AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

ELFORSK 350-005

Rapport

Energistyring i et "Smart Home" med integrerede solceller, elbiler og varmepumper

December 2020

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

Titel: **Energistyring i et “smart home” med integrerede solceller, elbiler og varmepumper**

Udarbejdet for:

Udarbejdet af: Department of Energy Technology, Aalborg University

December 2020

Forfatter:

Amin Hajizadeh

Mohsen Soltani

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

CONTENTS

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

1- Introduction

The Department of Energy Technology, Aalborg University has led one project under Dansk Energis Elforsk's program: 350-005: Energy management in a "smart home" with integrated solar cells, electric vehicles and heat pumps.

Smart Homes (SH) can use a variety of renewable energy sources, including photovoltaic (PV) arrays, micro-wind turbine, Heat Pumps (HPs), and Plug-in Electric Vehicle (PEV) as an energy storage. Due to the integration of volatile renewable energy resources, stochastic PEVs mobility patterns, and random energy consumption in the buildings, uncertainties have become the major concerns for the operation of energy-efficient in the buildings. Thus, incorporating uncertainty into the scheduling process has the potential to improve energy efficiency. In this project, a novel stochastic model predictive controller (MPC) will be applied for a smart home with the integration of renewable energy resources, HPs, and PEVs. The main objective of this project is minimization of the daily electricity consumption cost by using flexible renewable resources in an efficient way, while also regarding the uncertainties.

2- Background

Figure 1 shows the overall architecture of a representative smart HEMS. The HEMS Center includes a centralized intelligent control that equips households with monitoring modules and control functions based on the home communication network. The house gateway, such as smart meter, can be used as an interactive communication interface between electrical installations and the smart building. PEVs / EVs and HPs are special types of loads that can be planned. PEVs / EVs not only consume energy from the grid, but also constitute an emergency stream for other household consumption within the smart community. Therefore, PEVs and space heating with HPs are promising candidates for demand-side management (DSM) applications. In addition, they are well suited to the electrification of the transport and heating sector as well as to the energy efficiency of buildings, which are seen as key roads to low-emission energy systems along with an increase in the use of renewable energy sources. Today, the electricity distributed from renewable energy sources in residential areas most often includes photovoltaic systems. Due to the inevitable fluctuating and random energy production of photovoltaic systems, the energy storage units play a key role in improving the power quality and energy efficiency as well as in maintaining the reliability of the energy system.

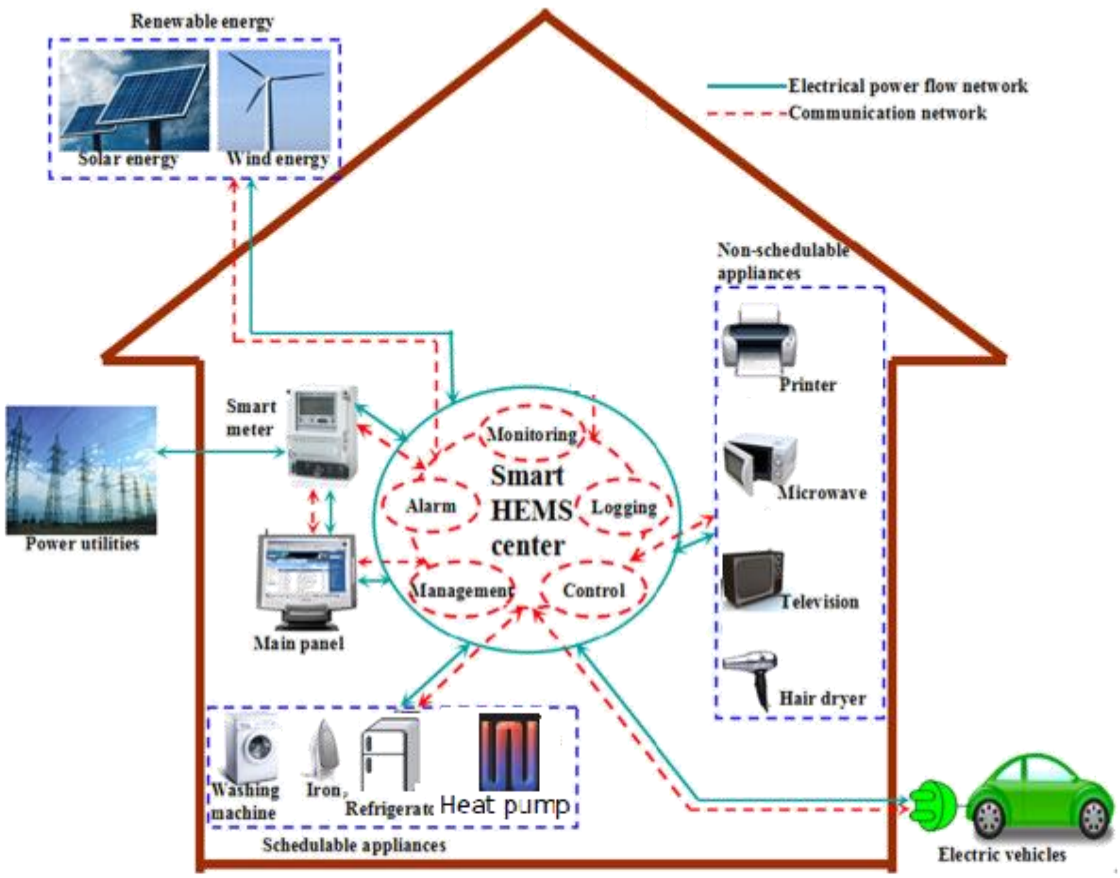


FIG. 1. The overall architecture of HEMS.

HEMS is an important home system for successful demand management of the smart electricity network. With the rapid development of advanced power electronics and alternative energy technologies, renewable and stored energy sources installed in residential areas can be incorporated into HEMS with the aim of improving the efficiency of energy conversion and utilization. In this way, HEMS is defined as the optimal system for the provision of energy management services to efficiently monitor and manage electricity production, storage and consumption in smart buildings. Thanks to easy installation and low cost, photovoltaic systems are widespread in smart buildings. Panel current can vary greatly due to weather conditions, local transient shade and the time of day. If left unchecked, there may be a significant impact on the electricity grid, including degraded performance, congestion and overproduction, especially when using large-scale production units and PEVs. Therefore, stochastic dynamic energy planning is essential. Thus, it will be a very interesting topic for future work to develop effective control for the integration of PEVs and renewable energy in household consumption and the electricity grid.

