving). In the case of parking proportion, the results of the simulation show that on average 97.7% of the fleet is parked at any time of the day. This value is very similar to those found in the literature in which it is suggested that an average vehicle is parked 96.5% of the time (Bates and Leibling, 2012). However, the proportion of plugged and charging vehicles is much lower. According to the simulation results and with limited access to charging infrastructure, 56.2% of the fleet is plugged-in and only 4.9% is charging in average during the day. These results are relevant to assess the level of flexibility that the PEV fleet can offer for charging management strategies that take advantage of the best time in the day to charge the PEVs. In this sense, these strategies will necessarily be constrained by the level of PEVs plugged at different times and locations throughout the urban area.

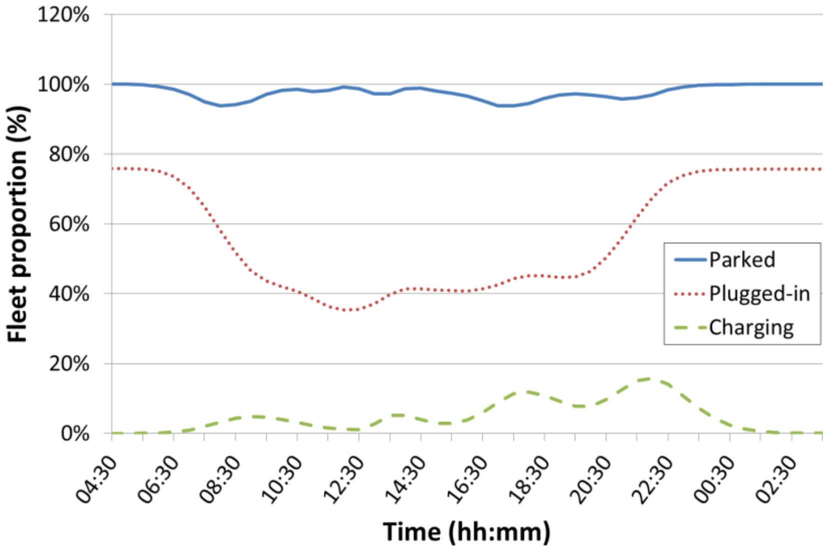

Figure 3-10. Temporal variation in simulated transport and charging behaviour.

Another way of analysing the flexibility related to the charging behaviour is to compare the duration of plugged-in and charging events. For this calculation, two different probability functions are used. For the case of charging events, the *Cumulative Distribution* characterises the probability of an event lasting less than or equal to a certain time. In this analysis, charging events in charging stations (used by agents when PEVs are running out of battery charge before reaching a destination with access to charging infrastructure) are also considered. For the case of plugged-in events, they are characterised by the *Exceedance Distribution*[12] to represent the probability of an event lasting more than or being equal to a certain time. This function is also used to characterise the PEV flexibility defined as the time the vehicle is plugged-in but not actually charging. Using the curves shown in Figure 3-11 user behaviour can be statistically described. For example, it can be shown that most of the charging events (90%) last less than two hours,

[12] Also called *Complementary Cumulative Distribution*.

while most of the plugged-in events (92%) last more than two hours. In terms of flexibility, most of the time (90%) PEVs are plugged-in but not charging for more than 1.5 hours.

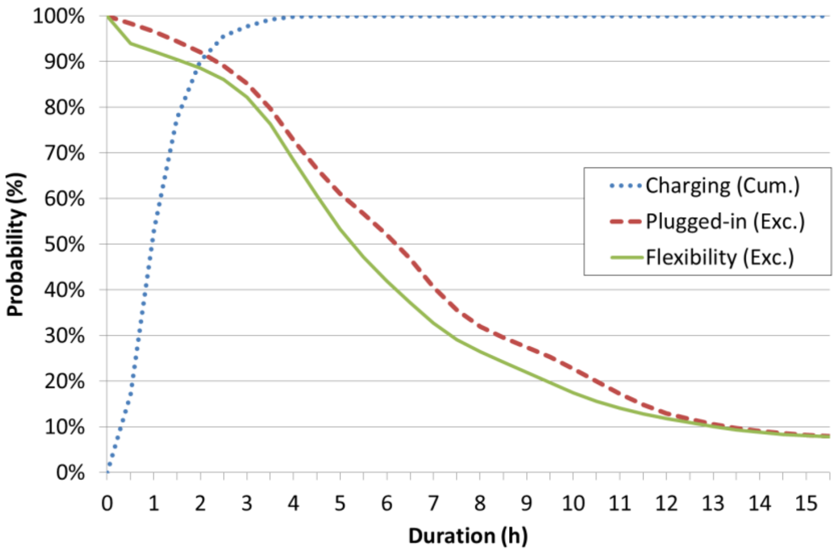

Figure 3-11. Probability distribution functions for charging, plugged-in and flexible durations.

In terms of statistical indicators, Table 3-9 shows a summary for the charging, plugged-in and flexibility durations.

Table 3-9. Charging statistics summary.

Parameter	Charging	Plugged-in	Flexibility
Events per vehicle per day (#)	1.08	1.78	1.78
Average duration per event (h)	1.06	7.52	6.88
Average time per vehicle per day (h)	1.14	13.39	12.24

The previous indicators are important in the assessment of various levels of charging infrastructure, and for exploring how this level affects the level of demand flexibility a PEV fleet can provide to the grid. However, a full assessment is out of the scope of this paper and this charging flexibility is only used as input for the design of different charging strategies.

Finally, the charging of PEVs generates an electricity demand in different zones (boroughs) of the urban area, depending on the agent's activity schedule, travel and charging behaviours, vehicle technology and charging infrastructure access. Figure 3-12 shows the aggregated charging profiles of the whole PEV fleet for the different boroughs considered.

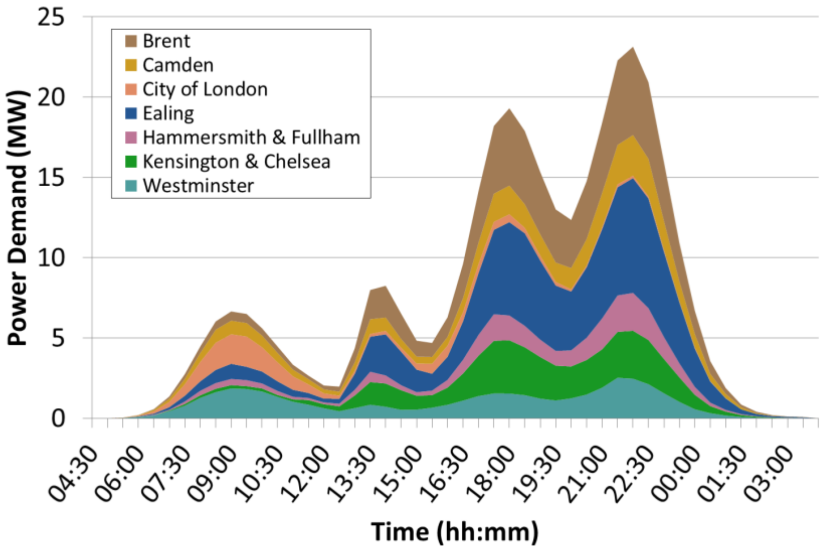

Figure 3-12. PEV charging demand profiles for different boroughs (with 10% PEV adoption).

Results of the simulation show how the charging demand varies temporally and spatially depending on the land use and agents' activity schedules. For example, boroughs with prominent levels of workplace land use (e.g. City of London, Westminster) present an important PEV charging demand during the peak hours in the mornings, associated with agents who connect their PEV at work. A different result is obtained for boroughs with high residential and leisure floorspace (e.g. Ealing, Brent, Kensington and Chelsea) where the charging demand is focused on the evenings when drivers plug in their vehicles when they arrive at home. For the analyses presented in the next sections these results will be referred to as the "plug & forget" scenario, in contrast with the "smart charging" scenario.

3.3.2. Base case (plug and forget) scenario

According to the methodology presented in Section 2.1, the trips made by the agents also generate occupancy patterns that can be translated into energy consumption profiles. In this case, the residential demand is estimated to assess the impact of the different PEV charging management strategies on the base load in each zone. Figure 3-13 shows these residential electricity profiles for each borough[13].

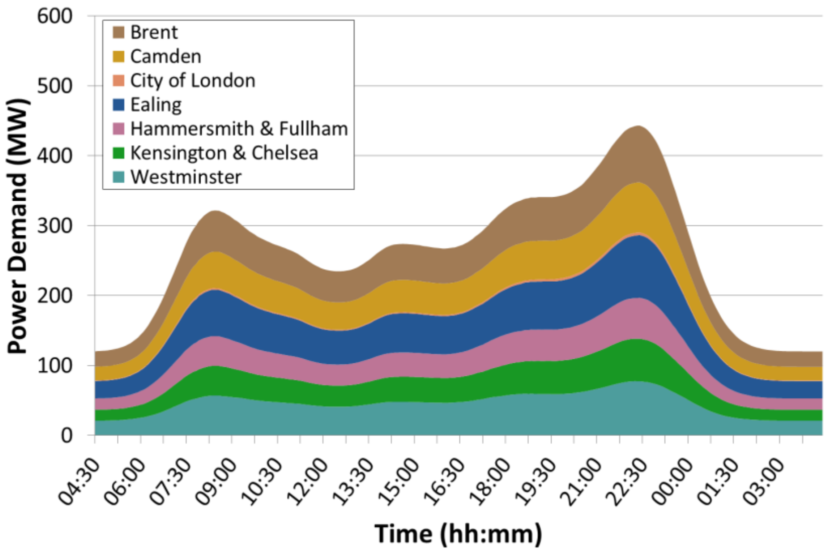

Figure 3-13. Residential electricity demand for the different boroughs.

In Figure 3-14 the plug & forget PEV charging demand is added on top of the residential demand for various levels of PEV adoption (from 10% to 50%). This figure represents the total residential electricity demand of the whole urban area, while similar graphs could also be generated for individual areas to consider local distribution network constraints, for example. In the same figure, the charging price is shown for both tariff types and for both seasons. It can be seen that an important part of the demand falls into the high price period (between 17:00 and 18:30). This is particularly significant in the case of the commercial tariff (Tariff 1) in the winter period. In this case, it is expected smart charging strategies would be more attractive in terms of charging costs reductions.

13 These electricity profiles, together with heat profiles, are compared with real data in next chapter 4

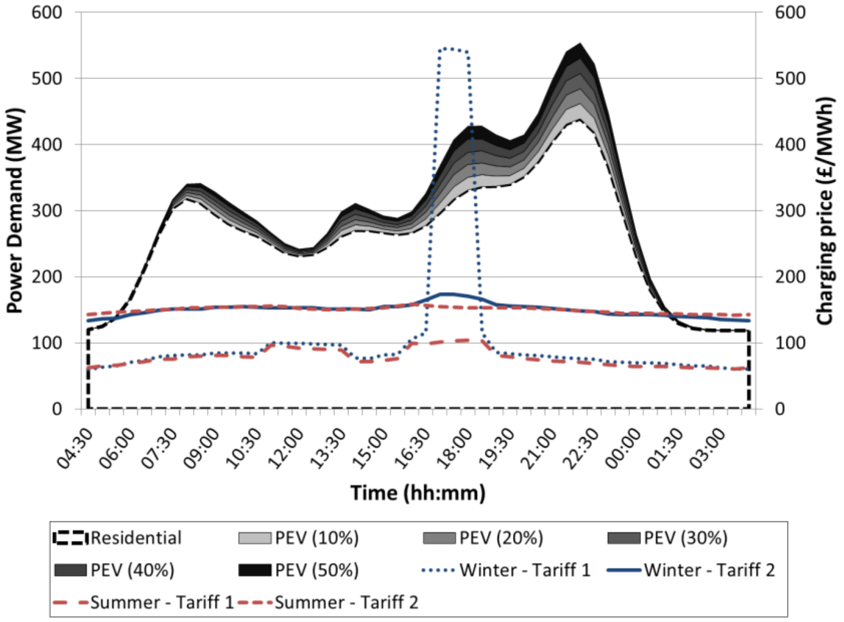

Figure 3-14. Plug & forget scenario for different PEV adoption levels and charging prices

The results show that the additional electricity demand for PEV charging could represent an important proportion of the residential demand, when considering high levels of PEV adoption. For example, for a 10% adoption level the additional demand represents just 2% (on average) of the residential load, with a maximum of 6% at 18:00, but for a 50% adoption, PEV demand represents 11% of residential demand (on average) with a peak of 29%. Table 3-10 summarises the results for the different levels of PEV adoption.

Table 3-10. Percentage of PEV charging over residential demand.

Indicator	Level of PEV adoption				
	10%	20%	30%	40%	50%
Max	6%	12%	17%	23%	29%
Average	2%	5%	7%	9%	11%

3.3.3. Single-objective optimal solutions

In this section, smart charging strategies are introduced to optimise the charging process of the PEV fleet, assuming there is a central operator coordinating the charging at each borough. To define the constraints of the optimisation problem, the simulation is run for the same period but without considering the charging of the PEVs. In this way, the right hand side of maximum charging power and energy flexibility constraints (see Eq. 14 and Eq. 15 in Section 2.2.3) are obtained with the simulation as it keeps track of the number of plugged PEVs and their state of charge in each urban area and at each time step. Figure 3-15 and Figure 3-16 show these two profiles used in the optimisation considering the 50% of PEV adoption case, to represent a situation with significant impact on the residential electricity demand. These parameters as well as the residential energy demand and the price and carbon content of electricity are used as the main inputs for the single objective optimisation.

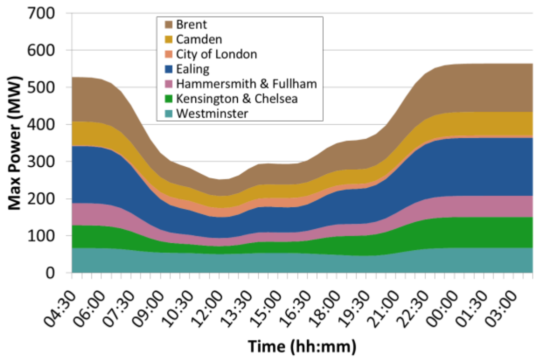

Figure 3-15. Maximum PEV charging power

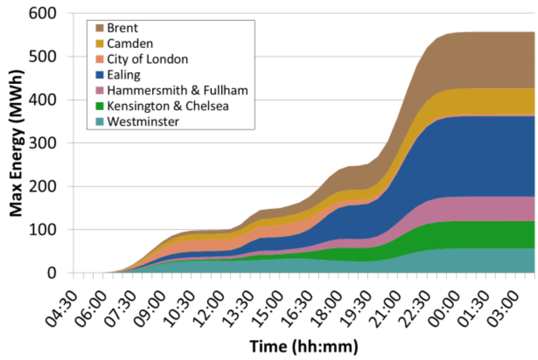

Figure 3-16. Maximum PEV charging energy (energy flexibility)

The results of the single-objective optimisation are shown in Figure 3-17 and Figure 3-18 for a winter weekday simulation. The different smart charging strategies optimise the charging of PEVs for every spatial unit, but the results are shown for the aggregated charging profiles in the whole urban area. In the first case (Figure 3-17), PEVs are mostly charged in the late night (between 2:00 and 04:00) taking advantage of the lower electricity price. Only the charging schedule for Tariff 1 is shown in the figure as the results for Tariff 2 are very similar in terms of charging profiles as they both coincide with the low-price period. In Figure 3-18 the charging profile that minimises the CO_2 emissions related with the grid shows that most of the vehicles would be charged between 23:30 and 01:00, and some of them between 3:30 and 4:00. These periods also represent times when the carbon content of the grid is low compared with the rest of the day. The resulting charging profiles for the summer weekday are not shown as they are very similar to the winter case.

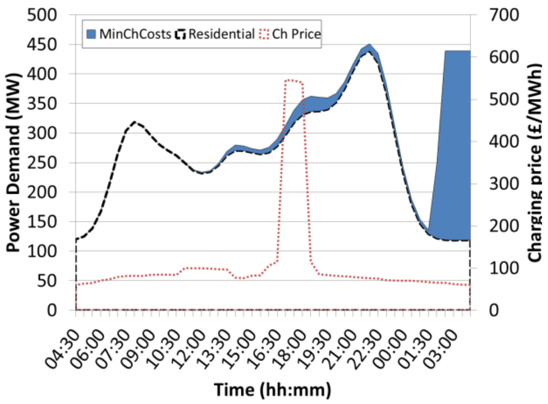

Figure 3-17. Smart charging profile for minimum charging costs (shown only for tariff 1).

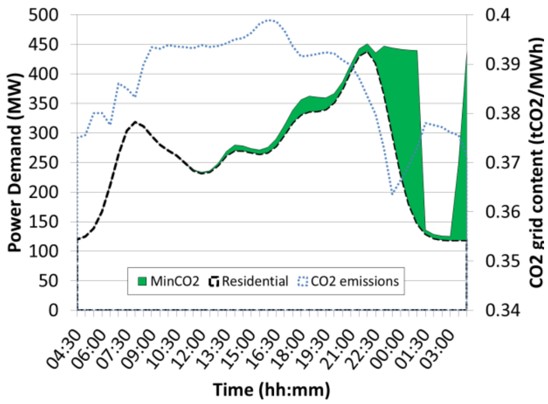

Figure 3-18. Smart charging profile for minimum charging emissions.

In table 3-4 and 3-5, the results for the single-objective smart charging strategies are compared in terms of charging costs and CO_2 emissions per day. For better comparison, the values are shown for a group of thousand vehicles, and the values in brackets show the reduction compared to their respective plug & forget scenario.

Table 3-11. Single-objective results for winter day. Values are shown per thousands of PEVs per day.

Objective	Plug & Forget	Min (PEV ChCosts)	Min (PEV CO_2)
Charging Costs – Tariff 1(£)	684.1	376.2 (45.0%)	391.9 (42.7%)
Charging Costs – Tariff 2(£)	702.5	632.4 (10.0%)	646.6 (8.0%)
CO2 emissions (tonCO_2eq)	1.759	1.710 (2.8%)	1.693 (3.8%)

Table 3-12. Single-objective results for summer day. Values are shown per thousands of PEVs per day.

