Energy Management System for Smart Homes

Modeling, Control, Performance and Profit Assessment

Yousefi, Mojtaba

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BY
MOJTABA YOUSEFI

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DENMARK

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Mojtaba Yousefi

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PhD supervisor: Associate Prof. Amin Hajizadeh,
Aalborg University

Assistant PhD supervisor: Associate Prof. Mohsen Soltani,
Aalborg University

PhD committee: Assoicate Professor Tamas Kerekes (chairman)
Aalborg University

Professor Mohan Lal Kolhe
University of Agder

Associate Professor Hamid Rexa Shaker
University of Southern Denmark

PhD Series: Faculty of Engineering and Science, Aalborg University

Department: Department of Energy Technology

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ABSTRACT

Recent studies of designing home energy management systems (HEMSs) have indicated that considering uncertainties and random parameters of various home resources such as photovoltaic (PV) arrays, plugged-in electric vehicles (PEV), and home load demand can significantly improve the HEMS optimal performance. Therefore, the subject of this thesis is to design a HEMS incorporating uncertainties arise from PV power output, home load demand (thermal and electricity), PEV trip time, and PEV state of charge (SOC) at plugged-in time. the contribution of this thesis is divided into three parts: 1) modeling of building resources 2) control-oriented modeling strategies and 3) performance and profit assessment of implementing the designed HEMS for building with different energy labels (determine the building storage efficiency).

A contribution of this thesis is to provide a comprehensive comparison of the existing modeling techniques such as physics-based modeling (equation-based models), data-driven or combination of them (hybrid modeling) techniques for different resources of a building. Then, these techniques are employed to capture the uncertainties of PV, home load demand (thermal and electricity) and PEV. The accuracy of the obtained models from each technique are validated by the historical data. Then, the pros and cons of each technique are presented. The results demonstrate the conditions, under which the methods can provide a reliable and accurate description of smart home dynamics. Eventually, a holistic model for the entire building is provided with considering building electrical and thermal parts. This holistic model is used by the controller to minimize the main objective of the problem while should not violate the problem constraints. In this section, some famous empirical PV models and current machine learning techniques such as artificial neural networks

The second contribution is to develop a closed-loop online optimization controller to deal with uncertainties, stochastic parameters and nonlinearities of the problem. Therefore, a predictive HEMS is designed through nonlinear model predictive control (MPC) to minimize the building cost of energy and meet the user's preference in terms of the need for electricity and thermal energy. To the best of author’s knowledge, this is the first study in the smart home context that considered the user's thermal and electrical requirements by using the following home energy storages (HESs) technologies; 1) PEV battery and 2) building thermal mass (heating/cooling the building through HP) as home energy storages. Using the following, technologies as the building storages make the system economic. Furthermore, a trade-off is made between the HEMS optimal operation and PEV battery lifetime degradation cost. The last but not least, the simulation results are validated by comparing it with an off-line optimization counterpart in which all the future inputs are known in advance.

Finally, the third contribution is to investigate the profit assessment of the designed HEMS in different buildings with different storage efficiency (different thermal

resistance) which indicates by the building energy label ranges from “A” to “G”. Moreover, the impact of having different heating emission systems, which affect the building thermal capacity, is investigated as well. The simulation results prove that not even the HEMS optimal performance in building with proper storage efficiency (Label “A”) is much better than the poor storage efficiency, but also the HEMS performance in meeting the optimization constrains is much close to desire point than the building with poor insulation quality. The last but not least, it is shown that in a building with the same energy label, the floor-radiator heating system can improve the HEMS performance in both energy cost minimization and fulfilling constraints than the radiator-only heating systems, because the floor-radiator heating system increases the building thermal time constant (by improving building thermal capacity). Although, the improvements reduce as the building energy label moves to label “G”.

SYNOPSIS

Nyere undersøgelser af bygningsenergistyring (Home Energy Management System- HEMS) viste, at betragtning af usikkerheder og sandsynligheder for parametre kan forbedre HEMS-optimale ydelse. Disse usikkerheder stammer fra forskellige hjemmressourcer såsom fotovoltaiske (PV) solceller, tilsluttede elektriske køretøjer (PEV) trippetid, PEV tilstand af opladning (SOC) ved tilsluttet tid og hjemmebelastning efterspørgsel (termisk og elektricitet) i en boligbygning. Denne ph.d.-afhandling foreslår derfor design af en HEMS, der inkorporerer disse usikkerheder og tilfældige parametre. Denne ph.d.-afhandlings bidrag er opdelt i tre dele: 1) modellering af bygningsressourcer 2) kontrolorienterede modelleringsstrategier og 3) evaluering af resultater og fortjeneste ved implementering af det foreslåede HEMS til bygning med forskellige energimærker.

Et af bidragene er at give en omfattende sammenligning af de eksisterende modelleringsteknikker såsom fysikbaseret modellering (ligningsbaserede modeller), datadrevet eller en kombination af disse to metoder (hybrid modellering). Derefter anvendes disse teknikker til at fange usikkerheden omkring PV, energiforbrug (termisk og elektricitet) og PEV. Nøjagtigheden af de opnåede modeller fra hver teknik blev valideret af de historiske data. Derefter præsenteres styrke og ulemper ved hver teknik. Resultaterne viser betingelserne, under hvilke metoderne kan give en pålidelig og nøjagtig beskrivelse af smarthusdynamikken. En holistisk model for hele bygningen blev opnået med hensyn til bygning af elektriske og termiske dele. Denne holistiske model bruges af controlleren til at minimere hovedomkostningerne ved problemet, mens den ikke må ramme problembegrænsningerne.

Det andet bidrag er at udvikle en lukket-sløjf onlineoptimeringscontroller til at håndtere usikkerheder, stokastiske parametre og ikke-lineær opførsel af problemet. Derfor er en prædiktivt HEMS designet baseret på et ikke-lineær model prædiktive kontrol (MPC) for at minimere bygningsenergiomkostningerne og imødekomme brugerens præference med hensyn til behovet for elektricitet og termisk energi. Efter det bedste fra forfatterens viden er dette den første undersøgelse i smarthus-konteksten, der overvejede brugerens termiske og elektriske krav ved hjælp af følgende HES-teknologier (home energy storeages); 1) PEV-batteri og 2) bygning af termisk masse (opvarmning / afkøling af bygningen gennem varmepumpe (HP)) som hjemmenergilagring. Brug af følgende teknologier som bygningslagre gør systemet mere rentabelt. Derudover foretages en afvejning mellem HEMS optimal drift og PEV-batteriets levetidsnedbrydningsomkostninger. Sidst, men ikke mindst, er simuleringsresultaterne valideret ved at sammenligne dem med et off-line optimeringsmodpart, der bruger alle fremtidige input på forhånd.

Endelig er det tredje bidrag at undersøge overskudsvurderingen af det designede HEMS i forskellige bygninger med forskellig opbevaringseffektivitet (forskellig termisk modstand), som blev indikeret af bygningsenergimærket fra “A” til “G”. Desuden undersøges virkningen af forskellige opvarmningsemissionssystemer, der påvirker bygningens termiske kapacitet. Resultaterne viser, at ikke kun den HEMS optimale ydelse ved bygning med korrekt opbevaringseffektivitet (Lable “A”) er mere bedre end den dårlige opbevaringseffektivitet, men også HEMS-ydelsen ved at opfylde optimeringsbegrænsningerne er meget tættere på det ønskede punkt end det bygning med dårlig isoleringskvalitet. Sidst, men ikke mindst, vises det, at gulv-radiatoropvarmningssystemet i en bygning med den samme energimærke kan forbedre HEMS-ydelsen i både energiomkostningsminimering og opfyldelse af begrænsninger sammenlignet med radiatoropvarmningsbygninger. På grund af gulv-radiatorvarmesystemet øges bygningens termiske opbevaringskapacitet. Forbedringerne er dog minimale for bygninger med energimærket “G”.

PREFACE

This thesis is submitted to the doctorate School of Engineering and Science as a collection of papers in partial fulfillment of the requirements for the Ph.D. degree at the Department of Energy Technology, Aalborg University, Denmark. The work was performed under the supervision of Associate Professor Amin Hajizadeh and Associate Professor Mohsen Soltani at the Department of Energy Technology, Aalborg University Campus Esbjerg in the period spanning from April 2017 to July 2020. During the Ph.D. six months study abroad was considered at the University of New South Wales (UNSW) in the School of Electrical Engineering and Telecommunications under the direction of Branislav Hredzak from August 2019 to February of 2020. However, I could not be there in person, I kept my connection and worked with Dr. Branislav Hredzak through online meetings. This work has been carried out in cooperation with the industrial partner Solar Flex (new name as Smart Enrgi) under the project "Smart home" and is partially supported by Dansk Energi (Elforsk program, Project No.350-005).

I would like to thank all my friends at Aalborg University, Campus Esbjerg for wonderful times we had during my Ph.D. program. I would like to thank all my colleagues at the Department of Energy Technology for providing resourceful and positive research environment. I would like to express my gratitude to my supervisors Amin Hajizadeh and Mohsen Soltani for their great supports, and their efforts to create excellent circumstances for both professional and personal development. Also, I would like to thank Branislav Herdzak for his contribution and his technical comments during my visiting research.

Lastly, I would like to express my sincere gratitude to my wife Nasrin Kinapoor for her endless support and to my family for encouraging me to follow my dreams throughout my entire life.

Mojtaba Yousefi

Aalborg University, July 01, 2020.

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PART I

EXTENDED SUMMARY

1. INTRODUCTION

1.1 MOTIVATION

Electricity consumption in Denmark is going to change in the upcoming years, especially in residential sections. The electricity demand is increasing as end-users are replacing traditional petrol-powered vehicles with plug-in electrical vehicles (PEV) and oil-fired burners with electric heat pumps (HPs). Therefore, the power network must be updated according to these changes with the same delivery quality as today. Moreover, these new upgrading has to meet Denmark's ambitious climate and energy-policy targets regulations such as reducing CO2 emission, improving energy efficiency means and integrating more renewable energy resources.

To meet the future end-users' energy demand with the contribution to the above targets, the exciting residential buildings should turn to smart buildings or nearly zero energy buildings (nZEB) according to the EU Commission after 2020 [1]. Buildings play a significant role in the future of sustainable power networks as about 40% of the total energy consumption and 36% of the European Union's emissions caused by them [2]. In a smart home, changing and increasing of electricity consumption can be managed efficiently as it provides a dynamic interaction between its resources, power system and consumers through metering, controlling and automation (similar to a smart grid). Therefore, a home energy management system (HEMS) is essential for a successful smart home. HEMS shifts and curtails households' demand through smart home resources to improve the smart home performance according to electricity price and consumer comfort [3]. A smart home can have a variety of resources, including renewable resources (photovoltaic array (PV)) and energy storage systems (ESSs) such as batteries, plugged-in electric vehicles (PEV) and thermal storages (building thermal mass and hot water tank). Due to the integration of volatile renewable energy resources, stochastic PEVs mobility patterns, and random household energy consumption, randomness parameters and uncertainties have become the major challenges for the HEMS performance in terms of efficiency and economics. Thus, stochastic dynamic energy management or closed-loop real-time optimization has to be implemented to reduce the uncertainties and stochastic parameters impact on a HEMS performance. Recently, researchers have focused on developing stochastic energy management for integrating HPs, PEVs, and renewable energy into the household's loads and grid.

Therefore, in this thesis a new energy management strategy is proposed for the smart home to minimize the daily electricity cost through a nonlinear model predictive control (MPC) (closed-loop online optimization) while fulfilling the energy load demand, PEV charging/discharging and user's comfortability requirements.

1.2 BACKGROUND

All the research disseminated in this thesis is accomplished as a part of the smart home project in cooperation with Solar Flex (new name as Smart-Energi) and co-funded by Dansk Energi (Elforsk program grant number: 350-005). Solar Flex (Smart Energi) provides advanced power electronics, alternative energy technologies, and building stored energy to turn the residential buildings to smart homes. The smart home project aims to significantly increase the HEMS performance and efficiency compared to the current HEMS by incorporating uncertainties.

1.3 SMART HOME CONFIGURATION AND OPERATION

A conceptual sketch of the smart home project is shown in Figure 1.1. The configuration includes PV, PEV, HP, grid, appliance (thermal and electrical), real-time internet-based data and HEMS. According to this figure, HEMS communicates with different home resources to ensure the power balance among all components in a way to minimize the cost of energy and meet the user's energy needs. The HEMS saves the extra PV power generation either in an EV battery pack, if available, or in the building's thermal capacity mass via heating/cooling the building space by HP, or by injecting the extra power into the grid. As can be seen in Figure 1.1, the HEMS uses weather forecast data, smart meter data and electricity price to improves its performance. In this thesis, irradiance, temperature, wind speed and humidity which influence the PV production and energy consumption are used as the meteorological data. The accuracy of PV and household load demand models increase by incorporating meteorological data such as outside temperature, wind speed, etc [4]. The PEV and HP are responsible for balancing the power flow between the grid, PV and household load demand. In other words, the extra PV power generation is saved as electricity in the PEV battery pack when it is available or is stored in the building thermal mass capacity. It is also barely possible to inject the PV power generation to the grid when both the PEV is not available and user comfort conditions are close to its acceptable maximum or minimum amount (close to its boundary constraints).