3- Current Technical and research levels

Electricity consumption is rising in residential and commercial buildings, and this rising demand for electricity is leading to a significant increase in greenhouse gas emissions. As a result, many countries, including the EU [1-2], have already begun to review their climate and energy policies. Innovation in the field of sustainable energy supply is thus crucial to provide reliable and clean energy sources and improve the quality of life on this planet. With this goal in mind, buildings play an important role, as they account for 40% of domestic, primary energy consumption, 36% of natural gas consumption and 72% of US electricity consumption [1]. To achieve this goal, the idea of smart buildings or energy-neutral buildings is launched. Technological advances promise that all homes can be transformed into smart homes that allow for remote control of energy consumption in the home. An smart building with HEMS could reduce the operating costs of electricity by 23.1% or reduce peak demand in residential areas by 29.6%. The literature in the field of energy management of homes is extensive and growing. We focus here on related works on the modeling and management aspects of HEMS. In recent years, several optimization methods have been reported for optimizing and implementing the planning of electrical household appliances with electrical energy services for private consumers in smart buildings, such as mixed-integer linear programming (MILP), approach with model prediction control, rolling time horizon strategy and game theory. The use of PEVs as dynamic energy storage with their travel patterns to coordinate the optimal energy planning of the home in a residential area has been proposed in many literatures. A HEMS is proposed in the building to reduce the operating costs of a DC distribution system. The PEVs are used for energy storage units for energy management. Normally a number of PEVs serve as a storage unit for the supply of both energy and capacity, so that the building can improve the power supply. In these studies, PEVs are mainly considered as an additional component for the operation of smart buildings. Sustained integration which derived optimal PEV charging schemes based on expected solar cell power and power consumption. A non-linear, intelligent energy management method for buildings with photovoltaic systems and battery storage was proposed, which predicted the household's own consumption via artificial neural networks. The biggest challenge in energy management in smart buildings stems from the uncertainty of several sources, such as renewable electricity production, customer demand for electricity, PEV mobility, etc. There are only a few plants that explicitly consider this. To minimize the consumer's expected electricity costs, the optimal planning algorithm for electricity consumption with uncertain future price is derived using Stochastic Dynamic Programming (SDP). A planning algorithm for stochastic energy consumption with the aim of reducing costs is proposed by modeling the randomness of customers' energy consumption [3-5].

When looking at the literature published and presented here, there are some challenges related to this project. First, all the previous articles focus on the problem of energy management of micro-electricity grids using stochastic optimization based on one and only one random factor: either the electricity price of PEV mobility, the production of renewable energy or household consumption. The interplay between different variables in renewable energy is constantly overlooked. However, the stochastic and uncertain way in which photovoltaic systems, household consumption and PEV behave should be assessed together in order to improve the energy efficiency of smart buildings. Second, the integration of electrical and thermal loads makes the problem of energy management more realistic and complex. This issue adds several limitations to energy management systems for the home. The purpose of this project is therefore to develop a new energy planning that can incorporate uncertainty in the management process and thereby improve the energy efficiency of smart buildings.

4- The proposed method

Most of the related literature aims to evaluate the potentials of the technology behind smart buildings. Only a few consider a real-time management system, which optimizes energy management with an explicit consideration of stochastic household consumption, renewable energy production and PEV mobility patterns. The main challenges in energy management in smart buildings stem from several different sources of randomness such as PEV mobility, customer demand for electricity and renewable energy production. Therefore, if uncertainties are considered in the planning process, there is potential for improving energy efficiency.

Energy management characterized by uncertainty has not yet been fully penetrated into the literature on HEMS. Where some methods incorporate the uncertainty into the mathematical model, other methods rely on updating algorithms to reduce the impact of the uncertainty, such as the online planning algorithm and MPC. MPC is the most common method of dealing with forecast errors and is an open-loop online control system that approaches the desired solution by reducing the impact of the undesirable dynamic properties of the system. Model prediction management is a methodology rather than a single technique. MPC is often used to make short-term decisions over a long time horizon. While MPC is typically used in conjunction with deterministic point forecasts. It is a general method that can also work with stochastic optimization approaches. Using time series modeling, MPC generally plans over a planning horizon (T), waits for a predefined period, updates its forecasts, and repeats this process.

The project aims to solve one of the main challenges in modeling uncertainties in smart buildings by using stochastic optimization methods to reduce the effects of uncertainty. Therefore, Markov's chain models are proposed to model the stochastic dynamics of PEV mobility, and MPC is also introduced because of its ability to handle uncertainty, problems with renewable energy source variability and the uncertainty of household consumption; in other words, we have proposed the MPC method for the following reasons:

- The intuitive concept, easy to understand and implement in a variety of systems.

AALBORG UNIVERSITY
DENMARK
Department of Energy Technology
Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

• Systematic handling of restrictions.

• Handles MIMO systems and powerless time without changes.

• Handles challenging dynamics.

At the same time, it is also a method that can work properly along with approaches to stochastic optimization. In this project, a stochastic MPS is proposed as an adaptive and dynamic optimization technique for application to the energy planning problem of smart buildings with different energy sources.

In this project, 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 2. 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.

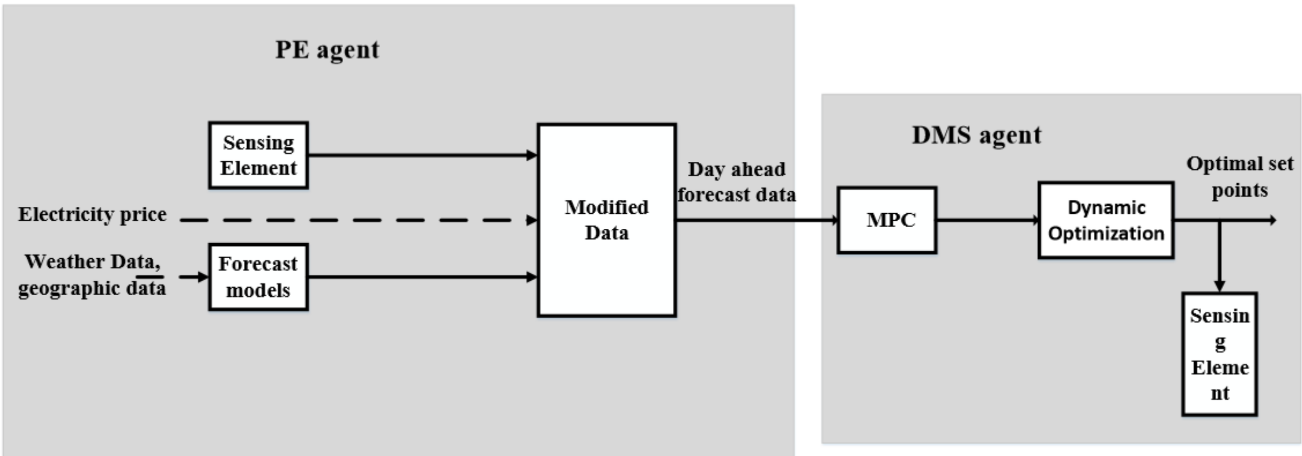


Figure 2. The HEMS structure and agents.