Objective	Plug & Forget	Min (PEV ChCosts)	Min (PEV CO2)
Charging Costs – Tariff 1(£)	367.8	297.1 (19.2%)	301.3 (18.1%)
Charging Costs – Tariff 2(£)	685.7	652.9 (4.8%)	655.9 (4.3%)
CO2 emissions (tonCO_2eq)	1.569	1.511 (3.7%)	1.508 (3.9%)

The results of the optimisation show that smart charging schemes are more attractive in winter in terms of reductions in charging costs, and the benefits are even higher when considering the commercial tariff (Tariff 1), with reduction reaching up to 45%. This is due to high differences in prices between the peak period (TNUoS triads) and the rest of the day. In the case of carbon emissions, reductions are limited (up to 3.9%) and similar in both seasons, being slightly higher in summer (mainly due to a lower contribution of coal than in winter). In future energy scenarios, with higher participation of renewable energy sources, the carbon content of the electricity is expected to present higher variability throughout the day. In this context, smart charging strategies can exploit this variability and present greater benefits to the user and system.

3.3.4. Multi-objective optimal solution

Finally, in Figure 3-19 and Figure 3-20 the Pareto frontiers are shown for the multi-objective optimisation (MOO) which considers both cost (EV charging cost) and environmental impact (CO_2 emissions), as described in Section 2.2.2. This frontier is generated for the two different UK seasonal pricing and emissions (winter and summer) and for the two different electricity tariffs. For an easier comparison, the values are normalised with respect to the corresponding plug & forget scenario.

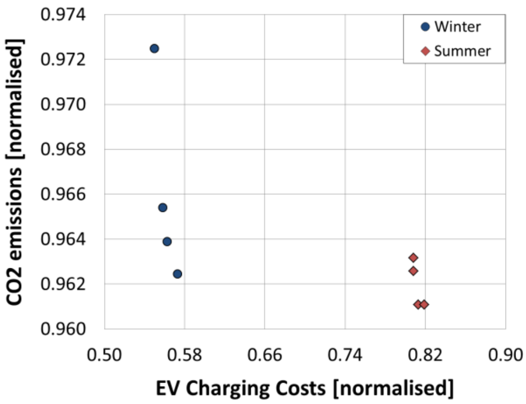

Figure 3-19. Pareto optimal solutions for multi-objective optimisation (Tariff 1).

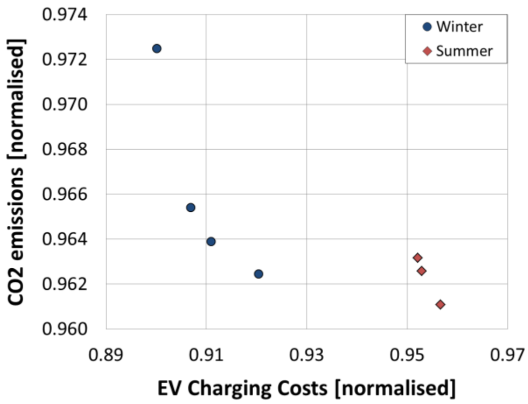

Figure 3-20. Pareto optimal solutions for multi-objective optimisation (Tariff 2).

The results of the MOO show the trade-off between the two different smart charging strategies. Greater reductions on costs can be achieved in winter period, especially when commercial tariffs (Tariff 1) are considered. On the other hand, slightly higher reductions in emissions are obtained during summer. Summer also presents a lower variation between objectives than in the winter period. This can be explained by the higher correlation between the carbon contents and the price of the electricity during summer (see Figure 3-5 and Figure 3-6) and therefore a more similar optimal PEVs charging schedule following the different objectives.

3.4. Conclusions

The case study described in this chapter is implemented to test part of the integrated modelling framework presented in this thesis. Using real data from London, the analysis is focused on the electrification of the residential transport sector and the integration of electric vehicles in urban energy networks through smart charging strategies. With the framework various levels of electric vehicle adoption are simulated to estimate the additional electricity demand and compare it to the baseline load. Then, different smart control strategies are assessed in terms of user costs and carbon emissions, as well as peak demand. For all these analyses, the methodology allows for different spatial and temporal resolutions to be considered.

In the next chapter, a second case study is presented to explore the electrification of the residential heating sector. Analogously to the case of electric vehicles, the integration of heat pumps is analysed through the design of smart operation strategies that minimise possible impacts associated with the introduction of these new low carbon technologies.

Chapter 4. Heat electrification

This chapter is focused on heat electrification analysis, particularly the integration of heat pumps in residential areas using advanced control strategies. First, a literature review is presented to show the state of the art in the modelling and analysis of heat pump integration with a focus on the different modelling approaches to characterise and analyse heat pump and building flexibility, and the different operational strategies used to take advantage of this flexibility. Then, a first case study is presented to analyse the electricity demand of heat pumps in an urban area, using the modelling approach presented in section 2.1. This analysis shows the impact of HP adoption in the overall electricity consumption of residential areas for different seasons. Finally, using the dynamic thermal model presented in section 2.3, the HP-building system flexibility is characterised for different building types comparing different operational strategies. These strategies are also applied to a pool of heat pumps to analyse the aggregated effect of the optimal operation in the overall electricity demand, including peak load reductions.

4.1. Smart control of heat pumps

A key element in the design of smart control strategies for heat pumps is the level of flexibility that the building, heat supply system and users can provide to the overall system. The potential for smart control systems will ultimately depend on the capacity of the system to adapt to the specific conditions in order to improve the overall performance. In the analysed literature, different ways of characterising the flexibility of a building-HP system are discussed. Generally, this flexibility is defined in terms of the amount of energy that can be shifted for some period of time without compromising thermal comfort of residents (Hong et al., 2013, Masy et al., 2015). Also, authors tend to measure the flexibility in terms of the benefits it can provide to the system. In this sense, heat pumps can be operated to achieve different objectives such as the reduction of costs, emissions, or the improvement of system efficiency, renewable energy integration, or grid services provision (Dar et al., 2014, Patteeuw et al., 2016). In this thesis, the flexibility of heat pumps will be characterised following this approach, measuring the benefits in terms of energy, costs, emissions and peak demand reductions. Among the control strategies discussed in the literature, a recently published literature review, done by Fischer and Madani (2017), classified them in two main groups. On one hand, “non-predictive” methods are the most common in current systems as they are simple to implement and avoid the need of predicting external signals related to the conditions of the rest of the energy system and environment. In these cases, rule-based controls or pre-defined schedules can be used to improve the operation of the heating system in terms of the different objectives. On the other hand, "predictive" methods take advantage of predicted information of the system such as electricity price (especially dynamic price tariffs), external temperature, heat demand, etc. to define an optimal heat pump schedule. In all these cases, the degree to which the heat pump operation can be optimised depends on the level of flexibility of the system. This flexibility however is not easy to be characterised as it depends on many factors, including the availability of thermal storage and the services or purposes this flexibility is used for. In the case of thermal storage, this capacity can be provided by either specific hot water tanks or by the building thermal mass (Masy et al., 2015). Although in general, authors agree that extra storage capacity is beneficial to improve the flexibility of the system (Fischer et al., 2017), in some cases the use of the thermal inertia of buildings can be the most cost-effective solution (Hedegaard et al., 2012). In general, the flexibility of the system is characterised using a combination of modelling techniques. The thermal behaviour of buildings is generally simulated using some dynamic building energy simulation tool (such as EnergyPlus, TRANSYS, ESP-r and Modelica), coupled with some ad-hoc optimisation model for temperature control. This similar approach is used in this thesis, where a simplified dynamic model is coupled with a linear optimisation model (see section 2.3).

In (Fischer and Madani, 2017), the authors suggest that some of the most important research topics that should be addressed in future work are the analysis of the potential for a group of heat pumps to provide flexibility to the energy system, and the use of capacity controlled heat pumps (using variable speed compressors) in smart grid applications. These two aspects of smart heat pumps are covered in the analysis presented in this chapter. Both the modelling framework and the case studies have been designed to analyse firstly, the impact of heat pumps in current urban energy systems, and secondly, different smart control strategies in individual as well as in a group of HPs, taking into consideration the diversity in terms of building occupancy and temperature set point adjustments.

4.2. Heat pump demand in urban area[14]

The case study of this section is based on the same urban context presented in 0 including the heat demand calculation described in section 2.1. For this, the residential floor area is estimated based on the total residential footprint area and weighted average building height, extracted from (Digimap, 2015). For the heat loss parameter, the average for the UK (3.2 W/m^2K) was considered (Palmer and Cooper, 2014). Finally, an average temperature profile is used for two days representing different seasons. These are based on hourly data available in (Met Office, 2016) for a weather station located in Heathrow, London for 2014.

To analyse the impact of the additional electricity demand related to heat pumps, a baseline electricity consumption is first estimated. The electricity profile shown in Figure 4-1 is compared with the average profile of a domestic unrestricted customer (profile class 1), based on (Elexon, 2015). Both curves present a similar trend, with two clear peaks in the morning and evening. In the case of the simulation, this evening peak occurs later than in the case of the typical profile. One possible explanation is the linear dependence between this demand and the zone occupancy, neglecting the effect of the shared use of electrical appliances by occupants. In this case, the peak in the electricity demand matches the peak in the zone occupancy, but in some cases, electricity peak demand occurs before the occupancy peaks as some appliances (e.g. lighting), are usually used before all the occupants arrive at the property.

[14] This section is part of the work presented in Bustos-Turu, G., Van Dam, K. H., Acha, S., Markides, C. N. & Shah, N. Simulating residential electricity and heat demand in urban areas using an agent-based modelling approach. IEEE International Energy Conference (ENERGYCON), 2016b.

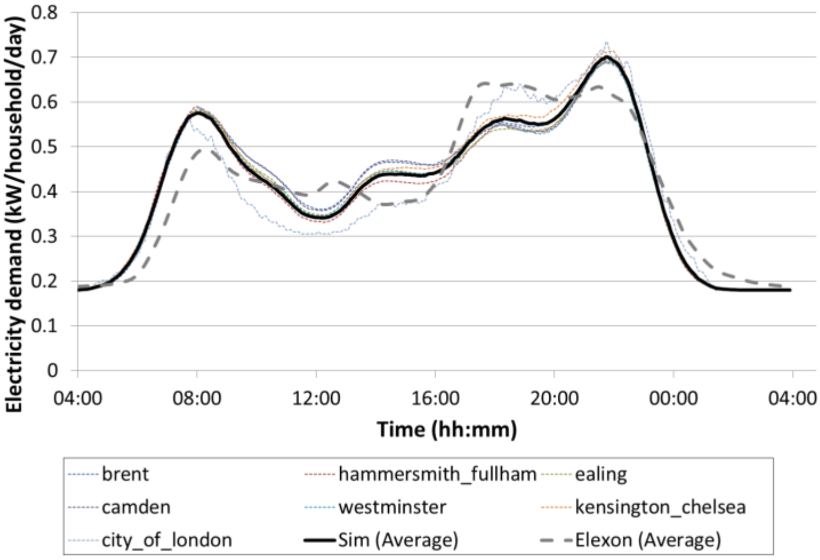

Figure 4-1. Electricity demand profile for baseline scenario. Simulation v/s typical UK profile.

In addition to the daily profile comparison, an aggregated value is calculated for an average consumption per household per day. Figure 4-2 shows the comparison between these aggregates for each borough with their corresponding measured energy demand based on national statistics (Office for National Statistics, 2015). On average, the difference between the simulation and the statistical data is 14.9%, with boroughs with significant difference, such as Ealing (38%), Kensington and Chelsea (25%), and City of London (21%). One element that can be influencing this difference is the base and peak load used to calibrate the curves. In this model, only an average UK value was used and no variation between boroughs was included. If information was available, a more accurate description would be to use borough-specific base and peak load values as input parameters, so a more realistic representation of the level of electrical appliances ownership can be included in the model.

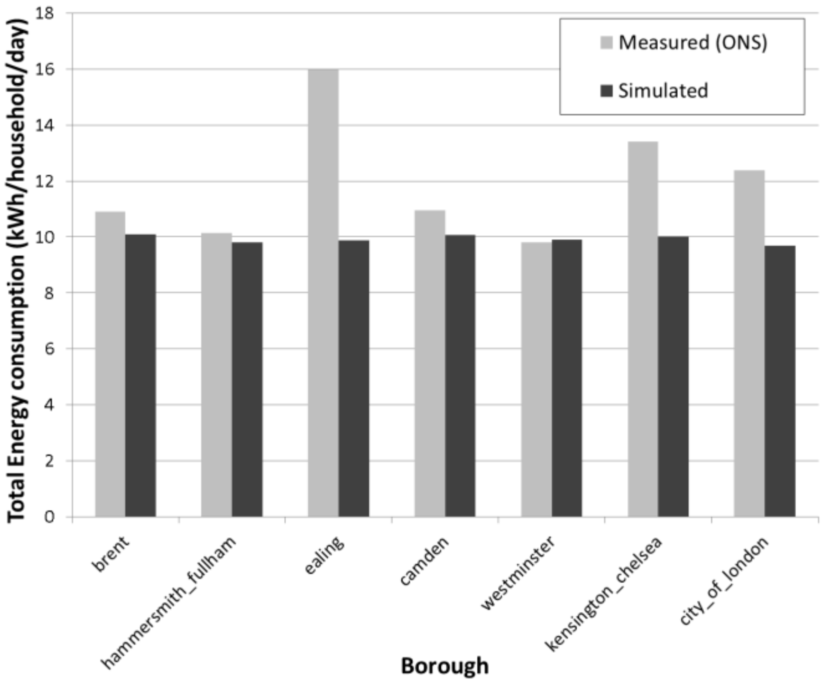

Figure 4-2. Aggregated daily electricity demand for baseline scenario. Simulation v/s ONS data.

In the case of heat demand, and due to the lack of publicly available data for typical daily profiles in UK, it was not possible to compare or calibrate the generated demand profiles with real measurements. Figure 4-3 shows the daily heat demand for each zone, with the average for the whole urban area. It is interesting to note the similitude of this curve with the electricity demand, as the occupancy is one of the main influencing factors. Depending on the specific situation, this assumption may underestimate the real demand as there could be cases where occupants use the heating system without having full occupancy in the property, or even keep the heating system running when nobody is using the property.

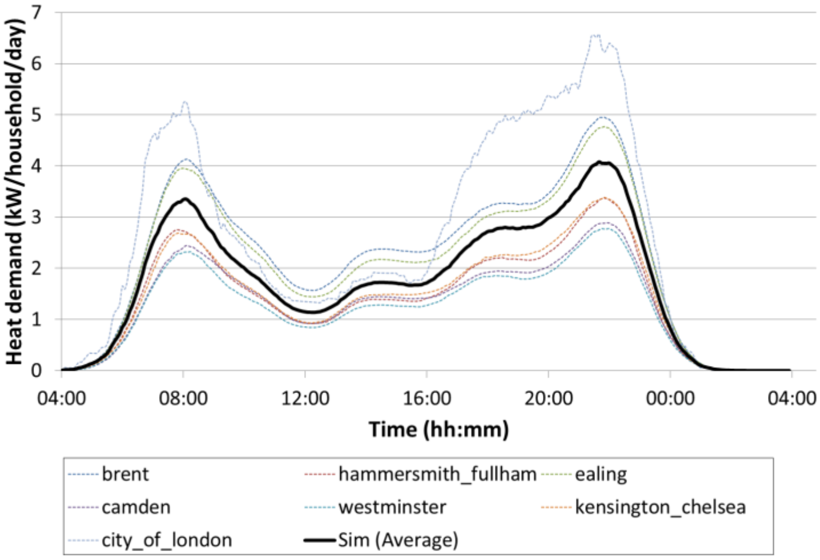

Figure 4-3. Heat demand profile for baseline scenario.

The effect of the outdoor temperature on the heat demand can be seen in Figure 4-4 where heat profiles are compared for two different seasons (summer and winter). It is important to note these temperature profiles represent the three-month averages for each season (winter and summer) and therefore the real level of temperature variability is smoothed.

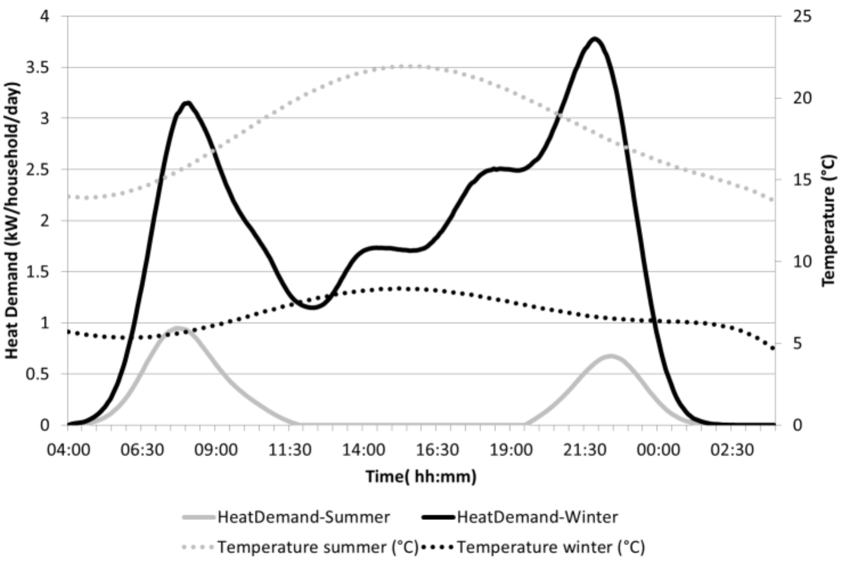

Figure 4-4. Heat demand and outdoor temperature profiles for different seasons.

Analogous to the case of electricity, the heating demand is also aggregated, but in this case, estimated for the entire year to then compare it with statistical data. For this, the real gas consumption, extracted from Office for National Statistics (2015), is converted to heat demand assuming only individual regular gas boilers with an 80.3% efficiency (DECC, 2009). Figure 4-5 shows that in general the heat demand is underestimated in the simulation, with an average difference of 15% with respect to the statistical data. One reason for this difference is that simulations estimate only space heating demand, without considering hot water consumption. Also, the assumption that heat demand is directly influenced by active occupancy can explain in part this difference. This assumption would represent an ideal scenario in which users do not make use of any heating system while they are away from their homes.