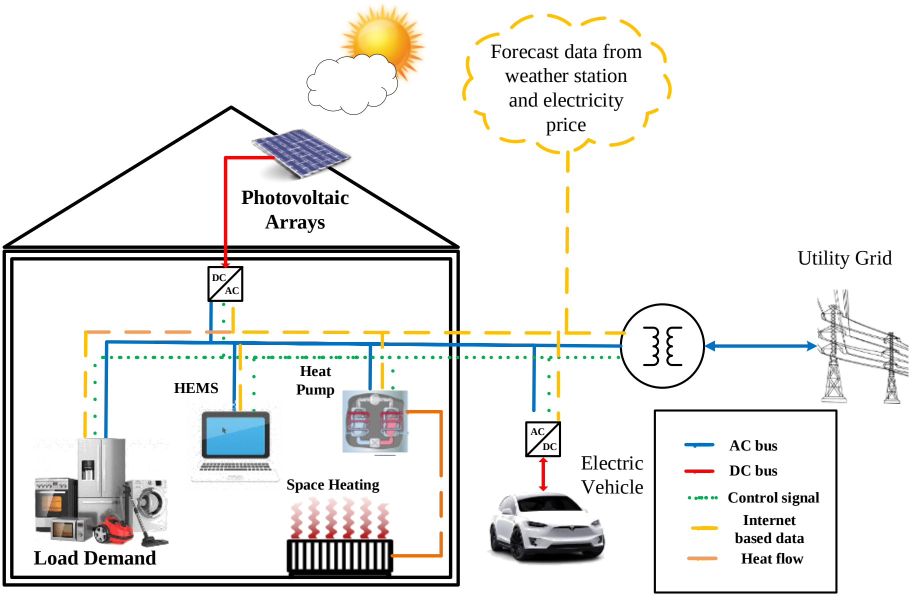


Figure 1.1. Overall structure of a smart home with its HEMS.

The power flow schematic is exhibited in Figure 1.2. The PEV is connected to a bidirectional AC/DC inverter and PV is coupled to a unidirectional DC/AC inverter to feed AC loads, HP, PEV and interface with grid. HEMS governess power flow among smart home components.

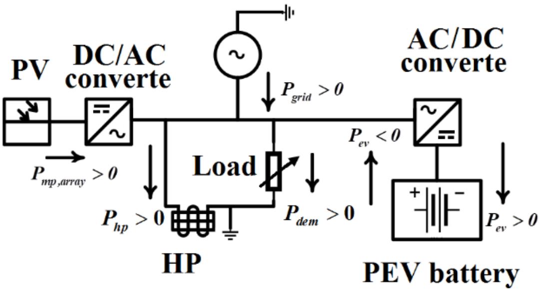


Figure 1.2. Electric circuit diagram of a smart home with power electronic technologies.

In this thesis, the home energy management system consists of two agents: Prediction Engine (PE) and Decision-Maker System (DMS). The overall schematic of the HEMS structure is shown in Figure 1.3. The proposed energy scheduling method is based on the moving window algorithm (MWA). According to this approach, the energy is scheduled in each period, and the agent will be updated in each period, as well. In the following, the tasks of these agents will be expressed.

Prediction Engine (PE) should provide the accurate prediction of all stochastic variables of the system such as wind speed, ambient temperature, electricity price, PEV status (plugged-in time and Plugged-out time), PEV battery energy at plug-in time, PV power production and home energy demand (electrical and load) for the DMS.

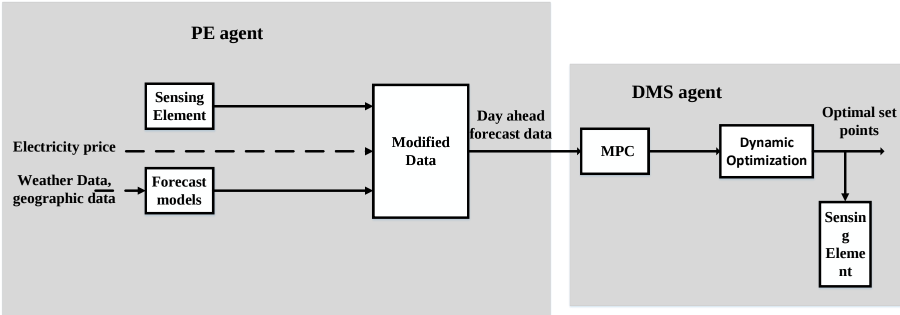


Figure 1.3. The HEMS structure and agents.

As mentioned above, the stochastic variables should be forecasted by PE. In this thesis, the PE uses weather station data and utility data to find forecasting of wind speed, ambient temperature and electricity price through the internet. The rest of random parameters such as PEV status, PEV battery energy at plug-in time, PV power production and home energy demand (electrical and load) are forecast by PE agent. DMS decides to charge/discharge PEV or heating/cooling the building based on the provided forecasted data such as electricity price, PEV status, building inside temperature, etc. Hence, the accurate forecasting of the PE can assist the DMS to fulfill the household requirements and minimize the cost of energy.

The task of the DMS is to make an optimum decision in the smart home. An optimum decision depends on the purpose of the smart homeowner. These aims can be minimizing the cost of the system, maximizing the profit of the system owner, increasing the reliability of providing the electricity, increasing the welfare of the resident, etc. Therefore, after the objective function is defined in the system, this agent should make an optimum decision. In this case, DMS faces a discrete optimization problem, which should satisfy different constraints related to different devices of the home such as loads, PVs, PEVs, and user’s thermal preferences. As mentioned before, the output signals of PE are the other inputs of the DMS that apply the uncertainty to the decision-making problem. There are different methods to deal with the uncertainty in the optimization problems like stochastic dynamic programming (SDP), interval optimization, robust optimization, online scheduling, Model Predictive Control (MPC), etc. MPC is the most common method for incorporating uncertainties to reduce the impact of forecast errors on DMS performance through smart meter data (real-time operation). The MPC manipulates the home resources variables to optimize the energy cost while satisfying the user's requirements. Then, the DMS (MPC) sets the optimum operating points for HP and PEV and sends the set points to the low-level controllers. Low-level controllers should control very fast and continuously between two-time steps of the discrete optimization of decision-making problem to keep the operating point of the home resources near the set points if the turbulence has happened in the system. At the end of each time step, smart meters measure real data and send new signals to DMS and PE to update them for the next time step to re-schedule the energy and update operating set points. In other words, the PE re-forecast the uncertainties and the DMS reschedules the optimum decision every time step according to the re-forecasted and smart meter data.

1.4 RESEARCH HYPOTHESIS

Following the discussion in the previous sections, the HEMS can improve the building energy efficiency, power quality, reliability and reduce the cost of energy and CO_2 emission using onsite renewable resources and flexible loads (PEV and HP).

The HEMS performance is highly dependent on the accuracy of forecasted data provided by PE and DMS performance to work with uncertainties. In order to find accurate models for home resources, the impact of uncertainties and random parameters on the PV, load demand, PEV and building inside temperature have to be modeled or estimated. For example, modeling the impact of wind speed and solar cell temperature (dependent on the ambient temperature) on the PV power output, improve the forecasting of the PV power output significantly. Therefore, a combination of physics-based modeling approaches (empirical model or numerical model) with data-driven models (using Artificial Intelligent (AI) (black box models)) is an alternative to capture the impact of uncertainties and un-modeled parameters for improving the PE forecasting. On the other hand, the DMS has to be able to reduce the effect of uncertainties and un-modeled parameters (forecast error) on the optimization performance through smart meter data, because it is not possible to find zero-error forecast models. Therefore, real-time closed-loop optimization techniques are the best candidates to deal with uncertainties such as MPC that swap its control signals in each time step according to smart predicted data. Hence, in this thesis, the expected outcome is to improve the energy efficiency by providing a proper MPC that can optimally coordinate the PEVs charge/discharging and HP rated power inside a smart home with significant penetration of renewable resources like PVs. Also, the system can potentially reduce the electricity consumption of the grid by 10-30% (depending on the profile of the user consumption and the building resources). Moreover, we expected that our work follows the policy climate and be economical, by the use of more renewable energy resources (maximizing PV self-consumption in buildings) and energy storage systems (ESS) such as PEVs and building thermal mass. Thus, in relation to improving the HEMS performance in minimizing the cost of energy and fulfilling the user's requirements, the research hypothesis is as follows:

- It is possible to improve the accuracy of forecasting using hybrid models (combination physics-based models with data-driven methods (massive measurement data or black-box models (AI and Artificial Neural networks (ANN)).
- It is possible to improve the optimization of the HEMS using adaptive controllers such as MPC and sensing elements (smart meters).
- Is the operating profits of the proposed HEMS improves in well-insulated buildings with different heat emission technologies.

1.5 OUTLINE OF THE PAPERS

Because the form of this thesis is a collection of papers, it is divided into an extended summary part and a part containing papers, which shows the contribution of the thesis. In the extended summery part, the background, motivation of the project and contribution of papers are presented.

Moreover, four conference papers, one book chapter and three journal papers (two published and one revised) on highly qualified peer-review journals are extracted from this thesis. The papers are numbered from A-H. However, only papers A, C, F and D are placed in the second part of this thesis because other papers are some parts of these papers. Furthermore, the chronology of the papers is exhibited in Figure 1.4 and the papers are described as follows:

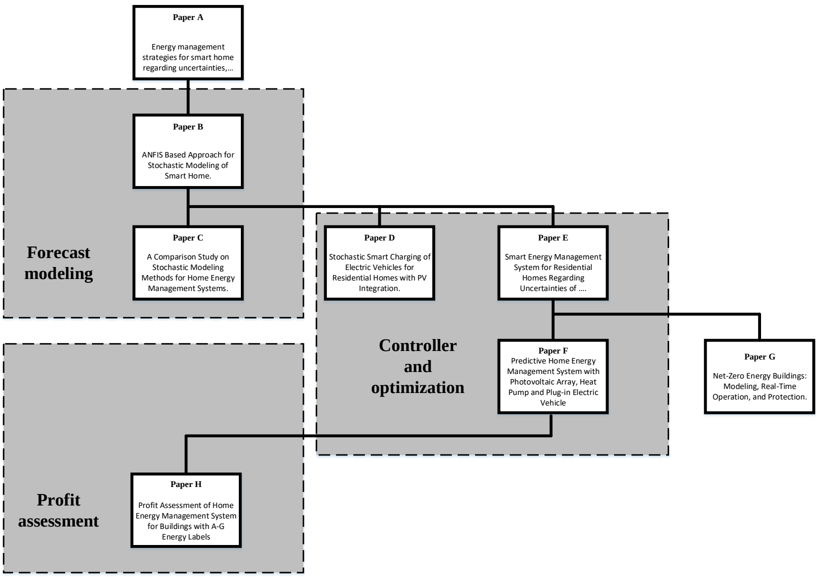


Figure 1.4. Chronology of the disseminated papers.

Paper A [5]

In this paper, a brief state of the art review of the context of smart home, HEMS, stochastic optimization methods, building resources and their different uncertainties is presented. Moreover, an overview of smart home and HEMS concepts in minimizing the cost of energy and CO_2 emission is given. The paper A is the starting point for the rest of the papers of this thesis.

Paper B [6]

The review in paper A proved that considering uncertainties and implementing stochastic methods can improve the HEMS performance in reducing the home energy cost. Therefore, in paper B, uncertainties related to the PV power output and home load demand are modeled through machine learning techniques such as ANN (multi-layer perceptron architecture) and adaptive neuro-fuzzy inference system (ANFIS). In this paper, it is proved that both ANN and ANFIS are proper tools for capturing the uncertainties of home load demand and PV power output. Finally, a stochastic model is obtained for the smart home with PV, PEV and HP. The results of the system are validated by the real measured data. The results of this paper lead to the study work in paper C.

Paper C [4]

As explained in paper B, some advantages of AAN models are their ability to approximate the nonlinearity of the system and they can keep improving as more data fed into them. But their downsides are highly dependent on the data quality & quantity, very bias to the data they trained based on them and not interpretable (black box). For this reason, in paper C, other data deriving modeling methods, which are combinations of physics-based modeling methods with either massive measurement data or data-driven approaches, are studied and compared with pure black-box models. The aim of paper C is to present a comprehensive comparison for modeling different smart home resources such as PV, PEV, building space heating and home energy demand through other data-driven and probability methods. Finally, the accuracy, pros and cons of each model are discussed and reviewed. The results of paper C give rise to works D, E, F, G and H.