As mentioned above, the stochastic variables should be forecasted by PE. In this project, 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 lowlevel 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 reschedule 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.

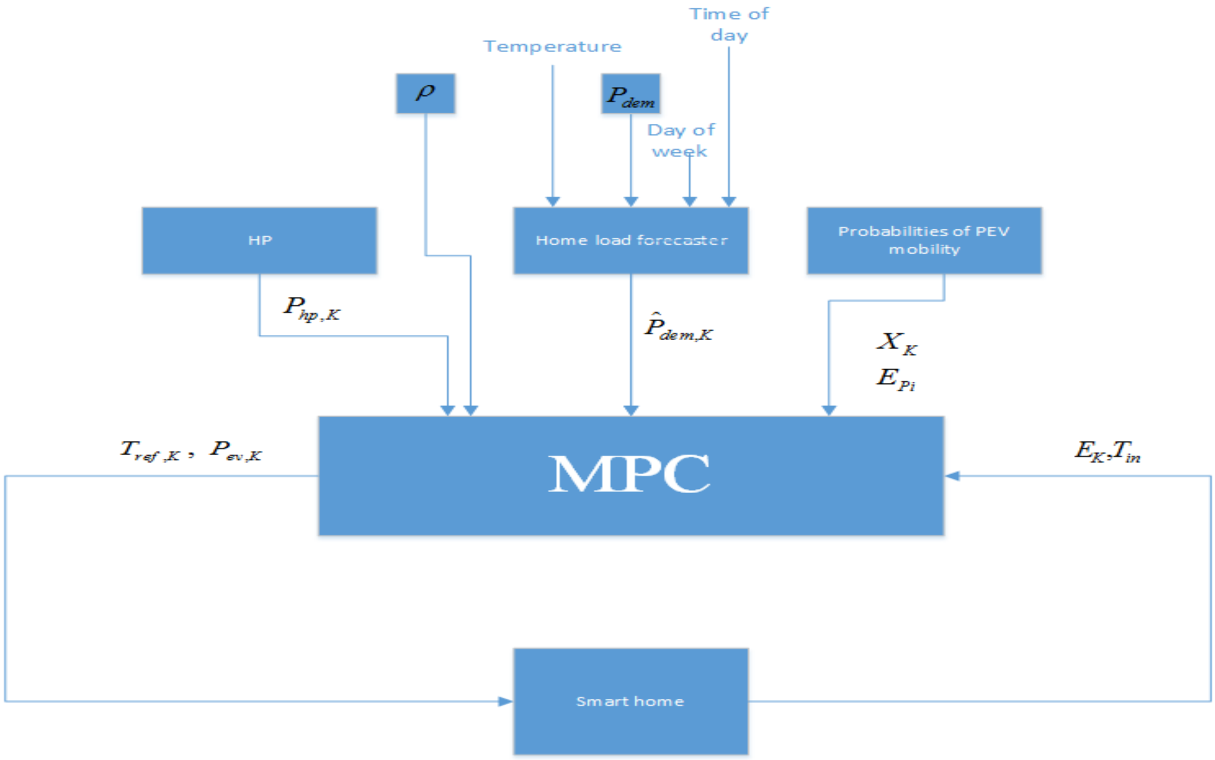


Figure 3: Blokdiagam af systemet.

5- Development of system model

The main challenges for energy management systems are due to uncertainties, and in this project, uncertainties will be addressed with these five parameters in mind: solar power supply, household consumption, PEV plug-in time, PEV plug-out time and PEV mobility. This section presents in-depth models for each component and the components' uncertainties.

PV Equivalent circuit model

There are many equivalent circuit models for PV systems such three-parameter model, four-parameter model, five, six or seven parameter-model, etc [6]. As an example, the four-parameter model is illustrated in this subsection. This model is an electrical circuit that includes an ideal current source paralleled with a diode and resistance R_p and series

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

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 [7]:

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

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

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

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

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

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. 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). For the rest of the models, you can conclude what type of modeling methods is used.

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 [8]:

$$P_{act} = P_{act,0}\left(\frac{V}{V_0}\right)^a$$
$$Q_{react} = Q_{reac,0}\left(\frac{V}{V_0}\right)^b$$

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 below equation 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 as given [8]:

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

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

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

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

PEV battery energy at plug-in time model

One of the critical values is the forecast amount of the PEV SOC at arrival time for HEMS to improve its effectiveness. The PEV SOC value at the plugged-in time affects by several factors such as traffic condition, driving distance, driving style, number of users, etc. In this project, only the effect of driving distance is considered. The PEV SOC value at plugged-in time is calculated as [10]:

$$SOC_{in} = \begin{cases} SOC_{\min}, & if\ SOC_{out} - SOC_{cc} \times d \le SOC_{\min}, \\ SOC_{out} - SOC_{cc} \times d, & otherwise, \end{cases}$$

where $SOC_{cc} = 0.159 / Q_{PEV}\ (1/km)$; SOC_{in} and SOC_{out} are PEV SOC values at arrival and departure times respectively; $SOC_{\min}$ is the acceptable minimum value of PEV SOC; d is the driving distance (km) and Q_{pev} is the PEV battery capacity (kWh). According to the equation, 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}.

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. However, it must 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' 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 [11]. A large proportion of the overall energy loss is passed through attics and walls, according to Figure 3. Therefore, using highly insulated materials can result in thousands of dollars saving in energy bills. In this project, 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 [12]. In this project, ground source HP is used and its structure is presented in Figure 4 for cooling and heating purposes. Furthermore, the building thermal dynamics is formulated as given:

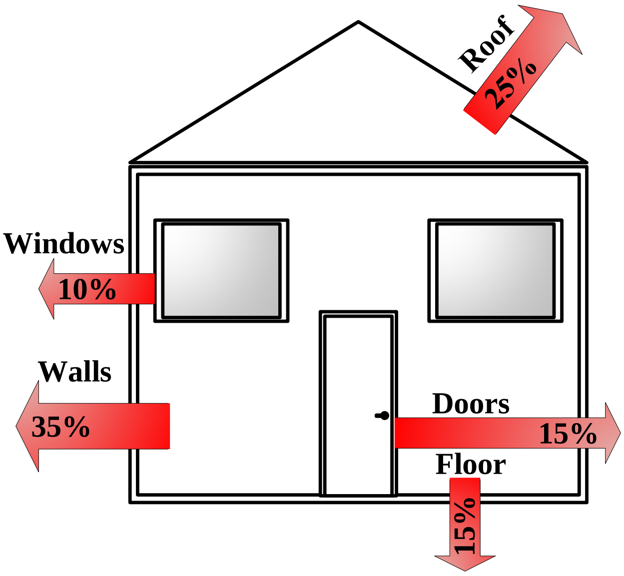


Figure 4. Heat transfer distribution among different parts of a building.