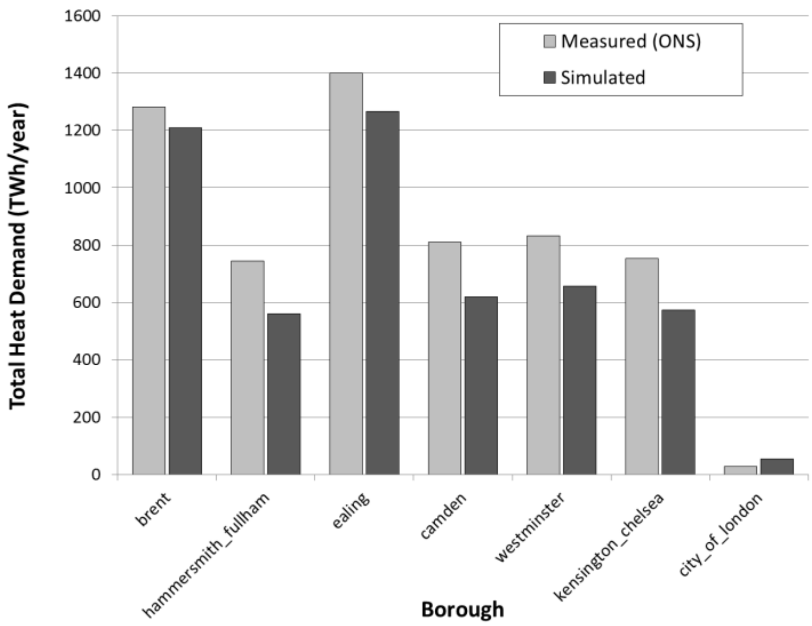

Figure 4-5. Aggregated annual heat demand for baseline scenario. Simulation v/s ONS data.

If part of this heat demand is supplied by heat pumps, it would represent an additional electricity demand. Figure 4-6 shows this extra demand for a 10% adoption of HPs, on top of the baseline electricity consumption for both seasons.

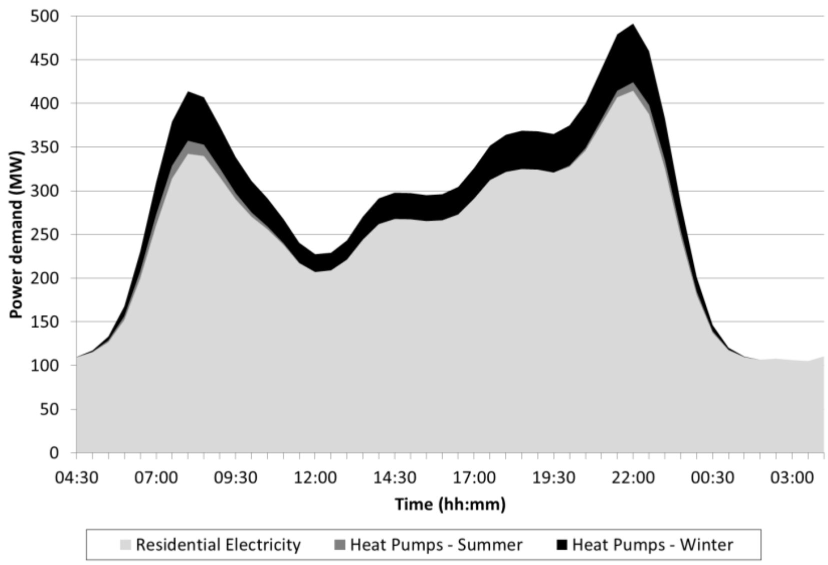

Figure 4-6. Electricity demand profile for a 10% adoption of HPs.

The simulations for different days show that the impacts will have a seasonal dependence, with winter being the most critical period of the year. Although in summer, this demand can represent up to 5%, during winter peak times, the electricity demand of heat pumps can represent up to 17% of the baseline residential electricity demand in period of high demand (morning and evening peaks).

4.3.Smart heat pump analysis

In this section, the analysis is focused on the design of smart energy management strategies for heat pumps using the dynamic thermal model presented in section 2.3. First, the model is applied to a single building to explore the effects of the main parameters on the building thermal behaviour, and then applied to a group of heat pumps to discuss the potential of coordinating a large group of buildings to avoid peaks in the electricity demand.

4.3.1. Single building

For the single building analysis, the parameters are based on typical values found in the literature. Table 4-1 shows the range for each parameter and the average value considered for the base case simulation, with the corresponding references.

Table 4-1. Single-building parameters

Parameter	Symbol	Min	Max	Average	Unit	References
Floor space area	RFA_j	86	270	178	m^2	(Hong et al., 2013, Patteeuw et al., 2016)
Envelope surface area	ESA_j	265[15]	365	315	m^2	(Hong et al., 2013, Reynders et al., 2013)
Air volume	$BldVol_j$	215[16]	451	333	m^3	(Hong et al., 2013, Reynders et al., 2013)
Average U-value	U_j	0.152	0.56	0.356	W/K/ m^2	(Reynders et al., 2013, Masy et al., 2015)
Thermal mass parameter	TMP_j	150	432	291	kJ/K/ m^2	(Reynders et al., 2013, Hedegaard et al., 2012)
Air change rate	ACH_j	0.03	1.5	0.765	1/h	(Hong et al., 2013, Pallonetto et al., 2016)
Heat pump size	$hpCap_j$	6	13.8	9.9	kW	(Hong et al., 2013, Masy et al., 2015)

One of the main influencing factors in the operation of a heat pump is the heating requirement of the users, defined by a set point profile. In a real context, this set point would be influenced by social and economic factors such as age, gender, income, etc. (Wei et al., 2014). However, to simplify the analysis, only two heating periods, between 8:00 and 10:30, and between 18:00 and 00:00 are considered with a set point temperature of 21°C and a setback temperature of 15°C when the property is not occupied. With this, two different control strategies are compared. The first consists of a traditional feedback control in which the heat pump is operated to keep the internal temperature close to the set point, defined by the user. For this, a capacity controlled heat pump with a simple proportional controller is considered (with a gain assumed to be equal to the heat pump capacity but in kW/K). A set point advance is also considered as a variation of this

[15] Estimated assuming a cubic shape flat and a height of 2.5m

[16] Idem.

simple feedback control to account for the time the building takes to warm up[17]. This traditional feedback control is compared with an optimal predictive control strategy, based on the model presented in section 2.3. For this last control strategy, a temperature gap ($deltaTemp$) equal to 0.2 °C is used to make the results comparable, in terms of user comfort, considering the offset of the proportional-only controller. The simulation considers the external temperature profile estimated in section 4.2 for the winter period, and the dependence of the COP on the external temperature is characterised according to Eq. 6, presented in Section 2.1.5. For the dynamic price of the electricity, the tariff 1 (commercial end user tariff) of section 3.2.5 is considered. Simulations are run for one day, starting at 4:00 with an initial temperature of 20 °C.

The first simulations are run to estimate the potential benefits for the user (in terms of electricity costs), for the system (in term of energy demand), and for the environment (in terms of emissions), when the flexibility of the system is used in a smart control scheme. Figure 4-7 and Figure 4-8 show the internal temperature of the building and heat pump power demand when a smart control strategy, in which user costs are minimised, is considered.

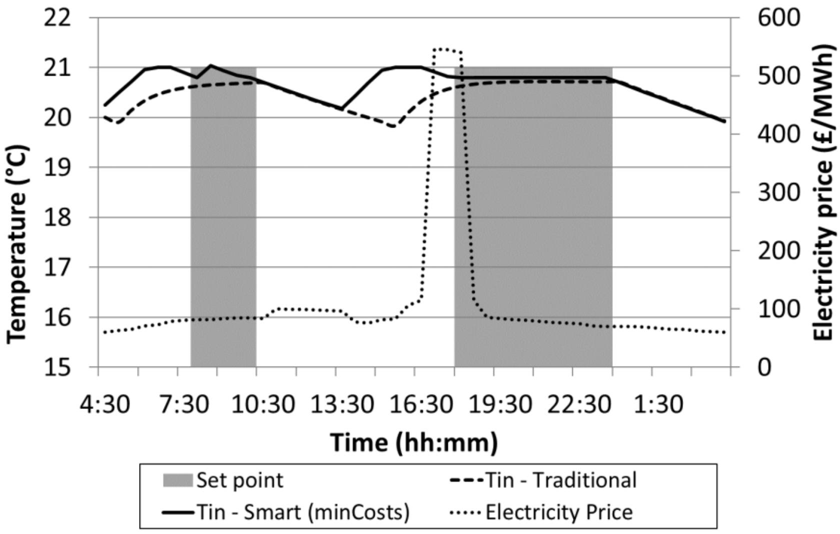

Figure 4-7. Building internal temperature of single-building (min Costs).

[17] This set point advance is set manually for the simulations, to a value of 3 hours in the morning and 2.5 hours in the afternoon heating periods.

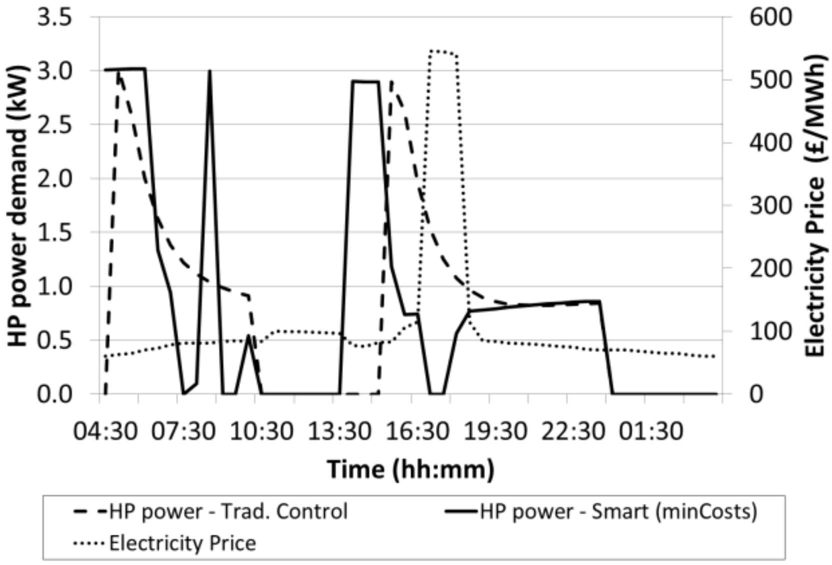

Figure 4-8. HP electricity demand of single-building (min Costs)

The simulation results show the internal temperature remains most of the time in the upper range of the set point temperatures (between 20 and 21°C). Due to the relatively high thermal inertia and slow power output of the heat pump, the internal temperature does not have important variations throughout the day. Comparing both control strategies, the smart control keeps the internal temperature closer to the set point, reducing the total temperature gap (sum over both heating periods) from 5.2°C to 3.0°C. This improvement in the thermal comfort can explain part of the increase in the energy demand. Another source of extra demand is the pre-heating effect. As the control system is minimising the electricity costs, the heat pump is operated before high price periods (see continuous line in Figure 4-8), pre-heating the building to 21 °C (see continuous line in Figure 4-7). During the evening, when the electricity price reaches its highest price, the heat pump stops operating and the temperature of the building drops slightly. Then, after the price goes down, the heat pump continues to operate but at a lower rate just to keep the temperature close to the set point. This control strategy allows a reduction of 31% in the total electricity costs, even with an increase of 9% in the energy demand (see Table 4-2).

In the case of a smart control strategy that minimises carbon emissions, the daily temperature gap is also reduced from 5.2°C to 3.4°C, with an increment on the energy demand of 7%. In this case, pre-heating behaviour is not observed as the variations on the carbon content are not high enough to justify this strategy (see Figure 4-9 and Figure 4-10). Moreover, as the energy demand increases, the total emissions also increase by 7%.

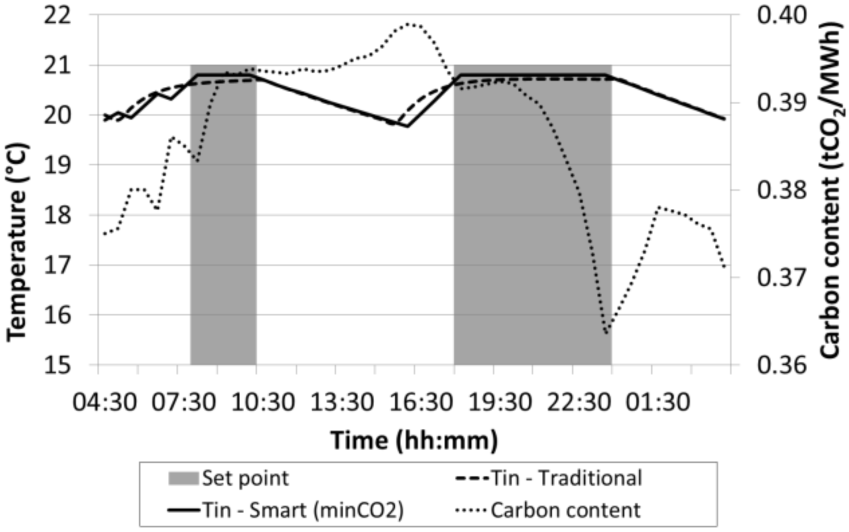

Figure 4-9. Building internal temperature for smart control (min CO_2).

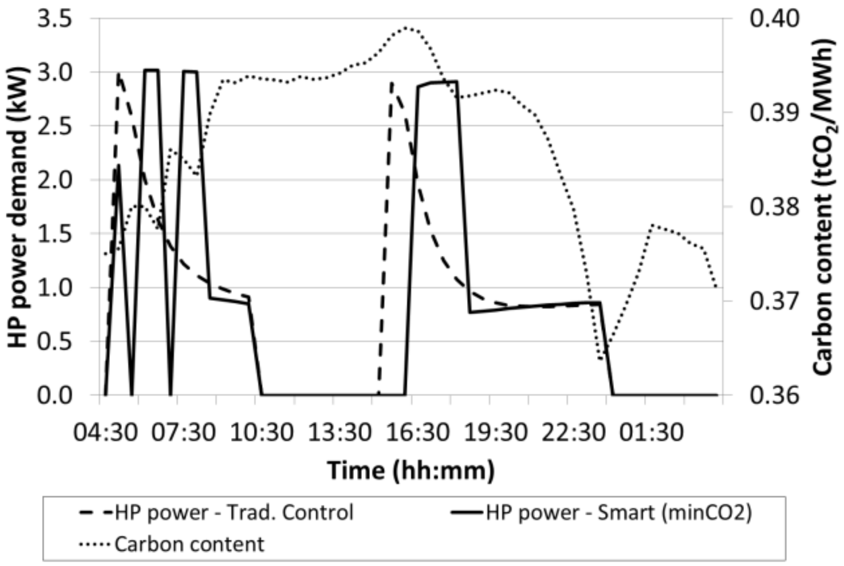

Figure 4-10. HP electricity demand for smart control (min CO_2).

In the previous simulations, only one day (representing average winter temperatures) has been considered. For annual estimations, these daily values are projected proportionally to the ratio between the annual heating degree days (in this case London[18] with HDD = 1609.1), and the daily simulated one (HDD = 8.7). The annual results are shown in Table 4-2.

Table 4-2. Results for the single-building case.

Results / Scenarios	Feedback control	Smart control (minCosts)	Smart control (minCO2)
Total annual electricity consumption (kWh)	3316.23	3601.96	3544.64
Energy reductions (%)		-9%	-7%
Total annual Electricity costs (£)	431.83	298.84	661.57
Costs reductions (%)		31%	-53%
Total annual CO2 emissions (kgCO2)	1286.40	1391.55	1372.11
CO2 reductions (%)		-8%	-7%
Daily temp difference (°C)	5.219	3.029	3.400
Temp gap reductions (%)		42%	35%

Results of the single-building simulation show that smart control systems can improve the thermal comfort of occupants but with an increase in the energy consumption. The temperature gap can be reduced to between 35% and 42% depending on the optimisation criteria (costs v/s emissions), but it is important to notice that this improvement is strongly influenced by the temperature gap defined in the optimisation model ($deltaTemp$ = 0.2). The advantage of this approach is that it is easier for the user to define the comfort level required. In the case of traditional feedback control, comfort level is strongly related with the set point advance (if set manually, in some cases it would not satisfy user comfort level, or it would increase the energy demand unnecessarily). When HPs are operated to reduce user costs, these can be reduced by up to 31%, with an increase in carbon emission of 9% compared to the traditional control. Finally, if the operation is designed to reduce carbon emissions, these can be slightly reduced compared to the minimum cost optimisation case, but they represent a 7% increase compared to the traditional control case, due

[18] Using London Heathrow station data for 2015. Obtained from http://www.degreedays.net.

to more energy being used to improve thermal comfort. In this last case also, the heat pump operates during the very high price period (between 17:00 and 18:30) increasing the final costs for the user by 53% compared to traditional control. This shows that the trade-off between economic and environmental benefits will strongly depend on the correlation between electricity costs and carbon factor of the grid. In this sense, and due to the complexity of the analysis, the results presented here are only relevant in the context of the specific building situated in a specific location and supplied by a particular electricity system. In the next sub sections, different parameters will be varied to analyse the thermal performance for a range of possible buildings and their level of flexibility that can be used in smart control systems.

4.3.1.1. Effect of property size

For this analysis, three parameters associated with the building size (floor area, envelope area and building volume) are simultaneously modified. Also, the size of the heat pump is modified accordingly, following the values shown in Table 4-1. The results of these simulations are shown in Figure 4-11 and Figure 4-12.

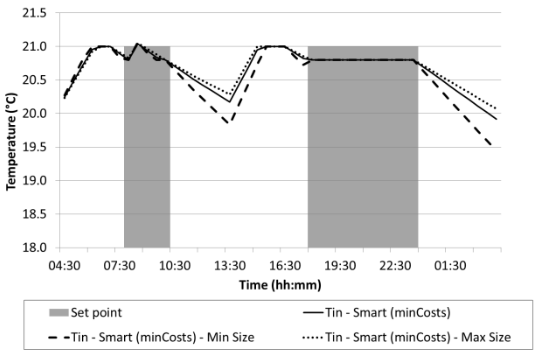

Figure 4-11. Building temperature for smart control (min costs).

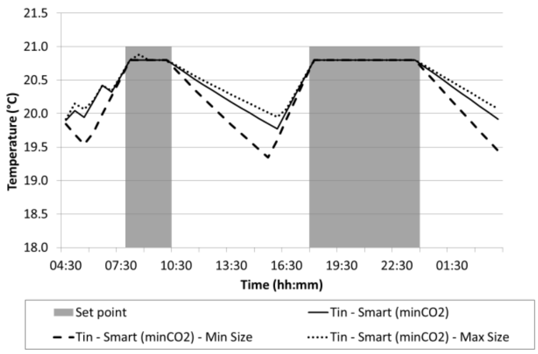

Figure 4-12. Internal temperature for smart control (min CO_2).