Paper D [7]

This paper aims to design a controller for smart charging/discharging of the PEV in a residential building with the models obtained in paper C. In this paper, the closed-loop controller has to track a desire set point (SOC) of the PEV when it is available.

This study is a fundamental study of the papers E and F to investigate the role of PEV on HEMS performance.

Paper E [8]

In paper E, a HEMS is formulated for a smart home to minimize the electricity cost under time-varying electricity price signals, PV, household demand and PEV uncertainties. Besides, the PEV charging/discharging and home electrical power demand requirements have to be satisfied smartly and optimally. In this study, only the electricity need for energy is satisfied and user's thermal comfort and thermal energy needs are not studied. Therefore, paper F is proposed to complement and improve paper E.

Paper F [9]

Paper F is a consist yet extended version of paper E. In this work, the HEMS has two effectively manipulate variables (PEV and HP) in order to minimize the cost of energy according to electricity tariffs of use. Moreover, the battery lifetime degradation, user thermal comfort level and fast dynamic behavior of the system studied. The outcomes of paper F utilized in paper H to investigate the profits of designed HEMS in highly insulated and poorly insulated buildings with different heat emission systems.

Paper G [10]

Paper G is a combination version of the all the above mentioned works with more details. This work aims to present a tutorial study for researchers who are interested in working in this context with different applications such as modeling monitoring, fault detection and protection applications.

Paper H [11]

In previous papers, the advantages of HEMS for residential buildings in terms of minimizing cost and improving comfortability are discussed. However, there is still a need for a study to evaluate the profit assessment of real-time HEMS in existing residential buildings with different energy labels (insulation quality). In paper H, the profits of implementing real-time HEMS in buildings with varying labels of energy are investigated. Moreover, the impact of building thermal capacity on the HEMS performance is studied considering two different heating systems: radiator only and a combination of floor–radiator system in each building. The results show that the HEMS performance increase in a building with proper insulation quality rather than building with poor insulation quality. Finally, it is observed that the floor-radiator heating system can improve the HEMS performance in terms of minimization of the energy cost and meeting the user's requirements rather than the radiator only system.

However, these improvements can be negligible for buildings with poor insulation quality (buildings with labels “F” and “G”).

2. STOCHASTIC MODELING OF SMART HOME RESOURCES

2.1 INTRODUCTION

The first essential step in designing an effective HEMS is to obtain appropriate models for the smart home resources, including PV model, building space heating/cooling dynamics, user's thermal preference model, PEV charging/discharging model, and electrical home load demand. Therefore, the uncertainties and stochastic parameters of each of the mentioned components are studied in this section. Then, some models are presented by different modeling techniques, such as physics-based modeling methods, data-driven methods and hybrid modeling methods (a combination of the two last modeling methods), which somewhat incorporate uncertainties. Last but not least, the strengths and weaknesses of each technique are discussed.

In this chapter, only different modeling methods of each component are introduced and discussed. The results about validation and accuracy of each model are presented in paper C [4], in which the introduced modeling methods in this chapter are used to model different home resources. Then obtained models are validated and their accuracies are compared.

2.2 PHYSICS-BASED MODELING

Physics-based modeling methods are the most common approach in the engineering community for modeling physical phenomena. It constitutes three following stages: 1) Observing a physical system of interest; 2) developing partial understanding 3) finding mathematical equations, which describe the process understandings, and solving them ultimately [12]. In the literature, these methods broadly subdivided into experimental and numerical modeling. Empirical modeling includes full-scale laboratory experiments to understand a physical phenomenon and find correlations and models of quantities of a system. On the other hand, numerical modeling is a process of developing mathematical modeling of a physical object and perform on a computer to predict the behavior of a physical system. One of the great advantages of physics-based modeling methods is that they are less biased than data-driven models because they are driven by natural laws. However, the main disadvantage of these methods is that they can only model known part of a system and a large part of the physics may be ignored according to the partial understanding and assumptions [12]. Moreover, they can be too computational demanding and can be led to numerical instability due to complexities of the equations. In order to address these issues, data-driven approaches are proposed.

2.3 DATA-DRIVEN METHODS

Nowadays, data-driven approaches are getting more and more attention because of abundant sources of data, open-source libraries (TensorFlow and openAI) and cheap computational infrastructures like CPU. By data-driven modeling, full physics of a process can be modeled because data is treated as a manifestation of both known and unknown natures' laws in these modeling methods. Generally, data-driven modeling consists of data generation, data processing, safety and advance data-driven modeling techniques. Thanks to the availability of cheap sensors technologies, the data can be generated and stored in comprehensive databases [13]. These data can be used for training machine learning (ML) models, which are broadly utilized for analyzing data. ML is a study of algorithms and statistical models that can keep on improving through feeding more and more data (experience) to them [14]. In the literature, ML is sorted into supervised, unsupervised and reinforcements learning. In this thesis, supervised algorithms, are discussed and presented for obtaining forecast models for building resources [12].

Supervised learnings are techniques to provide learning mappings from independent variables to dependent variables in classification or regression applications. Decision tree, ANFIS, ANN, deep neural network (DNN) are the most popular supervised learning. The most advantages of ML algorithms are that 1) their training models can be improved as more data fed into them, 2) they can model unknown physics of a process and uncertainties, 3) the trained models are very stable for prediction applications. However, it has some disadvantages as well, 1) they are uninterpretable, 2) they are not effective in the absence of enough data, 3) they are extremely biased upon the data they were trained on. Therefore, new modeling approaches which are a combination of physics-based models and data-driven methods are proposed as hybrid modeling methods to address the shortfalls of the aforementioned modeling methods [12].

2.4 HYBRID MODELING

Hybrid modeling is defined as a modeling method, which incorporates the understanding of a physics-based modeling approach with either the accuracy and pattern-identification capabilities of advanced data-driven algorithms or big data (measurements) or combination of all of them. In hybrid modeling, the known physics of a physical process (main principles roles of a physical system) is modeled by mathematical equations, whereas the unknown parts (disturbances, perturbation and stochastic parameters) are obtained through either ML techniques (ANN and DNN techniques) or big data measurement. The different modeling techniques are presented in Figure 2.1. As can be seen, the hybrid modeling can be placed at the intersection of big data, physics-based modeling and data-driven modeling.

All aforementioned modeling techniques are used in the smart home literature to model different components used inside the smart home. In sequence, they are explained.

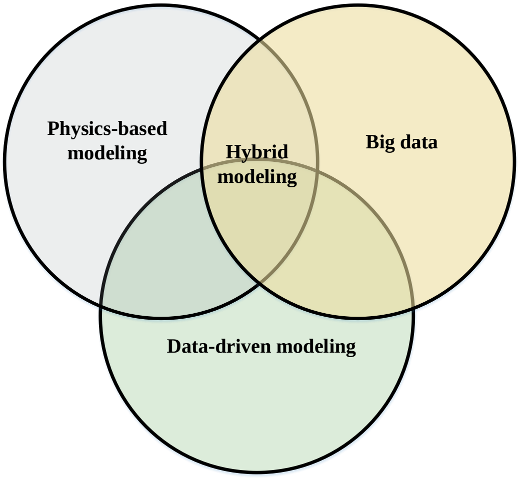


Figure 2.1. Hybrid analysis and modeling.

2.5 PV MODELING

PV systems are one of the critical components of a smart home, which can supply a big proportion of the needs for energy in a residential building in a clean way. Therefore, finding an accurate and proper model for PV systems is essential for the HEMS performance in minimizing the cost of energy and satisfying the user's needs. The PV power output is very stochastic and volatile, due to many factors such as the time of day, clouds, wind speed, pollution, humidity, etc [15]. Therefore, the effects of these factors have to be considered in the obtained PV model to improve the PV model accuracy. Many studies proposed some PV models which incorporate some of these uncertainties for calculation of the PV output. Physics-based modeling, data-driven approaches and hybrid modeling are utilized in PV modeling literature. In Table 2-1, an overview of PV generator models through the mentioned techniques are presented. According to Table 2-1, the PV physics model (obtained through physics-based modeling method) more often is used in research related to the manufacturing and development of solar cell materials and aimed to describe the behaviors of the photovoltaic materials (2D, 3D FEM models). The electrical equivalent models (can obtain through either physics-based modeling or hybrid modeling) are often used for maximum power point tracking (MPPT) control, shading modeling and PV depredation. Finally, the PV performance models (hybrid models, data-driven approaches and physics-based modeling) are often employed for planning, performance analysis and PV energy production. The PV performance and electrical equivalent models are presented in this thesis since the PV energy generation is essential for the HEMS.

Table 2-1

PV power generation models

Types Functions	**Physics-based models**	**Electrical equivalent models**	**Performance models**
Energy production			
Electrical behavior			
Physics behavior			

Not applicable	**Applicable**

2.5.1 PV EQUIVALENT CIRCUIT MODEL

There are many equivalent circuit models for PV systems such as three-parameter model, four-parameter model, five, six or seven parameter-model, etc [16][17]. As an example, the four-parameter model is illustrated in this subsection [18]. This model is an electrical circuit that includes an ideal current source paralleled with a diode and resistance R_p and series with a resistance R_s. The variable R_s represents the resistance between the conductor and semiconductor material, while the diode represents the semiconductor materials in this model. The four-parameter equation is given as follows [18]:

$$V_{cell} = V_d \times I_{Pv} R_s, \tag{2.1}$$

$$I_{pv} = I_{cs} - I_s \left[e^{\left(\frac{qV_d}{AKT_C}\right)} - 1 \right] - \frac{V_d}{R_p},$$

$$I_{cs} = \left[I_{cs,ref} + K_I (T_C - T_r) \right] {\rho_e}/{1000},$$

$$T_c = \rho_e e^{(a+bv_w)} + T_a, \tag{2.2}$$

$$p_{pv,array} = N_s N_m n_c V_{cell} I_{pv}, \tag{2.3}$$

where V_{cell} and V_d are the voltages of PV cell and diode respectively; I_{pv} is the output current of PV cell , I_s is the current saturation, and $I_{cs,ref}$ is the reference short-circuit current of the PV cell at standard test condition (STC) (25 $^\circ C$ and 1000 w/m^2); A, k and q are an ideal factor, the Boltzmann’s constant, and an electron charge, respectively; T_c , T_a and T_r are the PV cell, ambient temperature and reference temperature respectively; ρ_e and v_w are the effective solar irradiance and wind speed respectively; a and b are empirical parameters, and K_I is the short-circuit current temperature coefficient; $P_{pv,array}$ is the output power of the PV arrays, and n_c is the number of cells in series in a module’s cell string; the variables N_m and N_s are the number of modules and subarrays respectively. The variable ρ_e can be calculated through sun position and clear sky models [19][20]. In this model, since the parameters a and b are estimated through measurement-based data, therefore, this model is obtained through hybrid modeling techniques (physics-based modeling combined with data-driven methods and big data analysis). For the rest of the models, the reader can conclude what type of modeling methods are used.

2.5.2 SIMPLE PV PANEL EFFICIENCY MODEL (SIMPLE MODEL)

As shown in Eq. (2.4), the PV output is a linear function of effective irradiance ρ_e in this model. It can be parameterized from the PV panel datasheet. As it is evident, many parameters, such as the effect of temperature and wind speed, are not modeled, so, the model accuracy is not proper for PV power prediction [21].

$$P_{pv,array} = N_s \times N_m \times \left(\frac{\rho_e}{\rho_s} P_{pv,m} \right), \tag{2.4}$$

where $P_{pv,m}$, and $P_{pv,array}$ are the maximum point of the PV power for the PV module and array (kW), ρ_s is the solar irradiance under STC ($1000 W/m^2$).

2.5.3 PVWATT MODEL

In this model, the PV output power is a linear function of effective irradiance and solar cell temperature, as presented in Eq. (2.5). Because of solar cell temperature consideration (wind speed and ambient temperature impacts are modeled based on Eq. (2.2)), the accuracy of this model is more than the Simple Model. Likewise, the previous model, it can be parameterized from the PV module datasheet [22].

$$P_{pv,array} = N_s \times N_m \times P_{mp,m}\left[1+\gamma\left(T_c - T_r\right)\right]\frac{\rho_e}{1000}, \tag{2.5}$$

where the variable γ is the peak power normalized temperature factor ($1/^{\circ}C$).