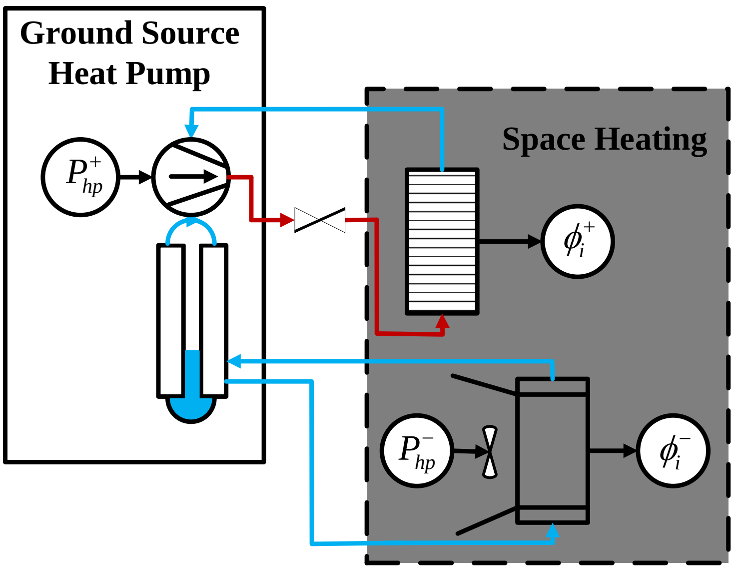


Figure 5. Heating system with a ground source heat pump.

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

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

where $C_{overall}\ (kWh/^{\circ}C)$, $R_{overal}\ (^{\circ}C/kW)$ 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 $\pm$ 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 $(^{\circ}C)$ respectively. According to Eq. **Error! Reference source not found.**, 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:

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

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 .

Table 1. AMPV standard comfortability level.

AMPV	-2	-1	0	+1	+2
Thermal Comfort	Very Cold	Cold	Ideal	Warm	Very warm

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

PV output power forecasting

In order to take the advantages of Artificial Neural Network 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. 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. A representative train ANFIS for PV power forecasting application is presented in Figure 6. 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 multiple input systems.

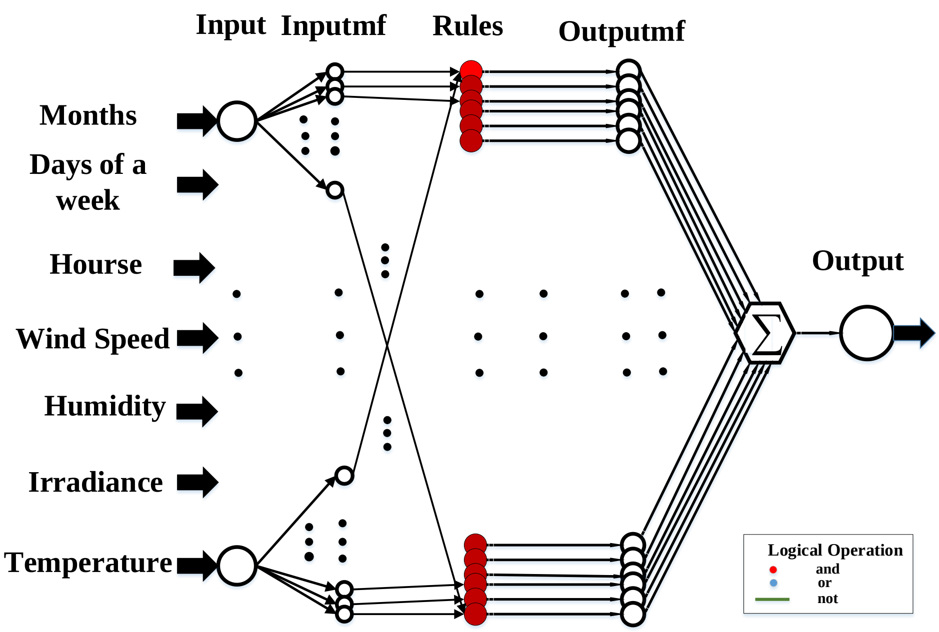


Figure 56. ANFIS structure for PV power generation.

6- Full Scale Test

For testing and validation of the energy management system, we have considered two test levels: Full scale testing in a "smart home" and full scale testing in the laboratory. Full-scale test in a "smart home": The project is supported by the company Solarflex A / S, which offers testing and validation as well as data collection of a "smart home" located in Ikast (Figure 7.). It currently contains solar cells, a battery storage system and a heat pump. It is also planned to equip it with electric cars. In order to provide necessary data for modeling we use these data from two real houses in IKAST and Esbjerg (Figure 8).

Figure 7. Residential house equipped by solar panels, heat pump and battery energy storage which is located in Ikast, Denmark.

Figure 8. Residential house equipped by solar panels which is located in Esbjerg, Denmark.

Moreover, Lab implementation in the university was done and a lab scale of microgird including PV and battery units, power electronic converters and DC and AC loads (Figure 9). Therefore, we implemented the proposed energy management system with all the information from real houses and it was verified in the Lab. The laboratory includes the folllwing equipment which is supported partly for Elforsk program.

- Solar panels (10 KW) which are set up on AAU Esbjerg's outdoor platform
- Convert DC / DC and DC / AC
- Batteries and loads for emulation of electric cars at AAU Esbjerg
- Heat pump and temperature emulator consisting of an AC / DC converter and DC load

AALBORG UNIVERSITY
DENMARK
Department of Energy Technology
Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

We implement the following method for emulator:

Electric car emulator: A mobile device is used to automatically report the distance traveled by a real car to an online system to discharge batteries according to mileage.

Heat pump emulator: A real-time simulator used for temperature control in a simulated house. On the electrical side, we control the said converter and load to represent a Hardware In the Loop (HIL) emulator.