As expected, the results show that larger properties will have a smoother temperature curve, mainly due to the increase in the total thermal inertia of the property that, in this case, is proportional to the floor area. Figure 4-11 shows that in all cases, smart control minimises the operating costs, pre-heating the property before the high price period. This pre-heating behaviour is not observed in the carbon emission minimisation case (see Figure 4-12). This can explain the smaller energy demand increase compared to the cost minimisation case, as shown in the estimated annual figures presented in Table 4-3.

Table 4-3. Annual results for different building/HP sizes.

Annual results (HDD aprox.)	Feedback control	Smart control (minCosts)	Smart control (minCO2)
Min size			
Total annual electricity consumption (kWh)	2414.67	2536.19	2479.65
Energy Reductions (%)		-5%	-3%
Total annual electricity costs (£)	333.97	233.88	433.68
Costs Reductions (%)		30%	-30%
Total annual CO2 emissions (kgCO2)	937.42	981.60	963.02
CO2 Reductions (%)		-5%	-3%
Average size			
Total annual electricity consumption (kWh)	3470.62	3601.96	3544.64
Energy Reductions (%)		-4%	-2%
Total annual electricity costs (£)	448.43	298.84	661.57
Costs Reductions (%)		33%	-48%
Total annual CO2 emissions (kgCO2)	1345.90	1391.55	1372.11
CO2 Reductions (%)		-3%	-2%
Max size			
Total annual electricity consumption (kWh)	4526.22	4664.35	4598.69
Energy Reductions (%)		-3%	-2%
Total annual electricity costs (£)	573.07	363.42	888.27
Costs Reductions (%)		37%	-55%
Total annual CO2 emissions (kgCO2)	1754.09	1799.81	1777.64
CO2 Reductions (%)		-3%	-1%

Simulations of different building sizes show that energy demand, costs and emissions increase with larger buildings. When smart control is considered, energy demand also increases due to thermal comfort improvements and this effect becomes slightly more important in smaller buildings. In terms of total costs, however, savings due to smart control system become more important (up to 37%) in larger buildings. Finally, smart control strategies trying to minimise carbon emissions cannot offset the increase in the energy demand, and for small improvements in carbon emissions (compared to cost minimisation strategies), costs can rise by 55% in large buildings.

4.3.1.2. Effect of insulation

Now, the effect of the general insulation of the property on the benefits of smart operation strategies is analysed. For these simulations, the U-value of the property is the only parameter which is varied. The curves shown in Figure 4-13 and Figure 4-14 follow a similar trend to that in the previous case (building size), with a smoother temperature curve for better insulated buildings, and with a pre-heating action for the cost minimisation case.

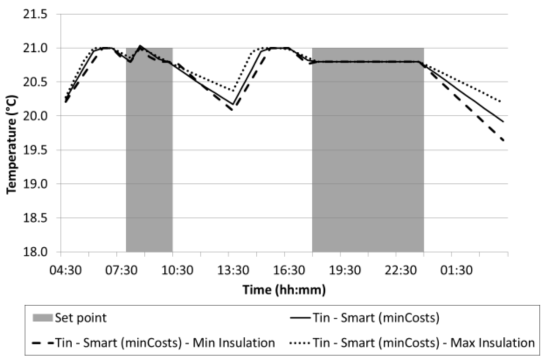

Figure 4-13. Internal temperature for smart HP control (min costs).

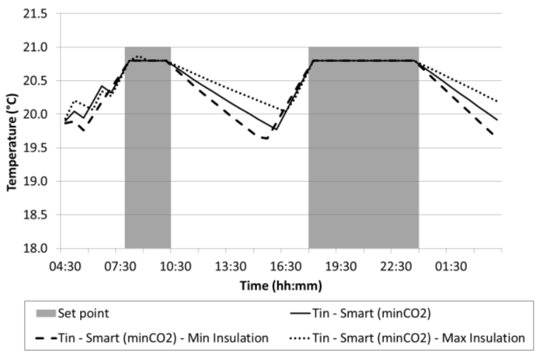

Figure 4-14. Internal temperature for smart HP control (min CO_2).

Analogous to the previous case, Table 4-4 shows the estimated annual figures for the different insulation levels.

Table 4-4. Annual results for different building insulations.

Annual results (HDD aprox.)	**Feedback control**	**Smart control (minCosts)**	**Smart control (minCO2)**
Min Insulation			
Total annual electricity consumption (kWh)	4288.87	4547.48	4462.20
Energy Reductions (%)		-6.0%	-4.0%
Total annual electricity costs (£)	598.58	407.17	743.67
Costs Reductions (%)		32.0%	-24.2%
Total annual CO2 emissions (kgCO2)	1664.70	1759.20	1731.67
CO2 Reductions (%)		-5.7%	-4.0%
Average Insulation			
Total annual electricity consumption (kWh)	3470.62	3601.96	3544.64
Energy Reductions (%)		-3.8%	-2.1%
Total annual electricity costs (£)	448.43	298.84	661.57
Costs Reductions (%)		33.4%	-47.5%
Total annual CO2 emissions (kgCO2)	1345.90	1391.55	1372.11
CO2 Reductions (%)		-3.4%	-1.9%
Max Insulation			
Total annual electricity consumption (kWh)	2631.65	2656.08	2619.19
Energy Reductions (%)		-0.9%	0.5%
Total annual electricity costs (£)	320.71	197.30	545.04
Costs Reductions (%)		38.5%	-69.9%
Total annual CO2 emissions (kgCO2)	1018.57	1023.33	1011.00
CO2 Reductions (%)		-0.5%	0.7%

Results show that dwellings with better insulation can reduce the energy consumption significantly up to 39% (compared to the min insulation case). Simulations also show that smart control can reduce the user costs significantly, by up to 38.5%, and these savings become more important with better insulation, with no significant impact on the emissions level. Finally, in buildings with high levels of insulation, smart control systems can slightly reduce carbon emissions, but most of this reduction is due to the savings in energy demand. Additionally, this small reduction comes with a significant rise of 70% in the electricity costs.

4.3.1.3. Effect of thermal mass

The last parameter to analyse is the thermal mass of the building. In this case, only the thermal mass parameter is varied taking the minimum and the maximum level, according to Table 4-1. Results of the simulations are shown in Figure 4-15 and Figure 4-16.

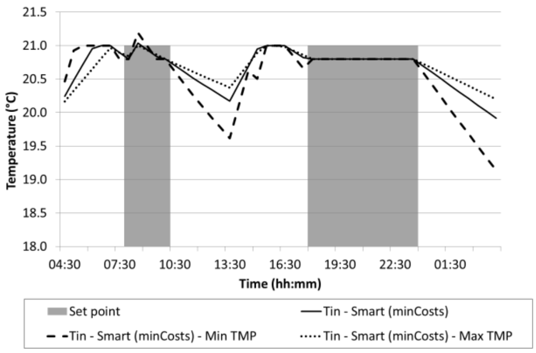

Figure 4-15. Internal temperature for smart control (min costs).

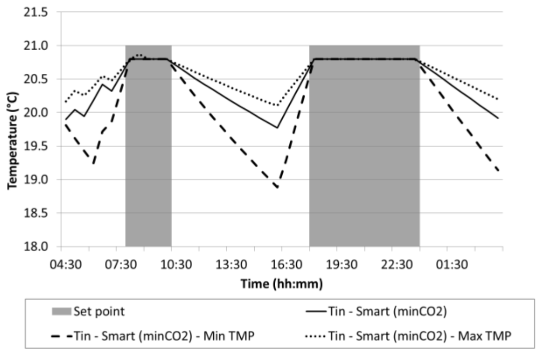

Figure 4-16. Electricity demand for smart control (min CO_2).

Here again, smoother curves are obtained with higher levels of thermal mass. However, in the case of low thermal mass buildings, the variations are the highest compared to the cases in which other parameters were modified. In this last case, smart control pre-heats the building above 21°C in order to reduce costs and keep the internal temperature within the comfort level, considering the faster cooling down rate for a low thermal mass building.

Table 4-5. Annual results for different building thermal mass.

Annual results (HDD aprox.)	Feedback control	Smart control (minCosts)	Smart control (minCO2)
Min TMP			
Total annual electricity consumption (kWh)	3169.35	3275.20	3170.68
Energy Reductions (%)		-3%	0%
Total annual electricity costs (£)	392.93	311.64	635.97
Costs Reductions (%)		21%	-62%
Total annual CO2 emissions (kgCO2)	1230.72	1267.47	1230.96
CO2 Reductions (%)		-3%	0%
Average TMP			
Total annual electricity consumption (kWh)	3470.62	3601.96	3544.64
Energy Reductions (%)		-4%	-2%
Total annual electricity costs (£)	448.43	298.84	661.57
Costs Reductions (%)		33%	-48%
Total annual CO2 emissions (kgCO2)	1345.90	1391.55	1372.11
CO2 Reductions (%)		-3%	-2%
Max TMP			
Total annual electricity consumption (kWh)	3746.94	3916.26	3881.36
Energy Reductions (%)		-5%	-4%
Total annual electricity costs (£)	486.05	297.99	682.12
Costs Reductions (%)		39%	-40%
Total annual CO2 emissions (kgCO2)	1452.11	1511.55	1498.30
CO2 Reductions (%)		-4%	-3%

According to the results shown in Table 4-5, buildings with higher thermal mass would require more energy demand to maintain the temperature, although this increment in the demand is not as important as in the case of the large size or poorly insulated building. In this case, greater benefits in term of electricity costs reductions are obtained with larger thermal mass, reaching up to 39% costs savings. Like previous simulations, carbon emissions can only be slightly reduced compared to the minimum cost operation. This can be explained by the building not being flexible enough to take advantage of the small variation in the carbon factor of the electricity grid, and therefore the extra energy used to pre-heat the building, as in the case of costs reductions, would not offset the reductions in the emissions. In the future, it may be the case that due to the integration of more renewable energy in the power system, there will be greater temporal variations in the carbon content of the electricity grid. In this case, it is reasonable to expect smart control strategies to have a greater impact on emission reductions.

4.3.2. Multiple-building

In this section, the analysis is focused on testing different operational strategies for a group of HPs in multiple buildings. The different heat supply systems are to be coordinated in order to reduce total energy, costs, emissions and peak demand. It is expected that in a real context a group of properties would present a level of diversity in terms of building properties (size, construction type, etc.) and user behaviour. To simplify the analysis presented in this section, diversity is included only in terms of occupancy as this is one of the main parameters that influences HPs scheduling. A diverse set of occupancy profiles, representing individual households, is generated using the agent-based model presented in section 2.1.6. For this, the model is implemented using a representation of an urban area with higher spatial resolution[19] and with a single occupant (one agent) per spatial unit. In this case, one hundred different occupancy profiles are generated and used in the smart control analysis to represent the operation of a pool of one hundred heat pumps. For this group, the baseline electricity demand is calculated using the methodology presented in 2.1.6 and implemented in the case study described in 0. For the multi-building simulation, an initial temperature of 21 °C is assumed to avoid convergence problems (as the simulation starts at 4:00, there would be cases of early occupancy where the heat pump does not have enough capacity to raise the internal temperature to the set point on time).

In order to examine the effect of including diversity on the occupancy profiles, two different simulations are run. The first one (see Figure 4-17) assumes the same occupancy profile for the whole group of buildings, using the profiles used in the single-building simulations. The second

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[19] The model used here is taken from the work developed in an industrial project: http://www.imperial.ac.uk/energy-futures-lab/research/our-projects/edf-flexifund/load-forecasting-of-electricity-and-heat-demands/

simulation (see Figure 4-18) considers the one hundred different occupancy profiles generated with the agent-based model. For both simulations, a traditional feedback control strategy (minimising the difference between internal temperature and set point) is considered.

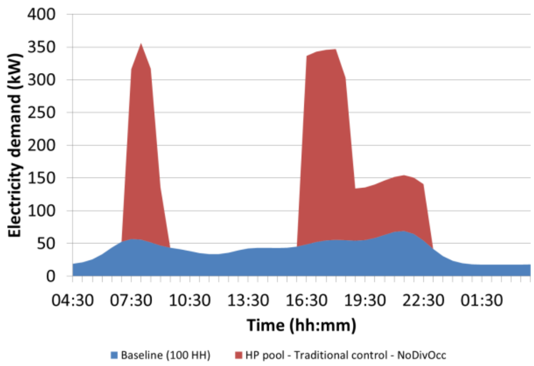


Figure 4-17. Electricity demand without occupancy diversity (traditional control).

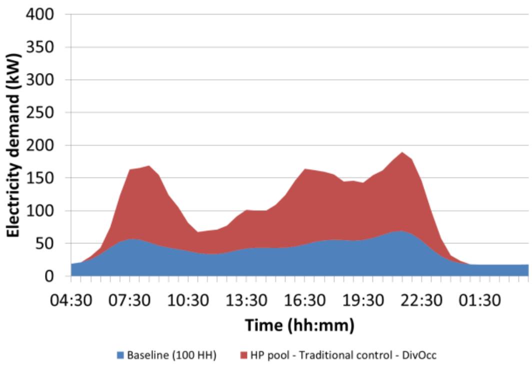


Figure 4-18. Electricity demand with occupancy diversity (traditional control).

These first results show how important it is to consider the diversity in the household occupancy when the aggregated electricity demand is estimated. In the case of using a single occupancy profile, peak demand reaches 356kW, compared to 190 kW when diversity is included. In both cases, this new peak demand significantly exceeds the baseline peak demand (69 kW). This could create problems in the electricity network that would need to be upgraded to cope with this new demand. In this context, smart control strategies can be designed to reduce this potential impact, coordinating the operation of a group of HPs in such a way that the capacity of the electricity network is not exceeded, or the need for upgrade minimised.

Figure 4-19 and Figure 4-20 show the effect of including a general constraint in the optimisation model to limit the overall consumption of HPs. In this case, the maximum overall demand can be reduced up to 126 kW, representing a 66% reduction compared to the uncontrolled scenario. In case occupancy diversity is included, this limit can be further reduced to 121 kW, representing a 36% reduction compared to the traditional feedback control.

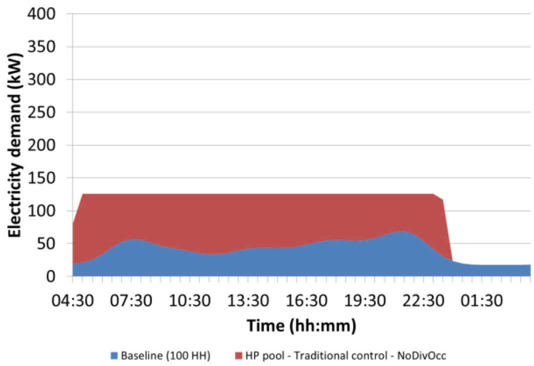


Figure 4-19. Electricity demand without occupancy diversity and cap constraint of 126kW.

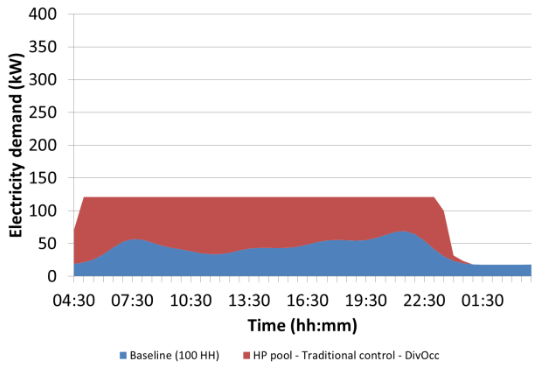


Figure 4-20. Electricity demand with occupancy diversity and cap constraint of 121kW.

Table 4-6 shows the energy, costs and emissions of the previously discussed simulations, considering diversity in the occupancy and including the capacity constraint.

Table 4-6. Results for multi-building simulation

Scenario	w/o occ diversity		w/ occ diversity	
	w/o cap cstr	w/ cap cstr	w/o cap cstr	w/ cap cstr
Energy (kWh/day)	1,494.08	1,531.88	1,394.49	1,432.23
Costs (£/day)	331.69	178.06	191.65	166.31
Emissions (kgCO2/day)	583.98	595.73	544.62	557.02

Based on the simulation results, the inclusion of diversity in the occupancy profiles reduces the energy demand by 7% independent of the limitation in the peak demand. On the other hand, the limitation of the peak demand generates a minor increase in the overall demand of 3% independent of the occupancy.

In terms of costs, when diversity in occupancy is not considered, most of the energy is consumed in periods of high price. Diversity in this case reduces costs by 42% when no capacity constraint is considered, but only by 7% when network limits are included in the optimisation. The overall effect of the network constraint is also to reduce costs due to the shift of some of the consumption to cheaper periods. When no diversity is considered, costs are reduced by 46% and when diversity is included, this reduction reaches 13%.

Results also show that diversity in the occupancy is related to a reduction in the carbon emissions, but it is not clear if this reduction is due to the overall decrease in the energy demand or to the shift of some of the demand to periods with lower carbon emissions. On the other hand, the limitation of the peak demand increases the emissions by 2% independent of the occupancy. The cause of this is again not clear, as it can be either an increase in the overall demand or heat pumps operating during periods with higher grid carbon content.

Previous results show that by including a limitation on the peak load, the system can run and keep the comfort levels within the user limits, even in the case where no diversity is considered in the occupancy profiles. However, looking at the individual operation of HPs, this reduction in the overall peak is achieved through the quick alternation in the operation of heat pumps. The examples of HP operation shown in Figure 4-21 and Figure 4-22 indicate that HPs are operated in a schedule with frequent starts and stops, with the shortest cycle equal to one time step (30 minutes). This short run time appears to be consistent with common practice. However, if the analysis needs the time step to be modified, it is important to consider HP operational constraints to avoid short cycle problems.