2.5.4 SANDIA PV ARRAY PERFORMANCE MODEL (SAPM)

The SAPM is an empirical model that is obtained by the solar technologies department at Sandia[23]. In this model, photovoltaic module characteristics such as electrical, thermal, and optical characteristics are considered in the model, and the model is designed to use hourly solar resources and meteorological data. In this model, the PV power output is a nonlinear function of effective irradiance and PV cell temperature. The SAPM equations are as bellows[23]:

$$\begin{aligned} I_{mp} &= \mathrm{I}_{mp,ref}\left(C_0\rho_e + C_1\rho_e^2\right)\left[1+\hat{\alpha}_{mp}\left(T_c - T_r\right)\right] \\ V_{mp} &= V_{mp,ref} + C_2 n_c \delta\left(T_c\right)\ln\left(\rho_e\right) + \\ &\qquad C_3 n_c\left[\delta T_c \ln\left(\rho_e\right)\right]^2 + \beta_{mp}\left(T_c - T_r\right), \\ P_{mp,array} &= N_s \times N_m \times I_{mp} \times V_{mp} \end{aligned} \tag{2.6}$$

$$\delta\left(T_c\right) = A\frac{kT_c}{q}, \tag{2.7}$$

where I_{mp} and V_{mp} are the PV current and voltage at maximum power point; $I_{mp,ref}$ and $V_{mp,ref}$ are the PV current and voltage at maximum power point under reference condition respectively; C_0 and C_1 are empirical parameters which determine the coefficients relating I_{mp} to effective irradiance respectively; likewise C_2 and C_3 are empirical parameters which determine the coefficients relating V_{mp} to effective irradiance respectively, α_{mp} and β_{mp} are the normalized temperature factor for I_{mp} ($1/^{\circ}C$) and temperature coefficient for module maximum power-voltage V_{mp} ($V/^{\circ}C$). $\delta(T_c)$ is thermal voltage' per cell at temperature T_c. It is about 26 (mV) per cell for diode factor of unity (n=1) and a cell temperature of 25ºC. The SAPM accuracy is about $\pm 1\%$, which is very high [23]. It can also be used for modeling various PV technologies. In this thesis, the system advisor model (SAM), which is a desktop application, is employed to compute the PV power output by using the above-mentioned PV performance models [21]. SAM calculates the PV power performance by given the system specification data and typical meteorological year data (TMY). The TMY data contains information associated with the location of the PV systems, including latitude, longitude, time-zone, elevation, as well as meteorology data, including ambient temperature, wind speed, and solar irradiance for one year. Thanks to this information, SAM can calculate sun position, effective irradiance, the temperature of PV cell, DC loss of arrays and inverter loss. More information related to SAM can be found in [21].

2.5.5 ANN-BASED PV PERFORMANCE MODEL

PV performance modeling literature is reached by different ANN architecture to forecast the PV output power. ANN are computational systems, inspired by the neural network of animal brains [24]. Different ANN architecture, including multilayer perceptron (MLP) [25], radial-basis function neural network (RBF-NN)[26], recurrent neural network (RNN) [27] and adaptive neuro-fuzzy inference system (ANFIS) [6] have been employed to obtain black-box models for the PV power generation. These methods are explained in this subsection.

2.5.5.1 MLP

The MLP structure is the most popular type of ANN for load and PV power production [28]. The MLP architecture includes input layers, hidden layers, and output layers. A representative of MLP architecture is illustrated in Figure 2.2. In this architecture, the inputs of the output layer are the outputs of the hidden layer. The MLP formulation is expressed for Figure 2.2 as given [28]:

$$y_k = \sum_{j=1}^{4}\left(U_{k,j} \bullet \frac{1}{1-\exp\left(-\sum_{i=1}^{3} W_{ji}x_i + \Theta_j\right)}\right) + \Theta_k \tag{2.8}$$

where W and U are the weight matrixes and Θ_k is the bias vector. For training the MLP, the back-propagation algorithm is frequently used, which employs the steepest descent approaches such as the Levenberg-Marquardt Algorithm by computation of the loss function gradient toward to the ANN parameters.

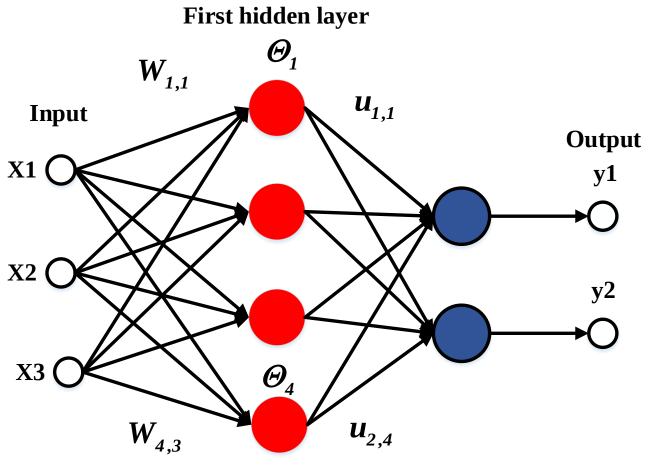


Figure 2.2. A representative MLP architecture with two hidden layers.

2.5.5.2 RBFNN

RBFNN is very similar to MLP in terms of structure and architecture, which is composed of input, hidden and output layer and the output of one layer is the input of another layer. However, the RBFNN has only one hidden layer compared with the MLP, which can have many layers. Besides, the transfer function in the hidden layer of the RBFNN is a radial basis function (RBF). A traditional RBFNN with n neurons and Gaussian RBF can be formulated as bellows [29]:

$$
\begin{aligned}
y_k &= \sum_{j=1}^{n} W_j h_j(x), \\
h_j(x) &= \exp\left(-\frac{\left(x_j - c_j\right)^2}{r_j^{\,2}} \right)
\end{aligned}
\tag{2.9}
$$

where C_j and r_j are the center and variance of the Gaussian function. RBFNN has frequently used for regression problems such as PV performance model application and the responses of RBFNN change (increase/decrease) with the distance to the central point.

2.5.5.3 RNN

Today, Deep learning algorithms are promoting tremendously compare with shadow learning algorithms such as MLP or RBFNN algorithms [30]. In contrast with RBFNN and MLP, the deep learning algorithms have a lot of numbers of hidden layers, which can capture more nonlinearities and uncertainties of the problem [31]. Thus, for capturing the nonstationary and long-term dependencies of the forecast problem, the RNN is employed as a powerful deep learning algorithm. The RNN formulation is proposed as [31]:

$$\begin{aligned} S_t &= f\left(U \times x_t + W \times S_{t-1}\right) \\ y_t &= g\left(V \times S_t\right) \end{aligned} \tag{2.10}$$

where the $f(.)$ and $g(.)$ are nonlinear functions of weight matrixes W, U V and network memory S_t . RNN architecture is exhibited in Figure 2.3.

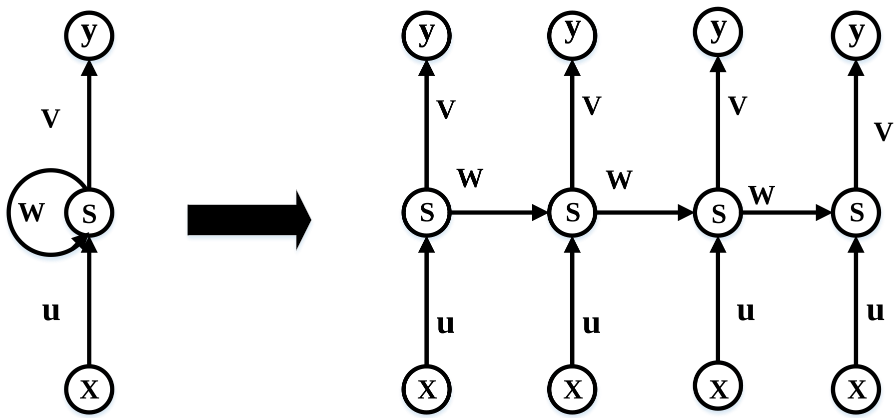


Figure 2.3. A simple schematic of an RNN architecture.

In the structure of the RNN, network memories (internal state) play critical roles as they process the sequence of inputs, unlike the weight connection in the basic neural network [32]. In RNN, the output is computed based on the current time and last memories, because the information of the former time step can be stored in the hidden states. For this ability (information transmission from the last node to the next node) the RNN performance is much better than shallow learning algorithms especially when the output is near to its related inputs. Due to the transmission of information from the last node to the next node, the performance of the RNN is quite good. Today, RNN is using widely in regression prediction problems such as load forecasting and PV power generations.

2.5.5.4 ANFIS

In order to take the advantages of ANN methods and the fuzzy inference linguistic expression function, ANFIS modeling approaches are proposed. ANFIS training is easier than ANN and needs less computational power because logics of a physical asset are involved during its training [33]. Nevertheless, because this is a data-driven approach, its performance is highly dependent on the quality of the provided data. In this approach, any nonlinear functions can be estimated by the fuzzy inference system part of ANFIS according to a set of fuzzy "if-then" rules [34]. ANFIS is frequently employed for load and PV power forecasting applications as well [35]. A representative ANFIS structure for PV power forecasting application is presented in Figure 2.4. Months, days of a week, hours, humidity, wind speed, solar irradiance, and ambient temperature are applied as inputs to the ANFIS and historical PV power is used as target or output of the trained ANFIS. Moreover, in literature, it is recommended to use Gaussian membership functions with subtractive clustering methods to generate fuzzy-inference for multiple input systems.

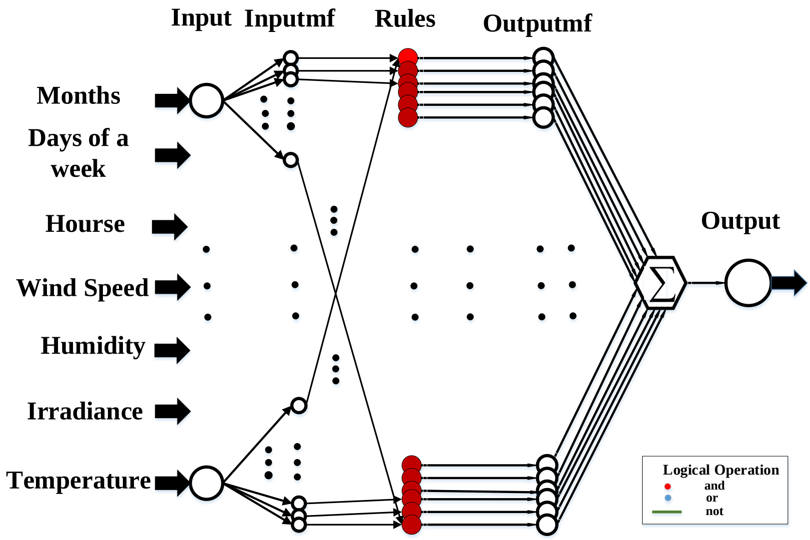


Figure 2.4. ANFIS architecture for forecasting PV power output.

2.6 HOUSEHOLD DEMAND MODEL

Similar to the PV performance modeling, load modeling has been obtained through different techniques such as data-driven methods or hybrid modeling methods. In this section, different load modeling techniques in literature are presented. Generally, load models can be divided into static models, dynamic models and composite load models which are obtained through data-driven modeling approaches.

2.6.1 STATIC LOAD MODEL

In this model, the home load power is a function of bus voltage magnitudes and frequency at any instant of time. Commonly, this model is used to represent static loads in power systems such as resistive loads, and sometimes as an approximation for dynamic loads, e.g., induction motors, but can be applicable for home load demand modeling as well. This model is presented as [36]:

$$\begin{aligned} P_{act} &= P_{act,0}\left(\frac{V}{V_0}\right)^a \\ Q_{react} &= Q_{reac,0}\left(\frac{V}{V_0}\right)^b \end{aligned} \tag{2.11}$$

where P_{act} and Q_{react} are power active and reactive at voltage bus magnitude V , respectively; subscribe 0 refers to the initial operating condition. In the literature, the Eq. (2.11) are widely rewritten as the ZIP model, which composed of constant current I, constant impedance Z and constant power P. In this model, the active power and reactive power modeled the voltage of the load in a polynomial format given by [37]:

$$\begin{aligned} P_{act} &= P_{act,0}\left[p_1\left(\frac{V}{V_0}\right)^2 + p_2\frac{V}{V_0} + p_3\right] \\ Q_{react} &= Q_{reac,0}\left[q_1\left(\frac{V}{V_0}\right)^2 + q_2\frac{V}{V_0} + q_3\right] \end{aligned} \tag{2.12}$$

where p_1 to p_3 and q_1 to q_3 are the model parameters that have to be identified through identification techniques.

2.6.2 DYNAMIC MODELS

The static model performance can be justified for fast dynamics loads, which reach their steady-state responses quickly. However, there are some cases that dynamic load components have to be accounted for accurate representation. In dynamic models, active power and reactive power are represented as a function of voltage and time. In a building, thermostatic loads such as refrigerators, heating/cooling systems and water heater are the most significant aspect of dynamic characteristics of building loads. The dynamic loads are explained in section 2.8 of this thesis.