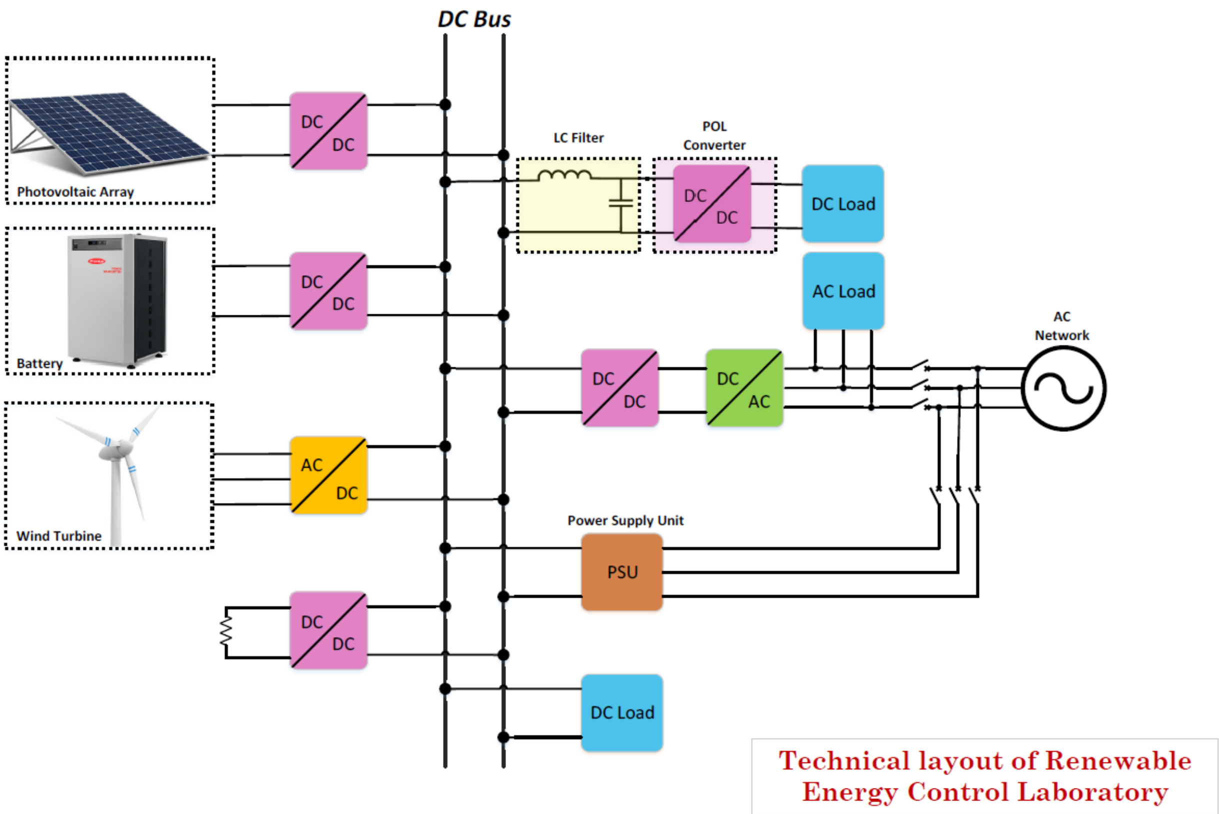


Figure 9. Lab scale of microgird including PV and battery units, power electronic converters and DC and AC loads

7- HEMS performance and profit Assessment

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 storage efficiency (different insulation quality or energy labels). Hence, in this part, a comprehensive comparison on the optimal HEMS performance in residential buildings with different storage efficiency (energy label) and different emission heating systems (floor-radiator heating system and radiator only system) is conducted. The HEMS is implemented as 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 improves 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. 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 EV (24 (kWh) lithium-ion battery pack), assumed same driving habits for all cases.
2) EV charging box of 240 (V), 16 (A),
3) 4 (kW) PV system including two paralleled subarrays with 8 PV series panels [13]
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 [14] is a criterion standard to measure the quality of a building in terms of energy use and loss of energy. In order to define an energy label for a building,

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

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 which 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. 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 2 have to be met for different parts of a building with energy label "A" in Denmark.

Table 2. Heat transfer parameters.

Building construction	Thickness (*mm*)	U value $(W/m^2.°C)$	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 2, the overall heat transfer conductivity is computed as given:

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

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

AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark

in Table 3 for different energy labels based on Denmark latest building regulation. Consequently, the building conductivity and building thermal time constant are computed for the above-mentioned size building and presented in Table 2 as well. For instance, the building with energy label A has a conductivity $\Lambda_{overall} = 0.066$ 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 0.0.66. 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 3: Overall building heat transfer conductivity and energy loss.

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

8- RESULTS

The HEMS optimal results are present for a building which is outlined in the last section with different energy labels (seven cases). The system parameters relating to building components and users are presented in Table 3. The HEMS controller is the MPC with time resolution 1 hour and time horizon 24 (h) from 00:00 to 24:00. The building load demand and PV output power are predicted by ANFIS. Moreover, the data related to weather forecast update at each time resolution by weather stations 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 cannot meet the user's thermal preference requirement for the building with energy label "G", so 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.

Table 4 -Smart home parameters

EV battery parameters				
P_{ev}^{max}	P_{ev}^{min}	Q	η	
3.5 (*kW*)	-3.5 (*kW*)	24 (*kWh*)	0.05	
SOC lower limit		SOC_0	SOC upper limit	
25%		0.6	90%	
Thermal parameters				
p_{hp}^{min}		p_{hp}^{max}	*COP*	
0 (*kW*)		6 (*kW*)	4	
$APMV^{min}$		$APMV^{max}$	$C_{building}$	$T_{in,0}$
-0.4		+0.4	1.32 $(kWh/^{\circ}C)$	25 $(^{\circ}C)$
User's clothing parameters				
Time Range		I_{cl}	Clothing Condition	
[7:00, 22:00]		0.7	Short sleeve shirt, light trousers, shoes	
[22:00, 7:00]		0.3	Underwear, T-shirt	

A rule-based controller is formulated to fulfill the problem requirements without optimizing the cost of energy for the baseline model. Figure 10, 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 10., the energy cost of the building reduces for either baseline performance or HEMS performance when the building energy label or building insulation quality improves (the best minimum case happens for building with energy label “A”). As an example, in Case I (label “A”) the home energy cost is 123.2 (*DKK/week*) and 72.33 (DKK/week) for baseline and HEMS performance with floor-radiator heating system respectively. While in Case VII (label “G”) the cost of energy is 557.55 (*DKK/week*) and 409.44 (*DKK/week*) for the same situation. As a fast result, the more insulation quality improves, the more reduction of energy cost guarantees whether the building performed with HEMS or not.