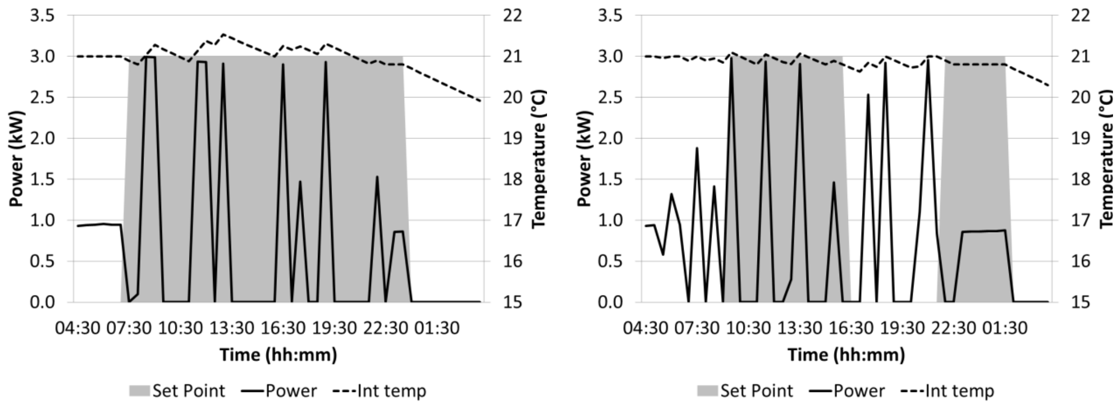


Figure 4-21. Examples of power demand for individual heat pumps participating in the coordinated operation.

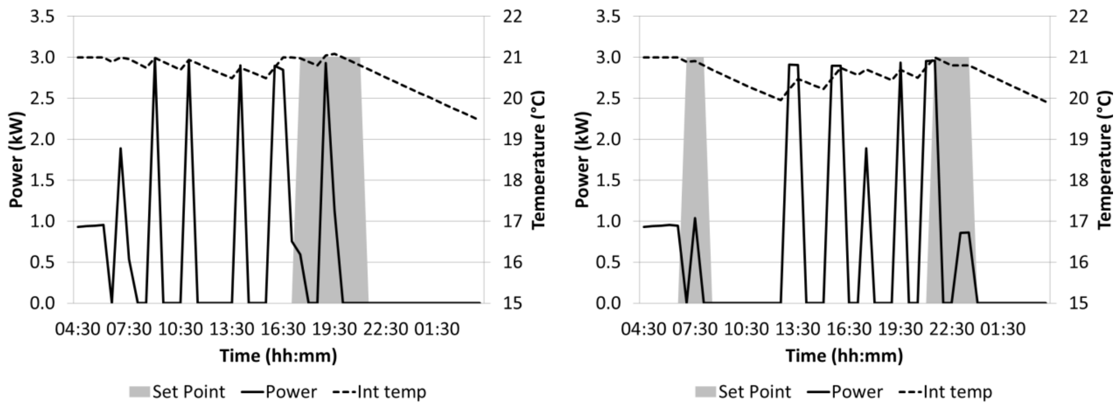


Figure 4-22. Examples of power demand for individual heat pumps participating in the coordinated operation.

Also, from Figure 4-21 and Figure 4-22, it can be seen the control strategy tends to keep the internal temperatures close to the set point level, even in periods without active occupancy. This behaviour would avoid the need for high levels of heat supply before the occupancy periods. This gives more flexibility to the overall operation, but it could increase the energy consumption (and therefore costs and emissions) of individual households, especially in those with short heating periods.

Now, the two different operation strategies (minimum costs, and minimum emissions) will be compared with the traditional feedback control. Simulation results for the minimum cost scenario are shown in Figure 4-23 and Figure 4-24.

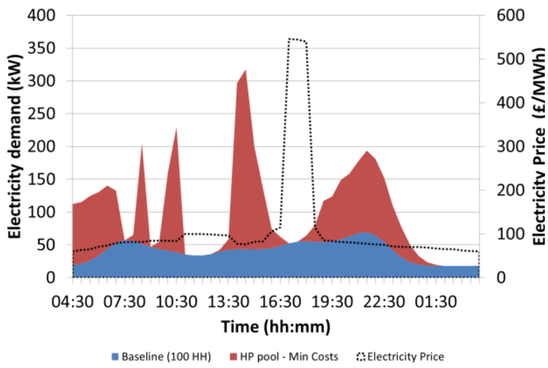


Figure 4-23. Multi-building cost minimisation, without capacity constraint.

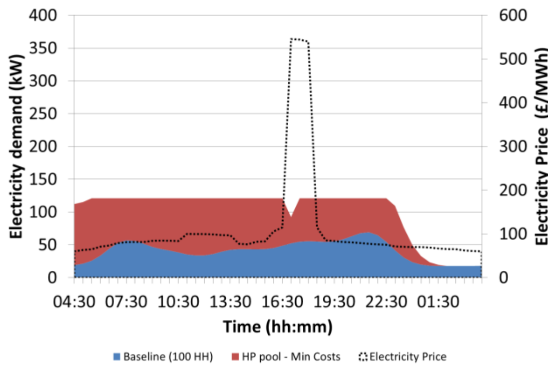


Figure 4-24. Multi-building cost minimisation, with capacity constraint.

Figure 4-23 shows the total electricity demand (HP + baseline) when cost minimisation is performed by individual households, without any limitation on the total demand. In this case, new peaks appear at times of cheap electricity. Figure 4-24 shows the effect of including a capacity constraint to limit the total electricity demand. In this case, the peak can be reduced by 62% (from 318 kW to 121 kW), smoothing the overall demand curve. However, this reduction comes with a cost increase of 42% due to some of the HPs being operated during the high price period. In the case of carbon emission minimisation, simulation results are shown in Figure 4-25 and Figure 4-26.

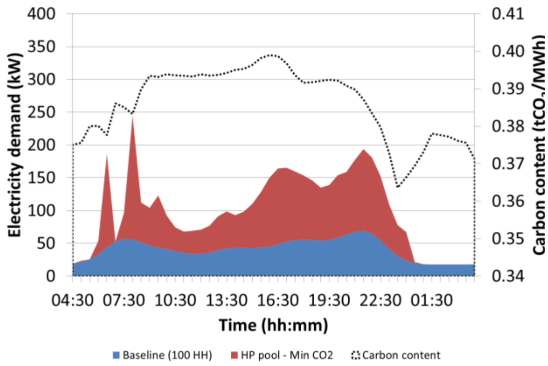


Figure 4-25. Multi-building CO2 minimisation, without capacity constraint.

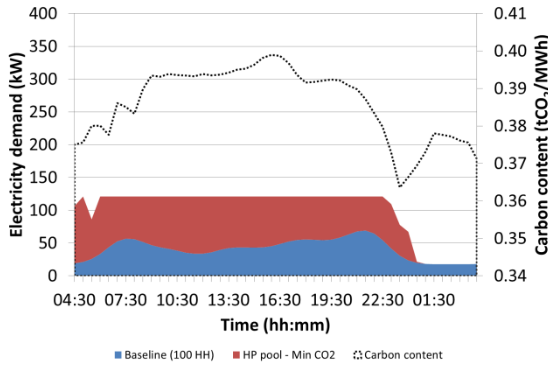


Figure 4-26. Multi-building CO2 minimisation, with capacity constraint.

Similar to the previous cost minimisation case, new peaks appear at times of low carbon emissions factor (see Figure 4-25). Figure 4-26 shows the effect of including a capacity constraint to limit the total electricity demand. In this case, the peak is reduced by 51% (from 245 kW to 121 kW), smoothing the overall demand curve. In this case, this reduction comes with a small carbon penalty of 3% increase.

Table 4-7 summarises the results of the simulations for the different control strategies for the multi-building case.

Table 4-7. Summary for different control strategies for multi-building scenarios.

Control strategy	Capacity Constraint	Energy (kWh/day)	Costs (£/day)	Emissions (kgCO2/day)
Feedback control (min temp gap)	w/o cap cstr	1,394.49	191.65	544.62
	w/ cap cstr	1,432.23	166.31	557.02
Min Costs	w/o cap cstr	1,419.27	112.52	550.97
	w/ cap cstr	1,435.31	159.51	557.89
Min CO2	w/o cap cstr	1,388.48	190.64	540.69
	w/ cap cstr	1,432.28	166.21	556.93

The previous table shows that when smart control is applied to a group of heat pumps, costs and emissions can be reduced, even when a strong capacity constraint is applied. For cost minimisation, these are reduced by 41% despite an increase in the overall energy demand by 2%. In the case of carbon minimisation, the reduction is very limited (0.7%). In these two scenarios, the introduction of the capacity constraint limits significantly the reduction of costs (only 4%)

and emissions (0.02%). In this sense, the capacity constraint makes the system less flexible to take advantage of low price and low carbon periods.

When both smart control strategies are compared, trade-offs between costs and emissions can be evaluated. In this case, smart control that minimises costs results in a 41% cheaper solution but with 2% more emissions than a smart control that minimises carbon emissions. Another way to compare results would be to say low carbon smart control can operate a group of HPs in which emissions are 2% lower but 69% more expensive than a low cost smart control system.

4.4.Conclusions

The case studies and analyses carried out in this chapter show the applicability and flexibility of the modelling framework proposed in this thesis. With the combination of modelling tools, various aspects of heat pump integration and smart control analysis are performed, considering different spatial and temporal resolutions. First, using a static approach, the impact of various levels of HP adoption can be analysed for large urban areas. Then, based on a simplified dynamic model for the building thermal behaviour, different smart control strategies can be assessed for individual as well as for a group of HPs, including diversity in buildings occupancy. In the case of smart operation, simulation results show there is an important potential for cost reductions, but limited reduction of CO2 due to low variability in carbon factor in the current electricity grid. These results are similar to the ones found in the previous case study focused on transport electrification as both consider the same price and carbon profiles for the grid. Further research, therefore, is expected in exploring the attractiveness of smart energy management strategies within low carbon scenarios in which higher levels of renewable energy sources are incorporated in the generation mix. Although the higher variability in the carbon content and prices could be exploited by means of smart control strategies, average carbon and price values could decrease, risking the overall attractiveness of smart control systems.

Chapter 5. Further applications: Life-cycle assessment and community energy planning

This chapter explores some further applications of the modelling framework proposed in this thesis. The different examples presented here show how the framework can be integrated as part of a more general methodology aimed at analysing distinct aspects of urban energy systems. These applications were developed in a collaborative and explorative way with other researchers at Imperial College London and therefore they are presented more as a proof of concept, with some preliminary results, rather than as a comprehensive set of analyses. Nevertheless, due to the relevance of the topics and the applicability of the modelling framework, they represent the first steps of potential future research areas.

The first example demonstrates the integration of life cycle assessment indicators in the design of smart charging mechanisms for electric vehicles. In this way, different charging options can be assessed environmentally from a life cycle perspective, considering emissions embedded in the various stages of the electricity cycle, from the extraction of the fuel to the distribution of the electricity to final consumers. The second application is related with the design and planning of community energy schemes. In the two case studies presented, the modelling framework is used to estimate energy demand profiles that can then be used to inform the design of the energy infrastructure. In the first case, electricity and heat demand profiles are estimated for an urban area located in East London to evaluate changes in the occupants heating requirements. In the second case study, the modelling framework is used to estimate the energy requirements of a fleet of electric vehicles that could be recharged using the electricity from a community energy scheme, located in Central London.

5.1.Life cycle assessment of EV smart charging[20]

As was mentioned in section 1.2, transport electrification is one of the viable solutions for the decarbonisation of light-duty transport. However, the environmental evaluation of plug-in electric

[20] This section is based on the work published by Bustos-Turu, G., Guo, M., Van Dam, K., Acha, S. & Shah, N. Incorporating life cycle assessment indicators into optimal electric vehicle charging strategies: An integrated

vehicles (PEVs) presents challenges as the precise footprint depends on complex factors such as driving and charging behaviour, the source of the electricity used to recharge PEVs batteries, etc. (Faria et al., 2013). In this research, the integrated modelling approach presented in 0 is combined with an electricity life-cycle assessment to evaluate the environmental impact of different PEV charging strategies. This integrated approach is tested based on the case study presented in 0.

5.1.1. Environmental impacts of electrical vehicles

Road transport represents one of the main sources of environmental impact in our current economy by releasing green-house gases (GHG) as well as pollutants that affect local air quality. These concerns as well as economic ones have triggered ambitious national/regional policies to decarbonise the European transport sector and reduce oil dependency (European Comission, 2011). The adoption of low carbon technologies such as plug-in electric vehicles (PEVs) have been projected as a favourable option to reduce environmental impacts compared to traditional internal combustion-engine vehicles (ICVs) (Thiel et al., 2010). Without considering non-exhaust particles[21], PEVs do not directly produce any tailpipe pollutants or GHG emissions during the vehicle operation. However, the electricity needed to supply the PEV energy demand may cause considerably higher emissions if the generation mix, at the time of recharging, is highly carbon intensive (Thiel et al., 2010). According to Hacker et al. (2009), the use of PEVs results in a small or even no reduction of emissions relative to ICVs when electricity is produced by coal-fired power plants. There are even some analyses showing that in some particular cases, ICVs would emit lower GHG emissions compared to PEVs (Hawkins et al., 2013). However, Richardson (2013) concludes that in general the use of PEVs reduces total CO_2 emissions even in electricity networks with high presence of power plants based on fossil fuel, due to the high efficiency of an electric motor compared with an internal combustion engine. These apparently conflicting points of view indicate the need for a more complete account of impacts throughout the vehicle's life cycle, especially focused on the operational phase. The energy supplied in this phase has an embedded environmental footprint depending on the generation mix that will be different

modelling approach. 26th European Symposium on Computer Aided Process Engineering: Part A and B, 2016a. Elsevier, 241-246.

[21] For a discussion about non-exhaust PM emissions from electric vehicles, see Timmers, V. R. & Achten, P. A. 2016. Non-exhaust PM emissions from electric vehicles. *Atmospheric Environment,* 134**,** 10-17.

depending on the time of the PEV recharging. This time in turn, depends on complex factors such as user's driving and charging behaviour as well as charging infrastructure availability. While the effects of different charging strategies have been widely researched, the majority of studies adopt simplified assumptions related to user's preferences (Davies and Kurani, 2013). Also, these works have generally tended to focus on strategies to minimise technical and economic impacts of PEV charging process with less attention on the social and environmental aspects (García-Villalobos et al., 2014). In 0, it was shown that the proposed modelling framework can be used to assess and minimise the CO_2 emissions related to PEV charging. In this section, this framework is extended, linking it with a life-cycle assessment tool to assess the environmental impacts of the operation of PEVs, comparing them with other stages of the life cycle such as their manufacturing, and to evaluate the effect of considering smart PEV charging strategies in the overall environmental impact.

5.1.2. Integrated methodology

The methodology proposed for the environmental design of PEV smart charging is shown in Figure 5-1. Here, the life-cycle assessment (LCA) tool is linked with the agent-based simulation (ABS) and the multi-objective optimisation (MOO) models (both described in 0 of this thesis). Within this integrated methodology, the residential electricity demand and PEVs charging requirements are simulated using the ABS. These results are then included in the MOO as optimisation constraints (as explained in section 2.2.3) and fed into the LCA for environmental evaluation. The LCA also generates environmental impact intensities associated with the electricity from the grid. These are used as main inputs for the MOO model where different charging strategies are designed to minimise charging costs and environmental impacts such as climate change and particulate matter formation (PMF). These optimal charging strategies are finally fed back to the LCA model to be assessed and compared with the baseline scenario.

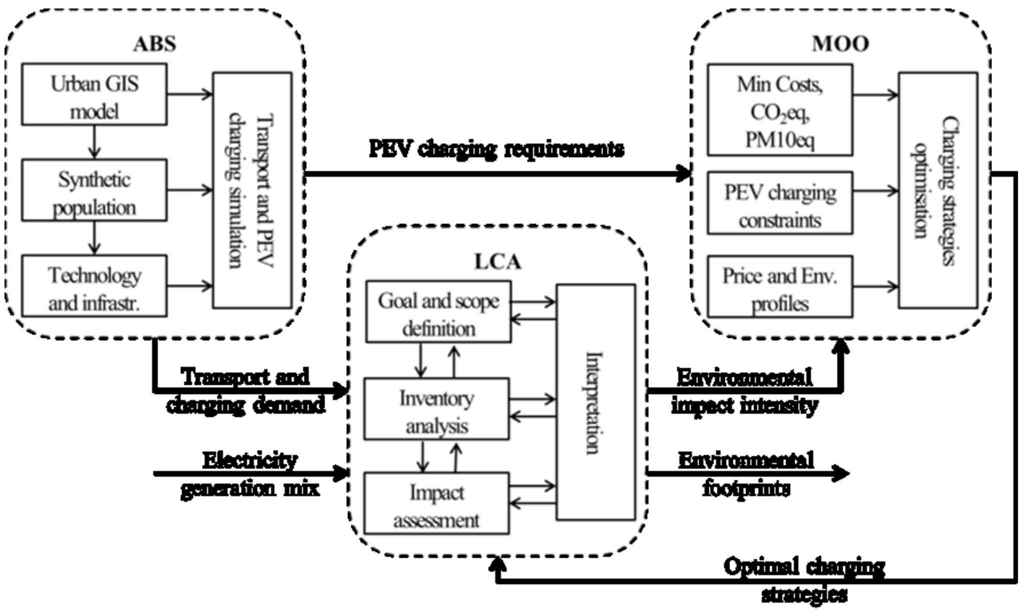


Figure 5-1. Integrated methodology for environmental design of PEV charging strategies. Source: Bustos-Turu et al. (2016a)

The ABS model, as described in 2.1, is used to determine the spatio-temporal distribution of charging requirements of a synthetic population of PEV users. The LCA model is used then to compare the environmental impacts of PEVs, related to not only their operation but also their manufacturing phases. Subsystems modelled within the LCA system boundary include the travelled distance by the PEV fleet, the time-dependent electricity supply mix for PEV charging, PEV production and maintenance, and road infrastructure. The functional unit was defined as ‘PEV fleet in the simulated urban area’ and a problem oriented approach (ReCipe Midpoint, (Goedkoop *et al.*, 2009)) was applied as the characterisation method. The input-outputs for material production or fuel-specific energy production were derived from the Ecoinvent database (v2.2) (Frischknecht *et al.*, 2007). More details about the LCA formulation can be found in (Bustos-Turu et al., 2016a). Finally, the MOO model described in section 2.2 is used for the design of optimal charging strategies under different objective functions. For the analysis presented in this section, the charging demands of the different spatial units are aggregated. For this analysis, one additional objective function, stated in Eq. 28 is included to account for the particulate matter minimisation charging strategy. For the case of multi-objective optimisation, the ε-Constraint method (Miettinen, 1998) is used to minimise the total user costs. The second objective (carbon emissions or particulate matter) is converted into an inequality constraint with an upper bound ranging between the objective function values from the single-objective optimisation problem, previously solved.

$$\min\left(evPM10(evP_k)\right) = \min\left(\sum_{k}^{K} PM10Grid_k \times evP_k \times \Delta k\right) \qquad \text{Eq. 29}$$

The grid intensity profiles $CO2Grid_k$ and $PM10Grid_k$ are estimated in the LCA model based on the electricity generation mix, similarly to the methodology presented in section 2.4. Finally, for the electricity price profile $priceGrid_k$, the dynamic commercial end user tariff (tariff 1) presented in section 3.2.5 is used.