2.6.3 COMPOSITE LOADS

Similar to PV performance modeling, data-driven modeling techniques such as different ANN architectures included MLP, RBFNN, RNN, and ANFIS are extensively utilized for load modeling [28], [26] and [38]. Both dynamic (thermostatic loads and induction motors) and static loads can be modeled through the above-mentioned techniques by having historical data of householders' consumption. In other words, ANN methods have no physical meaning and entirely rely on measurement data. An ANN is combined with a set of processing neurons or units which interconnected by weights. The ANNs are trained by using a sequence of input and output patterns, which leads to the final computed weighted values that determine the load model. Two ANN based modeling methods are presented in [39]. Moreover, [40] provided an ANN-based composite load model for stability study purposes in which a two-step RNN algorithm was developed in the first step an RNN trained with simulation data and the trained RNN update itself using measurement data in the second step. Although ANN is very powerful in modeling complex nonlinear systems, data quality and obtaining enough data over a wide range of operating conditions are still challenging.

To prevent duplicating sentences and approaches, these architectures are not illustrated in this subsection (refer to subsection 2.5.5), but these techniques are used in extracted papers of the thesis for both load modeling and PV forecast modeling.

2.7 PEV MODELING

The challenges for modeling a PEV in a building arise from uncertainties related to the PEV trip time model (plugged-in time and plugged-out time) and PEV state of charge (SOC) at plugged-in time. Thus, in this section, these uncertainties are modeled through famous probability-based techniques.

2.7.1 PEV TRIP TIME MODEL

The PEV status X_k (available $X_k = 1$/not available $X_k = 0$) is a very stochastic parameter. Therefore, to capture this uncertainty, probability-based techniques (data-driven methods) such as Markov chain and roulette wheels mechanism (RWM) with truncated Gaussian distribution are employed in literature to forecast the PEV plugged-in and plugged-out times.

2.7.1.1 Markov Chain

Markov chain is a kind of mathematical system based on a specific transient probability matrix, which experiences the transition from one state to another state [4]. In this system, the transition probability to any particular state only relies on the current state and time elapsed. The Markov chain is the most common method in the

PEV literature for modeling the PEV status. A represented Markov chain with two states is shown in Figure 2.5, which is an excellent example of the PEV status. As it is seen, if the transient probability from zero state to one state is equal to $C(k)$, the probability of the zero state to keep its current status is $1-C(k)$ at time k and vice versa. The transient probability matrix can be obtained through analyzing massive data relating to the householder's daily traveling patterns. More information related to the amount of transient probability can be found in [15].

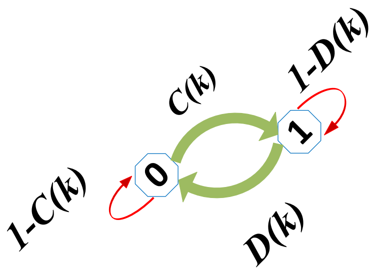


Figure 2.5. A representative Markov Chain with two states (zero state and one state).

2.7.1.2 RWM

RWM is another probability-based technique that is used in literature to forecast the PEV status by truncated Gaussian distribution. This distribution is widely employed for PEV plugged-in time, plugged-out time and even for PEV plugged-in SOC. For more information and distribution, details refer to [41].

2.7.2 PEV BATTERY ENERGY AT PLUG-IN TIME MODEL

One of the critical values is the forecasted amount of the SOC of the PEV battery at arrival time for HEMS to improve its effectiveness. The SOC of PEV value at the plugged-in time affects by several factors such as traffic condition, driving distance, driving style, number of users, etc. In this thesis, only the effect of driving distance is considered. The SOC value at the plugged-in time is calculated as [9]:

$$SOC_{in} = \begin{cases} SOC_{\min}, & if\ SOC_{out} - SOC_{cc} \times d \leq SOC_{\min}, \\ SOC_{out} - SOC_{cc} \times d, & otherwise, \end{cases} \qquad (2.13)$$

where $SOC_{cc} = 0.159 / Q_{PEV}\ (1/km)$; SOC_{in} and SOC_{out} are SOC values at arrival and departure times respectively; $SOC_{\min}$ is the acceptable minimum value of SOC; d is the driving distance (km) and Q_{pev} is the PEV battery capacity (kWh). According to Eq. (2.13), the amounts of SOC_{out} and d are needed for forecasting SOC_{in}. The amount of SOC_{out} is the known value while the amount of d is unknown. Thus, the conditional probability method and again RWM with truncated Gaussian distribution are utilized to estimate the driving distance which results in finding SOC_{in}. Because RWM is explained above, only conditional probability is presented here.

2.7.2.1 Conditional Probability

One of the essential concepts in the probability theory is the conditional probability that the probability of occurring an event is conditional to happening another event. It is a valuable method to calculate the conditional probability of $SOC_{in} = A$ for a given $SOC_{out} = B$. It can be calculated by analyzing massive data related to the daily driving distance of PEVs. In this thesis, the data are obtained from the US national household travel survey 2009 [42]. The conditional probability SOC_{in} for a Nissan leaf with a 24 (kWh) battery pack is presented in Figure 2.6 according to this data.

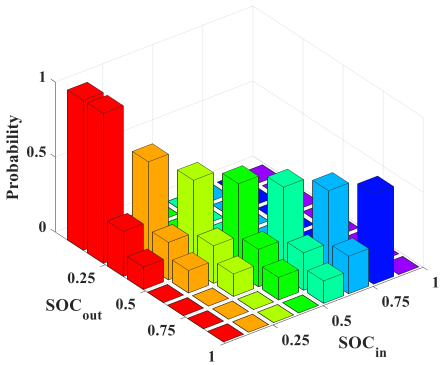


Figure 2.6. Conditional Probability of SOC_{in} by given SOC_{out}.

2.7.3 PEV BATTERY SOC MODEL

When the PEV is available for HEMS, its function is like stationary batteries and the PEV battery SOC charging/discharging dynamics is formulated as follows:

$$SOC_{k+1} = SOC_k + \Delta t\left(Z_k - \eta\left|Z_k\right|\right), \qquad (2.14)$$
$$Z_k = P_{ev,k}^{\pm} \big/ Q_{pev},$$

where Δt is the time interval; $P_{ev}^{\pm}$ is the power charging/discharging of the PEV (sign $\pm$ denotes to charging mode (the PEV power is positive) or discharging mode (the PEV power is negative)), respectively; η is the loss efficiency. Moreover, the SOC of the PEV battery has to meet the following constraint:

$$SOC_{\min} \le SOC_k \le SOC_{max} \qquad (2.15)$$

where SOC_{max} and $SOC_{\min}$ are the maximum and minimum amounts of the SOC respectively. To sum up, the SOC dynamics of the PEV battery for an entire day turn to a nonlinear peace-wise function which is presented below:

$$SOC_{k+1} = \begin{cases} SOC_k, & X_k = 0,\ X_{k+1} = 0 \\ \Pr o\left[\left(SOC_{in}\right)\right]_{SOC_{\min}}^{SOC_{\max}}, & X_k = 0,\ X_{k+1} = 1 \\ SOC_{k+1} = SOC_k + \Delta t\left(Z_k - \eta\left|Z_k\right|\right), & X_k = 1,\ X_{k+1} = 1 \\ SOC_{k+1} = SOC_k + \Delta t\left(Z_k - \eta\left|Z_k\right|\right), & X_k = 1,\ X_{k+1} = 0 \end{cases}, \qquad (2.16)$$

where the term "*Pro*" refers to the conditional probability of SOC_{in} by given a specific SOC_{out} .

2.8 SPACE HEATING/COOLING DYNAMICS AND USER THERMAL PREFERENCE MODEL

Building thermal mass or capacity is a potential candidate for use as energy storage systems in building, especially in highly insulated buildings [43]. However, it should not compromise the householder's thermal comfort preferences. Thus, the dynamic models of building space heating and user's thermal preference are very critical for HEMS's successful performance. In this section, the building thermal dynamics and user's thermal comfort model, such as adaptive predicted mean vote-percentage (APMV) are presented.

2.8.1 BUILDING THERMAL DYNAMICS

The building's thermal capacities and building thermal resistance are critical parameters to obtain proper models for space heating/cooling of a building. Building thermal capacity and building thermal resistance significantly affect building storage efficiency. The thermal capacity of a building can store or release the heat energy dynamically over time. Due to the ability to use heat gains in winter and smoothing temperature peaks in summer, the building's thermal mass or capacity plays a vital role in improving the building's energy performance [44]. Another critical factor is the building transfer of heat through the building's envelope. The overall heat losses in a building are included in heat losses from opaque surfaces (walls, roof and floors), heat losses from windows and heat losses through thermal bridges (window frames, and uninsulated slab edges) according to the standard EN ISO 13789:2007 [44]. The heat losses through different parts of a building distribution are exhibited in Figure 2.7 [44]. A large proportion of the overall energy loss is passed through attics and walls, according to Figure 2.7. Therefore, using highly insulated materials can result in thousands of dollars saving in energy bills. In this thesis, a detached single-family house with plinth foundations is considered. For simplicity, the building thermal dynamic load is considered as a first-order RC model based on the total building thermal capacity and whole building thermal resistance. In this model, the concrete slab floor, light, wooden and other parts of the building capacity are lumped to the overall building thermal capacity. Also, the walls, floor, windows and roof thermal resistance are lumped in the overall building thermal resistance. Moreover, different technologies like electric water heaters (EWH), heat ventilation air conditioner (HVAC) and HP are frequently employed for cooling and heating of buildings through either radiator only or floor-radiator combination heating system. In this thesis, ground source HP is used and its structure is presented in Figure 2.8 for cooling and heating purposes. Furthermore, the building thermal dynamics are formulated as given in [9] and [45]:

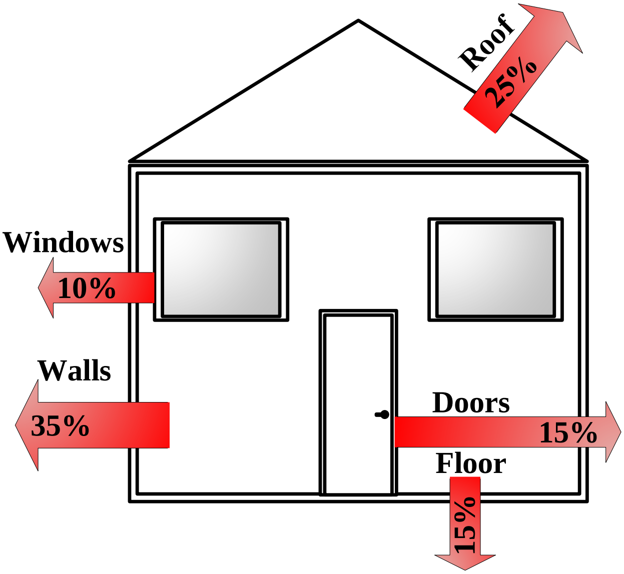


Figure 2.7. Heat transfer distribution among different components of a building.

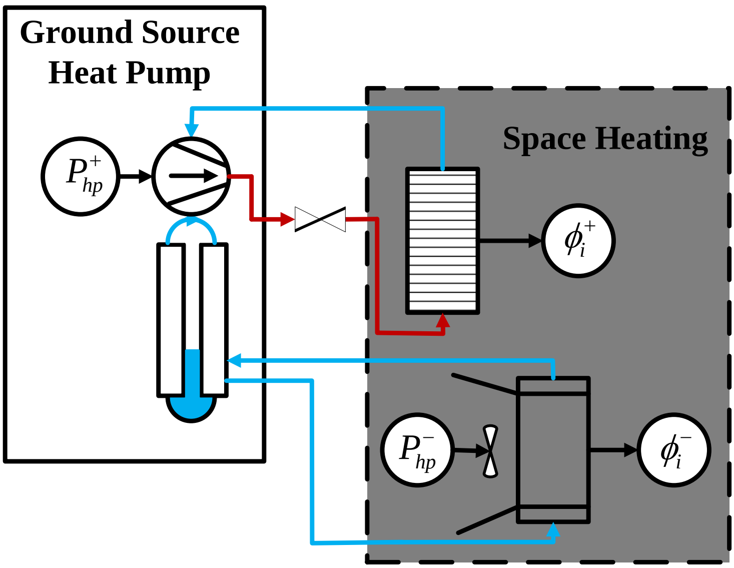


Figure 2.8. Heat emission system with a ground source heat pump.

$$T_{in,k+1} = T_{in,k} e^{-\frac{\Delta t}{\tau_{overall}}} + \left(T_{out,k} \pm R_{overall} \phi_{i,k}^{\pm}\right)(1 - e^{-\frac{\Delta t}{\tau_{overall}}}) \tag{2.17}$$

$$\tau_{overall} = C_{overall} R_{overal} = C_{building} \left(1/\Lambda_{overall}\right), \tag{2.18}$$
$$\phi_i^{\pm} = COP \times P_{hp,k}^{\pm},$$

where $C_{overall}$ $\left(kWh/{}^{\circ}C\right)$, R_{overal} $\left({}^{\circ}C/kW\right)$ and $\Lambda_{overall}$ $(kW/{}^{\circ}C)$ are the overall building thermal capacity, resistant and conductivity respectively; $\tau_{overall}$ is the overall building thermal time constant; $\phi_i^{\pm}$ and $P_{hp}^{\pm}$ are the heating/cooling thermal and electrical power (the signs ± denote the heating and cooling modes of HP) (kW) respectively; *COP* is the HP coefficient of performance; T_{in} and T_{out} are inside and outside of building temperatures $\left({}^{\circ}C\right)$ respectively. According to Eq. (2.18), the ambient temperature and $P_{hp}^{\pm}$ are inputs of the system, but the ambient temperature is like a stochastic disturbance. HEMS has to manipulate the $P_{hp}^{\pm}$ in a specific range to keep the user's thermal comfort (APMV criteria) in an acceptable interval as given by:

$$\begin{cases} P_{hp}^{\min} \le P_{hp}^{\pm} \le P_{hp}^{\max} \\ APMV^{\min} \le APMV \le APMV^{\max} \end{cases} \tag{2.19}$$

where $P_{hp}^{\max}$, $P_{hp}^{\min}$ are maximum and minimum power of the HP respectively; $APMV^{\min}$ and $APMV^{\max}$ are the maximum amount of householder's thermal condition. In this standard, the user's comfort scaled from -2 to +2. Each number appointed to certain thermal comfortability conditions, which is presented in Table 2-2.