The second and more important result is to analyses the difference impact of having HEMS for buildings with different insulation quality in reducing energy cost. Therefore, Table is presented to highlight the HEMS optimal performance for different cases. For instance, in Case VI (label “F”) the HEMS reduces the energy cost from 58.43 (baseline performance) to 258.07 (*DKK/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 10 and Table 5, it is clear that the HEMS performance is much better in building with good insulation quality than building with poor ones. For example, in case I the building energy cost with HEMS reduce by about 41% while in case VII the energy cost minimizes by around 26% (with the floor-radiator combination heating system). It shows that the HEMS can have a better optimal performance in building with high insulation qualities.

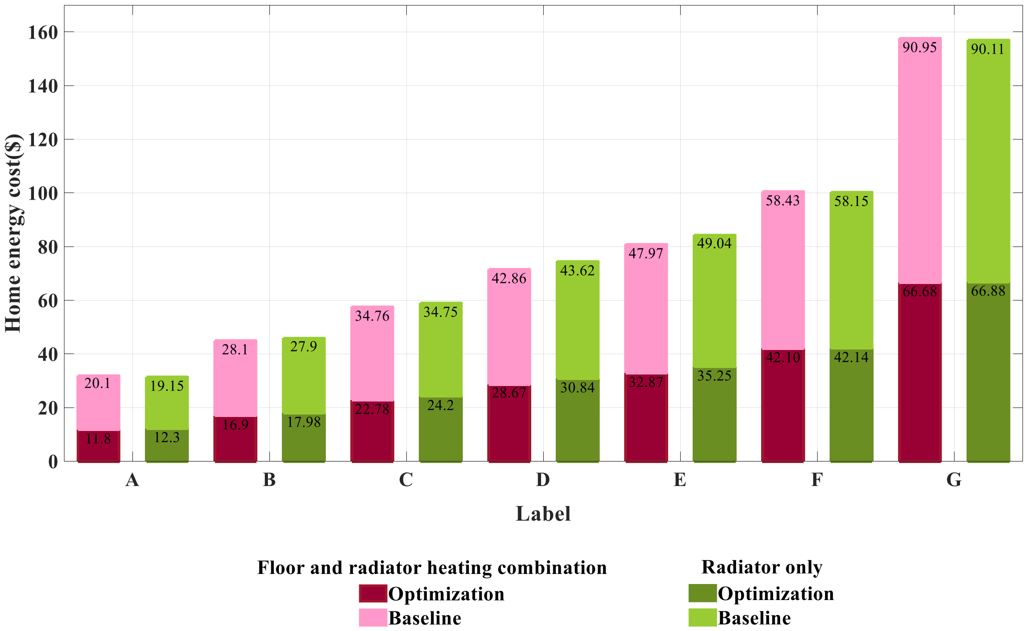


Figure 10. Total home energy cost for different energy labels (A-G) and two different heating systems (floor-radiator combination and radiator only), during January 2017.

Table 8: Reduction of the cost of home energy by HEMS as compared with baseline operation for different energy labels and two different heating systems

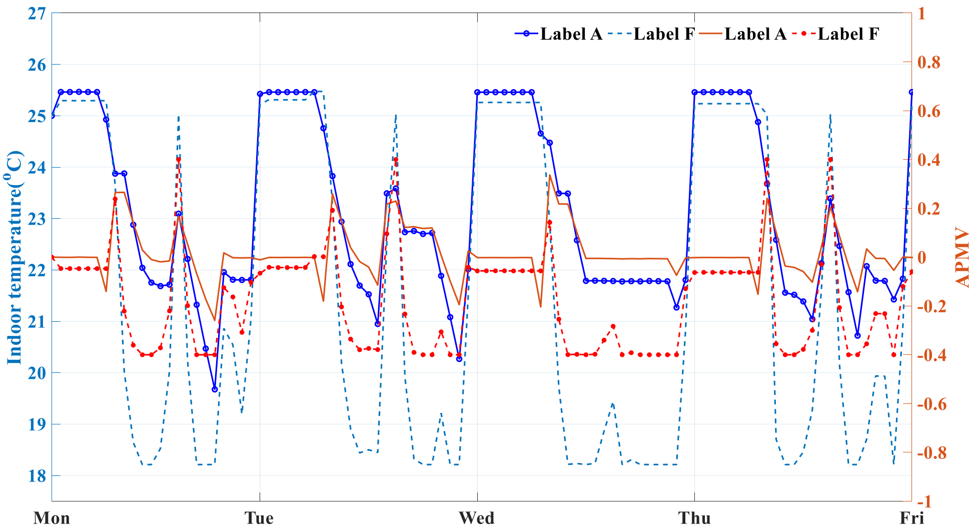
Building Label	Radiator Only (%)	Floor and radiator combination (%)
A	35.77	41.3
B	35.5	39.5
C	30.3	34.44
D	29.3	33
E	28.22	31.41
F	27.6	27.94
G	25.75	26.55

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 . For better resolution and clarity, the results are shown for four days from Monday to Friday. As it can be seen in Figure (a), the user's thermal comfort criteria (APMV) and building inside temperature is -0.4 and 18.5 $(^{\circ}C)$ most of the daylight time (marginal comfortability) for case IV(Label "F"). Similarly, in Figure (c), the SOC of 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 11(a), the APMV criterion is close to zero most of the times and the building inside temperature is above 20 $(^{\circ}C)$ all the week (except on Monday) even though the outside temperature is around 4 degrees on average for this week (Figure 11 (b)) for case I. Likewise, the PEV SOC changes are very small (results in improving battery lifetime [12]) for the case I compared with case IV as it is shown in Figure 11 As a consequence, when the building storage efficiency is poor (low building thermal resistance), the problem constraints move to the acceptable boundaries values in order 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 stay close to the desired points most of the time (APMV stays close to zero and SOC variation is small). Therefore for the case I, even the HEMS optimal performance is very good, the HEMS performance for fulfilling the requirements of the problem are much better than the cases with poor insulation quality.