5.1.3. Results

The methodology is tested using the urban area representation presented in 0. The simulations are run for a winter weekday and a 30% PEV adoption level is considered. Figure 5-2 shows how the different models are combined to analyse two different scenarios. First, for the baseline scenario, the non-optimised charging demand is simulated in the ABS and assessed with the LCA. For the smart charging scenarios, the charging requirements from the ABS are combined with LCA environmental intensities (CO2 and PM10) to optimise the charging process in the MOO. Finally, LCA quantifies the environmental impacts of PEVs considering the smart charging strategies.

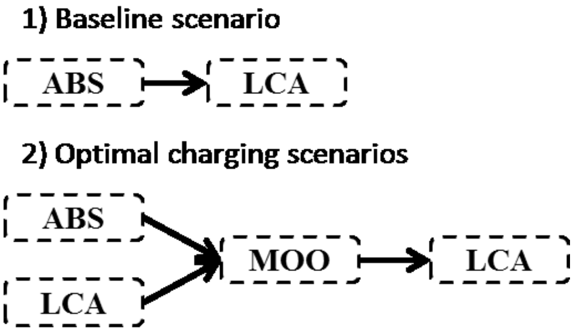
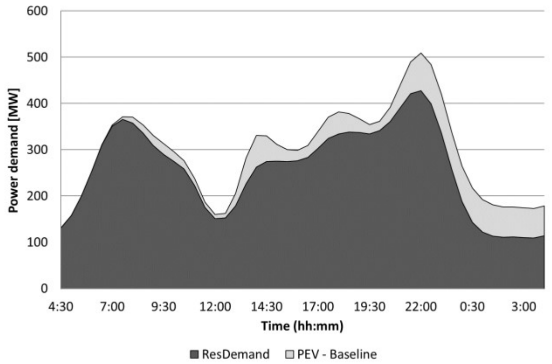


Figure 5-2. Data flow diagrams for the scenario analysis.

Figure 5-3 shows the aggregated electricity demand for the baseline scenario. The PEV charging demand is added on top of the residential demand to show the impact of an uncoordinated charging strategy. Figure 5-4 shows an example of an optimal PEV charging profile that minimises operational PM10 emissions, shifting part of the charging demand to times with lower PM10 associated to the electricity.



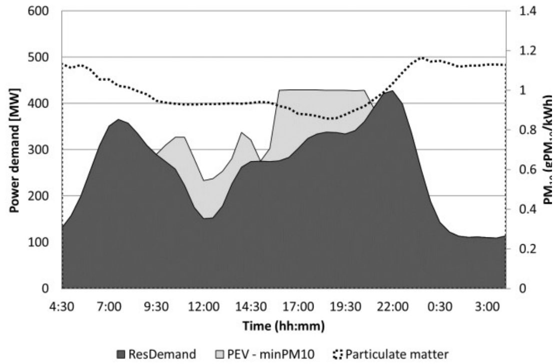
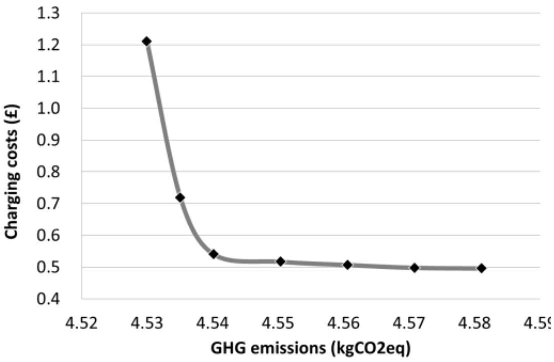


Figure 5-3. Electricity demand for baseline scenario

Figure 5-4. Electricity demand for min PM10 scenario.

Figure 5-5 and Figure 5-6 show the Pareto fronts generated by the MOO model, characterising trade-offs between economic and environmental criteria in the design of PEV charging strategies. Both curves show a similar "L" shape indicating that significant reductions in environmental impacts can be achieved with a slight increase on charging costs. However, further environmental improvements result in significant increases in charging costs.



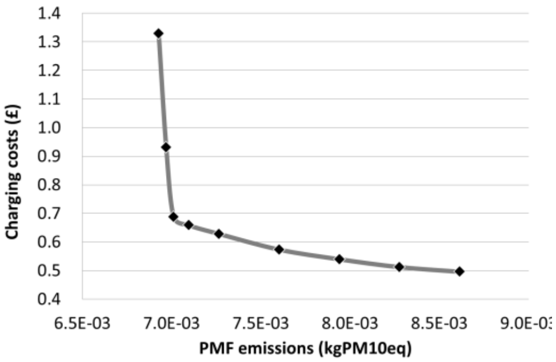


Figure 5-5. Pareto frontier for charging costs and GHG emissions. Values shown per vehicle per day.

Figure 5-6. Pareto frontier for charging costs and PMF emissions. Values shown per vehicle per day.

In the LCA model, PEV and ICV were assumed to be used for 2-passenger trips with a total lifespan of 200,000 km. As shown in Figure 5-7 and Figure 5-8, environmental profiles are dominated by the PEV operation stage, accounting for approximately 75% of climate change impacts and 64-68% of burdens in PMF. This can be explained by the UK electricity generation mix, where GHGs (CH_4, CO_2, N_2O, CF_4) and SO_x, NO_x, NH_3, PM come mostly from coal and natural gas combustion. It can be expected in future electricity systems with more renewable generation, these results will change as the CO2 and PMF emissions of these renewable technologies are lower compared to fossil-fuel technologies (Hertwich et al., 2014). This would reduce the emissions in the operational phase of electric vehicles, making them a cleaner option compared to internal combustion engines.

Electricity transmission and distribution cause 10-12% of the total environmental burdens. PEV manufacturing contributes to about 15% and 25% of climate change and PMF impacts respectively whereas less than 10% of overall environmental footprints are attributable to the road infrastructure. These proportions are directly related with the process data assumptions that are considered in the life cycle inventory database. In this particular case, and according to (Del Duce et al., 2016) the information related to the vehicle manufacturing is collected from (Schweimer and Levin, 2000), where the data is estimated for a commercial vehicle manufactured in Germany. As the final emissions will depend on the materials, processing technology, use of resources, etc. involved in the manufacturing of the vehicle, a detailed LCA should consider the effect of different manufacturing locations. Although a detailed analysis is out of the scope of this thesis, it is expected different manufacturers will use different technologies and different energy supply, therefore the results will change depending on the manufacturer location.

Compared with the baseline, GHG optimal charging strategies bring up to 1.5% environmental savings and PMF optimal solutions result in 6.8% reduction in PMF.

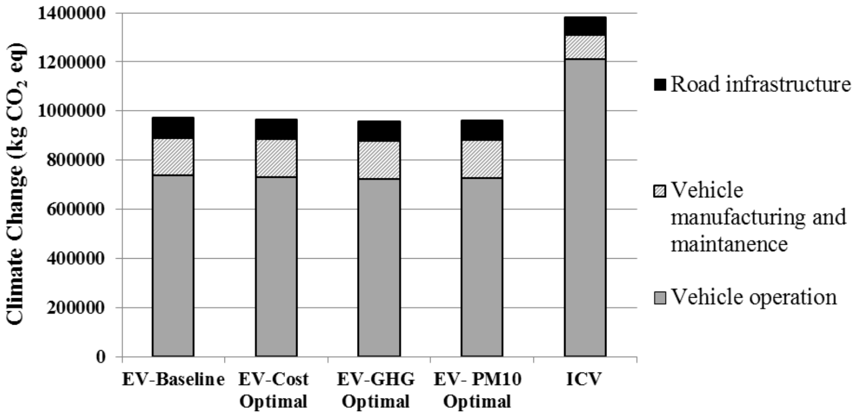


Figure 5-7. Greenhouse gases emissions for different scenarios.

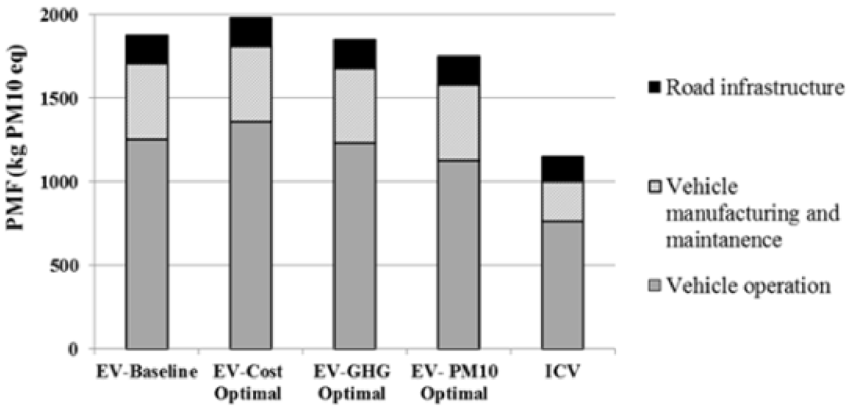


Figure 5-8. Particulate matter formation for different scenarios.

The results shown in Figure 5-8 indicate an increase in PM10 at a system level. As the LCA approach used here (problem-oriented or midpoint method) does not consider the human impact of this pollutant, results only show the overall level of particulate matter formation. Therefore, it does not consider the level of exposure of the population to this pollutant. Results suggest that in the case of EVs, the overall level of PM10 increases, but as this pollutant is emitted at the site of generation, there will be less human exposure than in the case of PM10 being emitted in an urban area.

5.1.4. Conclusions

In this work an integrated modelling approach has been proposed and tested with a case study based on real data for London, UK. Using a LCA model, different environmental indicators can be introduced in an optimisation model to design different PEV charging strategies, allowing the characterisation of trade-offs between economic and environmental objectives. In the case study, PEV represents a GHG advantageous transport system over ICV but delivers higher PMF impacts at the site of electricity generation due to the fossil fuel-dominated electricity profiles. Finally, the methodology and results of this study show that optimal charging strategies do have a limited influence on the GHG and PMF reduction as there is currently no significant intraday variation in the electricity generation mix.

5.2. Community energy planning

The next examples show how the modelling framework (or part of it) presented in this thesis can be used as a support tool for the design and planning of community energy schemes. These schemes are characterised by the integrated provision of heat and electricity for an urban district. In these cases, the framework is used mainly to estimate energy demand profiles (electricity and heat), considering in some cases the introduction of PEV fleet into the analysis.

5.2.1. Isle of Dogs

The case study presented here was developed within the context of a collaboration with an industrial partner[22]. The main objective of this research work was to estimate the energy demand of an urban area, around the Isle of Dogs in London, UK and to explore the impact of comfort temperature in this demand. For this, a combination of methods is considered to estimate spatial and temporal energy demand profiles, desegregated by MSOA (Medium Super Output Area). The residential energy demands were estimated using the agent-based model described in 0. For the electricity demand, most of the parameters are the same as the ones used in the case study presented in 0. For the heat demand though, further analyses were needed to estimate the floor area and the heat loss parameter (HLP) for the urban area. In the case of the floor area, this was estimated using two different approaches according to the data availability. For MSOAs within the area of Isle of Dogs, the floor area was calculated using the average floor area per household and the number of household for each MSOA. The average floor area per household is calculated using information from the EPC (Energy Performance Certificate) for a sample of properties in the area. The number of household is extracted directly from ONS data (Office for National Statistics, 2016). For the rest of the MSOAs, the residential floor area is estimated based on the residential footprint area (Office for National Statistics, 2016) and an average number of floors, in this case 3.5, extracted from information found in the *OS MasterMap Topography Layer* (Ordnance Survey, 2016). For the HLP estimation, Palmer and Cooper (2014) give this value for different building ages. With this information, and the number of buildings for each of those periods (DataStore, 2016), a weighted average HLP is calculated for each MSOA. Finally, the external temperature is extracted from (Met Office, 2016) where daily profiles for a whole calendar year (2014) are considered for the London Heathrow Airport weather station.

[22] More information in http://www.imperial.ac.uk/energy-futures-lab/research/our-projects/edf-flexifund/load-forecasting-of-electricity-and-heat-demands/

In Figure 5-9 an example of estimated residential heat demand profiles (normalised[23]) is shown for one MSOA, considering different comfort temperatures. Here, the effect of a setpoint variation in the energy demand can easily be observed, with expected results. Lower comfort temperatures result in savings in the energy consumption. In this case, the energy reduction is approximately 7% for each degree reduced.

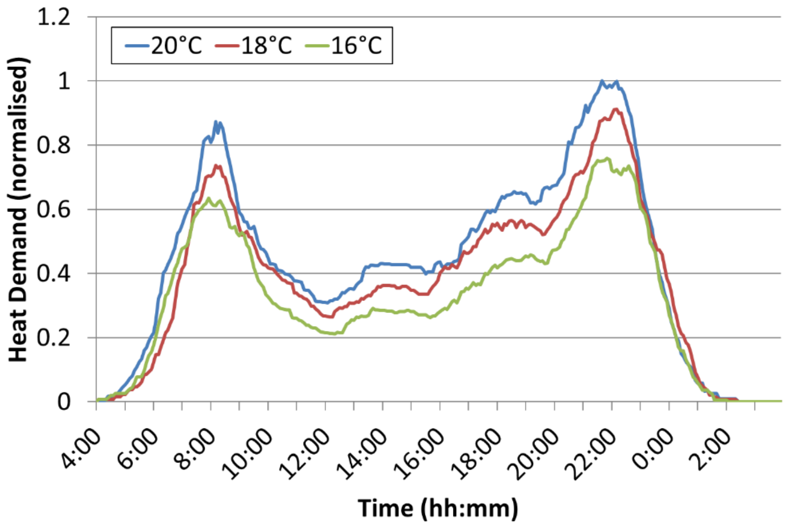


Figure 5-9. Effect of thermal comfort in energy demand profiles for one MSOA (normalised results).

The previous profiles are then estimated for an entire year, and aggregated into annual figures to be compared with real data, published by BEIS (Department for Business Energy and Industrial Strategy, 2016a, Department for Business Energy and Industrial Strategy, 2016b). Figure 5-10 shows this comparison for electricity consumption, while Figure 5-11 shows it for heat demand.

[23] Results are normalised to protect the confidentiality of the results.

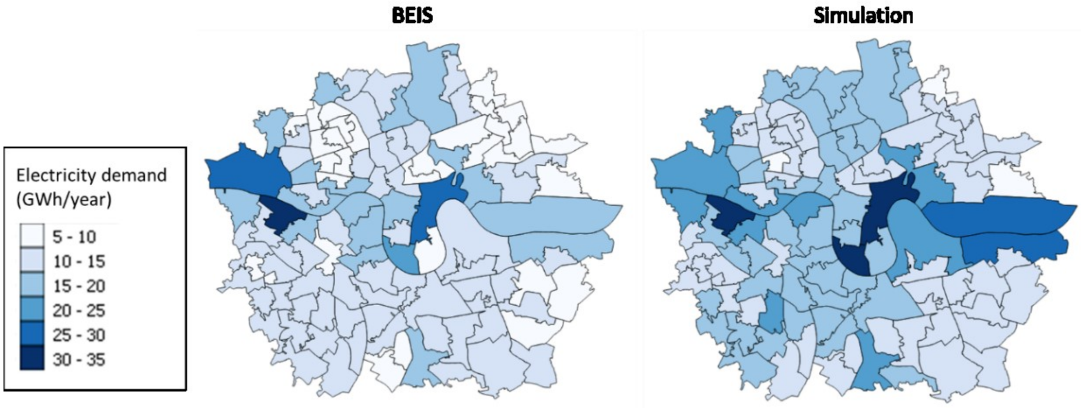


Figure 5-10. Graphical comparison of annual electricity demand.

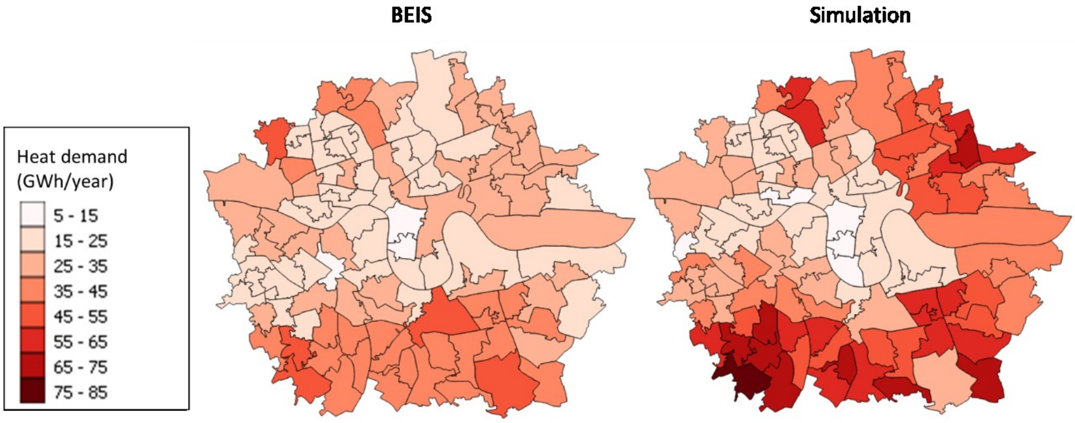


Figure 5-11. Graphical comparison of annual heat demand.

The previous figures (Figure 5-10 and Figure 5-11) show that the simulation model can estimate the energy demands of an urban area with a moderate level of accuracy (average absolute error of 29% and 43% for electricity and heat demand respectively). Further analyses are needed to understand these differences as the sources can be quite complex. For example, the underlying methodology used in the estimation of the BEIS figures considers a definition of domestic consumers that is not necessarily in line with the way the residential consumption is estimated in this thesis[24].