Table 2-2

AMPV standard comfortability level.

AMPV	-2	-1	0	+1	+2

Thermal Comfort	Very Cold	Cold	Ideal	Warm	Very warm

2.8.2 USER THERMAL PREFERENCE (APMV)

In classical research, to satisfy the user’s thermal comfort, only the indoor temperature was used as the comfort parameter, which has to be limited within a desired temperature in literature [46]. However, today it is not used longer because according to ISO 7730 thermal comfort model, many factors including indoor temperature, humidity, clothing condition, etc. have significant impacts on comfort level [47]. The ISO 7730 model is a thermal comfort standard provided by the American Society of Heating, Refrigerating and Air conditioning Engineers (ASHRAE) and is widely used in literature as the predicted mean vote–percentage people dissatisfied (PMV-PPD) [47]. However, this model still has some downsides, which should be addressed. For example, the human body is considered as a passive recipient in this model, while in practice, people react to thermal dissatisfaction through different ways such as taking off or wearing more clothes, opening or closing windows, etc. [48]. Therefore, considering the householders’ reaction, an adaptive version of the ISO 7730 model is provided lately [49]. In this paper, an adaptive predicted mean vote (APMV) percentage comfort model is presented as [50]:

$$PMV_k = A_1.T_{in,k} + B_1.P_{v,k} - C_1, \tag{2.20}$$

$$P_{v,k} = RH_k \times 10e^{(19.65-4030)/(T_{in,k}+273)} \tag{2.21}$$

$$APMV_k = PMV_k / (1 + \lambda_1.PMV_k) \tag{2.22}$$

The details about the parameters of the model can be found in [50]. In the next chapter, the control based modeling approaches are introduced and their weaknesses and strengths are expressed.

3. CONTROL AND OPTIMIZATION BASED MODELING APPROACHES

3.1 INTRODUCTION

In reality, in the field of operation research, which deals with future planning, it is hard to find accurate models, which are fully matched with real physical systems and predict the futures of events with zero error. These mismatches affect the HEMS performance during practical implementation because the impacts of uncertainties are not modeled or modeled with low accuracy. Thereby, stochastic controllers or real-time controllers are proposed as some solutions to deal with inaccurate models and unmolded uncertainties. The effectiveness of these controllers to reduce the impact of errors and un-modeled uncertainties are proved for different applications such as energy management systems, navigation, etc. These controllers are sorted based on their forecasting requirements in literature [51]. For instance, stochastic dynamic programming (SDP) methods incorporate the uncertainties into the models, online scheduling methods do not use forecast data and MPC uses forecast points to compute a set of optimal set points over a prediction time horizon. MPC is a well-known method for real-time applications to reduce the impact of the uncertainties on the HEMS performance through measurement data among the introduced methods, [51]. In [52], the strengths and weaknesses of these control approaches under uncertainties are completely expressed. These methods are briefly explained in the next subsections.

3.2 STOCHASTIC DYNAMIC PROGRAMMING

Similar to the dynamic programming, which is a general approach for solving the deterministic optimization problems, the stochastic/probabilistic dynamic programming (SDP) is aimed to solve stochastic optimization problems. Generally in the SDP approach, one or several parameters are modeled as stochastic variables in the optimization problem. It is introduced by Bellman and Dreyfus as a well-known technique for solving problems of decision making under uncertainties. Because, in this method, the stochastic programming technique is mixed with dynamic programming techniques which make it a powerful technique for solving optimization problems under uncertainties. This method depends on finite state-space models to minimize the cost function and can be solved by using backward recursion or forward recursion algorithms. In the backward recursion, the optimization problem solves from the final time step and recursively computes the optimal pathway back to the first state. In some literature, the SDP is named as Markov decision process because it is Markov chain generalization [51]. Moreover, due to the size of the problem which arises with respect to the state numbers, the SDP problem sometimes turns to a nondeterministic polynomial problem (NP-hard problem). Although, it can be approximated in polynomial time, which is commonly used for HEMS applications [53].

3.3 ONLINE SCHEDULING APPROACHES

Another famous optimization approach in optimal operation research is online optimization or online scheduling approach that deals with optimization problems with incomplete or no knowledge of the future. In contrast with classical optimization problems where the complete information is assumed for solving the optimization problem, online optimization algorithms solve the problem with no prior data of future inputs. Online optimization approaches are sorted in two main categories 1) online problems in which the optimal decisions are made consecutively according to a piece-by-piece input; 2) online problems where the optimal decisions are made only once. In the first class, once inputs appear, online optimization should find the optimal solution for the plan. In this method, since the uncertainties are not modeled, the scheduler should find some solutions for adding new items or information that appear in a queue. The Tetris problem is a famous classical online optimization, which has upcoming unknown inputs, and the programmer may develop some sub-optimal programs. In the second class, an optimal decision is made only once. The Ski rental problem is a good example of the second class of online optimization. In this online problem, the concept of online scheduling or online optimization is a little unclear, and it is misunderstood with the MPC concept in many types of research. However, they represent a different class of scheduling problems [54]. Online scheduling approaches are used in many applications. For example in [55], it is utilized for the HEMS application to minimize the peak loads. Generally, for evaluating the effectiveness of the online optimization approach, its output should be compared to a corresponding off-line optimization algorithm that all the inputs are knowns in advance.

3.4 MODEL PREDICTIVE CONTROL

MPC is a powerful advance control method that is employed widely in many industrial applications such as process industry, automotive, energy, aerospace, robotic, etc. since the 1980s. It is a feedback control method that uses a model of a process to predict the future outputs of a system. Hence, MPC performance is relayed on the process dynamics. The MPC strengths are listed as follows:

1) It can handle multi-input, multi-output systems (MIMO) that have interactions between inputs and outputs because MPC is a multivariable controller which controls a process outputs simultaneously by taking into account all the interactions between system variables.

2) MPC can handle constraints of a process in which the constraints can arise from either the physics of a system or safety requirements or monetary requirements. Overlooking constraints can lead to undesired results; hence, it is necessary to fulfill the constraints of a system.
3) The third feature of the MPC is its preview capability, which looks like feedforward controllers. MPC can easily incorporate future reference information into the control problem to improve its performance.

4) The last but not least feature of the MPC is that it is a very simple method, easy to understand and easy implementation for varieties of systems

Although the MPC performance is highly dependent on certain forecasts, it can work reasonably with stochastic problems as well. Because MPC can periodically, upgrade its decision-making while solves the optimization problems or controlling a process by receiving new information about the stochastic parameters. Due to the MPC is a greedy method (hope to find globally optimal solutions at the end by finding locally optimal solutions at each step), the scheduler has to be sure that the horizon time is long enough to prevent myopic optimization [51]. In general, for validating the MPC performance its outputs are compared to a corresponding off-line optimization approach with deterministic forecast points (the best-case scenario).
In this thesis, the MPC approach is selected as the controller of the smart home HEMS. Therefore, the MPC is in charge to manipulate the variables of $\mathrm{P_{hp}}$ and $\mathrm{P_{pev}}$ to reach the problem target, which is minimizing the electricity cost, whereas the problem constraints have to be met including user's thermal comfort conditions, household load demand (thermal and electricity), PEV charging/discharging requirements and battery life-time depredation cost. The overall schematic of the HEMS with its MPC is shown in Figure 3.1. As it is presented in Figure 3.1, by coordinating the PEV charging/discharging and handling P_{hp}, the MPC follows the objective of the problem.

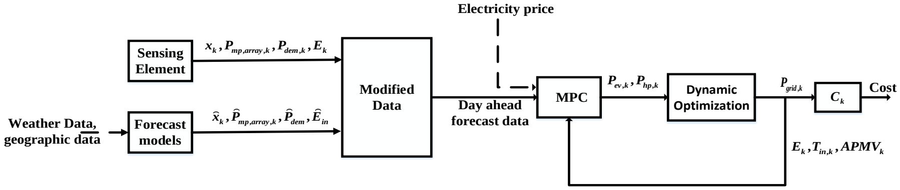


Figure 3.1. HEMS schematic with MPC and forecast blocks.

In this thesis, the state space representation of the HEMS is presented as given:

$$x_{k+1} = f\left(x_k, u_k, d_k\right),\ y_k = g\left(x_k, u_k, d_k\right), \tag{3.1}$$

where $x_k = \left[E_k \quad AMPV_k \;\; T_{in,k} \;\; P_{grid,k} \right]^T$, $u_k = \left[P_{ev,k} \quad P_{hp,k} \right]^T$, $d_k = \left[\widehat{p}_{mp,array,k} \;\; \widehat{p}_{dem,k} \;\; \widehat{X}_k \;\; \widehat{E}_k \right]^T$, and $y_k = p_{grid,k}$ are defined as the state, control signal, disturbance and output of the system respectively. For simplicity, the prediction horizon N is chosen to be equal to the control horizon, which is 24 (h) with time step $\Delta t = 1$ (h). Thereby, the cost function is given:

$$\min_{P_{ev,k}, P_{hp,k}} \sum_{k=0}^{N-1} \lambda \left(C_k y_k \right)^2 + (1-\lambda) C_{ev,k}{}^2 , \tag{3.2}$$

$$C_{ev,k} = X_k \gamma \left(P_{pev,k} + \eta^l E_k \right) \tag{3.3}$$

where C_k is the time-varying electricity price (\$/kWh) and $C_{pev,k}$ is the PV battery lifetime degradation cost model. The variables γ and η^l are cost factor and leakage loss factor of PEV battery respectively. According to the Eqs. (3.1), (3.2) and Figure 3.1, the MPC has to find a tradeoff between the optimal energy usage cost and PEV battery aging cost as the main objectives of the problem. Furthermore, the MPC has to guaranty satisfying all the problem constraints. In this thesis, since the control problem is a nonlinear dynamic optimization problem; the following numerical solutions are introduced to solve it.

3.4.1 NUMERICAL SOLUTIONS FOR NONLINEAR DYNAMIC OPTIMIZATION PROBLEMS

There are still many challenges to designing nonlinear control and optimization for systems with differential and algebraic equations (DEA). In recent years, advanced numerical techniques such as simultaneous methods, decomposition approaches, efficient nonlinear programming solver have addressed some of these challenges. In general, simultaneous and sequential approaches are two main numerical methods for solving dynamic optimization problems and nonlinear MPC [56]. In the sequential methods, the equations of the models are solved recurrently to converge to the tolerance of the provided objective function and gradient at each time step. The simulation process is repeated after defining the new decision variable for the next time steps of the optimization time horizon. The advantages of sequential approaches are their easy implementation and its ability to always provide feasible solutions with respect to the dynamic model because they solve the equations of the system by forwarding integration. However, its main disadvantage is that for problems with large numbers of freedoms it may provide sub-optimal solutions (fail to converge in a reasonable time).