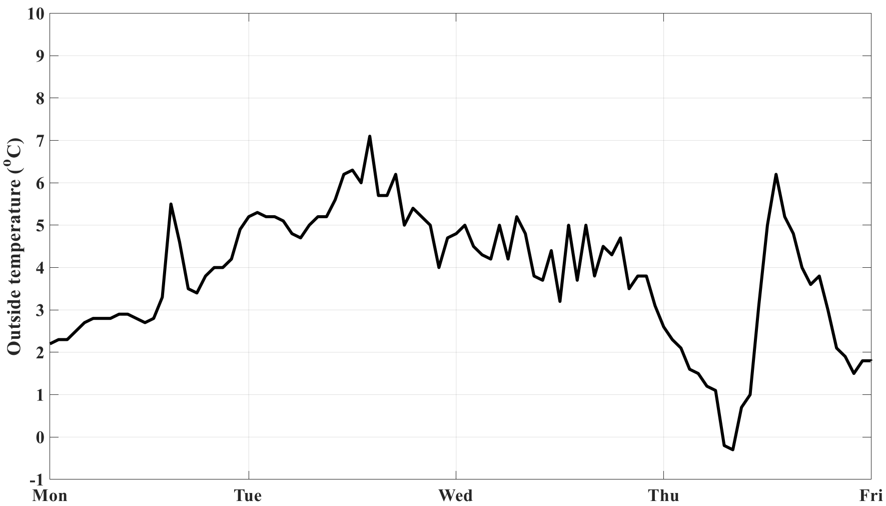
AALBORG UNIVERSITY
DENMARK

Department of Energy Technology

Niles Bohrs Vej 8, DK 6700 – Esbjerg, Denmark



(a)



(b)

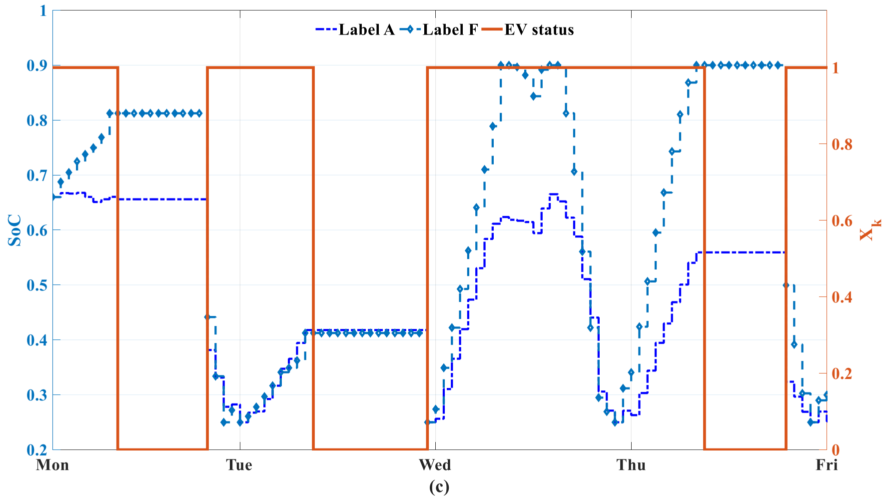


Figure 11. Comparison of HEMS performance in satisfying building's requirements with radiator heating system for buildings with label "A" and "F"; (a) stakeholder's thermal preference criteria (APMV) and indoor temperature, (b) outside temperature, (c) SOC and status of EV.

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 12. According to Figure (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 12 (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 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 Mon, Wed and Thu 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 12 (a). Furthermore, when the PV production is bigger than the load demand such as on Tue, Wed and Thu, 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 in order to avoid violating the problem constraints (either EV maximum charging or household's thermal preference). Hence, the grid power is not positive on Tue and Thu 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).

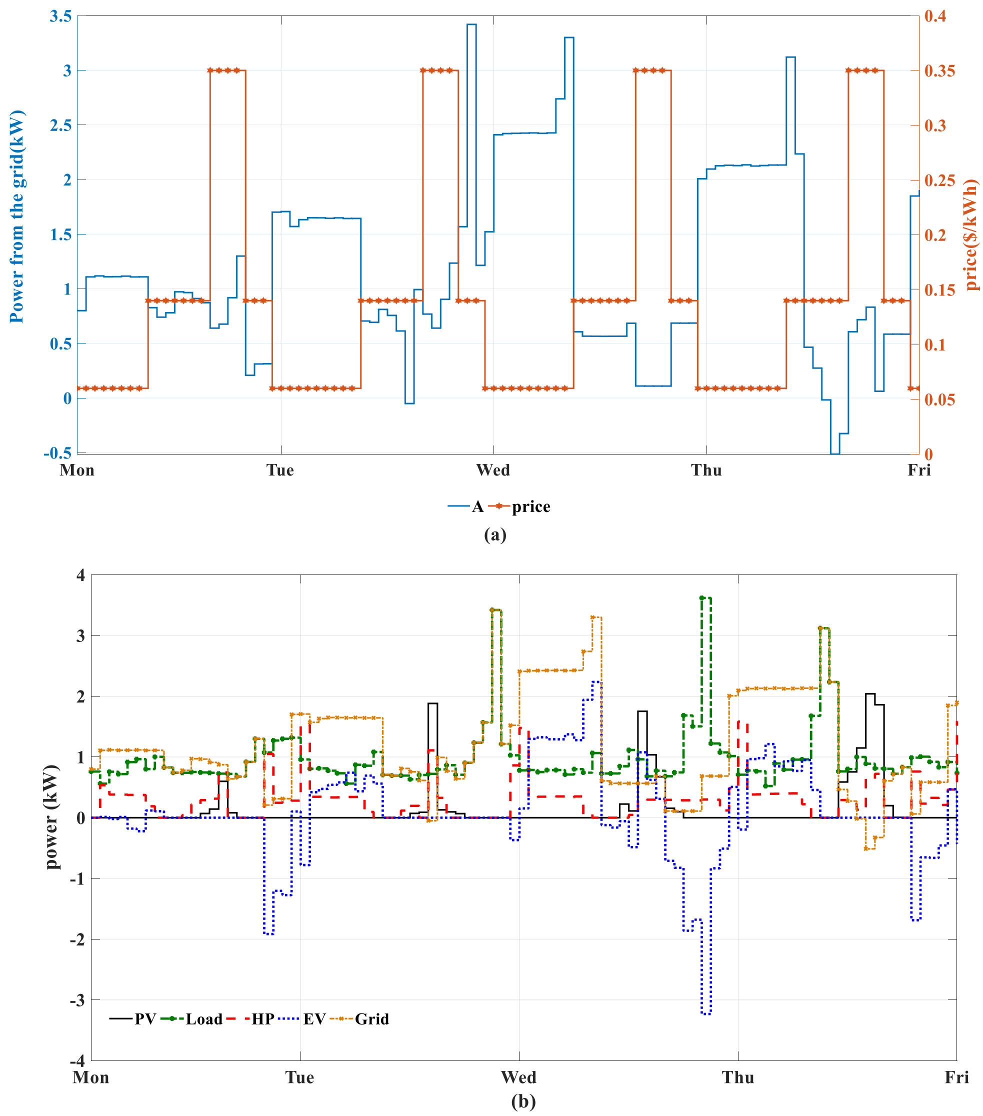


Figure 12 a) Grid power usage for different building energy labels (A-G) with a radiator system over four days in January 2017, (b) PV, HP, EV, and grid powers for Case I.