[24] For example, in BEIS report, consumers using less than 73,200 kWh of gas a year are classified as domestic consumers.

5.2.2. Islington district energy centre

The case study presented in this section is based on the analysis of a community energy scheme located in the borough of Islington, London. In this scheme, shown in Figure 5-12, the heat demand is supplied by a district heating network (DHN), supplied by a combination of two combined heat and power (CHP) plants, a heat pump (HP) and communal gas boilers. In this research, the analysis is focused on evaluating the option to supply the PEV fleet with the excess electricity from the CHP as an alternative to export it to the grid at a “grid buying price”. Given that an EV charging station would have to buy electricity from the grid at a “grid selling price”, as long as the energy centre sells electricity at a lower price, it can be assumed that the charging station owner would give preference to the locally generated electricity. Thus, by assuming a price that is higher than the “grid buying price” and lower than the “grid selling price”, both the DHN operator and charging station owner would benefit, which is where the motivation for the system integration arises. The operation of the community energy centre is designed through a mix integer linear programming (MILP) model, based on the work done by Corral Acero (2016) and adapted by Chakrabarti and Proeglhoef (2016).

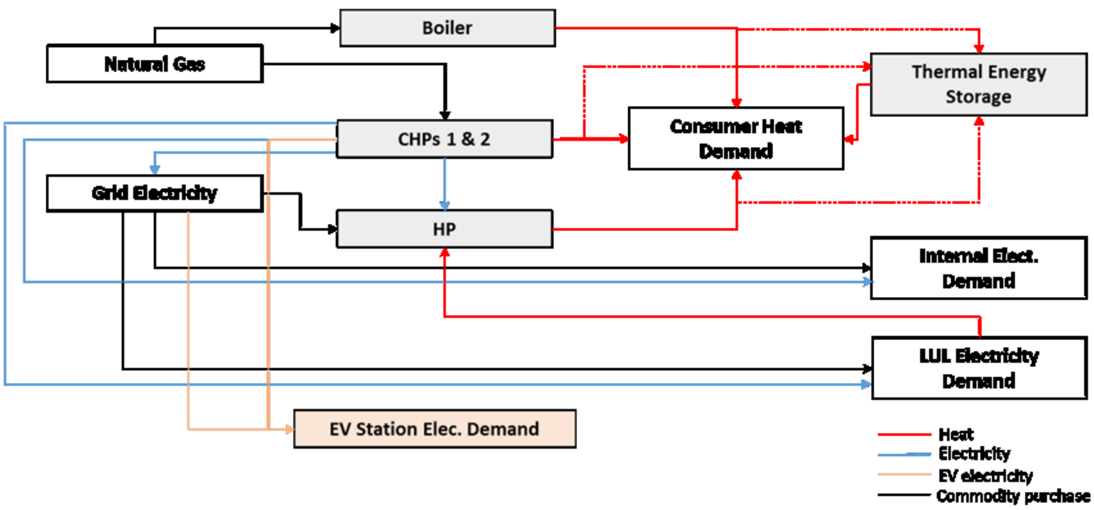


Figure 5-12. Integrated community energy scheme. Source: (Chakrabarti and Proeglhoef, 2016)

For the modelling of the scheme operation, the electricity demand of PEVs is assumed to be supplied through a public charging station where users would come exclusively to charge their PEVs, without the flexibility for managing the charging process through smart charging strategies. Therefore, this demand is considered as a fixed input parameter of the optimisation model. In this case, as real data is not available, the ABM model presented in 2.1 is used to generate synthetic data of a fleet of PEVs charging in the area under study. For this, the ABM is implemented in an urban area centred in Islington, considering the surrounding areas to account for trips made from and to the area. Figure 5-13 shows the simulated area, whereas Figure 5-14 shows the areas considered as being the potential area to be supplied with charging services by the energy centre. In this case, vehicles within Middle Super Output Areas (MSOAs) that are a radius of 2-3 km away from the energy centre are considered in the model as the group of potential customers.

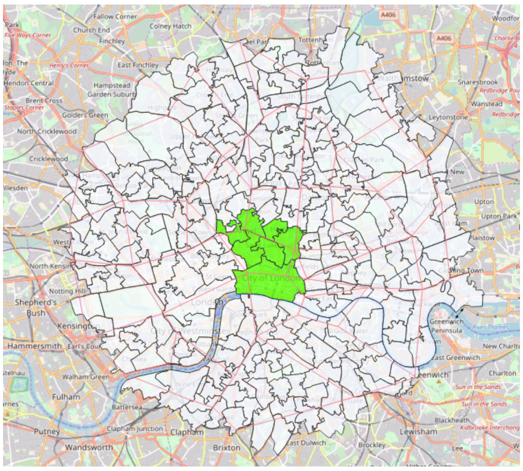


Figure 5-13. Area considered for PEV simulation.

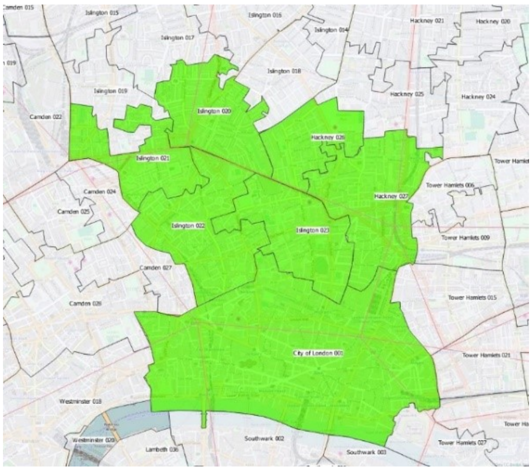


Figure 5-14. Energy centre PEV charging area.

Although residential charging is usually done by using 3.6 kW chargers, the model assumes that all charging points (whether residential or commercial) have a fast charging capacity (50.0 kW), in order to obtain a potential demand for fast charging in Islington area. Also, two types of users were considered; residential and commercial users. Residential users are agents who use their vehicles to go to their work and daily activities, while commercial users are agents who use their vehicles throughout the day for their business activities, such as delivery services vehicles or taxis. In the case of commercial users, they are assumed to travel between randomly selected commercial destinations in the simulated area, using a similar destination selection approach as described in section 2.1.3 (i.e. the larger the commercial floor space, the higher the probability for a commercial driver to select that destination). Two different shifts are considered for each day type (weekday, weekend). These are modelled using the activity schedule definition presented in section 2.1.2. Table 3-4 shows the shifts schedules for commercial PEV users. For residential users, the activity schedule is assumed to be the same than the one presented in section 3.2.4.

Table 5-1. Activity schedule definition for commercial PEVs.

Activity Schedule, $AS_i = \{(ACT_j, MDT_j, SD_j, PD_j)\}$	
Weekday (Shift 1)	**Weekday (Shift 2)**
(work, 8.0, 2.0, 1.0)	(work, 16.0, 2.0, 1.0)
(home, 16.0, 2.0, 1.0)	(home, 24.0, 2.0, 1.0)
Weekend (Shift 1)	**Weekend (Shift 2)**
(work, 11.0, 2.0, 1.0)	(work, 18.0, 2.0, 1.0)
(home, 19.0, 2.0, 1.0)	(home, 02.0, 2.0, 1.0)

For the residential PEV fleet simulations, two levels of adoption are considered; 10% and 30%. For the commercial fleet simulations, the number of PEVs was adjusted to match the peak electricity demand for the two residential adoption levels, so the different scenarios can be comparable. For simplicity, these are referred to as 10% and 30% adoption for both residential and commercial fleet. Figure 5-15 and Figure 5-16 show the results for the two client types, superimposed on the CHP electricity production (considering noise restriction between 22:00 and 07:00) to better understand the relationship between supply and demand. Only the results for a typical weekday have been shown as the demand profile for weekends provides no additional insight into the operation of the system.

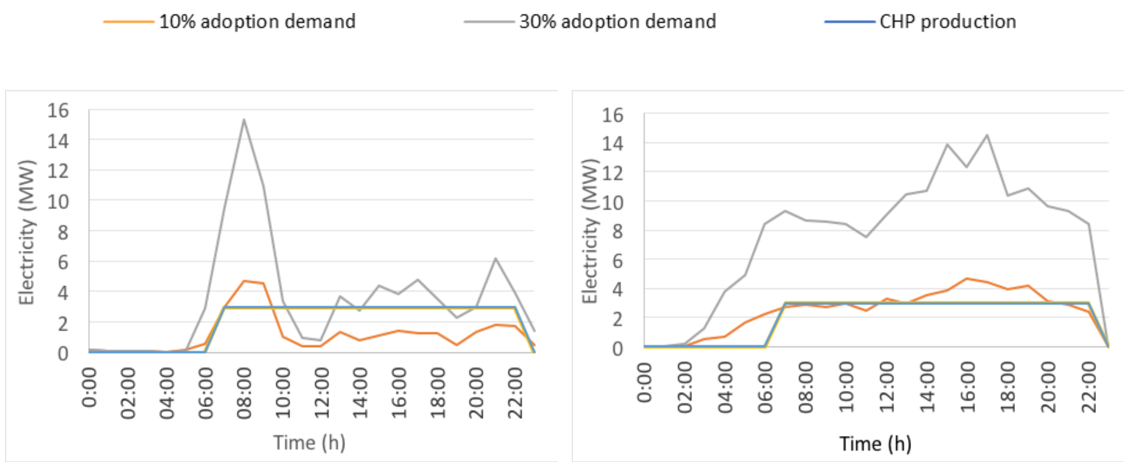


Figure 5-15. Residential PEV charging demand for 10% (orange) and 30% (grey) adoption levels for a weekday. Source: Chakrabarti and Proeglhoef (2016).

Figure 5-16. Commercial PEV charging demand for 10% (orange) and 30% (grey) adoption levels for a weekday. Source: Chakrabarti and Proeglhoef (2016).

Results show that in the case of residential users, the electricity demand for a 10% adoption level is most of the time lower than the CHP capacity, except at times of peak demand in the early hours in the morning (between 7:00 and 9:00). For a 30% adoption level, the PEV demand exceeds the CHP capacity most of the time, apart from a couple of hours before midday and some moments during the evening. In the case of commercial users, the electricity demand is generally higher, and with lower variability, compared to the residential demand. For a 10% adoption level, the demand is higher than the CHP capacity during most of the daytime. Whereas for a 30% adoption, the demand of commercial PEVs always exceeds the CHP capacity. These PEV demands will influence the optimal operation of the energy centre that will try to maximise the revenues coming from selling the electricity to the grid, to the LUL demand and/or to the PEV charging station. In this analysis, an electricity-led operation for the CHPs is considered. Therefore, some heat dumping is expected to result from the optimal operation. As part of the results, the next figures show the operation of the CHP with the different electricity flows going to the different components of the energy centre. Figure 5-17 shows the CHP operation considering a 10% adoption level for residential PEV users, while Figure 5-18 shows the same operation but considering a 10% adoption of a commercial PEV fleet. In all these scenarios, the CHP will operate at maximum capacity (3.0 MW) to supply heat and electricity demands, as it is always cheaper to produce the electricity locally than importing it from the grid.

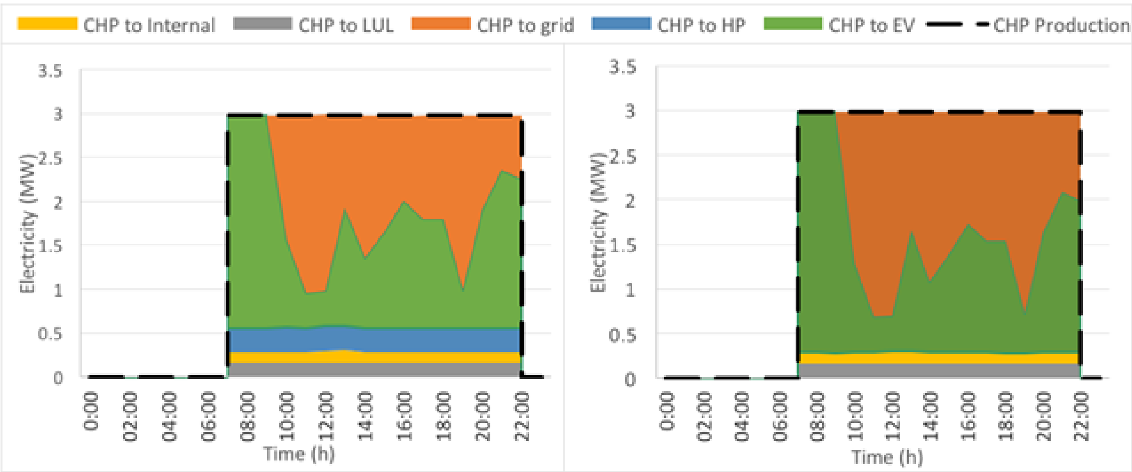


Figure 5-17. Energy centre operation with residential PEV users (10% adoption) for winter (left) and summer (right) weekday. Source: Chakrabarti and Proeglhoef (2016).

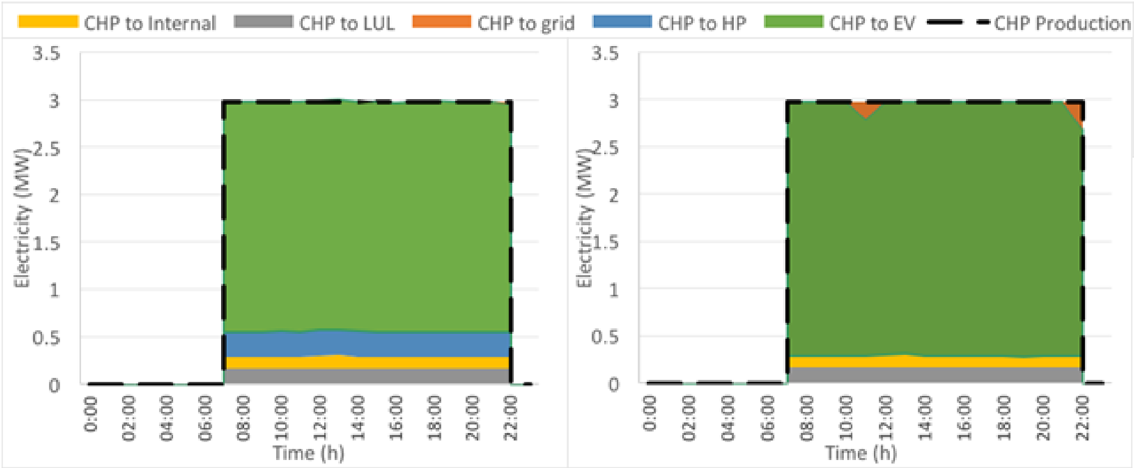


Figure 5-18. Energy centre operation with commercial PEV users (10% adoption) for winter (left) and summer (right) weekday. Source: Chakrabarti and Proeglhoef (2016).

The previous graphs show that for commercial PEVs, the energy centre exports much less electricity to the grid, compared to the scenario considering the residential PEV fleet, making the commercial scenario more profitable, as the selling price to PEVs is considered greater than the export price. The model also assumes this selling price is lower than the grid tariff, therefore PEV users (or charging stations operator) would prefer to charge PEVs using the electricity coming from the energy centre instead of from the electricity grid. This PEV integration would increase then the profits of the energy centre. Figure 5-19 shows the carbon emissions and profits for each of the PEV scenarios. Results show that commercial fleet is more attractive as they represent a more constant load to supply. In this case, profits are increased by 11.6% compared to the scenario without PEV integration. However, with higher adoption rates, the increase in profits becomes less important, as the energy centre cannot keep supplying electricity to PEVs further its capacity. In all these scenarios, the operation of the energy centre considers a profit maximisation strategy, therefore carbon emissions are not necessarily optimised. For this reason, carbon emissions are reduced only by 0.5%.

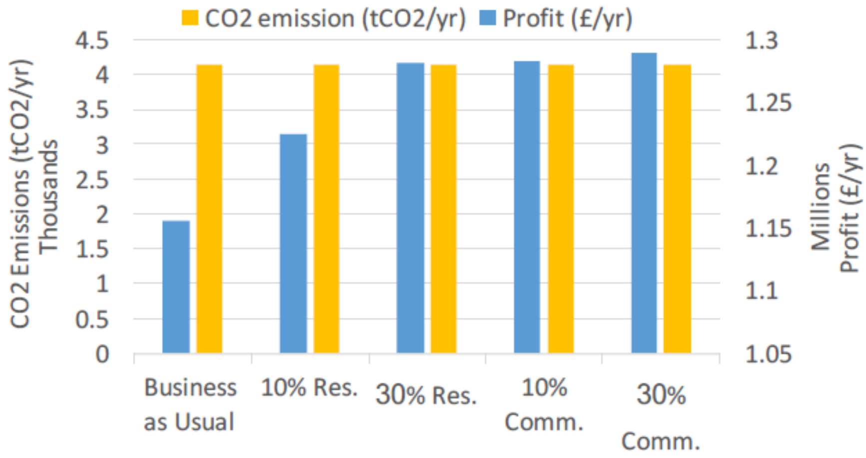


Figure 5-19. Profits and emissions for the different DHN-PEV integration scenarios. Source: Chakrabarti and Proeglhoef (2016).

5.2.3. Conclusions

In this section, the proposed modelling framework described in 0 was applied in two community energy schemes cases. In the first one, an area located in East End London was analysed to estimate energy demand profiles and to study the influence of user comfort temperature on these profiles. The energy estimation was desegregated by MSOA and for this, some heuristic methods were needed to estimate some of the parameters of the heat demand model. Results showed that heat demand can be reduced in 7% for each degree reduced in the set point. Also, these profiles were aggregated for a year and then compared with published data, showing that the model can predict annual energy demand with a moderate level of accuracy. In the second case, the analysis was focused in a community energy scheme located in the borough of Islington, London. In the current scenario, the heat demand is supplied by a district heating network using a combination of technologies that generates excess electricity. The research was focused then on evaluating the option of using this electricity to supply a PEV fleet as an alternative to export it to the grid. For this, the ABM model presented in section 2.1 was used to generate the charging requirements for a potential group of customers, including residential and commercial users. Results showed that commercial fleet is more attractive in terms of profits as they represent a more constant load to supply. However, considering more customers only increases profits until certain limit, as the energy centre reaches its capacity.