In contrast with sequential methods, the simultaneous method solves the optimization problems and equations of the models in parallel. Due to the computational advantage of the simultaneous method, it is recommended for control problems with many decision variables but with moderate sate variables. One of the features of the simultaneous methods is that they can convert a DEA optimization problem to one of the famous optimization programming forms such as LP, NLP or MINLP (depending on problem characteristics) through direct transcription which is known as orthogonal collocation on finite elements [26]. Then, the LP, NLP or MINLP problem can be solved by large scale solvers such as the interior point solver (IPOPT) and active set solver (APOPT). In this thesis, the optimization problem is converted to an MINLP problem and the APOPT solver is employed to solve the optimization problem. Hence, the APMonitor optimization Matlab toolbox is used. It is a powerful toolbox to perform estimation, optimization and predictive control by several solvers, including APOPT and IPOPT. APOPT solver is the only solver, which can handle MINLP problems in APMonitor.

4. HEMS PERFORMANCE AND PROFIT ASSESSMENT

4.1 INTRODUCTION

The strengths of the optimal operation of HEMSs for residential buildings are investigated comprehensively in existing literature, but there is still a need of study to evaluate the profit assessment of HEMS for building with different energy labels that determine the building energy storage efficiency (different insulation quality). Hence, in this chapter, a comprehensive comparison of the optimal HEMS performance in residential buildings with different energy labels and different emission heating systems (floor-radiator heating system and radiator only system) is conducted. In this chapter, the designed HEMS with the controller in section 3.4 is implemented to a residential building (building specification is outlined in section 2.8.1) in Denmark for different energy labels defined from A to G according to the latest Danish building regulations [58].

4.2 BUILDING ENERGY LABELS AND SCENARIOS

The HEMS is implemented in the following scenarios:

Case I: Building with energy label “A” (maximum storage efficiency)
Case II: Building with energy label “B”
Case III: Building with energy label “C”
Case IV: Building with energy label “D”
Case V: Building with energy label “E”
Case VI: building with energy label “F”
Case VII: Building with energy label “G” (worst storage efficiency)

The HEMS is performed for building with different heat emission systems including radiator-only heating and floor-radiator combination heating systems (slab thickness 9 cm) in each case study. The building thermal capacity is improved by the use of either a pure floor heating system or floor-radiator combination heating system. This improvement depends on the floor thickness, floor surface which equipped with floor heating and material type of the floor such as concrete, tile and carpet [59]. In this study, it is assumed that if 30% of the floor surface equipped with floor heating and the rest equipped by radiator heating systems, the thermal capacity of the building($C_{building}$) increases by 25% compared with radiator only heating system. Moreover, in this study, the building is equipped with the following technologies:

1) Nissan Leaf PEV (24 (kWh) lithium-ion battery pack), assumed the same driving

habits for all cases.
2) PEV charging box of 240 (V), 16 (A),
3) 4 (kW) PV system including two paralleled subarrays with 8 PV series panels
4) Solar Edge inverter (model SE4000) with a maximum AC output power of 4000 (VA) and 220/230 (V) (AC) output voltage.
The building energy label is a criterion to measure the quality of a building in terms of energy use and energy loss. In order to define an energy label for a building, many factors such as building insulation quality, building structure, etc. have to be taken into account. Building insulation is the most important factor in improving a building energy label and storage efficiency because the building performance in terms of saving thermal and cooling energy is determined by the insulation materials that are used in different parts of a building. Based on the latest Denmark building regulation BR2020, maximum energy use in a building with an energy label of “A” has to be less than $27\,(kWh/m^2)$ per year [60]. Hence, for a building with a floor area of 150 (m2), 15 (m) length, 10 (m) width and 2.7 (m) height, the following insulation requirements which are presented in Table 4-1, have to be met for different parts of a building with energy label “A” in Denmark.

Table 4-1

Building insulation requirements for a building with label “A” according to BR 2020 [11].

Building construction	Thickness (mm)	U value $(W/m^2.^\circ C)$	Area (m^2)
Exterior windows and doors	-	0.8	33
Floor	300 mm	0.1	150
Exterior walls	300 mm	0.12	102
Roof and ceiling	455mm	0.08	150

According to the regulation for a building with energy label “A”, the maximum windows and doors size is 22 (m^2), per 100 (m^2), of living space. According to Table 4-1, the overall heat transfer conductivity is computed as given [11]:

$$\Lambda_{ovrall} = A_{floor}U_{floor} + A_{Win}U_{win} + A_{wall}U_{wall} + A_{roof}U_{roof} \tag{4.1}$$

Moreover, for simplicity, it is presumed that the building energy loss is a linear function of the overall heat conductivity. Thereby, the building energy loss or use per

(m^2) is presented in Table 4-2, for different energy labels based on Denmark's latest building regulation. Consequently, the building conductivity and building thermal time constant are computed for the above-mentioned size building and presented in Table 4-2 as well. For instance, the building with energy label A has a conductivity $\Lambda_{overall} = 0.066 \ (kW/^{\circ}C)$ while for the same building with label "B" it is $0.2 \, (kW/^{\circ}C)$. It means improving the insulation results in reducing building conductivity from 0.2 to 0.66. Therefore, reducing the conductivity leads to improving the building thermal time constant from 6.675 (h) to 20 (h) and consequently reducing the energy loss from 84.66 to less than 27 (kWh/m^2) per year.

Table 4-2

Overall building energy loss and thermal specifications for buildings with different energy labels.

Building's label	Maximum energy loss for one year (kWh/m^2)	$\Lambda_{overall}$ value $(kW/^{\circ}C)$	τ value for radiator heating system (h)
A	<27	0.066	20
B	<70+2200/Area=84.66	0.2	6.675
C	<110+3200/Area=131.33	0.321	4.158
D	<150+4200/Area=178	0.435	3.06
E	<190+5200/Area=224.66	0.55	2.427
F	<240+6500/Area=283.33	0.7	1.9
G	>240+6500/Area	1.2	1.112

4.3 RESULTS

The HEMS optimal results are presented for a building which is outlined in section 2.8.1 with different energy labels (seven cases). The system parameters related to building components and users are presented in Table 4-3. The HEMS controller is the MPC which is outlined in secion3.4. The building load demand and PV output power are predicted by MLP and SAPM models which are explained in sections 2.5.5.1 and 2.5.4 respectively. Moreover, the data related to weather forecasting is updated at each time resolution by weather station services, which can be used via application programming interfaces. The simulation results are shown for week 2 in January 2017. Furthermore, the building with HP size in Table 4-3 cannot meet the user's thermal preference requirement for the building with energy label "G", therefore, the size of HP is increased 12 (*kW*) for this case. The baseline results (without HEMS) of each case is presented to be compared with the HEMS optimal performance to prove the effectiveness of the HEMS for each case. A rule-based controller is formulated to fulfill the problem requirements without optimizing the cost of energy for the baseline model.

Table 4-3

Smart home parameters [11].

<table>
<tr><td colspan="5">EV battery parameters</td></tr>
<tr><td>$P_{ev}^{\max}$</td><td>$P_{ev}^{\min}$</td><td>Q</td><td colspan="2">η</td></tr>
<tr><td>3.5 (kW)</td><td>-3.5 (kW)</td><td>24 (kWh)</td><td colspan="2">0.05</td></tr>
<tr><td colspan="2">SOC lower limit</td><td>SOC_0</td><td colspan="2">SOC upper limit</td></tr>
<tr><td colspan="2">25%</td><td>0.6</td><td colspan="2">90%</td></tr>
<tr><td colspan="5">Thermal parameters</td></tr>
<tr><td colspan="2">p_{hp}^{min}</td><td>p_{hp}^{max}</td><td colspan="2">COP</td></tr>
<tr><td colspan="2">0 (kW)</td><td>6 (kW)</td><td colspan="2">4</td></tr>
<tr><td colspan="2">$APMV^{\min}$</td><td>$APMV^{\max}$</td><td>$C_{building}$</td><td>$T_{in,0}$</td></tr>
<tr><td colspan="2">-0.4</td><td>+0.4</td><td>1.32 $(kWh/^{\circ}C)$</td><td>$25\left(^{\circ}C\right)$</td></tr>
<tr><td colspan="5">User's clothing parameters</td></tr>
<tr><td colspan="2">Time Range</td><td>I_{cl}</td><td colspan="2">Clothing Condition</td></tr>
<tr><td colspan="2">[7:00, 22:00]</td><td>0.7</td><td colspan="2">Short sleeve shirt, light trousers, shoes</td></tr>
</table>

[22:00, 7:00]	0.3	Underwear, T-shirt

In Figure 4.1, the HEMS optimal performance is compared with the baseline performance for seven different cases with two heating systems to prove the effectiveness of the designed HEMS. According to Figure 4.1, the energy cost of the building is reduced for either baseline performance or HEMS performance when the building energy label or building insulation quality is improved (the best minimum case happens for building with energy label “A”). As an example, in Case I (label “A”) the home energy cost is 20.1 (*$/week*) and 11.8 ($/week) for baseline and HEMS performance with floor-radiator heating system, respectively. While in Case VII (label “G”) the cost of energy is 90.95 (*$/week*) and 66.8 (*$/week*) for the same situation. As a fast result, the more improvement in building insulation is made, the more reduction of energy cost has happened whether the building used HEMS or not.

The second and more important result is to analyze the impact of having HEMS for buildings with different insulation quality in reducing energy cost. Therefore, Table 4-4 is presented to highlight the HEMS optimal performance for different cases. For instance, in Case VI (label “F”) the HEMS reduced the energy cost from 58.43 (baseline performance) to 42.1 (*$/week*) (about 27.6%) with the floor-radiator combination heating system and reduced by 27.94% with a radiator-only heating system. At the first glance, it is obvious that the HEMS can reduce the building energy cost for all cases with different heating systems (by more than 26% in all cases (except case VII with radiator only).

However, by analyzing Figure 4.1 and Table 4-4, it is clear that the HEMS performance is much better in a well-insulated building than poor-insulated building. For example, in case I the building energy cost with HEMS is reduced by about 41% while in case VII the energy cost is minimized by around 26% (with the floor-radiator combination heating system). It shows that the HEMS can have better optimal performance (in terms of minimizing the building energy costs) in highly insulated buildings.

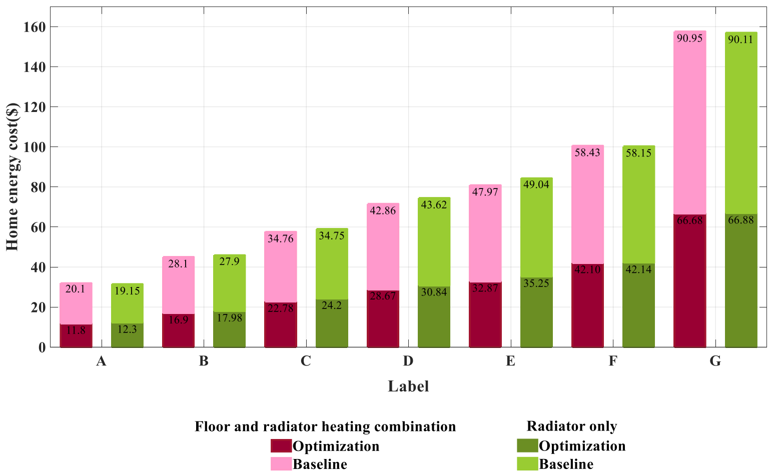


Figure 4.1 Total home energy cost for different energy labels (A-G) and two different heating systems (floor-radiator combination and radiator only), during January 2017.

Table 4-4

Energy cost reduction by HEMS as compared with baseline operation for buildings with different energy labels and different heating systems [11].

Building Label	Radiator Only (%)	Floor and radiator combination (%)
A	35.77	41.3
B	35.5	39.5
C	30.3	34.44
D	29.3	33
E	28.22	31.41
F	27.6	27.94
G	25.75	26.55

The second aspect, which has to be checked, is analyzing the HEMS performance in fulfilling problem constraints. Therefore, the HEMS performance for satisfying problem constraints such as the user's thermal preference and EV battery energy are presented for the case I (Label “A”) and VI (Label “F”) with radiator-only heating system in Figure 4.2. For better resolution and clarity, the results are shown for four days from Monday to Friday. As it can be seen in Figure 4.2 (a), the user’s thermal comfort criteria (APMV) and building inside temperature are -0.4 and 18.5 $\left({}^{\circ}C\right)$ during most of the daylights (marginal comfortability) for case IV(Label “F”). Similarly, in Figure 4.2 (c), the PEV battery charge and discharge between the minimum and maximum of its acceptable values in order to compensate the lack of building storage efficiency for case IV. In contrast, as it is shown Figure 4.2 (a), the APMV criterion is close to zero most of the times and the building inside temperature is above 20 $\left({}^{\circ}C\right)$ all the week (except on Monday) even though the outside temperature is around 4 degrees on average for this week (Figure 4.2 (b)) for case I. Likewise, the SOC of PEV battery changes are very small (results in improving battery lifetime [9]) for the case I compared with case IV as it is shown in Figure 4.2 (c). As a consequence, when the building storage efficiency is poor (low building thermal resistance), the problem constraints move to the acceptable boundaries values to meet the main objective of the problem (minimizing the energy cost as much as possible). Otherwise, when the building storage efficiency is proper, these parameters remain near the desired points most of the time (APMV stays close to zero and SOC variation is small). Therefore, for case I, even the HEMS optimal performance is very good, the HEMS performance for fulfilling the requirements of the problem is much better than the cases with poor insulation quality.