9- Project achievements

The following achievements have been realized:

- Minimize the cost of energy consumption by using photovoltaic and implementation proper energy management system, while satisfying space-heating requirements, taking into account limitations when charging PEV, as well as household consumption.
- Reduction of CO2 emissions around 40% by using renewable energy sources such as solar cell systems: this project promotes the using of photovoltaic for residential building to supply the electrical power for the home demands. The proposed energy management maximizes the self-consumption of PV units and this makes reduction the dependency to the grid and finally it can reduce the CO2 emissions.
- Promoting the PEV owners to use the energy management system to reduce the cost of electricity and improve the battery life time or PEV. In this case, it reduces the CO2 emissions.
- Improving energy efficiency by using PEV and HP to provide the best possible living conditions for homeowners: One of the aspect of smart home project is improving the energy efficiency. Because the proposed energy management system maximize the self-consumption of PV power and decreases the amount of power form the grid, finally the power loss in the grid will reduces. Therefore, energy efficiency will improve. If more peoples are encouraged using the smart home energy management system, therefore, it will have huge impact on the energy efficiency. Moreover, tracking the comfort temperature helps the heat pump consume energy efficiently and the power consumption reduces. Moreover, by integration IoT sensors, Smart homes save energy by keeping track of which rooms you use and when you use them.

- Improving power reliability in residential systems: Utilization more renewable energy resources and integration energy storage to building makes the dependency to grid reduces and during the outage the reliability of power supply to home increase. Moreover, this system helps the peak shaving in the grid during peak time. In the home side, demand management and consumption shifting will help the peak shaving and finally it will increase the reliability of power.

- Improving the flexibility of energy management by leveraging PEV and HP: Since the energy management system determines when the power should be supplied or delivered form/to the grid by considering the electricity price, load demand and availability of PEV, the flexibility of the energy management system increases. In this case, demand power form the home has this flexibility to be supplied form the renewable energy resources and energy storage or from the grid based on the satisfying the technical requirements. In order to provide this flexibility, there should be investment in solar units, sensors, heat pump and control based computer systems. In the other hand, because of energy saving and reduction of energy cost, this amount of investment will be returned.

10- Research and development

1- Modeling of smart home energy management systems

2- Using Artificial Intelligence (AI) tools for prediction of PV outputs and load profile

3- Development of statistical tool for calculation of PEV demand profile

4- Using Model Predictive Control (MPC) for home energy management system

5- Publication:

   a. *"Profit Assessment of Home Energy Management System for Buildings with A-G Energy Labels"*, accepted for Publication in Applied Energy Journal. (https://doi.org/10.1016/j.apenergy.2020.115618)

b. "Predictive Home Energy Management System with Photovoltaic Array, Heat Pump and Plug-in Electric Vehicle", accepted for publication IEEE Transactions on Industrial Informatics (DOI: https://doi.org/10.1109/TII.2020.2971530) .

c. *"A Comparison Study on Stochastic Modeling Methods for Home Energy Management System."* In: IEEE Transactions on Industrial Informatics. 2019 ; Vol. 15, No. 8. pp. 4799 - 4808. (DOI: https://doi.org/10.1109/TII.2019.2908431)

d. ANFIS Based Approach for Stochastic Modeling of Smart Home. In Proceedings of 2018 2nd European Conference on Electrical Engineering and Computer Science (EECS) IEEE Press. https://doi.org/10.1109/EECS.2018.00091

e. Energy Management strategies for Smart Home Regarding Uncertainties: State of the art, Trends, and Challenges. In Proceedings - 2018 IEEE International Conference on Industrial Technology, ICIT 2018 (pp. 1219-1225). IEEE. https://doi.org/10.1109/ICIT.2018.8352352

6- External Collaboration

- SmartEnergi , Denmark
- Remoni, Denmark

11- References

[1] European Commission, “Nearly zero-energy buildings,” European Commission, 2014.

[2] X. W. Zhou, Bin, Wentao Li, Ka Wing Chan, Yijia Cao, Yonghong Kuang, Xi Liu, “Smart home energy management systems: Concept, configurations, and scheduling strategies,” Renew. Sustain. Energy Rev., vol. 61, pp. 30–40, 2016.

[3] X. Wu, X. Hu, S. Moura, X. Yin, and V. Pickert, “Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array,” J. Power Sources, vol. 333, pp. 203–212, 2016.

[4] P. Gilman, N. A. DiOrio, J. M. Freeman, S. Janzou, A. Dobos, and D. Ryberg, “SAM Photovoltaic Model Technical Reference 2016 Update,” 2018.

[5] X. Wu, X. Hu, X. Yin, and S. Moura, “Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage,” IEEE Trans. Smart Grid, vol. 9, no. 3, pp. 2065–2075, 2016.

[6] Technical Standards for Solar Home Systems (SHS), [Online]. Available: https://energypedia.info/wiki/Technical_Standards_for_Solar_Home_Systems_(SHS)

[7] Sandia National Laboratories, Ed., Stand-Alone Photovoltaic Systems: A Handbook of Recommended Design Practices. Springfield, VA: NTIS, 1995.

[8]"Load Representation for Dynamic Performance Studies", IEEE Transactions on Power Systems, vol. 8, no. 2, pp. 472-482, May 1993.

[9] Amin Hajizadeh et al, "Plug-in Electric Vehicle Behavior Modeling in Energy Market: A Novel Deep Learning-Based Approach with Clustering Technique", IEEE Trans. Smart Grid, 2020.

[10]"IEEE recommended practice for sizing lead-acid batteries for standalone photovoltaic (PV) systems," IEEE Std 1013-2007 (Revision of IEEE Std 1013-2000), pp. 1-54, 2007.

[11] R. Yao, B. Li, and J. Liu, “A theoretical adaptive model of thermal comfort – Adaptive Predicted Mean Vote (aPMV),” Build. Environ., vol. 44, no. 10, pp. 2089–2096, 2009.

[12] International ISO standard 7730, “Ergonomics of the thermal environment — Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria,” 2005.

[13]"IEEE guide for array and battery sizing in stand-alone photovoltaic (PV) systems," IEEE Std 1562-2007, pp. i -22, May 2008.

[14] “Energy labeling of homes.” [Online]. Available: https://sparenergi.dk/forbruger/boligen/energimaerkning-boliger/huse.