Chapter 6. Conclusions

International environmental concerns such as air pollution and climate change are forcing cities worldwide to incorporate low carbon technologies in their energy infrastructure, and to change the way they have traditionally been producing, distributing and consuming energy. In this shift towards energy sustainability, the electrification of transport and heat supply in buildings are two important strategies that cities are considering in order to improve air quality and reduce their carbon footprint. The integration of these technologies has an impact not only in the way urban energy systems are designed and planned, but also in the way they are operated. In a system where the conditions are dynamically changing due to the fluctuating nature of non-dispatchable renewable energy sources, the flexibility that demand-side technologies can provide to the system is becoming a highly valuable aspect, necessary to operate the energy infrastructure more efficiently. Assessing this flexibility is not trivial though as it depends on a complex interaction of many interrelated factors. The flexibility that a group of users can provide will depend on the way they use the different technologies. And this use is influenced not only by economic but also by social and environmental factors.

In this thesis, two main demand-side technologies were analysed. For the case of the transport sector, the technology considered was the plug-in electric vehicles (PEVs). For the case of heating, the use of heat pumps (HPs) in residential buildings was explored. In these two cases, the analysis was focused on characterising the demand flexibility for a group of users (PEVs or HPs) and on evaluating the benefits of managing that flexibility in terms of minimising operational costs, carbon emissions and peak demand (to reduce the need for network upgrades), without compromising the user energy requirements. It is with this analytical objective in mind that the methodology presented in this thesis was developed.

6.1.Main findings

Combining descriptive and normative models, a novel and integrated methodology was developed in this thesis. This methodology served as a framework to explore and evaluate smart operational strategies for low carbon demand-side technologies, considering the spatio-temporal characteristics of energy demand flexibility. This framework was tested on different case studies presented throughout this thesis, showing the capacity of the framework to be adapted and expanded as required by the specific analysis.

The contribution of this work relies on the development of a novel tool that can analyse demand side aspects of urban energy systems that are usually neglected in available tools. To the best of the author knowledge, there is no available tool in the market able to analyse DSM strategies in a holistic way, considering the diverse aspects of urban energy demand including social, technical, economic and environmental features.

Two main considerations were essential in the development of the tool and these represent specific contributions of this thesis. The first one relates to the diversity in terms of energy requirements for a group of urban energy users. The agent-based simulation model developed in this work allows for the representation of a heterogeneous group of users, each one with their own specific energy requirements, interacting with the rest of the energy system. Taking this generative and bottom-up modelling approach, time-driven energy demand profiles were produced and analysed for different zones in the urban area. The second consideration is the existence of conflicting objectives in the decision on how to optimally operate demand-side technologies in real life systems. This led to the implementation of a multi-objective optimisation tool to support the evaluation of economic, environmental and technical aspects of demand-side management strategies. With this tool, the trade-offs between these multiple criteria can be easily quantified, and constraints related with these can be explicitly incorporated in the analysis.

The first case study was based on a future scenario where the private residential transport is largely electrified. The study was focused on understanding the energy requirements related with the charging of the electric vehicles, and on assessing different smart charging strategies, quantifying trade-offs between charging costs and carbon emissions while considering also the impact of limiting the electricity peak demand. Before estimating the PEV charging profiles, the transport demand was first characterised in terms of travelled distance and parking v/s travelling time, and then compared with real data sets. Results of this comparison showed that the model can generate realistic transport behaviour which is necessary to estimate the charging and energy requirements. Then, the simulation model was shown to be a useful tool to estimate daily profiles for charging demand in different zones of the city, and to explore the influence of land use and agents' activities on the transport and charging demand. Results of this case study showed that the charging of a large group of PEVs can represent a significant proportion of the residential demand when the coordination of charging events is not taken into account. Simulations showed that for a 50% adoption level, PEV charging demand represents on average an 11% of the residential power demand, with a peak of 29%. On the other hand, when smart charging strategies were applied, a limitation in the peak demand was considered so that the current peak was not increased. In this smart control scenario, charging costs were reduced by between 4.3% and 45%, depending on the tariff and season considered, with commercial tariffs and winter as the most attractive cases. In terms of carbon emissions, smart charging strategies were shown to have a limited impact, with reductions in the range of 2.8-3.9%, slightly higher in summer days. Finally, using a multi-objective optimisation approach, Pareto frontiers were generated for user costs and carbon emissions, and a trade-off analysis was performed considering the effect of different seasons and tariffs. Analyses showed that due to the higher correlation between carbon factor and electricity prices, there is a greater similarity among optimal charging schedules in summer than in winter, reflected in the shape and size of the Pareto frontier.

The second case study looked at the electrification of domestic heat supply in buildings. Here, the analysis was focused on characterising the heat energy requirements and flexibility for a single as well as for a group of buildings, considering diversity in terms of occupancy and building thermal properties. Then, using this flexibility, optimal operational strategies for the individual and pool of heat pumps were designed and compared. The first analysis considered a static simulation approach to explore the additional demand that a group of heat pumps would represent. In this case, results showed that considering a 10% of heat pump adoption level without smart energy management strategies, the additional demand can represent between 5% and 17% of the residential electricity power demand during peak hours, depending on the season, with winter being the most critical season due to the high use of heating systems. The analysis was then focused on the evaluation of the potential for smart heat pump operation in individual buildings, and the effect of building properties on this potential. In this way, trade-offs between energy demand, operational costs and carbon emissions were calculated for different property sizes, insulation levels and thermal masses. For this, a simplified dynamic model was used to simulate the dynamic thermal response of buildings when they were supplied by heat pumps, considering different control strategies. In general, simulations showed that when smart control was implemented, the internal temperature of buildings stays closer to the set point. Also, when user costs were minimised, and high price periods coincided with the occupancy of the building, there were cases when the buildings were pre-heated before occupancy periods to avoid the operation during high price periods. While these effects would improve user's thermal comfort, they also increase heat demand in the range of 7-9% with a consequent increase in carbon emissions.

When building properties were analysed, results showed that smaller buildings present lower demand, costs and emissions independently of the control mechanism. When smart control was considered, costs reductions were proportionally higher in larger buildings (up to 37%) compared to a traditional feedback controller. Simulations also showed that independently of the building size, smart control slightly increases the energy consumption due to the improvement in thermal comfort. Due to this effect, carbon emissions are also increased even when the smart control was designed to reduce these emissions. Results also showed that better insulated buildings can reduce the heat demand significantly, by up to 39% when compared to a low insulation building. And when smart control is applied, user costs can be reduced by between 32% and 38.5% with higher reductions in high insulated buildings. In terms of carbon emissions, simulations showed these can only be reduced in buildings with high insulation levels, but part of this reduction is due to the reduction in energy demand. This slight reduction (0.7%) comes however with a significant rise in user costs (70%). Finally, it was shown that high thermal mass buildings would require more energy to keep the internal temperature within comfort levels, although this demand increase is not as high as in the case of large or poorly insulated buildings. Smart control can achieve costs reduction in the range of 21%-39% with higher reduction for high thermal mass buildings. As in the previous cases, carbon emissions can only be slightly reduced through smart control strategies. This suggests that in general, buildings flexibility is not high enough to take better advantage of the small intraday carbon factor variation in the electricity grid. Therefore, a pre-heating strategy is not justified as the additional energy would not offset the emissions reduction. This may change if the future power system experiences larger intra-day emission factors.

For the multi-building analysis, the modelling considered diversity in terms of occupancy. Using the agent-based simulation model, one hundred different occupancy profiles were generated, and simulations were run to assess the effect of including this heterogeneity in the peak demand, obtained for one day simulation. Results showed that including a diverse set of occupancy profiles reduces the peak demand in 47%. Additionally, if a smart control strategy is applied this peak can be reduced by a further 36% compared to a conventional feedback control. In term of user costs, centralised control can reduce these by up to 41% despite a small increment (2%) in the energy demand. Carbon emissions, on the other hand, present a very limited reduction (up to 0.7%). When peak demand is limited, these costs and emissions savings are reduced significantly, as the system has less flexibility to shift heat demand among the different buildings and to take advantage of low price and low carbon periods. In this case, costs can only be reduced by 4% and emissions by 0.02%.

The analyses developed in this thesis showed that spatial resolution is an important element to be included in modelling urban energy demands. Energy requirements partially depend on the movement and occupancy patterns of users around cities, and therefore the diversity in the energy profiles will be influenced by the different origin and destination locations and by individual activity schedules. In this thesis, these transport and occupancy profiles are generated through the simulation of users travelling around the urban area and they are used to calculate daily EV electricity and building's energy demands. Analysis done in this thesis show how important is to consider this diversity in the design of energy management strategies.

After presenting these two cases on transport and heat demand electrification, this thesis explored further applications of the modelling framework as first steps for future research areas. In the first application, the proposed framework was extended to integrate life cycle assessment and smart charging analysis. This integration allowed not only the incorporation of LCA indicators into optimal PEV charging strategies, but also the evaluation of the relative environmental benefits that smart control can bring to the life-cycle assessment of PEVs. Results of these analyses showed that PEV present lower CO2 equivalent emissions compared to ICV, but the PMF emissions are higher at the site of electricity generation due to the relatively high proportion of fossil fuel generation in the electricity system in UK. The LCA analysis showed that the impact of including smart charging strategies is very limited in the overall environmental footprint of PEVs, as there is currently a small intraday variation in terms of generation mix.

In the second application, two community energy schemes were analysed. The first one was focused on an area in the East End of London, called "Isle of Dogs", where there is currently an operating district heat network supplying around 700 homes. The purpose of this analysis was to estimate the heat and electricity demand for the whole Isle of Dogs area and to explore the impact of comfort temperature in heat demand. Using the agent-based simulation approach, different heat demand profiles were generated for each spatial unit (in this case MSOA) considering different set point temperatures. Results showed that energy demand can be reduced in approximately 7% for each temperature degree reduced. Then, the results for one-year simulation were compared to data published by BEIS. The comparison showed that the simulation model estimates energy demands with a moderate level of accuracy and that further analyses are needed to understand the differences among MSOAs.

The second community energy scheme analysed is located in Islington, London. In this case, the analysis was focused on exploring the integration of PEVs within a district heat network, currently supplied by an energy centre composed of CHP, HPs and boilers. The main objective of the analysis was to evaluate the economic benefits for the energy centre to sell excess electricity to supply PEVs charging demand instead of exporting it to the grid. For this, the agent-based simulation model was used to estimate the potential group of customers (domestic and commercial) and their energy requirements, without considering smart charging strategies. Then, this energy demand profile was included in the design of the optimal operation of the energy centre. Results showed that there is an increase in profits assuming the price PEVs pay is higher than the grid export price but lower than the grid import price, so the scheme would be beneficial for all parties. This increase in profits however becomes less important for higher number of PEV users as the energy centre cannot keep supplying electricity to PEVs further than its capacity.

6.2. Recommendations for future work

Many different streams for further research have been identified throughout the development of this thesis. Some of them are concerned with the proposed methodological framework and others relate with the specific case studies. In terms of methodological work, three main research areas are proposed to be further explored. The first one is related with the data collection and processing. The second one is related with the testing and evaluation of different control strategies and the third has to do with the analysis of integrated smart control solutions considering the overall operation or urban energy systems.

The bottom-up and disaggregated nature of the modelling framework proved to support a rich characterisation of energy demand flexibility and a broad evaluation of smart energy management strategies. However, this same disaggregated resolution requires an important amount of data to populate the models, which is not always directly and publicly available. In the case of the agent-based model, it requires data related to urban land use, built environment, socio-demographics and user behaviour. In terms of urban design and built environment, most of the information used in the case studies (based in London) could be accessed through public repositories. However, this is likely to not be the case for other cities in the world and can represent an important challenge in the implementation of the proposed methodology. In these cases, when the information is not directly available, suitable methods for data extraction and processing would need to be developed. One example of this was shown in section 5.2, where heuristic methods were used to estimate some of the physical and thermal parameters of residential buildings. For socio-demographic data, the data needed would be directly related with the way the different energy users and their corresponding energy behaviour are modelled. In this thesis, a simplified approach was taken, in which only a small number of user types were considered, and rule-based decision-making processes were adopted for the interaction between users, transport, and heating systems. However, the way the agent-based simulation model is designed and implemented allows analysts to incorporate more sophisticated representations or user behaviours if needed, especially those related with economic activities, building occupancy, and interactions with low carbon technologies and control systems. Representations of user-technology interaction could be potentially improved as real energy consumption data becomes available in the future. The adoption of more sophisticated metering technologies could allow energy systems operators to better understand the energy requirements of a group of users. This understanding could help create more realistic models of energy-related user decisions, as long as the data is available to populate and calibrate the model. In the case of the optimisation model, data about energy mix and electricity price were shown to be the most important ones to implement the different case studies. This information was collected from the public domain for the case of the UK, and it is expected that most large cities will have access to this information through the electricity system operator. However, when alternative scenarios are to be explored, some further modelling would be needed to estimate generation profiles with high temporal resolution.

The aim of this thesis was to quantify, at a high level, the overall benefits of implementing smart controls for demand side management. Therefore, for simplicity, a centralised approach for the control system was assumed and no other control structures were analysed. Especially in cases with a very high number of users, other decentralised or hybrid control strategies can be designed and compared in terms of computational effort and optimality, considering also other practical aspects such as user data privacy and user autonomy. These control strategies should also consider important aspects of implementation such as the design of individual charging profiles, to guarantee each vehicle gets enough energy for its daily trips Another important area for further analysis is the effect of different market arrangements and incentives (direct control, price-based incentives) in the benefits that the system and users can obtained from DSM strategies.

The last stream for future research covers the analysis of integrated urban energy systems, in which interactions between transport and heat networks can be further characterised. A first approach was explored in the work presented in section 5.2.2. However, more work can be done in evaluating the benefits and challenges of co-optimising the electric vehicles charging process and heat networks operation.

In terms of case studies, further work is envisioned to create more realistic cases and to evaluate different energy scenarios, as part of the planning and design of smart urban energy systems. In this sense, specifically for transport electrification, some possible research streams are identified as relevant for further development. For example, further work on a more diverse representation of EV users can be done, considering not only residential consumers but also commercial and public transport systems. A deeper exploration on the representation of the user behaviour related with travel and charging decisions seems to be an interesting area of research that could be improved by multi-disciplinary research between social scientists and engineers. Also, in terms of sustainable transport analysis, other technologies could be incorporated into the simulations. For example, hybrid and fuel cell electric vehicles are technologies that could be part of future urban energy scenarios, and therefore they would require further analysis to support their integration in the design, planning and operation of energy infrastructure.

In the case of heat electrification analysis, the following research areas can be developed in future work. As the case of transport electrification, a more detailed analysis of the impact of users' behaviour in the heat energy requirements could be of interest in future work. These analyses could be supported by real data if in the future the use of smart meters is generalised, and the data is available. Further analysis can also be done in understanding the relationship between user comfort levels and the flexibility that buildings can provide to the system to improve the operational performance and to avoid upgrades in the energy infrastructure. This would help to integrate the user behaviour and user experience in the analysis of trade-offs between technical, economic and environmental benefits of smart control in heat supply systems. Finally, to further explore building heat demand flexibility, it is important to explore different heat storage technologies that can enhance the possibilities of energy system operators to reduce operational costs and carbon emissions, taking advantage of the period when more low carbon generation technologies are supplying energy into the electricity system.

The aim of the case studies was to illustrate the use of the modelling framework. This means that this work was not aimed to predict any specific future scenario, but to show that the modelling framework can be used to quantitively assess operational benefits that can be exploited through the implementation of smart control strategies. In this context, this thesis considered the current electricity system for the simulations and therefore electricity costs and emissions do not necessarily reflect a future scenario in which these technologies will operate. If future electricity scenarios are available and the operation can be simulated with high temporal resolution, further analysis could be done with the proposed framework. For example, in a future scenario with higher participation of renewable energy sources, the carbon content of the electricity is expected to present higher intraday variability. In this case, smart charging strategies could take advantage of this variability, generating greater benefits to the user and system. Also, the lower dispatchability of these supply technologies will create the need for the system operator to increase balancing mechanisms. In this context, flexible demand technologies such as the ones analysed in this thesis, together with the right energy management mechanisms, can play an important role in this new scenario, providing balancing services to the system operator, adding new revenue streams and making them more attractive.

The previous ideas presented for further exploration show how broad is the field in which the modelling framework developed in this thesis can be applied. The topics covered in this work are by nature complex and multi-disciplinary, and therefore research activities can take multiple directions. To make progress in this area and find holistic and integrative solutions to current and future challenges, a collaborative research approach seems to be the most effective one, in which different disciplines can learn different viewpoints from each other of the phenomena under analysis. Most of the material presented in this thesis has been developed in a context of collaborative and multi-disciplinary research and therefore it represents an example of how an integrated analytical framework can be developed and used to support the design and planning of future smart and sustainable urban energy systems.

6.3. Final remarks

At the beginning of this PhD project, the initial aims were, as it was recognised afterwards, quite ambitious. Initially, the project aimed to develop novel modelling tools to analyse the global operation of urban energy systems. After the initial literature review and preliminary analysis, the aims of the thesis were narrowed to be more focused on a deliverable analysis after the completion of the project. The objectives were therefore refined to focus on the analysis of energy management strategies of demand-side technologies such as electric vehicle and heat pumps. These technologies were selected as they were recognised as two important technologies in the electrification of transport and heat sector in the pathway to decarbonise urban energy systems. Aspects of energy supply and distribution were left out of the scope of this thesis as it became clear the complexity of the analysis. Instead, it was preferred to put more emphasis in the different aspects of energy demand, as it was found that in general, this aspect of urban energy system modelling was generally overlooked in current energy systems modelling efforts.

The transport electrification case was the first to be developed, as it was part of the research the author was doing during his previous MSc, therefore it felt more natural to start with that sector. Then, the heat electrification scenario was the second to be analysed. For this, the modelling framework kept expanding to incorporate the building thermal and HP energy management models. The development of these analyses was in line with a couple of industrial projects, creating a very useful context of real stakeholders interested in using the results and insights of these tools. The regular feedback from industrial partners helped to steer the directions of the research in terms of modelling and simulation.

After the completion of the thesis, it is easier to recognise the multitude of possible paths that a research area like the one explored in this PhD project can take. The collaborative and multi-disciplinary environment in which the author developed this thesis was fundamental in the completion of this work. Building the framework in a direction that seem to fit well into the ongoing efforts to develop city scale system analysis tools, made the whole research process a fruitful and rewarding journey.

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