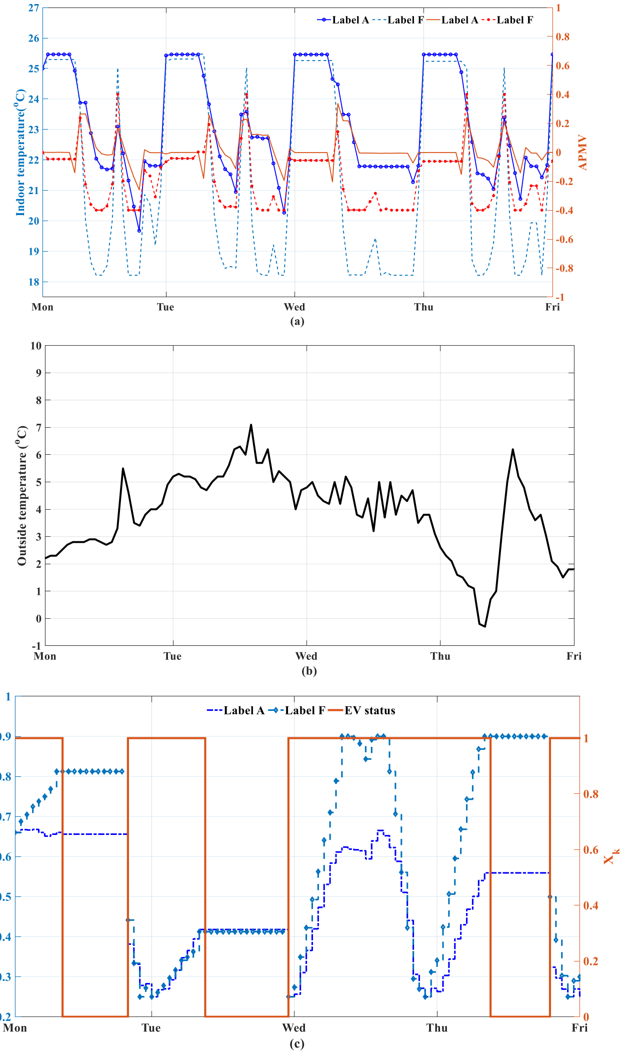
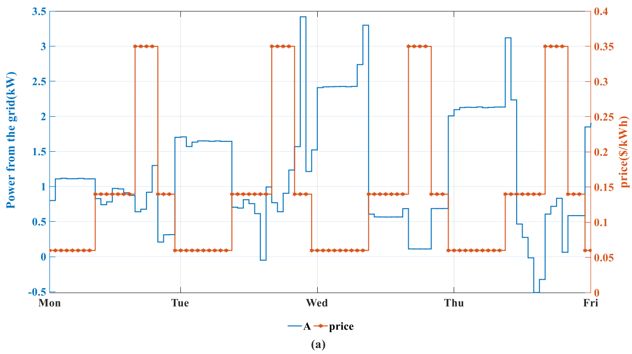


Figure 4.2. HEMS performance comparison for satisfying building's requirements with radiator heating system for buildings with label "A" and "F"; (a) user's thermal preference criteria (APMV) and indoor temperature, (b) outside temperature, (c) SOC and status of PEV.

For better understanding, the grid power pattern compared with electricity price and power distribution among the building resources (HP, PEV, PV, load and grid) are presented for the case I with the radiator-only system in Figure 4.3. According to Figure 4.3 (a), the HEMS maximizes the usage of grid power from midnights to mornings around 7:00 when the electricity price is minimum. While the HEMS minimizes the use of power from the grid during peak loads when the electricity price is maximum. According to Figure 4.3 (b), the HEMS uses the HP to store thermal energy in building and charges the PEV battery after the midnights when either the electricity price is minimum or when the PV has extra production. In contrast, the HEMS reduces or stops the HP power to decrease the building temperature or discharge the PEV battery (if available) during the peak electricity price to minimize the use of grid power as much as possible. As can be seen, on Monday, Wednesday and Thursday evenings, the PEV is available; so, it is discharged to supply a proportion of the user's load demand (thermal and electricity). Similarly, the HEMS only stops HP working in Tue evening (peak load), because the PEV is not available and HP is the only manipulated variable to decrease the power from the grid which results in reducing APMV criteria and building temperature Figure 4.2(a). Furthermore, when the PV production is bigger than the load demand such as on Tuesday, Wednesday and Thursday, the HEMS charges either the PEV (if available) or building thermal storage as heating or cooling the building to maximizes the share of PV consumption in the building. Otherwise, the extra PV production is sent to the grid by the HEMS to avoid violating the problem constraints (either EV maximum charging or household's thermal preference). Hence, the grid power is not positive on Tuesday and Thursday afternoon because it is not possible to store the PV power as thermal or electrical energy in home energy storage (PEV battery and building thermal mass).



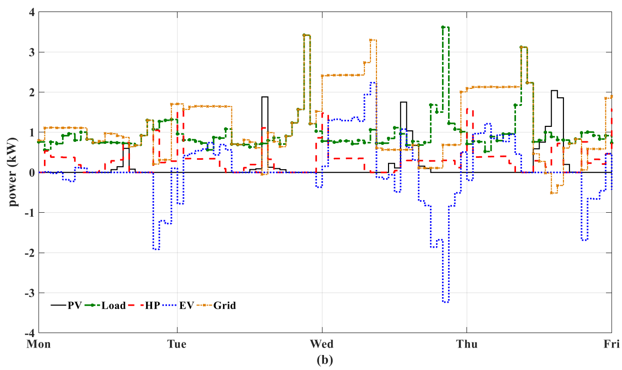


Figure 4.3. a) Grid power usage for a building with energy labels "A" and a radiator system over four days in January 2017 according to electricity price; (b) power distribution among PV, HP, PEV, and grid for Case I.

For more details about the HEMS, optimal performance and its effectiveness refer to papers F and H.

5. CLOSING REMARKS

5.1 CONCLUSION

The thesis studied the improvement of HEMS in three parts: 1) modeling, 2) control-oriented modeling and optimization, 3) performance and profit assessment of the developed HEMS. The HEMS state of the art was established in paper A. The current modeling techniques were explained including physics-based, data-driven and hybrid modeling techniques. The building resources models with their uncertainties were obtained through these techniques in paper C. Then a nonlinear MPC was designed as the HEMS controller to minimize the cost of energy through manipulating the power flow among the smart home resources (HP, PEV, load and grid). The controller structure and HEMS effectiveness were explained in paper F with details. The last but not least, the HEMS profit assessment was studied for building with different energy labels (storage efficiencies) and different heat emission systems (floor-radiator combination or radiator only heating systems) in Paper H comprehensively.

As emphasized in the paper A (state of the art review paper), only a few works took into account the uncertainties and stochastic parameters of building resources when designing HEMS for smart homes. Hence, in paper C, a comprehensive comparison was conducted to analyze the advantages and disadvantages of current modeling techniques for modeling the building resources regarding their uncertainties and stochastic parameters. Then these techniques were used to find proper models for building resources such as PV power output, PEV status (plugged-in time and plugged-out time), PEV state of the charge at plugged-in time and home load demand. The results for PV model comparison showed that equation-based models with measurements (empirical models) especially the SAPM model is more accurate than other methods. According to the results, it is observed that PV equation-based models could be generalized for a variety of PV systems only by knowing the system PV size and the PV specifications. However, black-box techniques are very biased to the data that they are trained in. The load modeling comparison showed that the quality of data has a high impact on the ANN performance in terms of reducing the error and variance especially when enough data is utilized for ANN training. The accuracy of the obtained Markov Chain model was computed by analyzing the daily driving pattern of three different electric vehicles. Finally, a holistic model was present for a smart home integrated with PV, HP and PEV to be used for monitoring, control and fault detection applications.

According to the obtained models from paper C, a novel predictive HEMS was formulated for a smart home with PV, HP and PEV in paper F. Moreover, in paper F, the building thermal mass and PEV battery were used as home energy storage for saving thermal and electrical energy, respectively. Using these items made the system economic because their main tasks are for other purposes such as transportation and living situations (no need for batteries or other thermal storage which highly increase the capital investment cost). The recommended models obtained in paper C were used by a nonlinear MPC to minimize the building energy cost while satisfying the user's requirements as well. The simulation was performed for different scenarios. First, the simulation was performed with the objective function of minimizing only the building energy cost. In the second scenario, the simulation results were provided with a trade-off objective function between the building optimal performance and PEV battery aging cost. In the second scenario, the simulation results demonstrated that the proposed HEMS could reduce the electricity cost up to 27.6 % in comparison with a non-optimization rule-based controller. Moreover, the effectiveness of the optimal performance of the designed novel predictive HEMS was validated by an off-line optimization counterpart with having all the entire future inputs in advance. Last but not least, the MPC performance with different time horizons and time-steps in a day were analyzed for the case of fast dynamic behavior.

In connection with the previous study (paper F), the designed predictive HEMS were employed for a residential building with different storage efficiency (energy labels) in paper H. Then a comprehensive profit assessment presented for designed HEMS with two heat emission systems 1) floor-radiator combination heating system and radiator only heating system. The impact of building storage efficiency (different insulation quality) on improving HEMS optimal performance and fulfilling the optimization constraints was analyzed and discussed. Also, the impacts of EV to home technology and having different heating emission systems (having different building thermal capacity) in improving the HEMS optimal performance were presented and analyzed. As a consequence, it was proved, that having high building thermal capacity (floor-radiator heating system technology) improves the HEMS optimal performance and user's comfort level as it was compared with low building thermal capacity (using radiator only system). The simulation results demonstrated, that the more improvement happens in building thermal capacity (floor-radiator combination heating system) and building thermal resistance (moving towards the energy label "A"), the more HEMS' performance could improve in terms of optimal performance and the user's requirements fulfillment. Finally, it was observed that the HEMS increased the role of PEV when building insulation was poor (low thermal resistance) because the building storage efficiency is decreased when the building thermal resistance reduce: so, the building can not keep the thermal energy for later use.

5.2 FURTHER WORK

This Ph.D. topic is completely a broad study and has to cover various technologies to design a HEMS in the context of smart homes or nZEB. But it is not possible to cover all the parts of the system in three years and still some parts need more research improvements. In this section, the improvements are divided into three parts: 1) modeling, 2) controlling 3) implementation. These improvements are explained as follows:

- The first part which still needs improvement is the modeling section. There is still a need for better models to capture more uncertainties and stochastic parameters of the building variables. For example, only deriving distance parameter is considered for modeling the SOC of PEV battery at the plugged-in time. However, in reality, other factors affect the SOC of PEV battery such as traffic situation, deriving style, etc. Therefore, it is needed to use cutting-edge modeling techniques to find models for unknown parts of components. Today, the hybrid modeling technique is a hot topic for modeling different technologies by mixing physics based-modeling and data-driven techniques.
- The second part is in the control section. There is still a need for a holistic control approach which not only deals with slow dynamics but also needs fast reaction to fast dynamics of the systems. The idea of multi time scale MPCs seems potential methods for dealing with the fast dynamic behavior of the system. The control structure of this idea consists of one centralized MPC and many local MPC (equal to building components which supposed to be controlled). In this idea, the main MPC can work in a one-hour resolution and deal with slow dynamics and define set-points for building components, while the local controller works continually at each discrete time resolution of the main controller to follow the defined trajectory set-points.
- The third section is laboratory-scale implementations of the designed HEMS in the context of a smart home or nZEB. There are many research studies in the field of nZEB which only presented numerical results (simulation results) but no studies can be found related to the real implementation of an nZEB or smart home with a real-time HEMS to present experimental results for proving the HEMS effectiveness. All the existing results are performed in simulations and there is a need for presenting experimental results of a designed HEMS in the context of smart home or nZEB

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PART II

CONTRIBUTIONS

LIST OF PAPERS

Paper A: Energy management strategies for smart home regarding uncertainties: State of the art, trends, and challenges.

Paper B: ANFIS based approach for Stochastic modeling of smart home.

Paper C: A comparison study on stochastic modeling methods for home energy management systems.

Paper D: Stochastic Smart Charging of Electric Vehicles for Residential Homes with PV Integration.

Paper E: Smart energy management system for residential homes regarding uncertainties of photovoltaic array and plug-in electric vehicle.

Paper F: Predictive Home Energy Management System with Photovoltaic Array, Heat Pump and Plug-in Electric Vehicle.

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